Survey and Analysis of the Use Statistical Process Control Methods in Selected Czech Manufacturing Companies

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***Abstract*—**The aim of this paper is to see if the selected statistical methods cited in scientific publications related to statistical process control (SPC) are really used in practice and whether the degree of difficulty of used methods depends on company size. We decided to use the questionnaire in combination with personal interview with quality engineers to map the current situation in the Czech manufacturing companies in the application of statistical methods in process management. 80 Czech manufacturing companies from various sectors in which was assumed the use of statistical tools for quality management were addressed. Information on the results of this survey and the most common problems with the use of SPC tools will be described in the following text.

***Keywords*—**Quality control, Questionnaire survey, SPC (Statistical Process Control), Statistical methods

I. Introduction

Current research concerning the use of exact methods in quality control indicates a growing trend in the application on these methods.

This paper will take the issue of statistical methods and tools research where the goal will be to determine whether the selected statistical methods reported in scientific publications related to the issue of SPC (statistical process control) are actually used in practice. To perform research, data were collected and this was obtained through working with managers of companies and managers in production. It was used a web interface and database for collecting and storing data. The last step was the evaluation of these data with adequate statistical methods including interpretation of the conclusions provided by them.

At this point, we must point out that similar surveys were already made in Japan in the 70 years. Using mathematical and statistical methods for process control is a preventive quality management tool since the early detection of significant deviation in the process from a predefined level allows the process to implement interventions in order to maintain it at acceptable and long-term stable level or eventually enable process improvement. In addition to classical methods such as descriptive statistics, ANOVA, hypothesis testing, regression analysis, reliability analysis, there are still some special statistical methods to the needs of quality management. These are especially different types of control charts, the analysis of discrete variables, statistical acceptance, capability analysis, sampling, reliability analysis, Pareto analysis and others. It is obvious that a worker without adequate education or good training cannot effectively and properly use these tools.

Manufacturing organizations are looking for SPC to help them with the following areas:

- *Improve Product Quality* – One way to improve product quality is to reduce the variation in the output of company process. By identifying the sources of variability that go into the manufacture of company product, and using SPC to analyze their impact, identify problems, and monitor the results they can improve achieve their quality goals.
- *Reduce Scrap and Rework* – Scrap and rework costs consist not only of lost labour and material, but the unexpected organizational cost on managing and handling these scrapped parts. Since SPC analysis provides trends of their process capabilities they can take action to correct process problems before scrap is generated.
- *Increase Manufacturing Yield* – Fewer scrapped parts means a higher yield for company investment in materials and equipment. It also means a more productive workforce.

Meet Customer Requirements – Customers want to see evidence that company processes will product parts that meet their requirements. In the Automotive industry, the TS 16949 standard specifically calls for evidence that their organization can use SPC for the monitoring and measurement of company process capabilities. Implementing SPC allows them to satisfy their customer while improving their product.

II. Literature review

Companies are constantly under pressure not only to design new products faster, but also accelerate their production in today's competitive environment. Minimization of time, which

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is necessary for the product introduction to the market, is required as well as cost prediction and last but not least the increasing demands on product quality [10].

The result of the implementation and active use of statistical methods in the process data analysis is more accurate image of the process or even construction of a model of interdependencies and influencing the various elements and phases of technology.

This model can be used to find the causes of variability and instability and to real increase in quality and stability. The aim of introducing statistical analysis is mainly to improve quality. Absolutely dominant tool for these tasks is a computer statistical analysis. The vast majority of programs only replace the routine work of practitioners.

This state is often considered to be satisfactory. But problems arise when methods assumptions are not met (e.g. normality, absence of gross errors, sufficient sample size, statistical process stability, etc.) From this perspective, some statistical programs or their combination is better. They allow complex statistical data analysis and also control chart construction and other additional tools for quality management [1].

Integration of statistical analysis in economic activities is strictly required by many regulations and standards. The best known is a series of ISO 9000. Generally, we can name ČSN and ČSN ISO from the field of applied statistics, standards from statistical regulation, standards from statistical acceptance, standards ČSN and ČSN ISO from reliability and a new standard ISO 22514 series (Statistical Methods in Process Management – Capability and Performance – Part 1: General Principles and Concepts) [7].

In this era of strains on the resources and rising costs of manufacturing, it becomes increasingly apparent that decisions must be made on facts, not just opinions. Consequently, data must be gathered and analysed. This is where statistical process control (SPC) comes in. For over 70 years, the manufacturing arena has benefited from the tools of SPC that have helped guide the decision-making process. SPC is one of the techniques used in quality assurance programs and/or total quality management (TQM) practices, for controlling, monitoring and managing a process either manufacturing or service through the use of statistical methods [11]. According to Vijaya and Arumugam, 2010 in [12], SPC is a set of tools for managing the processes, and hence, determining and monitoring the quality of the outputs of an organization.

In particular, the control chart has helped determine whether special-cause variation is present implying that action needs to be taken to either eliminate that cause if it has a detrimental effect on the process or to make it standard operating procedure if that cause has a beneficial effect on the process. If no special-cause variation is found to be present, SPC helps define the capability of the stable process to judge whether it is operating at an acceptable level [14].

Control charts are graphical displays of some summary statistic of the observed data (e.g. indicators) against the order index of the sample (e.g. time), together with reference "marks" based on the in-control mean and variance, that are designed to detect whether a worrisome change in process output is indicated by the current data and action is required to fix it. Since there are costs associated with both false alarms and quality losses in commercial products, the charts' parameters are tuned to achieve a desired trade-off between the risk of false alarm and the ability to detect changes promptly. The terms of the detection/decision problem in manufacturing contexts, as just outlined, should sound familiar to whoever is involved in monitoring the status of fish stocks or marine ecosystems for advising managers. The latter typically expect that experts raise a timely signal when a worrisome change is occurring in marine resources, warranting corrective action, while requiring that the alarm is based on strong evidence. There are thus good reasons to believe that the SPC tools are relevant for natural resources management [15].

