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INSTITUTE OF MATHEMATICS

ÚSTAV MATEMATIKY

**STATISTICAL ANALYSIS OF ATTRIBUTIVE
DATA OF DEFECT RATES**

STATISTICKÉ ZPRACOVÁNÍ ATRIBUTIVNÍCH DAT O ZMETKOVITOSTI PROCESU

MASTER'S THESIS

DIPLOMOVÁ PRÁCE

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As provided for by the Act No. 111/98 Coll. on higher education institutions and the BUT Study and Examination Regulations, the director of the Institute hereby assigns the following topic of Master's Thesis:

Statistical analysis of attributive data of defect rates

Brief Description:

Statistical analysis of attributive data of defect rates, corresponding to described technical process. Using relevant statistical hypotheses testing and process stability tools is expected.

Master's Thesis goals:

1. Summary of basic statistical hypotheses tests and confidence intervals for attributive data.
2. Summary of relevant control charts.
3. Description of analyzed technical process.
4. Data analysis and interpretation of the results.

Recommended bibliography:

MONTGOMERY, D. C. Introduction to statistical quality control. 7th ed. Hoboken, NJ: Wiley, c2013. ISBN 978-111-8146-811.

MONTGOMERY, D. C. a G. C. RUNGER. Applied statistics and probability for engineers. 5th ed. Hoboken, NJ: Wiley, c2011. ISBN 978-047-0053-041.

Deadline for submission Master's Thesis is given by the Schedule of the Academic year 2022/23

In Brno,

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ABSTRACT

This master's thesis deals with a statistical analysis of the private company's data about product defect rate and mistakes found during final quality inspection. It describes the product and its manufacturing process in process flow chart, which are furthermore used for statistical analysis. It uses a method of statistical hypothesis testing to prove statements about company's data. Data analysis aims to figure out if there is any difference in selected categories, this is linked to Pareto diagrams. The conclusion summarized the knowledge gained and results of data analysis.

KEYWORDS

Poisson distribution, control charts, quality control, hypothesis testing

BIBLIOGRAPHIC CITATION

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Also i would like to pay tribute my boss and his team for enourmous support and help. It was a great pleasure to be guided. Even if i can't write names here, i will never forget.

DECLARATION OF AUTHENTICITY

I hereby declare that I wrote my master's thesis "Statistical analysis of attributive data of defect rates" independently and without outside assistance. I did not use any other sources apart from the ones stated in the bibliography and that I have clearly cited all passages (including graphics, tables, etc.) in the thesis that were taken from other sources. This thesis has never been submitted in its current or similar form in any other degree programme (wording of the declaration of authenticity should be consulted with the thesis supervisor).

26.05.2023

Date

Anna Kuleshova

TABLE OF CONTENT

1	INTRODUCTION.....	13
2	STATISTICAL METHODS.....	15
2.1	Statistic in Quality.....	15
2.2	Pareto Principle	15
2.3	Statistical Methods in Quality Improvement	16
2.4	Discrete Distribution	17
2.5	Poisson Distribution	17
2.6	Mean and Variance of a Poisson Distribution.....	18
2.7	U-chart.....	19
3	STATISTICAL HYPOTHESES	21
3.1	P-value.....	21
3.2	Confidence Interval	21
3.3	Type I and Type II Error	21
3.4	General Procedure for Hypothesis Tests	22
3.5	Testing for the Equality 2-Sample Poisson Rate.....	23
3.6	Poisson regression	24
4	PROCESS AND PRODUCT DESCRIPTION	25
4.1	Defects.....	26
4.2	Mistakes Description.....	26
5	DATA ANALYSIS	28
5.1	Comparison Mistakes by Product Type	29
5.2	Comparison Mistakes by Product Subtype	31
5.3	Poisson Regression Analysis.....	32
5.4	Foremen.....	39
5.5	Foreman's Prediction	40
5.6	Foreman's Prediction by CH Subtype.....	41
5.7	Pareto analysis.....	42
6	CONCLUSION.....	45
7	REFERENCES	46
8	LIST OF ABBREVIATIONS.....	48
9	ATTACHMENTS.....	49

1 INTRODUCTION

The term of quality is defined as the degree to which a set of inherent characteristics of an object fulfil requirements. [1] For quality assurance industrial companies are using quality tools, including statistical analysis and process control. With industry 4.0 and digitalization as well more often are using deeper data analysis, with process control to improve production process and prevent defects during manufacturing. One of the master thesis goal is support company with statistical analysis for future possible statistical process control.

In chapter two are described statistical techniques which are used in the quality field such a hypothesis testing, regression analysis, atatistical process control. Control charts and Pareto principal are the main statistical methods used in quality improvement.

In chapter three is described statistical hypothesis approach. The main parametrs are P-value, confidence interval. Type I and Type II Error are also described. The hypothesis-testing procedure is represented in 8 steps. Hypothesis method (principle) are practically used later for statistic analysis of company's data.

In chapter four is described the product and process background of cooperating company. Manufacturing process is explained in process flow chart. The meaning of defect and mistake are determined. Furthermore it is also clarified the mistakes category such as mechanical, electrical, supplier, engineering and mistakes fixed by inspector during final control. These categories are used for later analysis.

Chapter five contains description of the product types and subtypes and how the data preprocessing for further analysis. The test for two-sample Poisson rate, Poisson rate regression analysis and Poisson prediction are using for data analysis. U-charts are using for graphical interpretation of the results. It was investigated if there is any dependence between mistakes of product subtypes and foremen. To understand the mistakes impact and behavior it was analyzed the 10 worst orders for each quarter.

2 STATISTICAL METHODS

2.1 Statistic in Quality

The American Society for Quality defines quality as “the totality of features and characteristics of a product or service that bears on an ability to satisfy given needs.” [2] The goal of quality engineering is to identify potential quality issues before production and include quality into the design of products and processes. To figure out whether quality requirements are being fulfilled, a series of inspections and measurements are made as part of quality control.[3]

Nowadays managerial tools and practices are replacing outdated manufacturing approaches to quality control. The approach of hypothesis testing is the foundation of the statistical processes for process control. The production process being in control is how the null hypothesis is formulated. The alternative hypothesis is put forth as the production process being unregulated.[3]

Statisticians tabulate, represent, and describe data sets as part of their work. The application of gathered data and quality standards to discover novel ways for improving products and services is known as statistical methods in quality improvement. It is a structured corpus of methods that frequently include attempting to infer the characteristics of a large amount of data.[3]

Numerous statistical techniques are applied to quality improvement, such as:

- 1) *Hypothesis Testing* - two hypotheses are evaluated: a null hypothesis and an alternative hypothesis. The null hypothesis is a "straw man" used in a statistical test. The conclusion is to either reject or fail to reject the null hypothesis;
- 2) *Regression Analysis* - determines a mathematical expression describing the functional relationship between one response and one or more independent variables;
- 3) *Statistical Process Control (SPC)* - monitors, controls, and improves processes through statistical techniques. SPC identifies when processes are out of control due to special cause variation (variation caused by special circumstances, not inherent to the process). Practitioners may then seek ways to remove that variation from the process;
- 4) *Design and Analysis of Experiments* - planning, conducting, analyzing, and interpreting controlled tests to evaluate the factors that may influence a response variable. [3]

2.2 Pareto Principle

One of the most famous quality tool, which implemented Kaoru Ishikawa is the Pareto Principle, which specifies that 80% of consequences come from 20% of the causes, stating that the inputs and outputs are not equal. The quality and efficiency can be significantly improved by identifying and fixing these problems. It's needed to gather data regarding the quality indicators over time. The analysis will be more precise the more data you have. The next step is to sort or arrange the data according to the kind, groups or frequency of the quality issues. In order to pinpoint the 20% of factors that result in 80% of quality issues, a Pareto chart is a useful visual aid. It combines a bar chart and a line chart, where the bars show the frequency or magnitude of each cause and the line shows the cumulative percentage of the total effect. To

implement and monitor solutions should use the same quality metrics and data sources that you used before, and compare them with your baseline.

2.3 Statistical Methods in Quality Improvement

A control chart gives a starting point for determining if the variable output is caused by assignable reasons or common causes.

Control charts indicate if a process is steady and under control or out of control and requires change. In any process, some degree of variance is unavoidable, see the fig. 1. Control charts assist in preventing overreactions to regular process variability while also motivating timely responses to exceptional variation.

A control chart displays process data over time, as well as upper and lower control limits that define the process's expected range of variation. When extraordinary variability occurs, these restrictions alert you. Control limits are calculated using statistical calculations based on historical records or sample data. Unusual patterns and out-of-control points on a control chart indicate the presence of unique cause variation.

- Determine whether a process is stable.
- Find problems as they occur in an ongoing process.
- Assess the effectiveness of a process change.
- Predict the range of outcomes for a process.
- Assess patterns of special cause variation to identify non-routine events.
- Determine whether improvements should target non-routine events or the underlying process itself.[4]

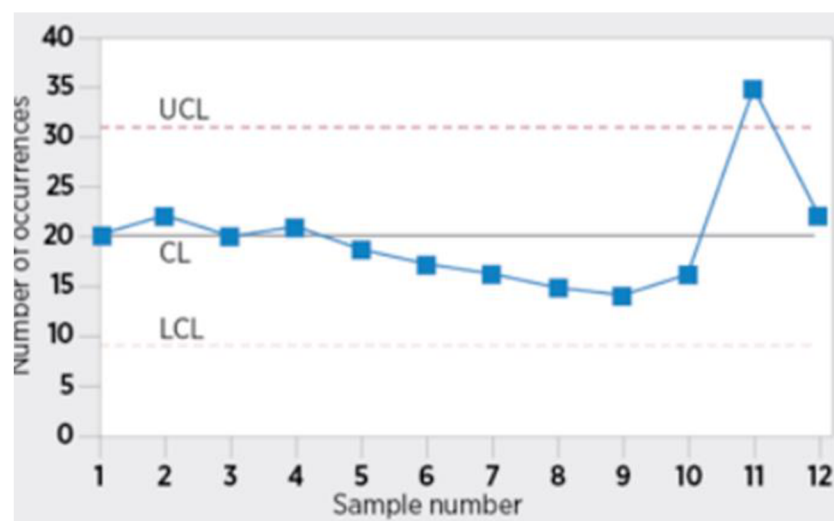


Fig 1 Example of control chart [4],

where: UCL – upper control limit, LCL – lower control limit, CL – control limit

2.4 Discrete Distribution

Statistical distributions can be either discrete or continuous. The components of a continuous distribution are results that fall on a continuum, such as any number greater than zero. The basic principles of probability theory and statistical analysis are the ideas of discrete and continuous probability distributions and the random variables they describe.

A discrete distribution is a probability distribution that depicts the occurrence of discrete (individually countable) outcomes, such as 1, 2, 3, yes, no, true, or false. [5]

Using the same or similar random experiments and random variables, many physical systems can be described. It is possible to evaluate the distribution of the random variables, which are involved in each of these common systems, and the results can be put to use in a variety of ways. Because random variables are so crucial to random experiments, we may neglect the experiment's initial sample space as a result to focus on the random variable's probability distribution. The probability distribution of a random variable X is a description of the probabilities associated with the possible values of X . the distribution for a discrete random variable is frequently described by only a simple list of all possible values and their associated probabilities.[5] [16]

2.5 Poisson Distribution

A Poisson distribution is a discrete probability distribution. It gives the probability of an event happening a certain number of times (k) within a given interval of time or space. A widely used distribution emerges from the concept that events occur randomly in an interval (or, more generally, in a region). The random variable of interest is the count of events that occur within the interval. The Poisson distribution has only one parameter, λ (lambda), which is the mean number of events. The graph below, Fig. 2, shows examples of Poisson distributions with different values of λ . [6]

In general, consider subintervals of small length Δt and assume that as Δt tends to zero:

1. The probability of more than one event in a subinterval tends to zero.
2. The probability of one event in a subinterval tends to $\lambda\Delta t$.
3. The event in each subinterval is independent of other subintervals. [7]

These assumptions imply that the subintervals can be thought of as approximate independent Bernoulli trials with the number of trials equal to $n = T/\Delta t$ and success probability $p = \lambda\Delta t = \lambda T/n$. [7]

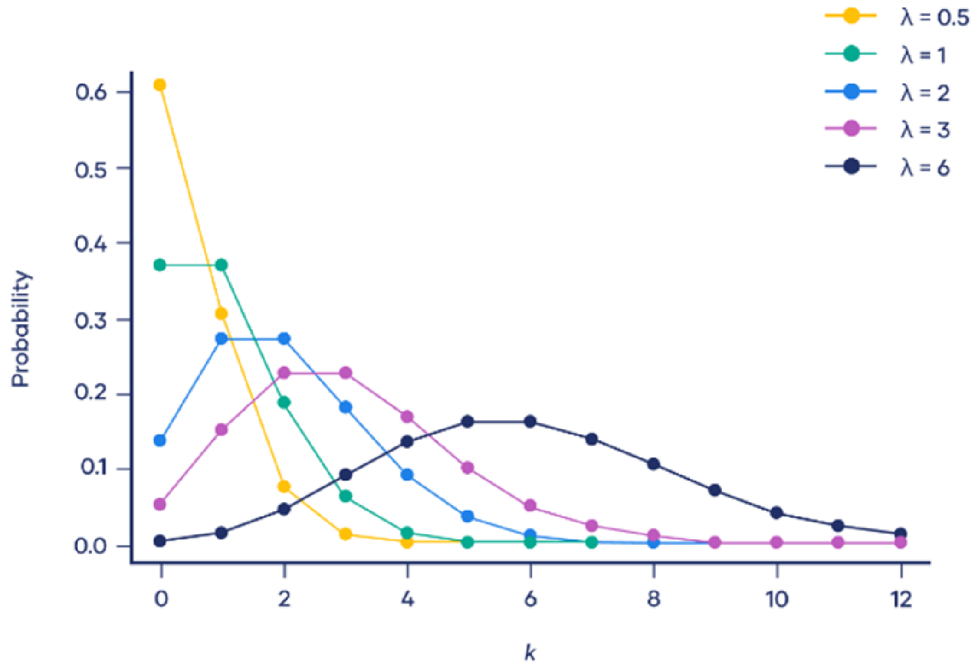


Fig. 2 Graph of Poisson distribution for different values of λ [6]

The random variable X that equals the number of events in a Poisson process is a Poisson random variable with parameter $0 < \lambda$ represented in the equation (1):

$$f(x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad (1)$$

where X is a random variable following a Poisson distribution, $x = 0, 1, 2, \dots$

λ is the average number of times an event occurs

e is Euler's constant (approximately 2.718).[7]

The sum of the probabilities is 1 because the summation on the right-hand side of the previous equation (2) is recognized to be Taylor's expansion of e^x evaluated at λ . Therefore, the summation equals e^λ and the right-hand side equals 1.[7]

$$\sum_{x=0}^{\infty} \frac{e^{-\lambda} \lambda^x}{x!} = e^{-\lambda} \sum_{x=0}^{\infty} \frac{\lambda^x}{x!} \quad (2)$$

2.6 Mean and Variance of a Poisson Distribution

The Poisson distribution has only one parameter, called λ .