Accountability with hard data, not fuzzy opinions, is being demanded. Existing processes must be examined and new ones discovered. The good news is that improved quality inherently lowers costs as it provides a better product and/or service [13]. Statistical Process Control provides accountability and is an essential ingredient in this quality effort.

Statistical Process Control is not an abstract theoretical exercise for mathematicians. It is a hands-on endeavour by people who care about their work and strive to improve themselves and their productivity every day. SPC charts are a tool to assist in the management of this endeavour. The decisions about what needs to be improved, the possible methods to improve it, and the steps to take after getting results from the charts are all made by humans and based on wisdom and experience [6].

It is advisable to mention the most frequently research issue in the field of Statistical Process Control. The change point belongs to them without any doubt.

In fact, change point problems have originally arisen in the context of quality control, but the problem of abrupt changes in general arises in many contexts like epidemiology, rhythm analysis in electrocardiograms, seismic signal processing, study of archeological sites and financial markets. In particular, in the analysis of financial time series, the knowledge of the change in the volatility structure of the process under consideration is of a certain interest.

Various authors have studied change point detection problems using parametric and non-parametric procedures quite extensively. In some cases, the study was carried out for known underlying distributions, namely the binomial, Poisson, Gaussian and normal distributions, amongst others. This chapter discusses some of the work that has been done on change point detection.

CUSUM is one of the widely used change point detection algorithms. Basseville & Nikiforov (1993) described four different derivations for the CUSUM algorithm. The first is more intuition-based, and uses ideas connected to a simple integration of signals with an adaptive threshold. The second derivation is based on a repeated use of a sequential probability ration test. The third derivation comes from the use of the off-line point of view for multiple hypotheses testing. The fourth derivation is based upon the concept of open ended tests. The principle of CUSUM stems from stochastic hypothesis testing method.

Nazario, Ramirez and Tep (1997) developed a sequential test procedure for transient detections in a stochastic process that can be expressed as an autoregressive moving average (ARMA) model. Preliminary analysis shows that if an ARMA(p,q) time series exhibits a transient behavior, then its residuals behave as an ARMA(Q,Q) process, where: $Q \leq p + q$. They showed that residuals from the model before the parameter change behave approximately as a sequence of independent random variables - after a parameter change, the residuals become correlated. Based on this fact, they derived a new sequential test to determine when a transient behavior occurs in a given ARMA time series.

Blazek, HongJoong, Boris and Alexander (2001) developed efficient adaptive sequential and batch-sequential methods for an early detection of attacks from the class of “denial-of-service attacks". Both the sequential and batch-sequential algorithms used thresholding of test statistics to achieve a fixed rate of false alarms. The algorithms are developed on the basis of the change point detection theory: to detect a change in statistical models as soon as possible, controlling the rate of false alarms. There are three attractive features of the approach. First, both methods are self-learning, which enables them to adapt to various network loads and usage patterns. Second, they allow for detecting attacks with a small average delay for a given false alarm rate. Third, they are computationally simple, and hence, can be implemented online. For more about false alarm rates e.g. for the Shewhart control charts see in [29].

Huat and Midi (2010) in [33] examine a process-monitoring tool that not only provides speedy detection regardless of the magnitude of the process shift, but also provides useful change point statistics.

Lund, Xiaolan, Lu, Reeves, Gallagher and Feng (2007) looked at the change point detection in periodic and auto correlated time series using classic change point tests based on sums of squared errors. This method was successfully applied in the analyses of two climate changes.

Moskvina and Zhigljavsky (2003) developed an algorithm of change point detection in time series, based on sequential application of the singular-spectrum analysis (SSA). The main idea of SSA is performing singular value decomposition (SVD) of the trajectory matrix obtained from the original time series with a subsequent reconstruction of the series.

Mboup, Join and Fliess (2008) presented a change point detection method based on a direct online estimation of the signal’s singularity points. Using a piecewise local polynomial representation of the signal, the problem is cast into a delay estimation. A change point instant is characterized as a solution of a polynomial equation, the coefficients of which are composed by short time window iterated integrals of the noisy signal. The change point detector showed good robustness to various types of noises.

Auret and Aldrich (2010) used random forest models to detect change points in dynamic systems. Wei, Hanping, Yue and Wang (2010) used Lyapunov exponent and the change point detection theory to judge whether anomalies have happened. Aldrich and Jemwa, (2007) used phase methods to detect change in complex process systems.

Vincent (1998) presented a new technique for the identification of inhomogeneities in Canadian temperature series. The technique is based on the application of four linear regression models in order to determine whether the tested series is homogeneous. Vincent’s procedure is a type of “forward regression” algorithm in that the significance of the non-change point parameters in the regression model is assessed before (and after) a possible change point is introduced. In the end, the most parsimonious model is used to describe the data. The chosen model is then used to generate residuals. It uses the autocorrelation in the residuals to determine whether there are inhomogeneities in the tested series. At first, it considers the entire period of time and then it systematically divides the series into homogeneous segments. Each segment is defined by some change points, and each change point corresponds to either an abrupt change in mean level or a change in the behavior of the trend. [16] – [56]

Statistical methods play a vital role in quality improvement. Some applications are outlined below:

1. In product design and development, statistical methods, including designed experiments, can be used to compare different materials, components, or ingredients, and to help determine both system and component tolerances. This application can significantly lower development costs and reduce development time. [56]
2. Statistical methods can be used to determine the capability of a manufacturing process. Statistical process control can be used to systematically improve a process by reducing variability. [57]
3. Experimental design methods can be used to investigate improvements in the process. These improvements can lead to higher yields and lower manufacturing costs. [57]
4. Life testing provides reliability and other performance data about the product. This can lead to new and improved designs and products that have longer useful lives and lower operating and maintenance costs. [57]

It is essential that engineers, scientists, and managers have an in-depth understanding of these statistical tools in any industry or business that wants to be a high-quality, low-cost producer.

III. Problem Formulation

The first survey was conducted for the issue of statistical methods and tools. It consisted in studying the available literature on these instruments. The aim of this research was to analyse which methods and tools are recommended with a focus on statistical process control. It was studied 25 (of which 4 Czech and 21 English) professional publications on the theme of the use of statistical methods in quality control. Each has its own unique approach to characterize this strategy as well as different approaches to methods and tools in the SPC issue.

The list of most frequently reported methods and tools according to the literature is shown in Fig. 8. It was subsequently conducted second survey which consisted in questioning the applicability of statistical methods in quality management in selected enterprises. 26 companies (32.5 %) involved to a questionnaire survey of all 80 surveyed companies. The aim was to determine whether the selected statistical methods presented in professional publications related to the SPC are really used in practice.

Two research hypotheses were defined:

1. Does the degree of difficulty of used statistical methods in the SPC depend on the firm size?
2. Are the selected statistical methods reported in scientific publications related to the SPC really used in practice?

A. Research methods conducted

Qualitative and also quantitative research was used for the issue solution.

When solving these research problems methods are adequate to issues and objectives – a combination of qualitative and quantitative methods of research. Quantitative research method is used for summarizing the results of comparative survey and a questionnaire. Statistical methods (descriptive and mathematical statistics – statistical induction) used in processing the results are based on the experience of the authors.

B. Processing the Results of Research by Analyzing the Dependence of Two Categorical and Two Numerical Variables

This section defines the statistical methods used in processing the results of our research. When investigating the possible dependence of two nominal variables defined in the first research hypothesis will be used χ^2-test in contingency table. The results of observations are recorded for easy reference in the contingency (pivot) table. Pivot table is created when we sort the file according to two variants of qualitative features A and B where A has r variants and B has s variants. The null hypothesis is: A variable and B variable are independent. Test statistic is displayed by following formula:

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{s} \frac{(n_{ij} - n^*_{ij})^2}{n^*_{ij}}, \tag{1}$$

where n^*_{ij} are the theoretical frequencies [2], [5]. The rejection region is defined by: $\chi^2 \geq \chi^2_{1-\alpha}((r-1)(s-1))$. If the value of the test statistic falls into rejection region we can reject the null hypothesis. It means that the dependence between A and B was proved [3].

When we want to know whether there is a correlation (dependence) between two categorial variables. Results can be assumed in the contingency table (a special case of 2D table for categorial variables).

There is the scheme of contingency table for A and B variables in Table 1 (*r* – number of rows; *s* – number of columns).

Tab. 1 Contingency table

A \ B	$\mathbf{B_1}$	$\mathbf{B_2}$	**...**	$\mathbf{B_s}$	$\sum_j$
$\mathbf{A_1}$	n_{11}	n_{12}	...	n_{1s}	$\mathbf{n_{1.}}$
$\mathbf{A_2}$	n_{21}	n_{22}	...	n_{2s}	$\mathbf{n_{2.}}$
...	...	...	...	...	**...**
$\mathbf{A_r}$	n_{r1}	n_{r2}	...	n_{rs}	$\mathbf{n_{r.}}$
$\sum_i$	$\mathbf{n_{.1}}$	$\mathbf{n_{.2}}$	**...**	$\mathbf{n_{.s}}$	**n**

The null hypothesis is: A and B are independent.
The alternative hypothesis is: A and B are dependent.

The Spearman rank correlation coefficient (similar to the Pearson paired correlation coefficient) is used in investigating if there a dependence between two numeric (ordinal) variables. It is defined by the following formula

$$r_s = 1 - \frac{6\sum (i_x - i_y)^2}{n(n^2-1)}, \tag{2}$$

where i_x and i_y are the ranks of values of variables *x* and *y*, *n* – sample size [4], [9].

Values of the Spearman rank correlation coefficient are from the interval <–1; 1>, while values around 0 indicate independence, values close to 1 or –1 indicate direct or indirect dependence.

C. Advanced Correlation Analysis

Nonparametric Measures (Rank Correlation)

We use often following two correlation coefficients as a measure of the degree of association between ranks:
a) Spearman rank correlation coefficient;
b) Kendall rank correlation coefficient.

1. Rank Correlation (Spearman Rank Correlation Coefficient)

The Spearman rank correlation coefficient (similar to the paired correlation coefficient) is defined by the formula:

$$r_s = 1 - \frac{6\sum (i_x - i_y)^2}{n(n^2-1)}, \quad (9.1) \tag{3}$$

where i_x a i_y are the **ranks** of variables *x* and *y*,
n – the number of observations.

The Spearman rank correlation coefficient can vary from –1 to +1 (inclusive). It measures the closeness of the relationship between the two sets of ranking.