In most distributions, the mean is represented by μ (mu) and the variance is represented by σ^2 (sigma squared). The mean and variance of a Poisson random variable are equal (equation

3 and 4). If the variance of count data is much greater than the mean of the same data, the Poisson distribution is not a good model for the distribution of the random variable. [7]

$$\mu = E(X) = \lambda \quad (3)$$

$$\sigma^2 = V(X) = \lambda \quad (4)$$

2.7 U-chart

One of the seven fundamental quality tools, this adaptable data collection and analysis tool is utilized by numerous sectors.

The control chart for defects per unit chart is another name for the u-chart. The majority of the time, it is employed to keep track of count-type data when the sample size is larger than one. The u-chart measures the average number of defects per unit and assumes the underlying data roughly follow the Poisson distribution, regardless of whether there is only one type of defect or multiple different types.[8]

In u-charts, the number of units or lots is represented on the x-axis, and the number of defects per single unit is plotted on the y-axis, see fig 3. The centerline \bar{u} is calculated by dividing the total number of defects in a sample by the sample's number of inspected items, equation 5. [8]

$$\bar{u} = \frac{\text{Total number of defects}}{\text{Number of inspected items}} \quad (5)$$

To create a u-chart it is needed to determine subgroup size, count the number of defects, calculate \bar{u} value, calculate the upper control limits (UCL) (the equation 6) and low control limit (LCL) (the equation 7). If the sample sizes are unequal, the control limits vary from sample interval to sample interval as it is shown on fig. 3. [8]

$$UCL_u = \bar{u} + 3 \frac{\sqrt{\bar{u}}}{\sqrt{n_i}} \quad (6)$$

$$LCL_u = \bar{u} - 3 \frac{\sqrt{\bar{u}}}{\sqrt{n_i}} \quad (7)$$

Where i = number of subgroup size, n = sample size.

Utilize an u-chart to track process stability over time and the results of process improvements before and after.

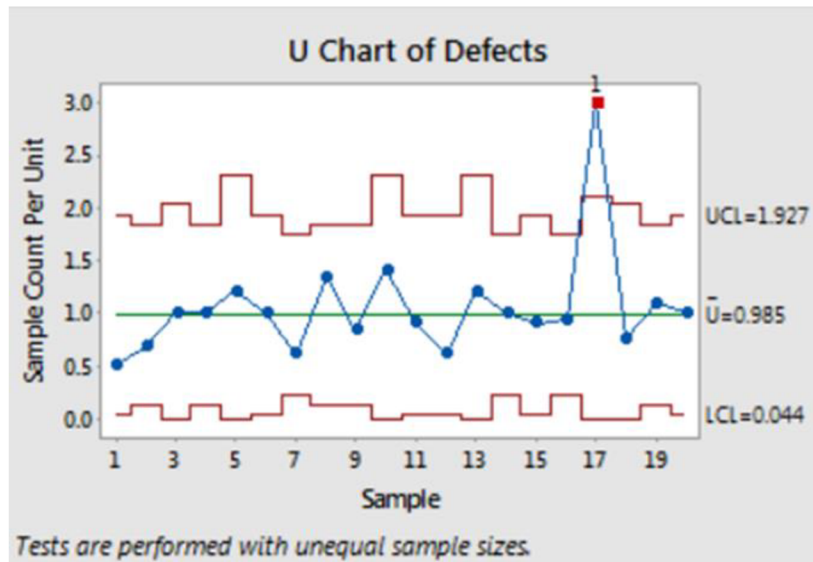


Fig 3 Example of u-chart [8]

3 STATISTICAL HYPOTHESES

In many engineering challenges, we must choose between two competing claims or statements regarding a particular parameter. The procedure of making decisions is known as hypothesis testing, and the statements are known as hypotheses. One of the most significant parts of statistical inference is that it allows for the formulation of a variety of decision-making problems, testing, and experimentation that are faced in the field of engineering. The essential techniques employed at the data analysis stage of a comparison experiment in which the engineer is interested, for example, in comparing the mean of a population to a certain value, are statistical hypothesis testing and confidence interval estimation of parameters. An assertion regarding the characteristics of one or more populations is referred to as a statistical hypothesis.[9]

3.1 P-value

One way to summarize the outcomes of a hypothesis test is to indicate whether the null hypothesis was accepted or rejected at a specified α -value or p-value. This is called fixed significance level testing. The fixed significance level approach to hypothesis testing is useful because it directly introduces the ideas of type II error and power, both of which are crucial for figuring out the right sample sizes for using in hypothesis testing. [9]

The P-value is the lowest level of significance at which the null hypothesis H_0 would be rejected given the available data. The probability that an observed difference may have happened by chance is expressed by a p-value. The statistical significance of the observed difference grows as the p-value decreases. The null hypothesis is rejected if the p-value is insufficient small. [9]

It is obvious that the P-value gives an indication of how likely the null hypothesis is. If we reject the null hypothesis H_0 , there is a chance that we selected the wrong choice. The chance that the null hypothesis is true is neither determined by the P-value, nor is it determined by $1 - P$. The P-value should be interpreted in terms of the risk of incorrectly rejecting the null hypothesis H_0 since the null hypothesis can only be true or false (there is no probability associated with this).[9]

3.2 Confidence Interval

The mean of the estimate plus and minus the range of that estimate constitutes a confidence interval. Within a specific level of confidence, this is the range of values you anticipate your estimate to fall within if you repeat the test. In statistics, confidence is another word for probability. [10]

Since it's simply point estimates, they provide no information regarding the number range. For expressing the variation surrounding a given estimate, confidence intervals are helpful. Critical values indicate the number of standard deviations that must deviate from the mean in order to achieve the required degree of confidence for the confidence interval. [10]

3.3 Type I and Type II Error

A sample may not always be representative of the population due to chance. As a result, the sample's findings do not accurately represent the population's situation, and the random

error causes an incorrect conclusion to be drawn. Rejecting a null hypothesis that is actually true in the population results in a type I error (false-positive); failing to reject a null hypothesis that is actually untrue in the population results in a type II error (false-negative). Although type I and type II errors cannot be completely avoided, the investigator may decrease their risk by increasing the sample size (the less likely it is that the sample will significantly differ from the population).[11]

Bias (observer, instrument, recall, etc.) can also lead to false-positive and false-negative outcomes. (Bias-related errors, however, are not classified as type I or type II errors.) Such errors are problematic since they are frequently impossible to quantify and may be challenging to identify. For better understanding there is a fig. 4.

A Type I error means rejecting the null hypothesis when it's actually true. It means that results are statistically significant when, in reality, they happened entirely by chance or as a result of unrelated circumstances.[11]

The significance level (alpha or α) you select determines the chance that you will make this error again. You determined that figure at the start of the analysis to determine the probability of getting your results (p value). The significance level is usually set at 0.05 or 5%. This means that your results only have a 5% chance of occurring, or less, if the null hypothesis is actually true. [11]

A Type II error means not rejecting the null hypothesis when it's actually false. Because hypothesis testing can only tell you whether you reject the null hypothesis, this is not precisely the same as "accepting" the null hypothesis. [11]

Instead, a Type II Error means the failure to recognize an effect when it actually existed. In truth, it's possible that research lacked the statistical power to identify an effect of a particular size. Power measures how well a test can identify an actual effect when it exists. Typically, a power level of 80% or above is regarded as appropriate.[11]

Null hypothesis is ...	True	False
Rejected	Type I error False positive Probability = α	Correct decision True positive Probability = $1 - \beta$
Not rejected	Correct decision True negative Probability = $1 - \alpha$	Type II error False negative Probability = β

Fig. 4 Type I and type II error [11]

3.4 General Procedure for Hypothesis Tests

The hypothesis-testing procedure is for many practical problems. It is recommended to use the following steps in applying hypothesis-testing methodology [7]:

1. *Parameter of interest:* From the problem context, identify the parameter of interest.

2. *Null hypothesis, H0*: State the null hypothesis, H0.

3. *Alternative hypothesis, H1*: Specify an appropriate alternative hypothesis, H1. Your first hypothesis, which predicts a link between variables, is generally your alternate hypothesis. The null hypothesis predicts no link between the variables of interest.

4. *Gather data*: data collection and sampling must be done in a way that is intended to evaluate your hypothesis for a statistical test to be considered valid.

5. *Test statistic*: Determine an appropriate test statistic. Pay attention on The types of variables (continuous or discrete), types of categorical variables (ordinal, nominal, binary). Choose a parametric test: regression, comparison or correlation, see Fig.

6. *Reject H0 if*: State the rejection criteria for the null hypothesis.

7. *Computations*: Compute any necessary sample quantities, substitute these into the equation for the test statistic, and compute that value.

8. *Draw conclusions*: Decide whether or not H0 should be rejected and report that in the problem context

3.5 Testing for the Equality 2-Sample Poisson Rate

Hypothesis test for a difference in rates for the normal approximation. The null hypothesis is that $\lambda_x = \lambda_y$.

To test the hypothesis of equality of parameters of two Poisson distributions the following procedure can be used[12]:

- Coaculate Z value
- Calculate P-value
- To accept or deny null hypothesis

The normal approximation test is based on the following Z-statistic, which is approximately distributed as a standard normal distribution under the null hypothesis, the equation 8:

$$Z = \frac{\lambda_x - \lambda_y}{\sqrt{\frac{\lambda_x}{m} + \frac{\lambda_y}{n}}}, \quad (8)$$

Where λ_x - observed value of rate for sample X,

λ_y - observed value of rate for sample Y,

m - sample size of sample X,

n - sample size of sample Y.

The variant of decision with respect of P-value:

$$H_1 : \lambda_x - \lambda_y \neq 0 \quad P - value = 2P (Z \geq |z| \mid \lambda_x - \lambda_y = 0)$$

3.6 Poisson regression

To compare multiple (more than two) poisson rates, Poisson regression with a categorical predictor will be used. In order to obtain this model one can use the mathematical apparatus of generalized linear models thoroughly described for example in [17]. For post-hoc analysis of different pairs according to their Poisson rates, confidence intervals constructed around the model predictions can be used. When 2 interval are disjoint, there is a statistically significant difference between the two corresponding groups, otherwise they Poisson rates will be considered equal.

4 PROCESS AND PRODUCT DESCRIPTION

Due to sensitivity of analyzed data, product and process description of process and product is described without sensitive data like product details and process know how.

Product can be described as a highly customized industrial product. Product is based on several basic configurations, which are modified as per customer requirements and specifications to the final solution. Products can be distinguished to two main product types. Each of the product types consists of several product subtypes.

General process is described in figure 5. Process includes high portion customer oriented engineering, also interaction with customer on clarification and approval of final technical solution. Due to customer oriented approach the manufacturing process also includes high portion of manual operations. That is why the manufacturing process is not a serial type of manufacturing. Whole process is impacted by higher risk of human mistakes.

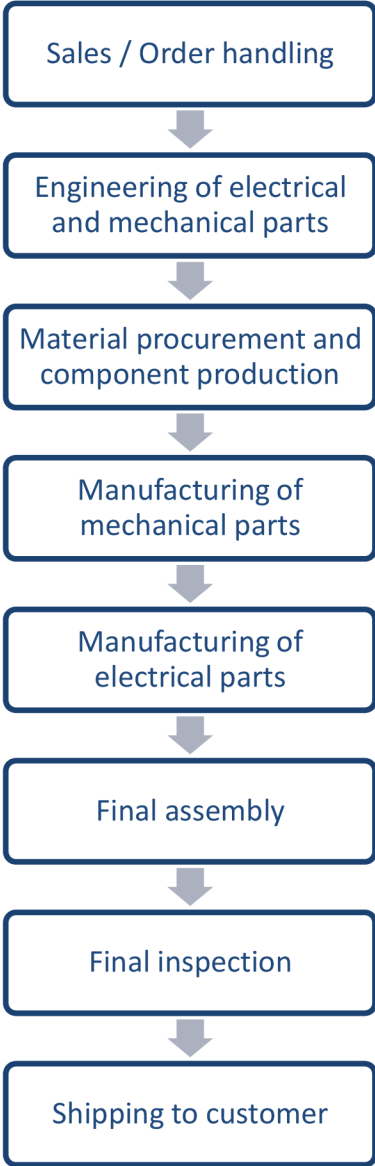


Fig. 5 Process flow chart

Defects, which have been found during inspection, are written in the documentation and recorded in company's information system. All corrections are verified by quality team so the product attains its full functionality before shipment.