Test of significance for r_s:

The null hypothesis H_0: $\rho_s = 0$ (not significant) against the alternative hypothesis H_1: $\rho_s \neq 0$ (significant).
The test statistic is:

$$t = \frac{r_s}{\sqrt{1-r_s^2}}\sqrt{(n-2)}\,. \tag{4}$$

Decision rule:

We can reject the null hypothesis if $|t| \geq t_{1-\alpha/2}(n-2)$, otherwise we do not reject it.
We can also use the critical values for r_s.
In case of the concordances in ranks, we have to adjust the formula (5) for r_s:

$$r_s = 1 - \frac{6\sum(i_x - i_y)^2}{n(n^2-1) - C}, \tag{5}$$

for the correction term C is used formula:

$$C = \frac{1}{2}\left[\sum_k (h^3_{x,k} - h_{x,k}) + \sum_{k'} (h^3_{y,k'} - h_{y,k'})\right]. \tag{6}$$

2. Kendall Rank Correlation

The Kendall rank correlation coefficient is used for more than two ranks (i.e. 3 or more).
Formula for r_k is:

$$r_k = \frac{12}{m^2(n^3-n)}\sum_{j=1}^{n} A_j^2 - 3\frac{n+1}{n-1} \in \langle 0;1 \rangle, \tag{7}$$

where *m* – the number of ranks,
n – the number of observation,
A_j – the sum of ranks.

If there are found concordances in ranks, we use following adjusted formula for r_k

$$r_k = \frac{12\left[\sum_{j=1}^{n} A_j^2 - \frac{m^2 n(n+1)^2}{4}\right]}{m\left[mn(n^2-1) - \sum_{i=1}^{m}\sum_{k=1}^{p_i}(h^3_{i,k} - h_{i,k})\right]} \in \langle 0;1 \rangle. \tag{8}$$

Test of significance for r_k:

The null hypothesis: r_k is not significant (H_0: $\rho_k = 0$) against the alternative hypothesis that r_k is significant (H_0: $\rho_k \neq 0$).
The test statistic is given by:

$$\chi^2 = m(n-1)r_k.$$

The rejection region is set to:

$$\chi^2 \geq \chi^2_{1-\alpha}(n-1).$$

IV. Problem Solution

First, we focus on the distribution of companies by sector in the questionnaire. The following Fig. 1 shows the relative proportions of respondents by the industry sector. Respondents answered the following question: “In which industry sector your company operates?”

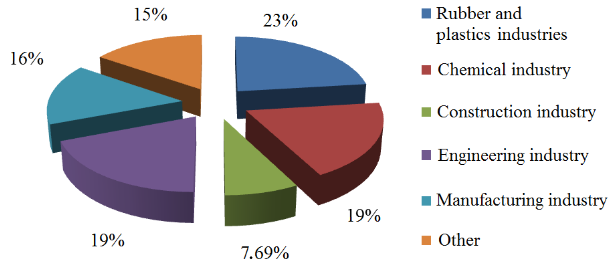

Fig. 1 Distribution of Surveyed Companies by Sector. Source: Own Processing

The previous graph shows that most of the companies surveyed were from rubber and plastics industries. The relatively high proportion was also observed in the area of chemical and engineering industries. Section Other includes companies operating in the food and service sector. Construction companies have the lowest proportion (7.69 %).
Another part of the questionnaire survey focused on the distribution of companies by the number of employees. Interviewed respondents answered the question: “How many employees work in your company?” Results are shown in Fig. 2.

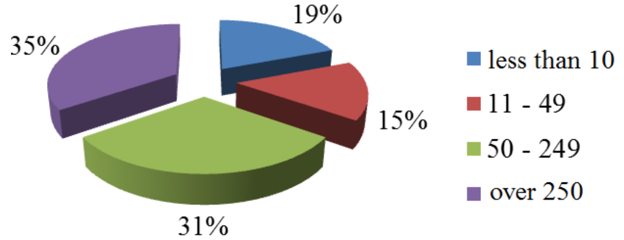

Fig. 2 Distribution of Surveyed Companies by Number of Employees. Source: Own Processing

Most respondents are companies that employ more than 250 employees and companies from 50 to 249 employees.
The question arises at this point whether the degree of statistical methods in the SPC difficulty depends on the company size. This question is answered below. The following Fig. 3 shows respondents´ answers to the question: “What does your company turnover in millions of Euros?”

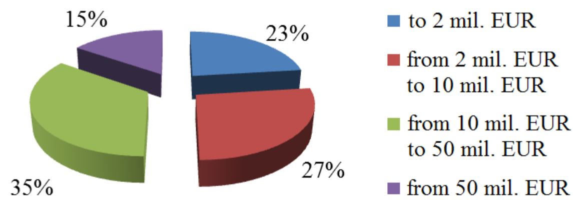

Fig. 3 Distribution of Surveyed Companies According to Annual Sales in Millions Euros. Source: Own Processing

The question:” Is there legislation in your company (instructions, directives, manuals, etc.) that would describe the statistical methods used?” replied 84.62 % of surveyed respondents in the affirmative suggesting that the companies actually use the statistical methods in quality control.

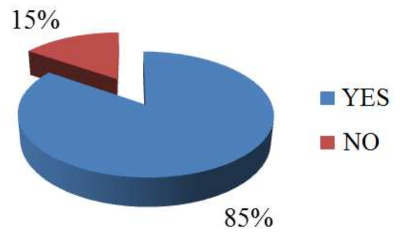

Fig. 4 The Existence of Regulation Which Would Describe the Statistical Methods Used in Companies.
Source: Own Processing

22 respondents answered in the affirmative in the absolute frequencies. Last but one question concerning the companies was: “Who carries out the application and evaluation of statistical methods?” As shown in the following Fig. 5, application and evaluation of statistical methods is most performed at the level of middle management and specialist. The statistical analysis is carried out by trained Black Belt at the level of top management in the large companies.

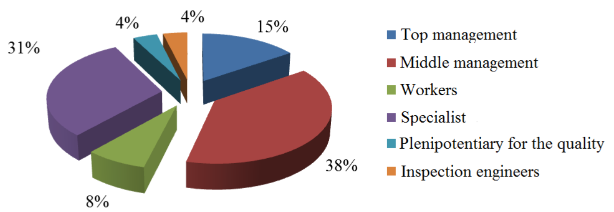

Fig. 5 The Level of Management That Performs Application and Evaluation of Statistical Methods According to Surveyed Companies. Source: Own Processing

A. Dependence of Degree of Difficulty of the Statistical Methods in Quality Control on the Company Size

We try to verify or reject this research hypothesis on the basis of statistical nonparametric χ^2-test of independence in the contingency table. Companies were divided into categories according to the number of employees and turnover according to [25]. Difficulty of the used statistical methods was divided as follows including their abbreviations in parentheses:

- **Elementary methods:** Pareto analysis (PA), cause and effect diagram (CED), histogram (HI), scatter plot (SP) and flowcharts (PM).
- **Medium intensive methods:** hypotheses testing (HT), analysis of variance (ANOVA), time series (TS), design of experiments (DOE), regression and correlation (RaCA).
- **Intensive methods:** statistical process control (SPC), investigation of process capability (ICP), measurement system analysis (MSA), method FMEA (FMEA), statistical acceptance (AS), multivariate methods SPC (MMSPC).

Consequently, we briefly define the most common methods:

- **Pareto analysis (PA)** – Pareto rule takes its name after the Italian economist Vilfredo Pareto, who claimed that a large part of the wealth (80 %) is in the hands of a small number of people (20 %). Therefore, this analysis is also called the rule "80-20". It is an effective, affordable and easy to apply decision making tool in the area of quality management [16].
- **Cause and effect diagram (CED)** – A Cause-and-Effect Diagram is a tool that helps identify, sort, and display possible causes of a specific problem or quality characteristic. It graphically illustrates the relationship between a given outcome and all the factors that influence the outcome. This type of diagram is sometimes called an "Ishikawa diagram" because it was invented by Kaoru Ishikawa, or a "fishbone diagram" because of the way it looks [16].
- **Histogram (HI)** – A histogram is one of the basic quality tools. It is used to graphically summarize and display the distribution and variation of a process data set. A frequency distribution shows how often each different value in a set of data occurs. The main purpose of a histogram is to clarify the presentation of data. You can present the same information in a table; however, the graphic presentation format usually makes it easier to see relationships. It is a useful tool for breaking out process data into regions or bins for determining frequencies of certain events or categories of data. These charts can help show the most frequent [17].
- **Hypotheses testing (HT)** – Statistical hypothesis means an assumption about the shape of the distribution or the parameters. This assumption may relate to characteristics of the random variable in the population or may be more general and apply only to the law of random variable (the distribution function, the probability function or probability density), the randomness, independence, etc. Assumptions that form the statistical hypothesis are based on previous experience and information and not based on random selection. This is the basis for the verification of statistical hypotheses and own inductive conclusion [18].
- **Analysis of variance (ANOVA)** – Analysis of variance (acronym ANOVA) in industrial applications allows the assessment of the influence of various factors on the production process. ANOVA can evaluate the effect of using different types of raw materials to production quality, etc. Analysis of variance in economic applications allows assess the influence of various factors on the economic process, to evaluate the effects of various measures taken, etc. ANOVA was originally derived by R.A. Fisher (1935) as a very effective procedure in the statistical analysis of biological (mainly agricultural) research. The essence of the analysis of variance is that the total variance is divided into partial variances belonging to each respective condition under which empirical data are sorted. Apart from these partial variances is one element in the total variance the residual variance, which is caused by other factors not included into analysis. We determine the factors that significantly affect the level of tested character by comparing the components of total variance [19].
- **Statistical process control (SPC)** – It was mentioned in the chapter Literature review. The reader can learn in [16] – [22] about this vastly extensive discipline.
- **Measure system analysis (MSA)** – Measurement and analysis is also a process – the process of measurement. Measuring equipment is only part of the measurement process.

Operator must know how to properly use the equipment and how to analyze and interpret the results. Management must provide clear operational definitions and standards, training and support. On the contrary, the operator has the responsibility to monitor and control the measurement process so as to ensure the stable and correct results. Each measured value will differ from the others even for rigorous compliance with the conditions under which it was measured. Individual values will vary from the value that should represent [20].

- **Scatter plots (SP)** – Scatter plot is a graphical representation of stochastic dependency of two random variables. This diagram provides primary information on the existence of stochastic dependence, the shape and the level of correlation [18].
- **Method FMEA (FMEA)** – It is a collaborative analysis of the possible causes of the considered design, coupled with assessment of risk, which is the starting point for the design and implementation of measures to reduce these risks. It is an important part of the design review. Its application can detect up to 90% of potential differences [18].
- **Design of experiments (DOE)** – When calculating the cost of quality, Taguchi methods are based on the assumption that the product is determined by a certain optimum value of T, to be achieved (such as shaft diameter, tensile strength, sulfur content in pig iron, etc). Failure in the production of T is a manifestation of poor quality, which brings financial loss. We deal with the question to determine which factors have the most significant effect on the monitored output Y by the design of experiments [21].
- **Statistical acceptance (AS)** – Statistical acceptance is a method of sampling inspection products. Its aim is to clear decision on whether controlled dose products, raw materials, etc. meets the requirements for quality and whether it should be accepted or not. Deeper theoretical basics of acceptance methods are given for example in [24]. Practical recommendations for different types of acceptances can be found in standards, specifically in [23] regarding the statistical acceptance
- **Flowcharts (PM)** – Flowcharts are universal tools that describe any process. It is a finite oriented graph with one start and one end. Structure and sequence of activities forming process is described in the chart showing blocks expressed by operating activities and decision blocks [20].
- **Regression and correlation (RaCA)** – The term regression means the systematic changes of some variables when change other variables and description of these changes by mathematical functions. So we try to fit observed values by an appropriate mathematical function. The term correlation means intensity of linear dependence between random variables [22].