4.1 Defects

Defect is deviation from design specifications during manufacturing resulting in a product's defect, frailty, or shortcoming. [13]

A manufacturing defect typically occurs when something goes wrong during the production process. Minor, major and critical quality defects are the three basic categories into which defects are typically divided in quality control. [14]

Minor defects are commonly meaningless, little issues that have no impact on the item's form or function.

Major defects are those that might affect a product's performance, look or functionality. Customers can easily identify these defects, which may lead them to return the item, complain, or ask for a refund.[14]

Critical ones make a product utterly useless and/or put the user or those nearby in danger. Companies are seriously at threat of product liability difficulties, lawsuits, and as a result of these defects the product recalls.[14]

The mistake is the result of an action performed inaccurately or incorrectly, contrary to the plan, but the most important thing is that the result that is obtained does not correspond to the intended or required, what leads to the defect. In another words mistake is persons fault, inattentiveness. In my work I pay attention to how many mistakes were made, which type and how it connects with each other, but not the defects' impact.

4.2 Mistakes Description

Mistakes are divided into categories that are mechanical, electrical, supplier, drawing and mistakes, which were fixed by quality control specialists during quality control. Now let's have a look at it a bit deeper.

Mistakes that have been made during assembly of mechanical part, are classified as mechanical mistakes. For instance, some parts can be assembled in a wrong way. Or the component can be missing at all. As an example the lack of screws or nor tighten well enough, labels can be missed or damaged during assembly, or location of labels is not matching with documentation. The component can be classified as defective, only in case the company produced this part by itself. If the part is delivered with a defect from supplier, it would be considered a supplier mistake.

During assembly electrical part can occur wrong or missed wiring connection, bad crimping, not well tightened screws on terminals and connectors, wrong cable colour, the way how cable is located, cable damaged, cable insulation, wrong assembly, cable labels, labels can be missed or damaged – it is all belongs to electrical kind of mistakes.

Some of the mistakes can occur in both mechanical and electrical part like wrong label position, missing components.

The inspector may fix some mistakes if they are sufficiently easy and fast to fix during final control. Such as tight screws or changing cable position. These mistakes can be classified

as mechanical or electrical ones. In gathered data, these mistakes are called mistakes solved by an inspector (quality specialist).

Some parts, which are not produced by the company, are bought from supplier. During assembly or quality control it may occur that part or device does not work properly or is completely broken. In this case, it will be replaced by a new one and if it was not damaged during assembling, it counts as a supplier mistake.

All manufactured product are a bit different due to clients' needs and their desired operational conditions. That's why the company's designers and engineers work on documentation for each order separately. Sometimes mistakes can happen during the engineering process. In this diploma thesis, drawing and supplier mistakes won't be included in data analysis.

5 DATA ANALYSIS


In this master thesis the goal is to find if there is a dependence between quantity of mistakes and type of the product. The number of units differs in each order from 1 up to 80. Number of units don't depend on product type and subtype, it is oriented only on client needs. For that it was implemented a new criteria "number of mistake per unit". Mechanical, electrical and mistakes solved by inspectors counting separately. For analysis mostly was used such tools as Minitab, Matlab and Excel.

Therefore, two described types are divided into more subtypes depending on client needs. During the 2022 year the company produced 21 unique types (952 orders). But for further analyses the decision was made not to include such subtypes as MP, GP, 5P, XP, 8P, US, 8S and ZZ due to the reason that it appears less than 5 times or due to the configuration inside the product (according to client request). It is necessary to mention that UP subtype apart cause it appeared 41 times during year but this product is not complete as well that is why there is no electrical part on which we can manipulate with data.

According to experts from the company subtypes UI and UE have similar enough configuration and therefore can be combined into one subtype IK. Subtypes YD and GC were aggregated into subtype YG for the same reason. After preprocessing, remains 2 product types, 10 product subtypes and 890 orders. See table 1.

Table 1 The product subtype selection

Product subtype	Sum of orders
CH	475
ZA	134
CO	71
UK	44
UP	41
UA	40
BL	28
AK	24
KD	23
YD	20
UI	18
GC	14
US	9
8P	6
UE	5
ZZ	4
XP	3
GP	1
LP	1
5P	1
8S	1
O1	1
MP	1



Product subtype	Sum of orders	Product type
CH	475	A
ZA	134	A
CO	71	B
UK	44	A
UA	40	A
BL	28	A
AK	24	A
KD	23	A
YG	34	B
IK	23	A

5.1 Comparison Mistakes by Product Type

Let's have a look on obtained data. During the 2022 year the company produced 890 orders in total. Out of those were 103 orders (12 %) of type B of the product and 787 one of type A (88%). Graphical summary of amounts of different the product types manufactured can be seen in pie-chart on Fig. 6.

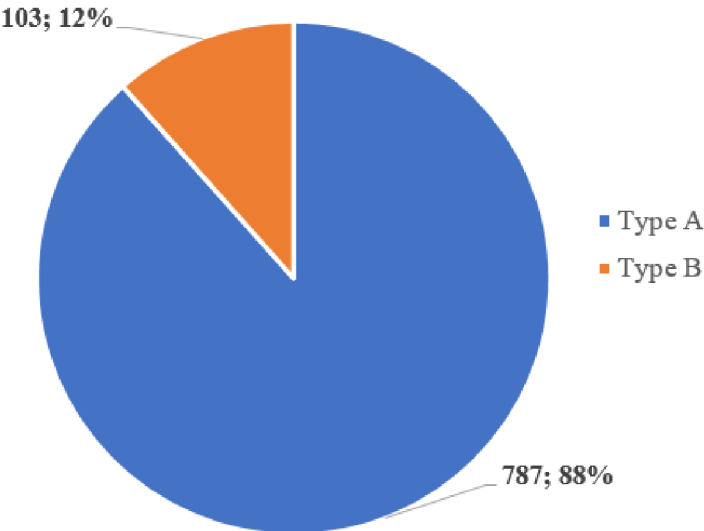


Fig. 6 Pie-chart of the product types

What is more insightful is the number of units and the quantity of mistakes. For summary see table 2.

Table 2 Summary of mistakes by the product type.

Variable	Product type	Sum
Number of units	A	7378,000
	B	840,000
Mechanical Mistakes	A	15866,00
	B	1633,00
Electrical Mistakes.	A	24233,00
	B	4483,00
Mistakes Solved by inspector	A	21421,00
	B	4064,00

Test for two-sample Poisson rates can be used to experiment whether there is statistically significant difference between the product types. The null hypothesis is that product type A and type B have the same number of mistakes per unit. The alternative hypothesis that product type A and B has difference. For that, it is needed summary of mechanical mistakes of the product type A and type B. Even though the estimated difference is only 0.2, the P-value of Two-Sample Poisson rates test is less than 5%, which means that null hypothesis is rejected and the

mechanical mistakes of product type A and B difference is statistically significant (see the Fig.7).

Descriptive Statistics

Sample	N	Occurrences	Sample Rate
Sample 1	7378	15866	2,15045
Sample 2	840	1633	1,94405

Estimation for Difference

Estimated Difference	95% CI for Difference
0,206400	(0,106349; 0,306450)

Test

Null hypothesis $H_0: \lambda_1 - \lambda_2 = 0$
 Alternative hypothesis $H_1: \lambda_1 - \lambda_2 \neq 0$

Method	Z-Value	P-Value
Exact		0,000
Normal approximation	4,04	0,000

Fig. 7 Two-Sample Poisson rates test for mechanical mistakes

Same way hypotheses were tested for electrical mistakes of the product type A and type B the product. Estimated difference is 2,05. The P-value of Two-Sample Poisson rates test is less than 5%, which means that null hypothesis is rejected and difference is statistically significant (see the Fig. 8).

Descriptive Statistics

Sample	N	Occurrences	Sample Rate
Sample 1	7378	24233	3,28449
Sample 2	840	4483	5,33690

Estimation for Difference

Estimated Difference	95% CI for Difference
-2,05241	(-2,21402; -1,89080)

Test

Null hypothesis $H_0: \lambda_1 - \lambda_2 = 0$
 Alternative hypothesis $H_1: \lambda_1 - \lambda_2 \neq 0$

Method	Z-Value	P-Value
Exact		0,000
Normal approximation	-24,89	0,000

Fig. 8 Two-Sample Poisson rates test for electrical mistakes

Same way hypotheses were tested for mistakes solved by inspectors of product type A and type B, it was got the average number is 2,90 mistakes per unit for type A and 4,84 for type B. Estimated difference is 1,93. The P-value of Two-Sample Poisson rates test is less than 5%, which means that null hypothesis is rejected (see the Fig. 9).

Descriptive Statistics

Sample	N	Total Occurrences	Sample Rate
Sample 1	7378	21421	2,90336
Sample 2	840	4064	4,83810

Test

Null hypothesis $H_0: \lambda_1 - \lambda_2 = 0$
 Alternative hypothesis $H_1: \lambda_1 - \lambda_2 \neq 0$

Method	Z-Value	P-Value
Exact		0,000
Normal approximation	-24,66	0,000

Estimation for Difference

Estimated Difference	95% CI for Difference
-1,93473	(-2,08848; -1,78099)

Fig. 9 Two-Sample Poisson rates test for mistakes solved by inspectors

None of one type of mistakes is behaved the same way for the product type A and type B. Product type A is produced 8 times more often than product of type B. it was assumed that number of mechanical mistakes will differ because due to mechanical part product is distinguished. Also it wasn't expected the big mistake range of electrical mistakes cause product has similar configuration. Results have disproved these assumptions, furthermore I seems that products of type B is much more difficult to make, with regards to its electrical components.

5.2 Comparison Mistakes by Product Subtype

Here is a graphical interpretation of the number of mechanical, electrical mistakes and the one, which were solved by inspectors. On Fig. 10 we can see that the sum of all kinds of mistakes is sufficiently higher in comparison with other subtypes. The reason is hidden in the quantity of the units - almost the half of all orders is the production CH the product.

Subtype	Sum of units
CO	422
KD	262
YG	418
UK	383
CH	3693
UA	597
IK	174
AK	470
BL	940
ZA	859

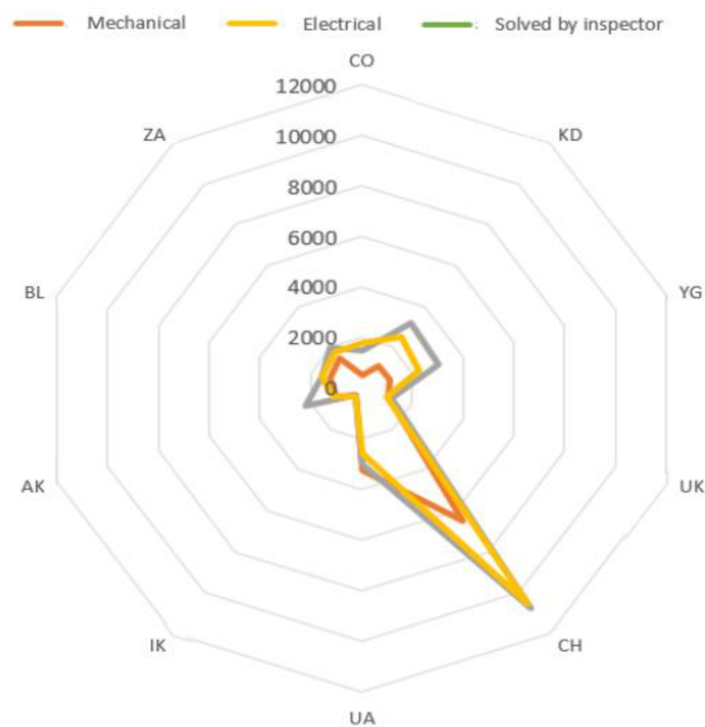


Fig. 10 Radar chart of sum of the mistakes with respect to the product subtype

On Radar chart (Fig. 11) we can notice that the mean value of mistakes per unit of CH subtype is relatively small in contrast with other subtypes. Subtype KD and YG showed the worst mean value mistake per unit results. just for information the quantity of units of subtype KD is 14 times less than the quantity of units of subtype CH, and the quantity of units of subtype YG is almost 9 times smaller than the quantity of units of subtype CH.

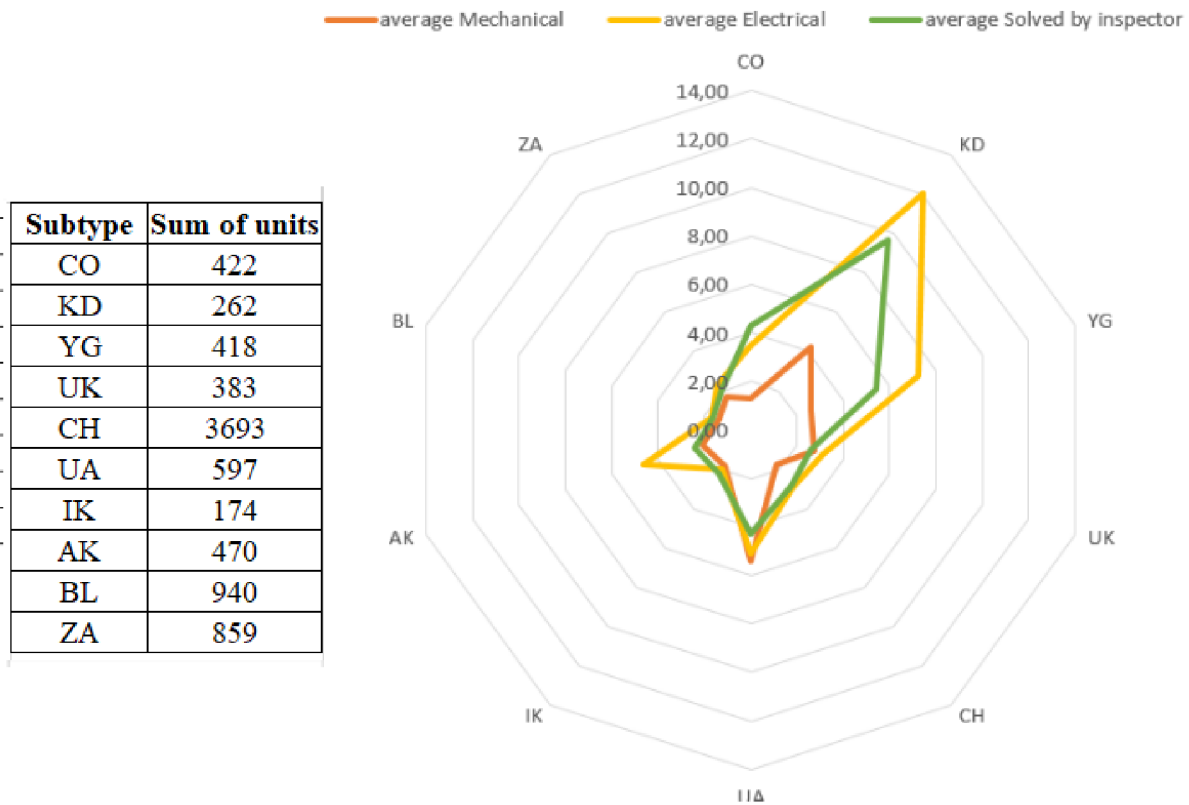


Fig. 11 Radar chart of mistake's mean value with respect to the product subtype

5.3 Poisson Regression Analysis

To determine whether any of the differences between the means are statistically significant, compare the p-value to significance level to assess the null hypothesis. The null hypothesis states that the population means are all equal. Usually, a significance level (denoted as α or alpha) of 0.05 works well, see the fig 12 analysis of variance with respect of mechanical mistakes and the fig. 13 for electrical mistakes. A significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference.

Next step is to find out if there is any dependence between the product subtypes and the quantity of mistakes by using Minitab. The Wald test, also called the Wald Chi-Squared Test, is a way to find out if explanatory variables in a model are significant. "Significant" means that they add something to the model; variables that add nothing can be deleted without affecting the model in any meaningful way. The test can be used for a multitude of different models including those with binary variables or continuous variables. Zero P-value tells us that our

hypothesis of equivalence of mistakes number per unit is rejected. All the product subtypes don't have the same mean value. [15]

Wald Test			
Source	DF	Chi-Square	P-Value
Regression	9	4052,33	0,000
Product Type	9	4052,33	0,000

Fig. 12 Analysis of variance the product subtype vs mechanical mistakes

Wald Test			
Source	DF	Chi-Square	P-Value
Regression	9	8277,27	0,000
Product Type	9	8277,27	0,000

Fig. 13 Analysis of variance the product subtype vs electrical mistakes

To test whether there is statistically significant difference between the product subtypes according to the average number of mistakes per unit, a Poisson regression with the product subtype categorical predictor can be used as it was done for the product types. We can combine the product subtypes into the group of the mistake by mean value. see the table 3.

For instance let's have a look at dependence subtype CO on electrical mistakes, see the fig. 14. Fit - the fitted response value is the point estimate for the specified variable setting, what is basically a mean value, CI is a 95% confidence interval.

Fit	SE Fit	95% CI
3,46209	0,0905754	(3,28904; 3,64424)

Fig. 14 Poisson prediction for the product subtype CO

Table 3 Electrical and mechanical mistakes interval group prediction

electrical mistakes				mechanical mistakes					
subtype	prediction			group	subtype	prediction			group
IK	Fit	SE Fit	95% CI	1	CO	Fit	SE Fit	95% CI	1
	1,98851	0,106902	(1,78964; 2,20947)			1,28673	0,0552189	(1,18293; 1,39964)	
BL	Fit	SE Fit	95% CI	2	BL	Fit	SE Fit	95% CI	2
	1,67447	0,0422040	(1,59376; 1,75926)			1,34149	0,0377772	(1,26945; 1,41761)	
ZA	Fit	SE Fit	95% CI	3	IK	Fit	SE Fit	95% CI	3
	2,31083	0,0518663	(2,21137; 2,41475)			1,82759	0,102486	(1,63736; 2,03991)	
CH	Fit	SE Fit	95% CI	4	CH	Fit	SE Fit	95% CI	4
	2,91552	0,0280975	(2,86096; 2,97111)			1,75305	0,0217875	(1,71086; 1,79627)	
UK	Fit	SE Fit	95% CI	5	ZA	Fit	SE Fit	95% CI	5
	3,12794	0,0903710	(2,95574; 3,31017)			1,66705	0,0440533	(1,58291; 1,75567)	
CO	Fit	SE Fit	95% CI	6	AK	Fit	SE Fit	95% CI	6
	3,46209	0,0905754	(3,28904; 3,64424)			2,08511	0,0666063	(1,95856; 2,21983)	
AK	Fit	SE Fit	95% CI	7	YG	Fit	SE Fit	95% CI	7
	4,62553	0,0992046	(4,43512; 4,82411)			2,60766	0,0789836	(2,45736; 2,76715)	
UA	Fit	SE Fit	95% CI	8	UK	Fit	SE Fit	95% CI	8
	5,06533	0,0921118	(4,88797; 5,24912)			2,72585	0,0843629	(2,56542; 2,89631)	
YG	Fit	SE Fit	95% CI	9	KD	Fit	SE Fit	95% CI	9
	7,22967	0,131511	(6,97645; 7,49207)			4,26718	0,127620	(4,02423; 4,52478)	
KD	Fit	SE Fit	95% CI	10	UA	Fit	SE Fit	95% CI	10
	12,0802	0,214711	(11,6666; 12,5084)			5,42546	0,0953303	(5,24180; 5,61556)	

It is prudent to construct U-charts of data to assess the stability of the manufacturing process with regards to different kind of mistakes and to identify extreme cases. Since only available data are average mistakes per unit for each order and not number of mistakes for each unit, it is necessary to manually implement formulas (3), (4) and (5) into Matlab. Due to the statistically significant differences in average number of mistakes per unit, it is necessary to stratify our dataset into categories according to table 3. Otherwise, variance represented by UCL and LCL will be significantly inflated. Unfortunately, only recorded timestamp for our data is expedition date which does not represent accurately date of completion of each order. Therefore, these U-charts cannot be used for detection of any kind of trend in the data. Mostly U-charts “tell similar stories”. Only selected few were directly included in the text (remaining U-Charts can be found in attachments).

Nice representation of constructed U-Charts is chart of mechanical mistakes for subtypes CO and BL (see fig. 15). As can be seen, there several orders, that are far above UCL. The highest average mistakes per unit recorded is more than twice larger than corresponding UCL. Since values above UCL are rather common, manufacturing process cannot be considered stable regarding to the observed mistakes. This holds for all categories of subtypes from table 3.

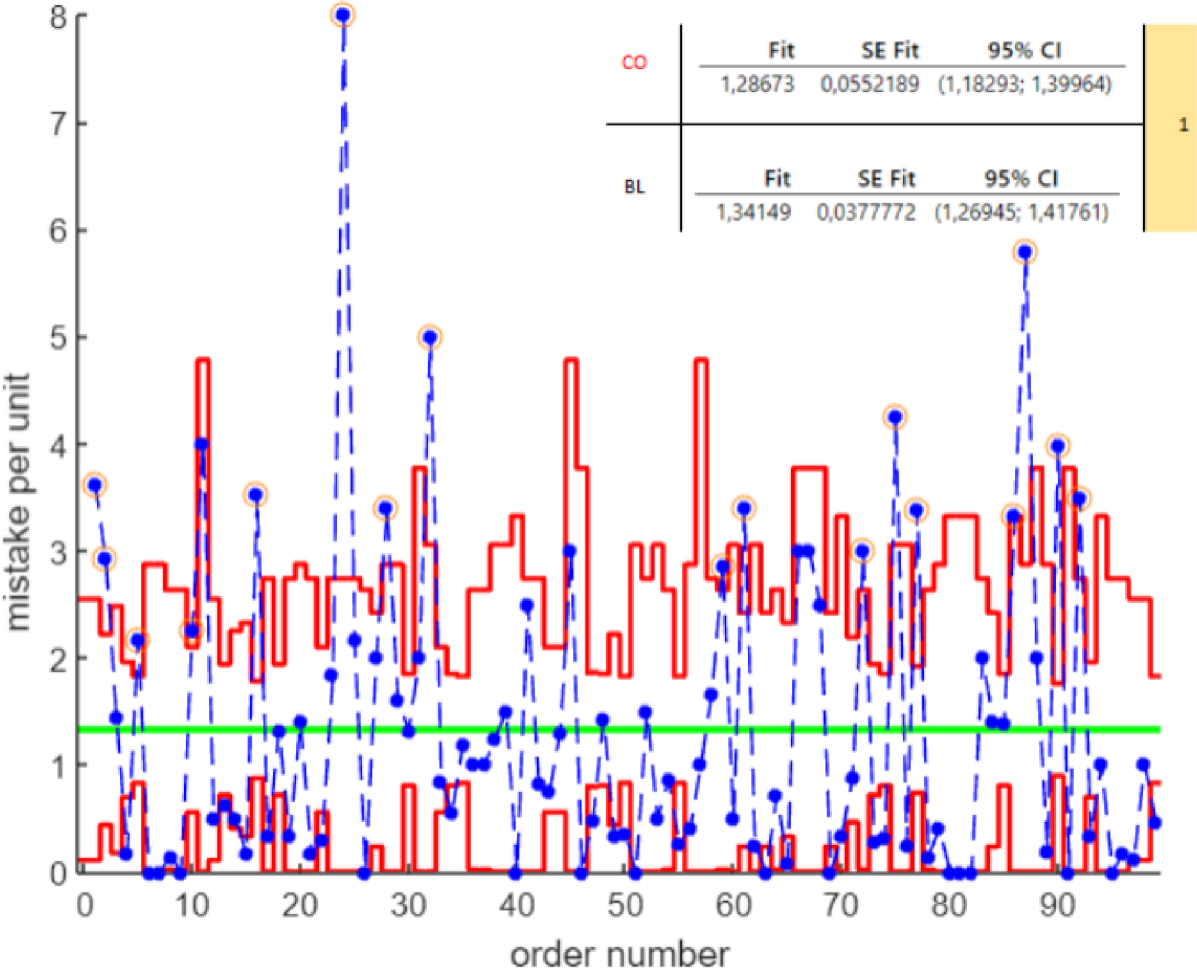


Fig. 15 U-Chart first group of mechanical mistakes

The graphical representation of second mechanical group included product of subtypes IK, UC, ZA and UM, is illustrated on Fig. 16. There are more than several orders, that are far above UCL. But with respect of number of orders is almost 700, it doesn't look so frustrating. Since values above UCL are rather common, manufacturing process cannot be considered as stable regarding to the observed mistakes.

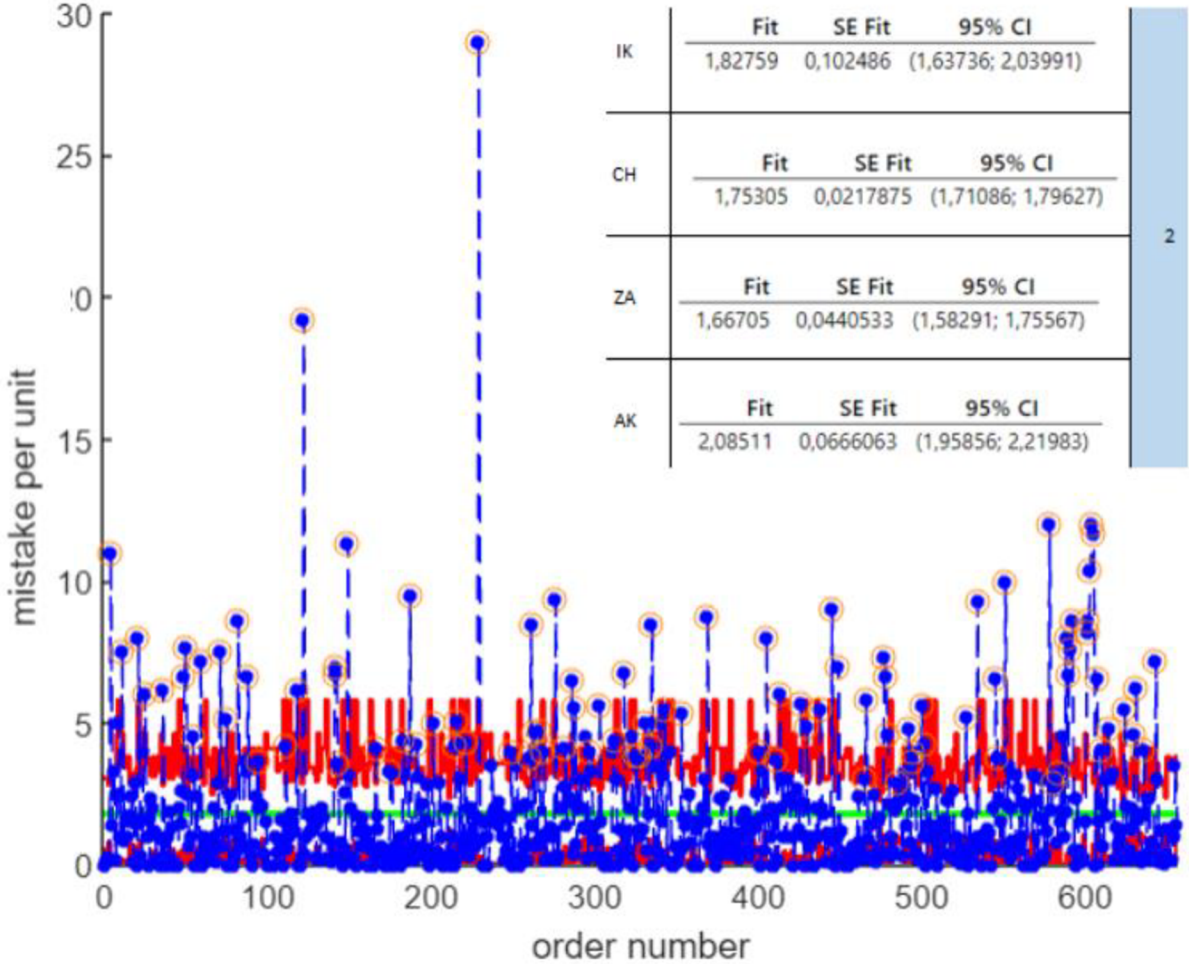


Fig.16- U-Chart second group of mechanical mistakes

The graphical representation of third mechanical group included product of subtypes YG and UM, is illustrated on Fig. 17. There are 5 orders, that are far above UCL. The high number of orders, which are under LCL represent a small number of mechanical mistakes. It also interesting to investigate what has impacted on product. Since values above UCL are rather common, manufacturing process cannot be considered as stable regarding to the observed mistakes.