Tab. 2 χ^2 Test of Independence in Contingency Table, NCSS 2007 Output. Source: Own Processing

Chi-Square Statistics Section	
Chi-Square	17.0093
Degrees of Freedom	6
Probability Level	0.00924
Cramer's V	0.29018
Pearson's Contingency Coefficient	0.37965
Tschuprow's T	0.26220
Kendall's tau-B	0.01980

Probability Level $\leq \alpha$ (0.05), we can reject the null hypothesis about the independence of two categorical variables. It follows that the complexity of the methods depends on the size of the company.

The contingency coefficients are measures of intensity of dependence. Following coefficients can be calculated in statistical software: Pearson's, Cramer´s contingency coefficients or Kendall's τ_b and Tschuprow's contingency coefficients.

We can say that exist a weak dependence but it is statistically significant from results displayed in Table 2. The last question was: “What statistical methods in quality control are used in your company?” The results are given in the next Fig. 6. It is obvious that most companies are satisfied only with histogram (69.23 %), capability index (65.38 %), Pareto analysis (65.38 %) and flowcharts (57.69 %).

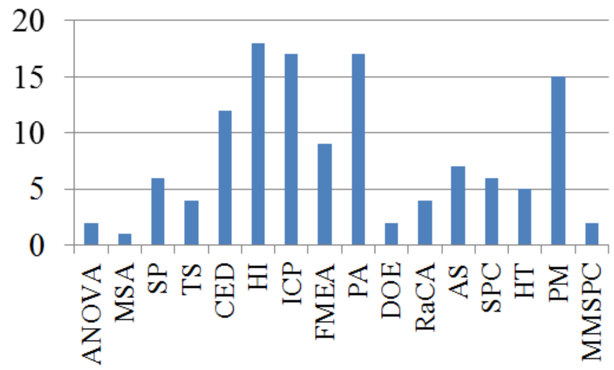

Fig. 6 The Most Commonly Used Methods and Tools by Surveyed Companies. Source: Own Processing

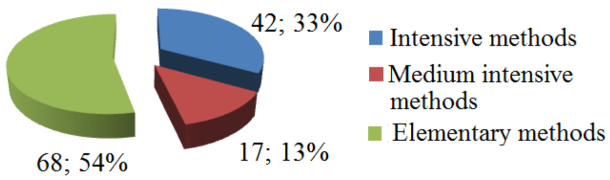

Fig. 7 The Most Commonly Used Methods and Tools by Surveyed Companies According to Difficulty. Source: Own Processing

The list of most frequently reported methods and tools according to the literature is shown in Fig. 8.

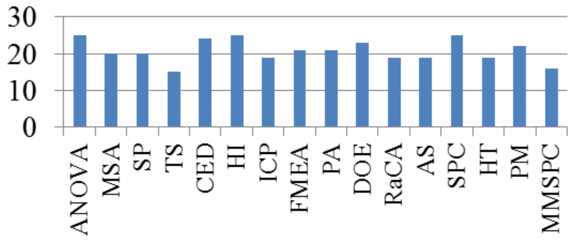

Fig. 8 The Most Frequently Used Methods and Tools According to Publications Studied.
Source: Own processing

It is apparent from previous graph that the most frequently mentioned methods (100 %) in scientific literature are statistical process control (SPC), analysis of variance (ANOVA), and histogram (HI). Other methods and tools according to publications studied are: measurement system analysis (80 %), scatter plots (80 %), cause and effect diagram (96 %), method FMEA (84 %), Pareto analysis (84 %), design of experiments (92 %) and flowcharts (88 %).

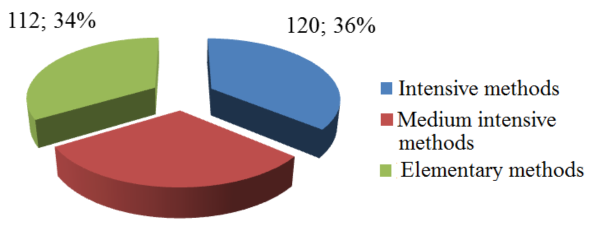

Fig. 9 The Most Frequently Mentioned Statistical Methods and Tools in Publications According to Difficulty.
Source: Own Processing

It is obvious in Fig. 9 that publication authors are equally focused on elementary, medium intensive, and intensive methods.

B. *Theory and Practice Accordance in Using Selected SPC Methods*

We continue with statistical data processing in program StatXact 7. Second hypothesis if the selected statistical methods reported in scientific publications related to the SPC are really used in practice. It is obvious from following Table 3 that the value of Spearman rank correlation coefficient equals to 0.2483 and the *p-value* for both sided exact test by the method Monte Carlo is 0.3454 (see Table 4).