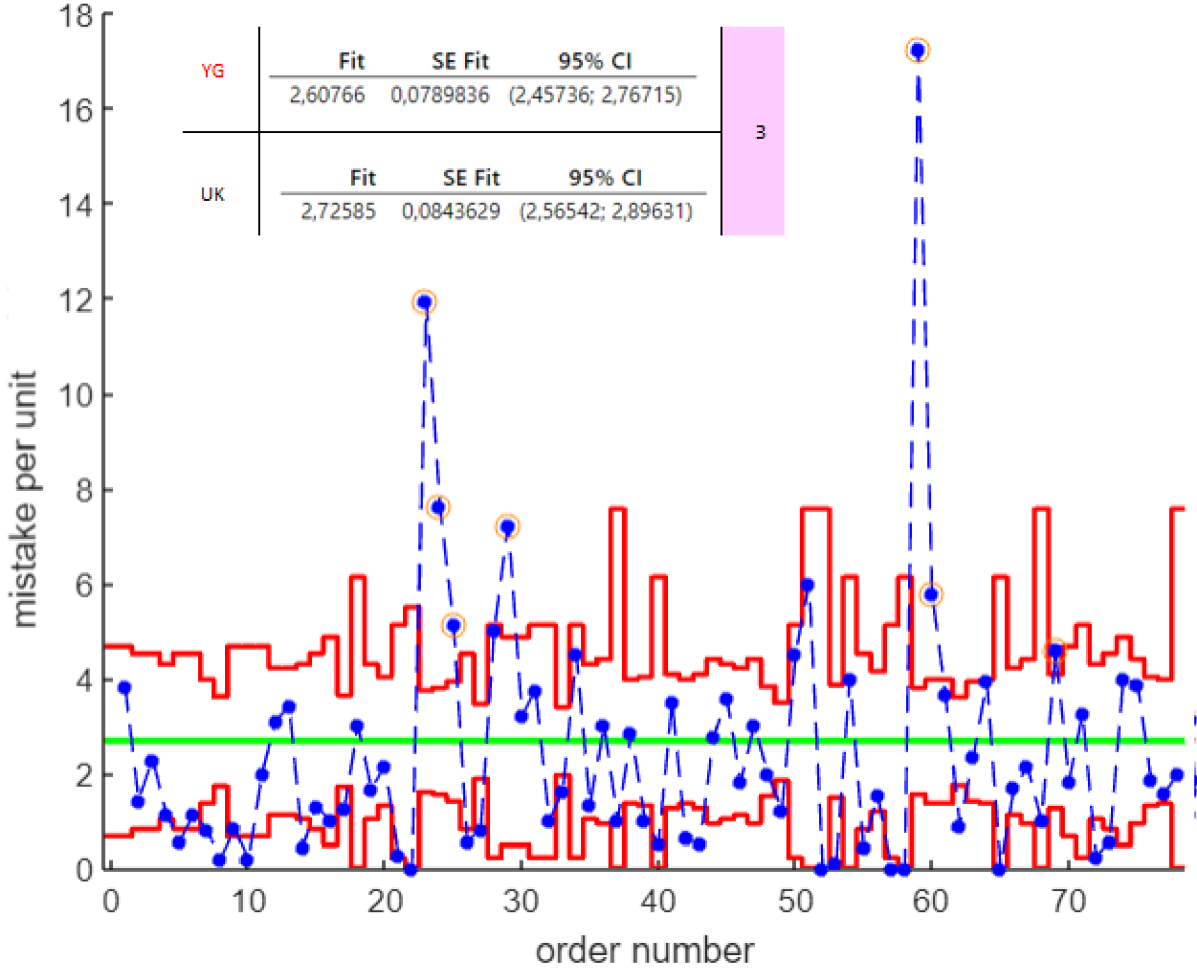


Fig. 17 U-Chart third group of mechanical mistakes

Even though the manufacturing process cannot be considered stable U-Charts can still be used to identify “the worst orders” according to any kind of mistakes. These extreme cases are then worth investigating for any irregularities that may have occurred during manufacturing process. Preventing these irregularities can lead to significant improvement of quality with regards to average mistakes per unit. Prime example of an order that would warrant such investigation is order XXX of the product subtype KD. As can be seen from U-charts of mechanical and electrical mistakes for subtype KD (fig. 18 and fig. 19) order XXX (referring to graph order number is 22) is significantly above UCL in both electrical and mechanical mistakes

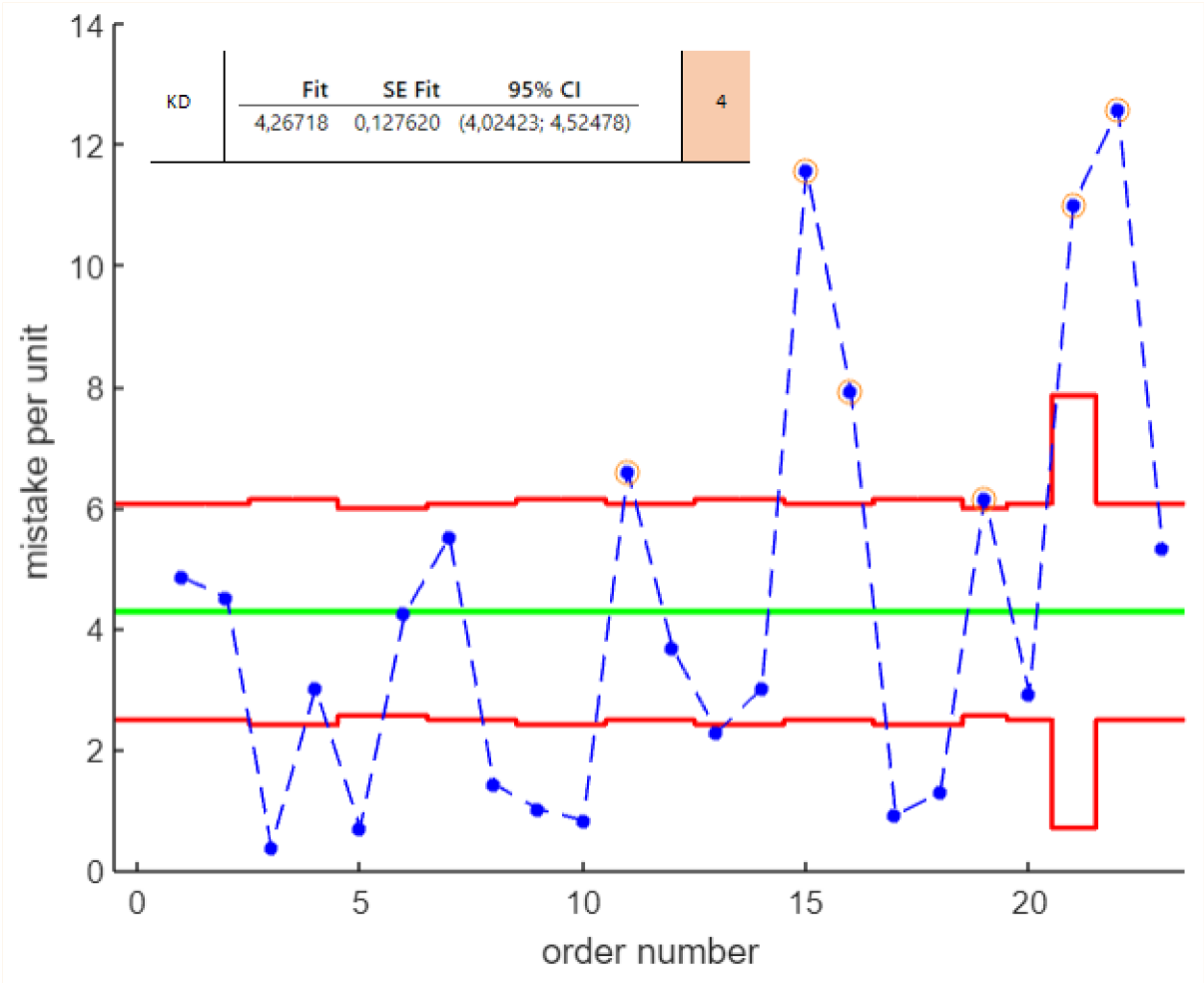


Fig. 18 U-Chart fourth group of mechanical mistakes

The graph for electrical group of mistakes shows the same mistake behavior. The form of LCL and UCL are look very similar, the difference is in the number of mistakes. The 22 order show extreme value. For improving manufacturing process it will be useful to analyze the root causes or mistake occurrence.

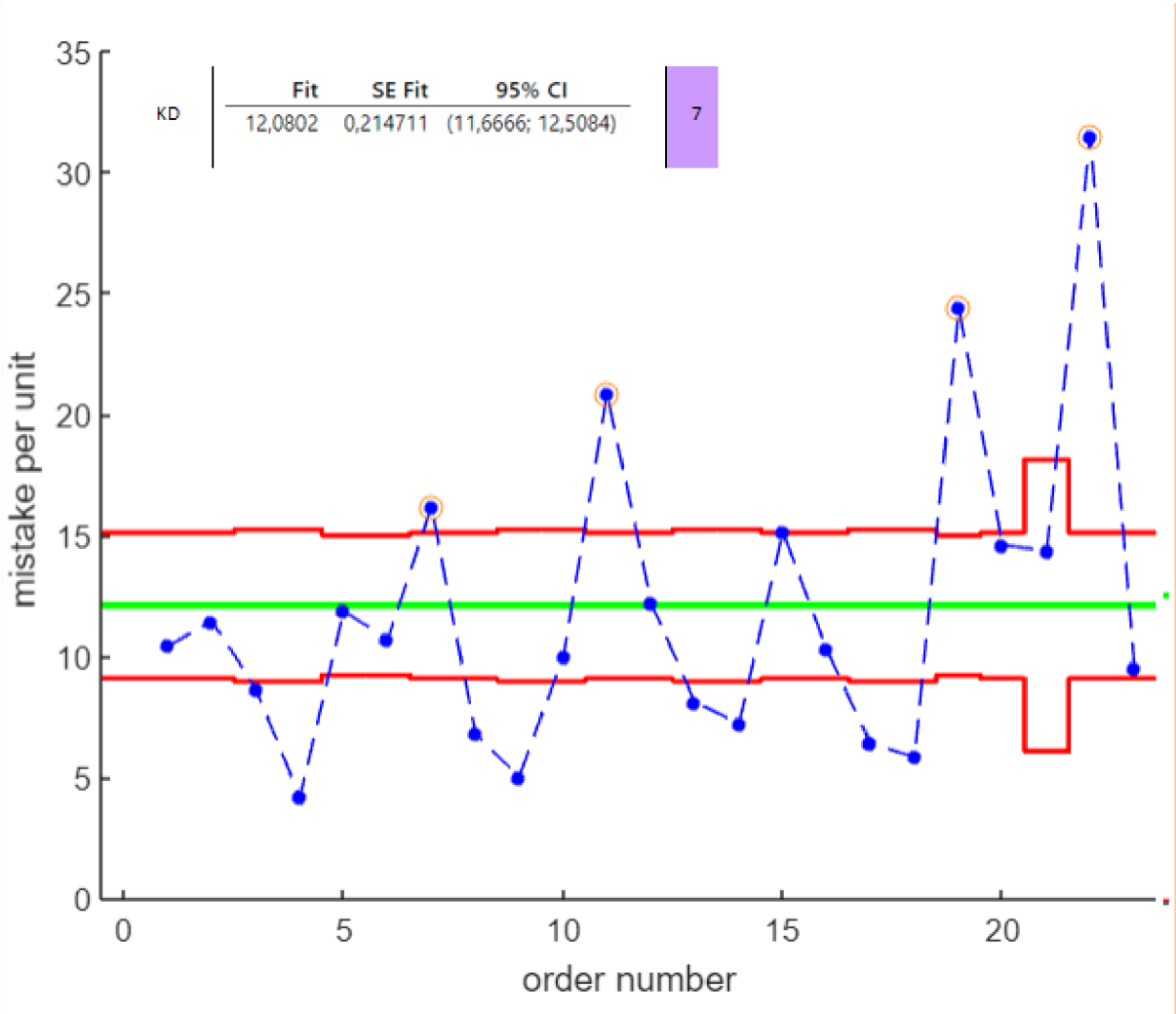


Fig. 19 U-Chart of seventh group of electrical mistakes

5.4 Foremen

Next step is to find out if there is any difference between foremen and the product subtypes. Each foreman has his own subtypes, for which he has responsibility, graphical representation is in table 4. Only one foreman for this list is caring type B the product, all others are making type A. Subtype CH is rather popular, which gives us an avenue to lower the influence of different subtypes.

Table 4 Dependence foreman of the product subtype

Foreman	CO	KD	YG	UK	CH	UA	IK	AK	BL	ZA	sum
MILLER					x				x		1325
JOHNSON					x	x				x	1222
BROWN					x	x					415
DAVIS					x			x			2051
SMITH		x		x	x		x				309
WHITE		x		x	x		x	x			923
GOODMAN	x		x		x						1143
LI					x	x	x				289
SIMPSON		x			x	x					541

Foreman	CO	KD	YG	UK	CH	UA	IK	AK	BL	ZA	sum
Miller					385				940		1325
JOHNSON					213	150				859	1222
BROWN					345	70					415
DAVIS					2025			26			2051
SMITH		51		110	133		15				309
WHITE		12		273	37		157	444			923
GOODMAN	422		418		303						1143
LI					190	97	2				289
SIMPSON		199			62	280					541

5.5 Foreman's Prediction

It was checked if there is any dependence between foreman and the quantity of mistakes by using Minitab. Zero P-value tells us that our hypothesis of equivalence of mistakes number per unit with respect to foremen is rejected. All foremen don't have the same mean value.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	719,8	89,972	13,34	0,000
Foreman name	8	719,8	89,972	13,34	0,000

Fig. - Analysis of variance foremen vs mechanical mistakes

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	2127	265,84	24,71	0,000
Foreman name	8	2127	265,84	24,71	0,000

Fig. - Analysis of variance foremen vs electrical mistakes

To test whether there is statistically significant difference between foremen according to the average number of mistakes per unit, a Poisson regression with a foreman categorical predictor can be used as it was done for the product subtypes. We can combine foremen into the group of the mistakes by mean value. see the table 5. A group can include both once and

twice or even three times, as we can see in the example of foreman WHITE or LI in electric part.

Table 5 Group of foreman combination by mistakes mean value

electrical mistakes				mechanical mistakes						
Foreman	prediction			group	Foreman	prediction			group	
MILLER	Fit	SE Fit	95% CI	1	MILLER	Fit	SE Fit	95% CI	1	
	2,12768	0,362240	(1,41673; 2,83863)			1,41267	0,286812	(0,849766; 1,97558)		
JOHNSON	Fit	SE Fit	95% CI			SMITH	Fit	SE Fit		95% CI
	2,31563	0,254595	(1,81596; 2,81531)			1,46235	0,400755	(0,675815; 2,24889)		
BROWN	Fit	SE Fit	95% CI	2	GOODMAN	Fit	SE Fit	95% CI	2	
	2,49665	0,427049	(1,65851; 3,33479)			1,49492	0,222707	(1,05783; 1,93201)		
DAVIS	Fit	SE Fit	95% CI	3	DAVIS	Fit	SE Fit	95% CI	2	
	2,81496	0,211298	(2,40026; 3,22966)			1,75174	0,167300	(1,42339; 2,08009)		
WHITE	Fit	SE Fit	95% CI			JOHNSON	Fit	SE Fit		95% CI
	3,51237	0,364469	(2,79705; 4,22769)		1,87418	0,201581	(1,47855; 2,26981)			
LI	Fit	SE Fit	95% CI	4	WHITE	Fit	SE Fit	95% CI	3	
	3,55459	0,525256	(2,52370; 4,58548)			2,66855	0,288577	(2,10218; 3,23493)		
SMITH	Fit	SE Fit	95% CI		BROWN	Fit	SE Fit	95% CI		
	3,94343	0,506149	(2,95004; 4,93682)		2,71337	0,338125	(2,04975; 3,37699)			
GOODMAN	Fit	SE Fit	95% CI		LI	Fit	SE Fit	95% CI		
	4,47259	0,281277	(3,92055; 5,02464)		4,49315	0,415883	(3,67692; 5,30938)			
SIMPSON	Fit	SE Fit	95% CI		SIMPSON	Fit	SE Fit	95% CI		
	8,87329	0,463893	(7,96284; 9,78375)		4,56943	0,367298	(3,84855; 5,29030)			

5.6 Foreman's Prediction by CH Subtype

To remove the influence of different subtypes manufactured by each foreman, it was decided to analyze the data for the CH subtype separately. Unfortunate consequence of this decision is that for some foremen there is low sample size.

Wald Test			
Source	DF	Chi-Square	P-Value
Regression	8	3456,37	0,000
Foreman name	8	3456,37	0,000

Fig.20 Analysis of variance foremen vs mechanical mistakes

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	198,0	24,751	3,87	0,000
Foreman name	8	198,0	24,751	3,87	0,000

Fig. 21 Analysis of variance foremen vs electrical mistakes

To test whether there is statistically significant difference between foreman according to the average number of mistakes per unit, a Poisson regression with foreman categorical predictor can be used as it was done for the product subtypes. We can combine foremen into the group of the mistake by mean value. see the table 6.

Table 6 Groups of foremen combination by mistakes mean value for subtype CH

electrical mistakes				mechanical mistakes						
Foreman	prediction			group	Foreman	prediction			group	
WHITE	Fit	SE Fit	95% CI	2	GOODMAN	Fit	SE Fit	95% CI	1	
	1,61626	1,26477	(0; 4,10162)			0,445545	0,0383464	(0,376384; 0,527413)		
GOODMAN	Fit	SE Fit	95% CI	1	SMITH	Fit	SE Fit	95% CI	2	
	2,09709	0,454320	(1,20432; 2,98986)			0,984962	0,0860566	(0,829946; 1,16893)		
BROWN	Fit	SE Fit	95% CI			MILLER	Fit	SE Fit	95% CI	3
	2,41502	0,341084	(1,74477; 3,08528)			1,30649	0,0582537	(1,19717; 1,42581)		
MILLER	Fit	SE Fit	95% CI		4	WHITE	Fit	SE Fit	95% CI	4
	2,46616	0,344228	(1,78973; 3,14259)				1,54054	0,204050	(1,18831; 1,99718)	
JOHNSON	Fit	SE Fit	95% CI				DAVIS	Fit	SE Fit	95% CI
	2,48719	0,516342	(1,47254; 3,50183)		1,61877	0,0282735	(1,56429; 1,67514)			
SMITH	Fit	SE Fit	95% CI	2	JOHNSON	Fit	SE Fit	95% CI	6	
	2,581	0,505909	(1,58685; 3,57515)			2,06103	0,0983677	(1,87698; 2,26314)		
DAVIS	Fit	SE Fit	95% CI	3	BROWN	Fit	SE Fit	95% CI	7	
	2,79576	0,163282	(2,47490; 3,11662)			2,44348	0,0841579	(2,28398; 2,61412)		
LI	Fit	SE Fit	95% CI			SIMPSON	Fit	SE Fit	95% CI	
	3,55624	0,433814	(2,70376; 4,40871)			4,03226	0,255022	(3,56216; 4,56439)		
SIMPSON	Fit	SE Fit	95% CI		LI	Fit	SE Fit	95% CI		
	6,99524	0,894330	(5,23782; 8,75266)			4,41053	0,152359	(4,12179; 4,71949)		

Interesting conclusion from tables 4, 5 and 6. Is that even after lowering the influence of difficult to make subtypes, Mr. Simpson and Mr. Li are still among the worst with regards to mechanical and electrical mistakes.

5.7 Pareto analysis

Let's have a look at mistakes in details. During each part of the manufacturing process different kinds of mistakes can appear. Here is the list of common mistake categories:

- Labels – missing, wrong picked, wrong location
- missing components – during manufacturing there weren't in storage
- wrong or damaged subassembly or part
- Wire and terminal connections
- Incorrect tightening of screw connections/ damaged screws

The 2022 year data was taken and processed. The company produced approximately 300 orders per quarter. From each quarter it was chosen 10 orders with the worthiest cases - the biggest number of mistakes. From inspectors notes it was identified every single problem/mistake and assigned a category. The Pareto chart, fig. 22, represents mistakes for the whole year.

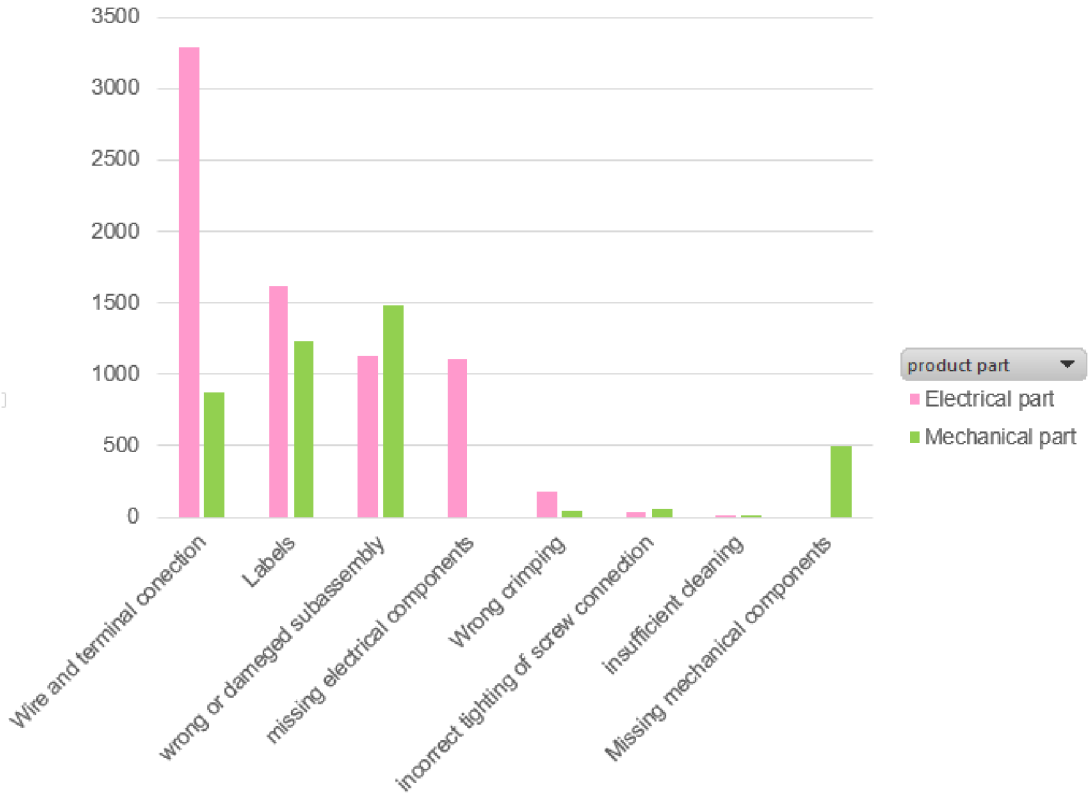


Fig. 22 Pareto chart mistake occurrence frequency

If you eliminate the wire and terminal connection and label mistake or reduce the frequency of its occurrence, you can buy a time to fix it and thereby speed up the shipment of the product.

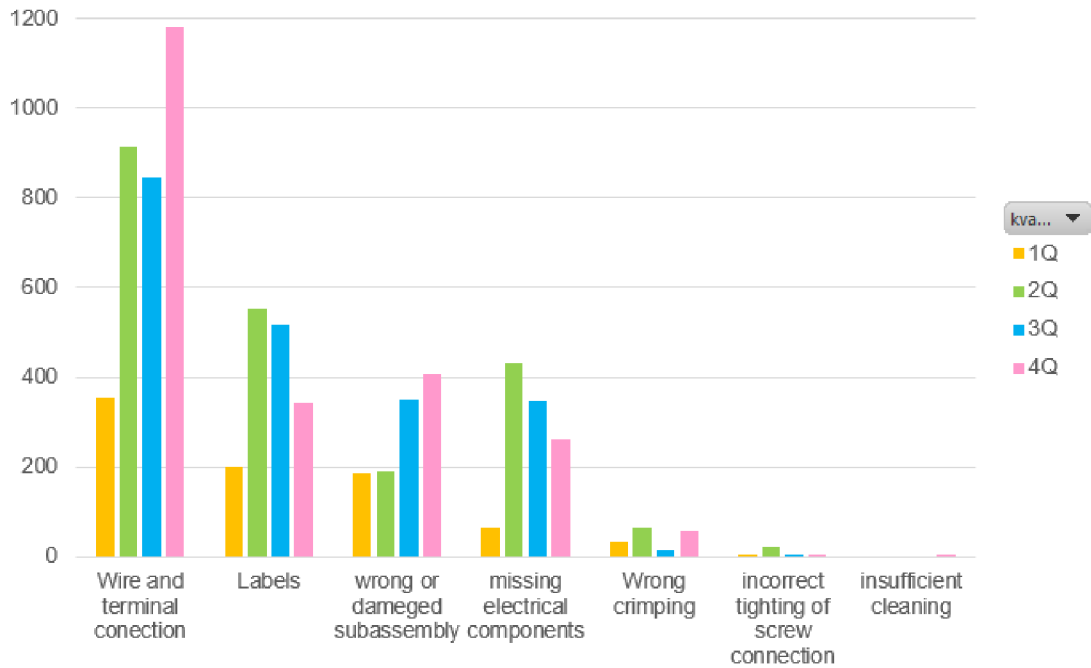


Fig. 23 Pareto chart of mistake occurrence during manufacturing electrical part

From fig. 23 and 24 can be seen that the biggest impact give wrong or damaged subassembly and labels. To improve the manufacturing process as a recommendation can be useful to make course skoleni. For operators for montage. Also the number of mistakes such as wire and terminal connection and missing mechanical components are increasing through time. Maybe it makes sense to make additional education as well.