Tab. 3 Calculation of Spearman Rank Correlation Coefficient. Source: Own Processing in StatXact 7

			95,00% CI Limits	
Coefficient	**Estimate**	**ASE1**	**Lower**	**Upper**
Spearman's CC	0.2483	0.2496	-0.2409	0.7376

Tab. 4 Asymptotic and Exact Test.
Source: Own Processing in StatXact 7

		P-Value	
Type	**DF**	**1-Sided**	**2-Sided**
Asymptotic	14	0.1769	0.3537
Monte Carlo		0.1718	0.3454
99,00% CI Lower Limit		0.1621	0.3332
99,00% CI Upper Limit		0.1815	0.3576

10000 Monte Carlo samples with starting seed 262676

If the *p-value* $\leq \alpha$ (0.05) we can reject the null hypothesis about independence of variables Y_i and X_i. In this case, the *p-value* of Spearman rank correlation coefficient is $|r_s| > r_s(\alpha)$, where $r_s(\alpha) = 0.5$, therefore we cannot reject the null hypothesis about the independence of variables Y_i and X_i at 5% confidence level. The above mentioned conclusion can be supported by the confidence interval for the Spearman rank correlation coefficient „95.00% CI Limits“(–0.2409; 0.7376) First, it includes zero and second, each hypothesis (in this case H_0: $|r_s| = 0$) is considered as the possible one and therefore cannot be rejected. The second hypothesis was not proved by the nonparametric test.

V. Discussion

On direct questioning of respondents regarding the use of statistical methods in quality management, we often met with a faulty analysis of multiple comparisons of mean values when were carelessly used *t*-tests instead of analysis of variance. Therefore low frequency by ANOVA method was observed. In this case, practitioners often posed a question whether to use ANOVA or *t*-test for two groups ($k = 2$). It does not matter, *p-value* is released in both cases exactly the same because F is the square of the t. We also met with nonparametric tests ignorance resulting in a low value for hypotheses testing.

Most surprising was the fact that only two respondents use multivariate control charts and multidimensional capability indices. This shows great ignorance of multivariate SPC methods among practitioners. The lowest frequencies were observed in the measurement system analysis (MSA) and design of experiments (DOE). But the majority of the scientific literature placed the greatest emphasis on these methods used in pre-production and production phases. The questionnaire survey also showed that elementary statistical methods are used most often in practice.

In our qualitative research, we also personally interviewed in selected manufacturing companies that use automated monitoring variability of data quality engineers. These companies, which enabled us to this interview, were 24. The biggest problems that we detected with these companies experienced in quantitative process analysis were as follows:

- calculation of process capability indices in asymmetric data,
- monitoring the variability of data in autocorrelated data,

• identification of the change point in the variability of processes.

The first practical problem, which we encountered in interviewing, was struggling with abnormal process data quality engineers disturbing real picture of the state of the process.

Control charts and process capability calculations remain fundamental techniques for statistical process control. However, it has long been realized that the accuracy of these calculations can be significantly affected when sampling from a non-Gaussian population. Many quality practitioners are conscious of these problems but are not aware of the effects such problems might have on the integrity of their results. Consider non-normality with respect to the use of traditional control charts and process capability calculations, so that users may be aware of the errors that are involved when sampling from a non-Gaussian population. Use is made of the Johnson system of distributions as a simulation technique to investigate the effects of non-normality of control charts and process control calculations. An alternative technique is suggested for process capability calculation which alleviates the problems of non-normality while retaining computational efficiency.

Almost all of these companies make the calculation of process capability indices automatically using an appropriate statistical software tool. According to information from quality engineers, the software in all cases does not verify the normality of the data or the detection of outliers. It is these two statistical anomalies have the greatest influence on distorsion of these indices. Only two of the surveyed companies have learned that this procedural computation of indices is carried out in collaboration with the statistical department, where they use various transformations or identification of the process data distribution, which stabilizes the variance, and thus more reliable estimate of process indices.

Another problem that we encountered during personal interview was estimating process characteristics and process monitoring in serially correlated or autocorrelated data.

Statistical process control techniques for monitoring serially correlated or autocorrelated processes have received significant attention in the statistical quality engineering literature. The focus of most studies, however, is on the detection of the mean shift of the process. The detection of changes in the variance and autocorrelation structure of the series due to some special causes of variation affecting the system is often overlooked. Ideally, one needs to maintain three control charts in order to effectively detect changes in the process: one each for detecting change in the mean, variance and autocorrelation structure of a series.

The most popular approach for monitoring processes with serially correlated observations is to model the inherent autocorrelation of the process measurements using an autoregressive moving average (ARMA) model. To detect changes in the process, residuals are generated using the chosen model. When the model is appropriately chosen and well estimated, these residuals approximate i.i.d. behaviour. Using this assumption, we can employ the traditional SPC charts to monitor the residuals. Any deviation of the residual from i.i.d. behaviour indicates a change in the process that must be due to a special cause of variation.

After consultation with the analytics at the companies surveyed, we concluded that the problem of serial correlation or autocorrelation is completely ignored. Only two of the companies surveyed, where cooperation of quality engineers takes place in collaboration with the statistical department, solve this problem. The most commonly used process data modeling is time series method (ARMA or ARIMA) or time series control charts such as EWMA, CUSUM or ARIMA control charts implemented in statistical software tools. According to their analytical experience, these time series control charts are recommended as a control charts for individual values in a wide range of applications, particularly in process monitoring. It is almost a completely nonparametric (independent of distribution) procedure. According to their opinion, these control charts are definitely better than Shewhart charts for individual values as well as for the features of the mean shift detection.