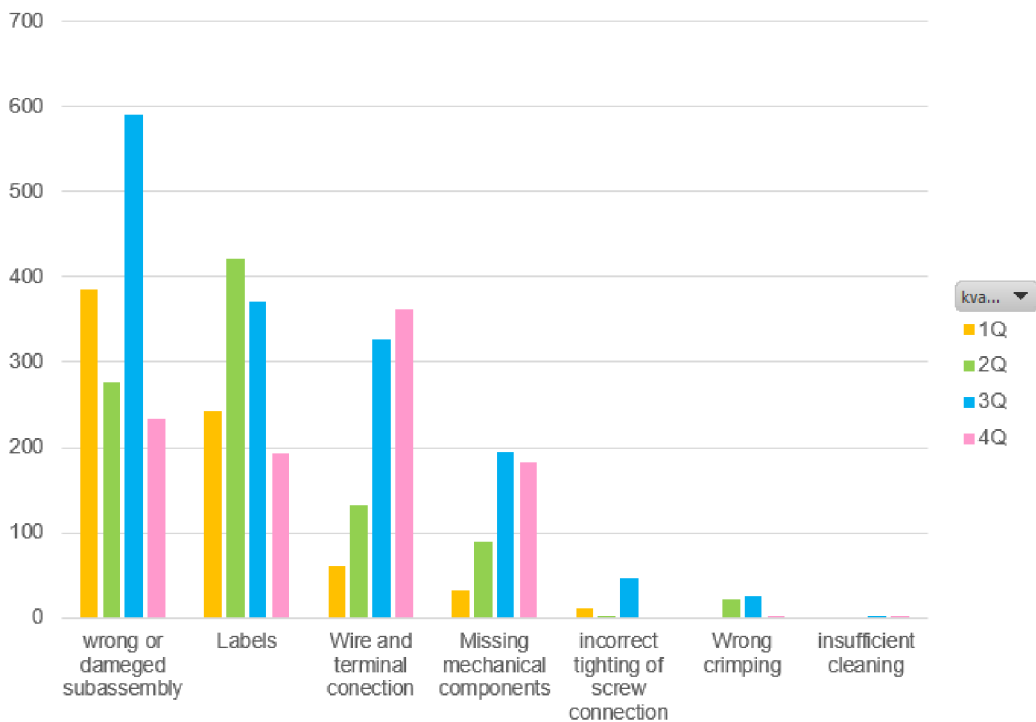


Fig. 24 Pareto chart of mistake occurrence during manufacturing mechanical part

6 CONCLUSION

First two chapters of this thesis contain a comprehensive summary of statistical methods, for analyzing attribute random variables, mainly for Poisson distributed variables. Described apparatus of hypothesis testing and application of control charts.

In chapter 4 was described the process from which analyzed data originated, product types and subtypes. The difference between defects and mistakes. It was described mechanical, electrical, supplier mistakes and mistakes solved by inspectors.

By statistical methods it was found out that there is a dependence between mistake behavior of product type A and type B. The null hypotheses that for product type A and type B mechanical, electrical and fixed by inspectors mistakes have the same average mistakes per unit are rejected. This is especially interesting because it defies expectation of the company experts, considering expected complexity of types A and B.

It was found out that mistakes of each category depended on product subtypes. The goal was to find a connection between each category: the product types, the product subtypes and foremen and time. By time it considers when the product was produced and sent. All documented data were evaluated after the product shipment.

There is for each mistakes category a connection between foremen, who are responsible for specific order. It was proved by zero p-value corresponding to Poisson regression results. Foremen were grouped into categories, that are not significantly different with respect to mean mistake per unit value. Similar grouping was made for product subtypes. This grouping was utilized to construct U-charts. U-charts show that the process cannot be considered stable, therefore the main purpose of U-charts was to find orders, which are breaking UCL the most. The stability of manufacturing process is probably violated mainly because the product is highly customized for each order. To analyze orders with extreme number of mistakes can help improve manufacturing process itself by identifying the causes of a extreme number of mistakes and make preventive actions for further orders of specific product subtype. Similarly it is possible to look for process improvements in orders that were bellow LCL.

To have a deeper look at the nature of mistakes the Parreto analysis was made by the supply of orders for the time period of one year. The results were presented in Pareto charts. The biggest impact is caused by wires connection and label mistakes. To fix or minimize these two categories of mistakes would lead to save a time to shipment, and extra material expenses.

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8 LIST OF ABBREVIATIONS

Abbreviation	Description
UCL	Upper control limit
LCL	Lower control limit
CL	Central limit
SPC	Statistical process control
H0	Null hypothesis
H1	Alternative hypothesis

9 ATTACHMENTS

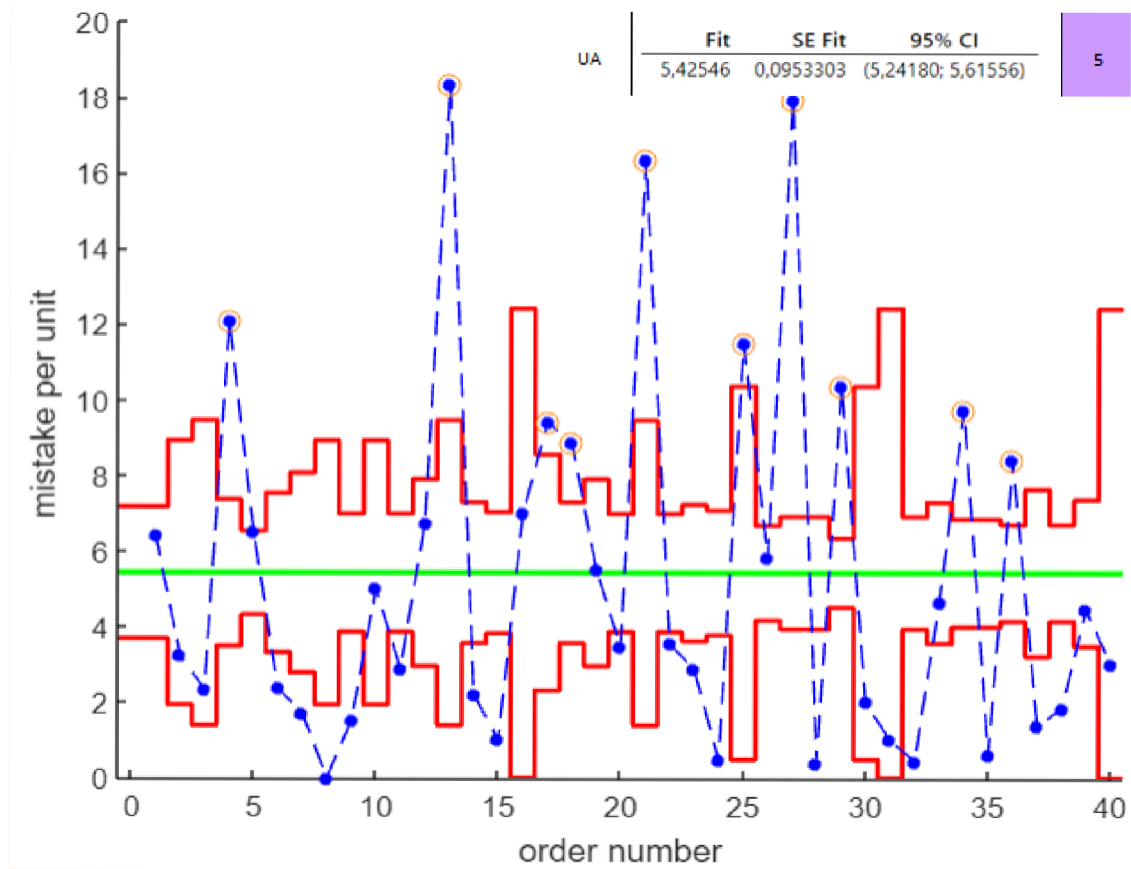


Fig. 25 U-Chart fifth. group of mechanical mistakes

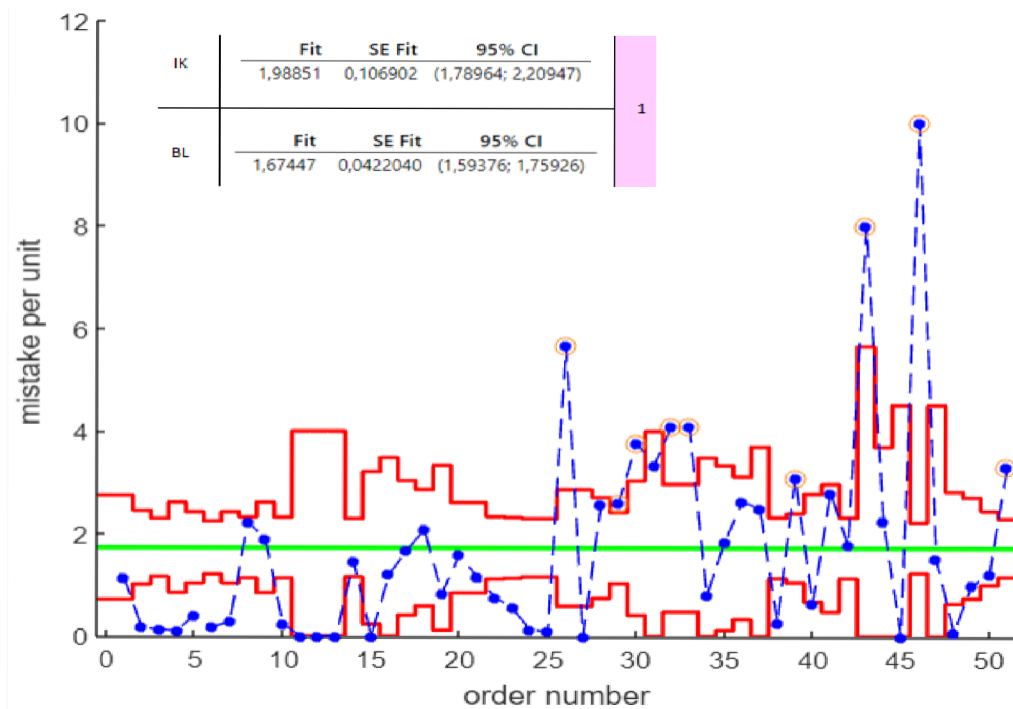


Fig. 26 U-Chart of first group of electrical mistakes

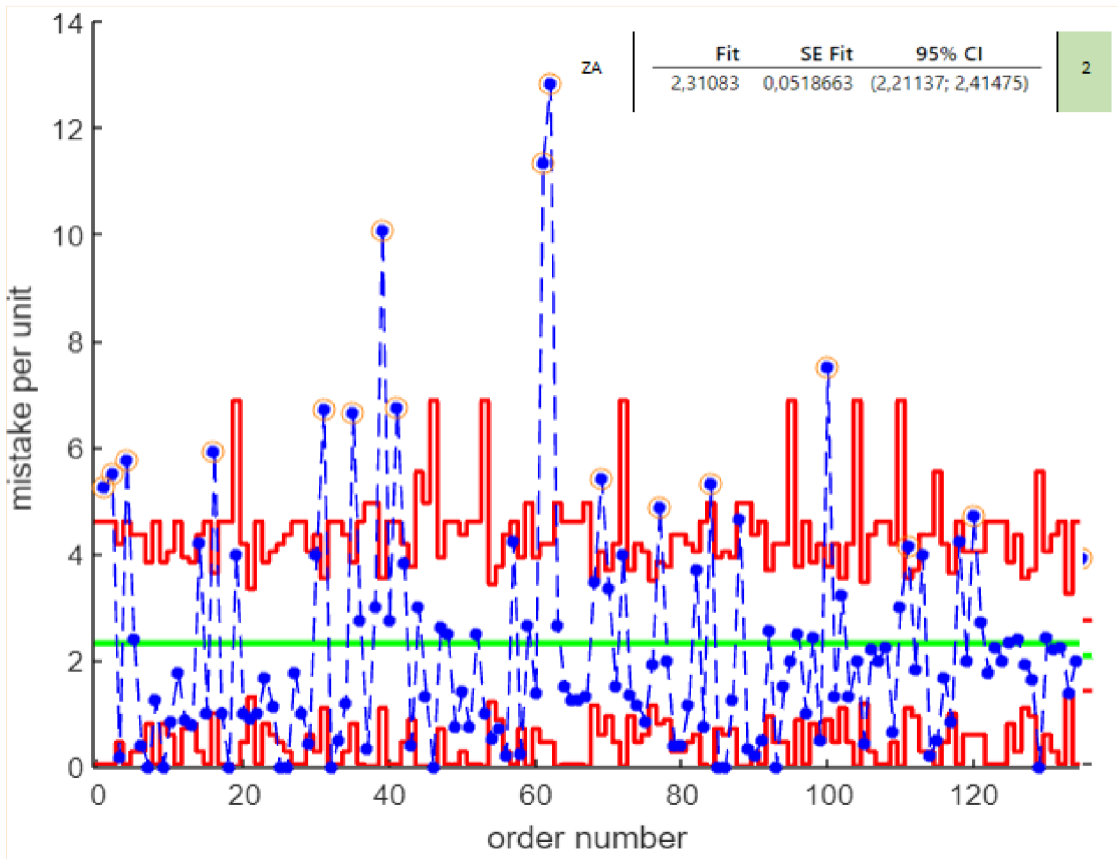


Fig. 27 U-Chart of second group of electrical mistakes

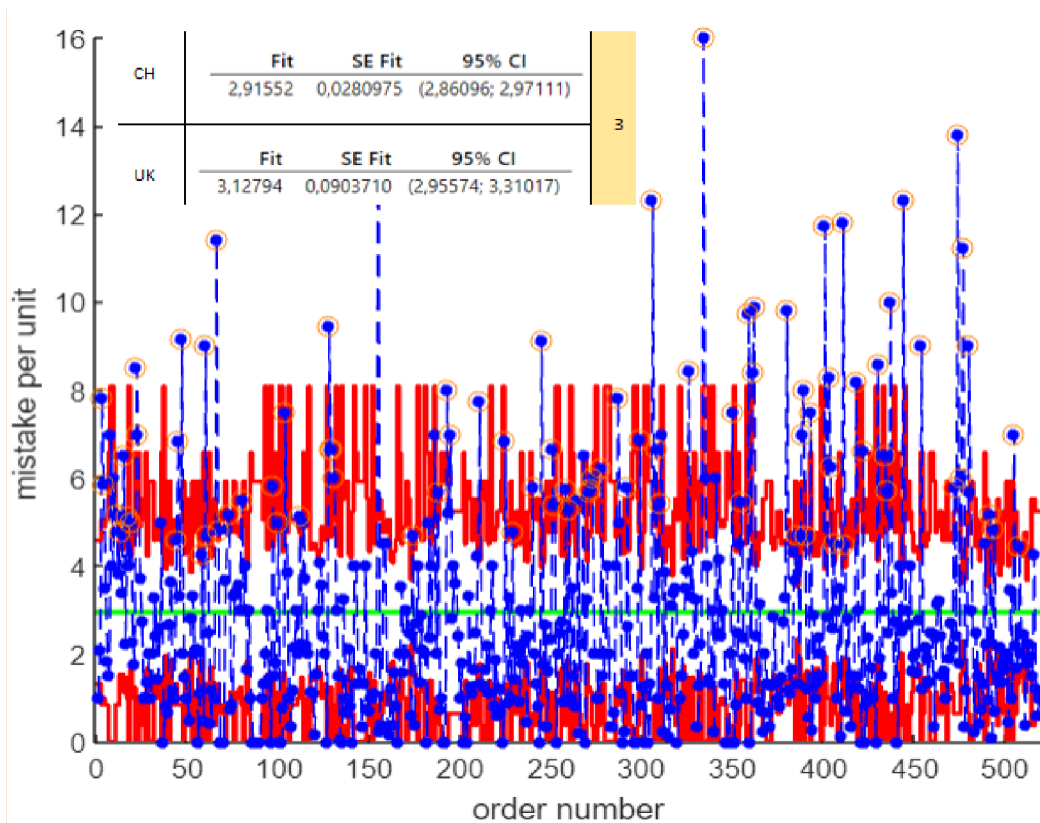


Fig. 28 U-Chart of third group of electrical mistakes

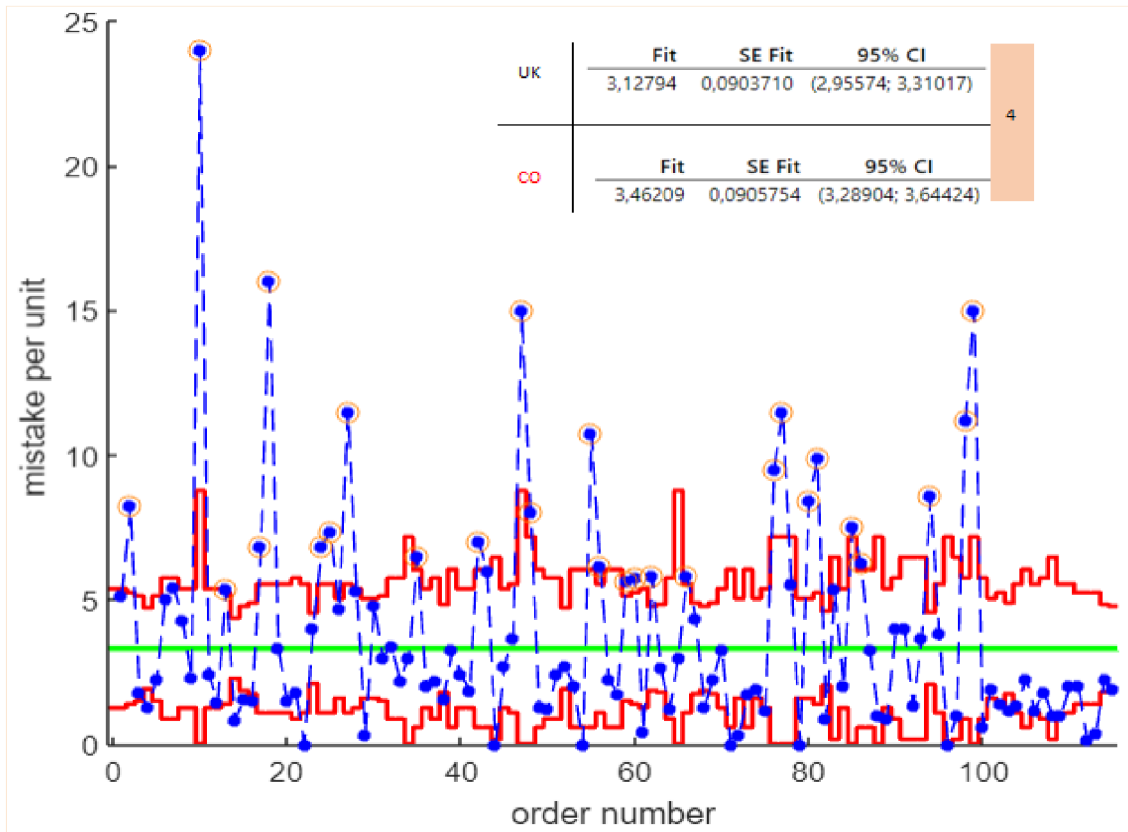


Fig. 29 U-Chart of fourth group of electrical mistakes

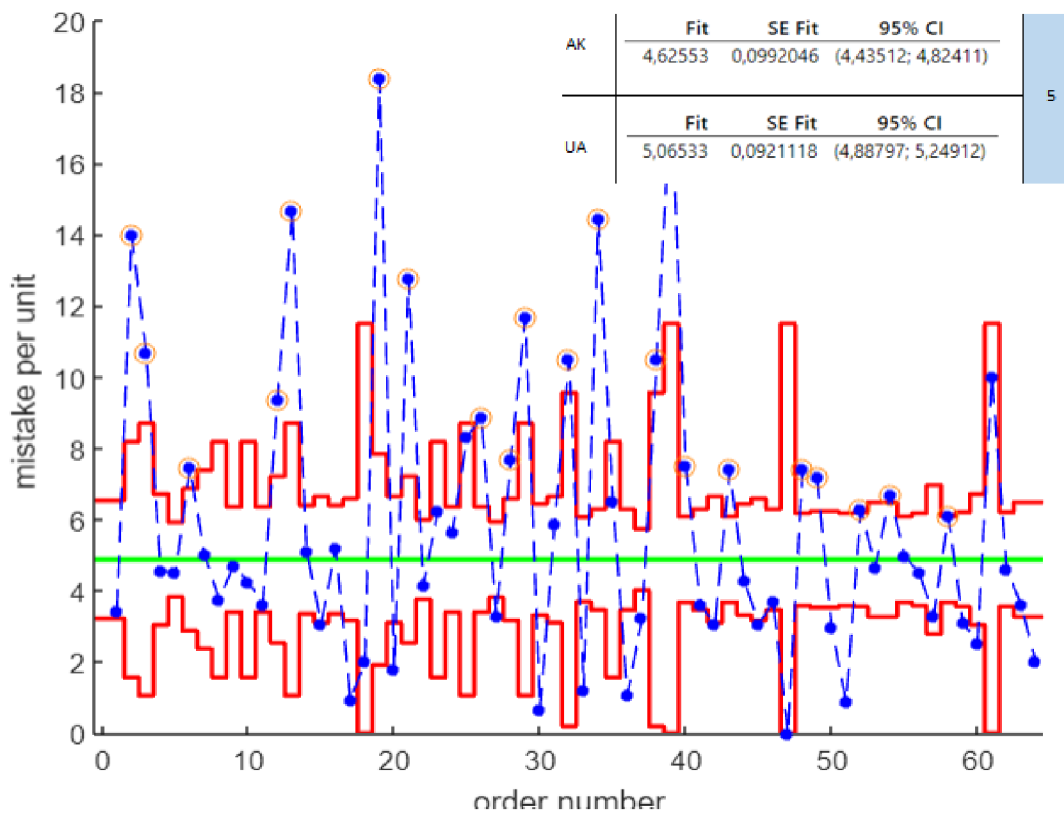


Fig. 30 U-Chart of fifth group of electrical mistakes

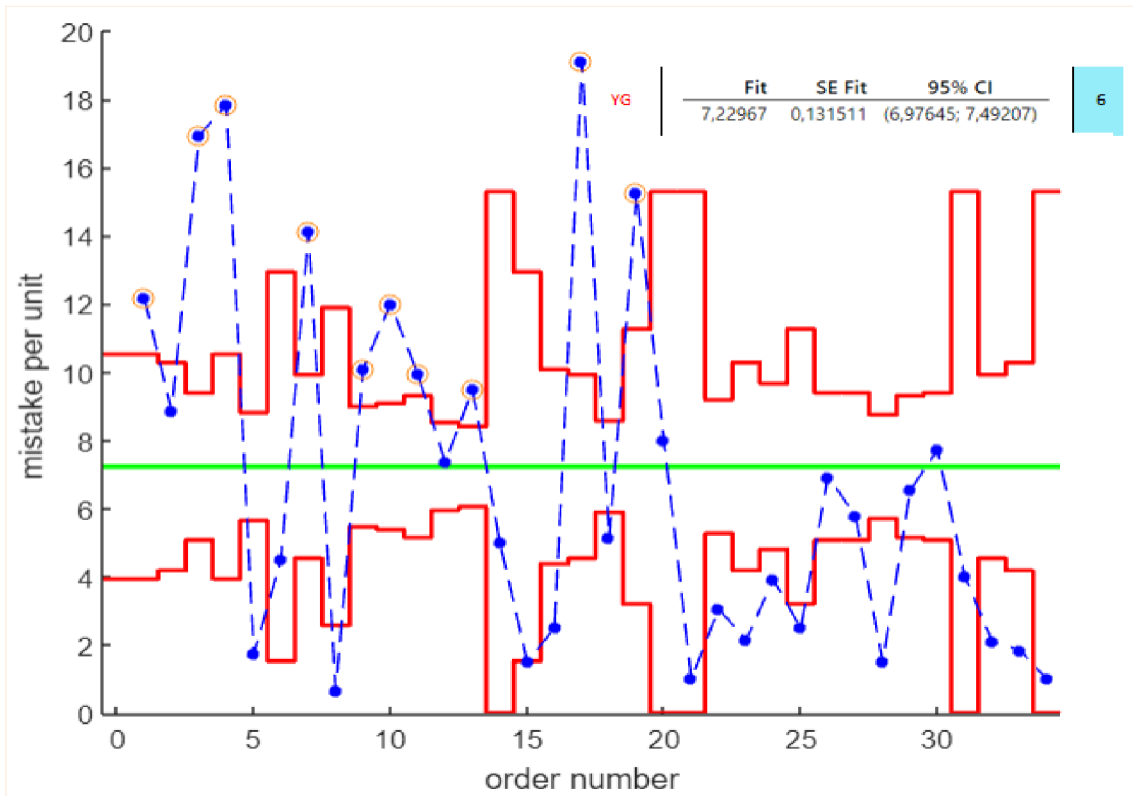


Fig. 31 U-Chart of six group of electrical mistakes

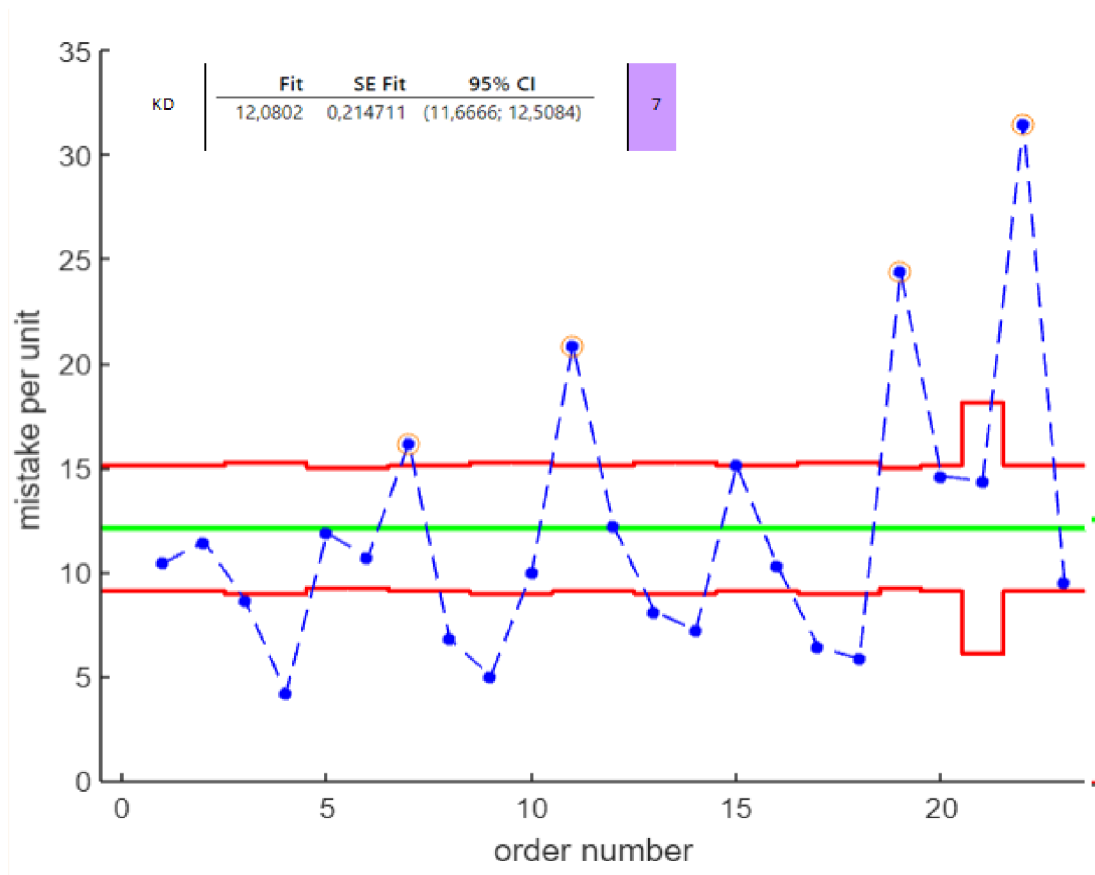


Fig. 32 U-Chart of seventh group of electrical mistakes