The last problem that we encountered during this questioning was to identify the change point in the variability of the process data. Change-point models have originally been developed in connection with applications in quality control, where a change from the in-control to the out-of-control state has to be detected based on the available random observations. Up to now various change-point models have been suggested for a broad spectrum of applications like quality control, reliability, econometrics or medicine. Again, only two of the surveyed enterprises do not ignore this problem. We learned that in these cases tends to create custom models, as for example, the algorithm of change point detection in time series, based on sequential application of the singular-spectrum analysis (SSA). The main idea of SSA is performing singular value decomposition (SVD) of the trajectory matrix obtained from the original time series with a subsequent reconstruction of the series. Another approach to the change point detection focuses on the area of stochastic processes, namely, changes in volatility estimation process data using stochastic differential equations.

VI. CONCLUSION

Statistical process control (SPC) involves using statistical techniques to measure and analyze the variation in processes. Most often used for manufacturing processes, the intent of SPC is to monitor process quality and maintain processes to fixed targets. SPC is used to monitor the consistency of processes used to manufacture a product as designed. It aims to get and keep processes under control. No matter how good or bad the design, SPC can ensure that the product or service is being produced as designed and intended. Thus, SPC will not improve a poorly designed product's reliability, but can be used to maintain the consistency of how the product is made and, therefore, of the manufactured product itself and its as-designed reliability.

A primary tool used for SPC is the control chart, a graphical representation of certain descriptive statistics for specific quantitative measurements of the manufacturing process. These descriptive statistics are displayed in the control chart in comparison to their "in-control" sampling distributions. The comparison detects any unusual variation in the manufacturing process, which could indicate a problem with the process. Several different descriptive statistics can be used in control charts and there are several different types of control charts that can test for different causes, such as how quickly major vs. minor shifts in process means are detected. Control charts are also used with product measurements to analyze process capability and for continuous process improvement efforts.

Acceptance sampling refers to the process of randomly inspecting a certain number of items from a lot or batch in order to decide whether to accept or reject the entire batch. What makes acceptance sampling different from statistical process control is that acceptance sampling is performed either before or after the process, rather than during the process. Acceptance sampling before the process involves sampling materials received from a supplier, such as randomly inspecting crates of fruit that will be used in a restaurant, boxes of glass dishes that will be sold in a department store, or metal castings that will be used in a machine shop. Sampling after the process involves sampling finished items that are to be shipped either to a customer or to a distribution center. Examples include randomly testing a certain number of computers from a batch to make sure they meet operational requirements, and randomly inspecting snowboards to make sure that they are not defective.

The quality of products and services has become a major decision factor in most businesses today. Regardless of whether the consumer is an individual, a corporation, a military defence program, or a retail store, when the consumer is making purchase decisions, he or she is likely to consider quality of equal importance to cost and schedule. Consequently, quality improvement has become a major concern to many U.S. corporations. This chapter is about statistical quality control, a collection of tools that are essential in quality-improvement activities. Quality means fitness for use. For example, you or I may purchase automobiles that we expect to be free of manufacturing defects and that should provide reliable and economical transportation, a retailer buys finished goods with the expectation that they are properly packaged and arranged for easy storage and display, or a manufacturer buys raw material and expects to process it with no rework or scrap. In other words, all consumers expect that the products and services they buy will meet their requirements. Those requirements define fitness for use.

Quality or fitness for use is determined through the interaction of quality of design and quality of conformance. By quality of design we mean the different grades or levels of performance, reliability, serviceability, and function that are the result of deliberate engineering and management decisions. By quality of conformance, we mean the systematic reduction of variability and elimination of defects until every unit produced is identical and defect-free. Some confusion exists in our society about quality improvement; some people still think that it means gold-plating a product or spending more money to develop a product or process. This thinking is wrong. Quality improvement means the systematic elimination of waste. Examples of waste include scrap and rework in manufacturing, inspection and testing, errors on documents (such as engineering drawings, checks, purchase orders, and plans), customer complaint hotlines, warranty costs, and the time required to do things over again that could have been done right the first time. A successful quality-improvement effort can eliminate much of this waste and lead to lower costs, higher productivity, increased customer satisfaction, increased business reputation, higher market share, and ultimately higher profits for the company.

Two surveys were conducted to prove both research hypotheses. The first survey was conducted for the issue of statistical methods and tools. It consisted in studying the available literature on these instruments. The aim of this research was to analyze which methods and tools are recommended with a focus on statistical process control. It was studied 25 (of which 4 Czech and 21 English) professional publications on the theme of the use of statistical methods in quality control.

It was subsequently conducted second survey which consisted in questioning the applicability of statistical methods in quality management in selected enterprises. 26 companies (32.5 %) involved to a questionnaire survey of all 80 surveyed companies. To perform research, data were collected and this was obtained through working with managers of companies and managers in production. It was used a web interface and database for collecting and storing data. The last step was the evaluation of these data with adequate statistical methods including interpretation of the conclusions provided by them.

The first research hypothesis (if the degree of difficulty of used statistical methods in the SPC depends on the firm size) was proved by the χ^2-test in the contingency table. Association coefficient detected only weak (but statistically significant) dependence between two nominal variables.

The nonparametric Spearman rank correlation coefficient was used for theory and practice concordance detection. In this case, the second research hypothesis (if the selected statistical methods reported in scientific publications related to the SPC are really used in practice) was not proved.

Very interesting results from our qualitative research problems in using SPC tools are included in the Discussion section, where we personally interviewed quality engineers about the biggest problems in their analytical work with the process data in selected manufacturing companies that use automated monitoring variability of data. These companies, which enabled us to this interview, were 24. We have discussed in the Discussion section the biggest problems that we experienced in these enterprises in a quantitative analysis of the processes.

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