COST ANALYSIS OF POOR QUALITY USING A SOFTWARE SIMULATION

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Abstract
The issues of quality, cost of poor quality and factors affecting quality are crucial to maintaining a competitiveness regarding to business activities. Use of software applications and computer simulation enables more effective quality management. Simulation tools offer incorporating the variability of more variables in experiments and evaluating their common impact on the final output. The article presents a case study focused on the possibility of using computer simulation Monte Carlo in the field of quality management. Two approaches for determining the cost of poor quality are introduced here. One from retrospective scope of view, where the cost of poor quality and production process are calculated based on historical data. The second approach uses the probabilistic characteristics of the input variables by means of simulation, and reflects as a perspective view of the costs of poor quality. Simulation output in the form of a tornado and sensitivity charts complement the risk analysis.

Keywords: poor quality cost analysis, Monte Carlo simulation

JEL Classification: C53, C88, D24, L15

Introduction

The problem of maintaining competitiveness of a company is growing in today's dynamic economic environment. Long-term competitiveness requires constantly increasing productivity, efficiency and product quality. This calls for putting new quality management methods and changes in approach into practice. The issue of quality management is the topic of numerous scientific articles. Some scientific work deals with the methods and techniques used in the field of quality on the theoretical level. For example Sokovic, Pavletic and Pipan (2010) introduced characteristics of PDCA tool and Six Sigma (DMAIC, DFSS) techniques and EFQM Excellence Model (RADAR matrix) and showed that some methodologies are more simple and therefore easily to understand and introduce (e.g. PDCA cycle). On the contrary Six Sigma and EFQM Excellence model are more complex and demanding–methodologies and therefore need more time and resources for their proper implementation. Schroeder, Linderman, Liedtke and Choo (2008) used the

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grounded theory approach and literature to propose an initial definition and theory of Six Sigma. Watson and DeYong (2010) examined the models that have been proposed for design for Six Sigma. Jasti and Kodali (2014) performed the analysis of literature review of lean production. Their study provided a taxonomical and integrated review of articles, put up perspective into the conceptualisation and various critical parameters for research.

Cost analysis due to poor production or process quality is the basis for the proposed changes and improvement in terms of quality management. The aim of one of the phases of the DMAIC method is to describe the current state of the process, its variability and capability. Using software and computer simulation allows incorporating variability and uncertainty of input variables in the analysis and review processes in probabilistic aspects.

This article presents a case study analysis of the production process from the quality aspect using computer simulation Monte Carlo. The structure of the article compounds of a few parts. First part briefly presents case study and defines a problem in quality management. Next part is focused on the methodology how to calculate the cost of poor quality and the method of analysis of the cost of poor quality using Monte Carlo simulation. The last part deals with the calculations and simulation results, results there are compared and the production process is evaluated in terms of sigma level and in terms of the statistical characteristics of the output variables, as well.

1. Literature review

Many case studies present application of the methods, practice knowledge or experience in the field of quality. Although, different methods are used in quality management, Six Sigma is a widely used method to improve processes from various industry sectors. Regulation of manufacturing processes by the methods of regulation of production processes is a unique feedback that can be used in the practice of mass and series production according to Panda, Jurko and Pandova (2016). Statistical Process Control has become a mandatory method for the automotive, as well as for other demanding industries. Pugna, Negrea and Miclea (2016) presented a creative solution for improving an assembly process in an automotive company in Romania by using Statistical Thinking and DMAIC Six Sigma methodology. Simanová (2015) introduced the proposal of the application and implementation of Six Sigma in furniture manufacturing. Pribulová et al. (2013) observed quality parameters of the moulding mixtures and determine tolerable content in the moulding mixture. Atanase and Schileru (2014) researched the normative frame, the speciality literature and assessed the perceptions related to service quality in tourism. The Six Sigma methodology has an important place for developing and reducing the actions which do not have inner process in a supply chain. Erbiyik and Saru (2015) explained a general structure of Six Sigma with regard to ‘how to define the complex problems which were encountered in the supply chain’. Aldowaisan, Nourelfath and Hassan (2015) declared that identifying whether the process data were of non-normal distribution was important to more accurately estimate the effort required to improve the process. Widely used assumption of a normally distributed process may lead to erroneous solutions. When a process is exponential, attaining desired performances may require greater quality-improvement effort. Similarly, Hsu, Pearn and Wu (2008) dealt with gamma processes. The substantial increase in quality of decision making according to Janekova, Kovac and Onofrejova (2015) in terms of respect of risk and uncertainty is brought by probabilistic methods. An important representative is the Monte Carlo simulation. The main reason for its use is a quantification of the probability distribution for the overall risk of a project.

There is a growing need for operations management models that contribute to the continuous improvement of company processes, among them Lean Manufacturing, Six Sigma and Lean Six Sigma (Drohomeretski et al., 2014). Combining Lean practices with Six Sigma has gained wide popularity in the last years. Whether a combined Lean-Six Sigma approach is the latest management fad, or leads to significant performance benefits is not yet apparent (Shah, Chandrasekaran and Linderman, 2008). Lean Six Sigma is widely adopted in non-manufacturing sectors such as financial, trade, services, etc. The methodology combines the Six Sigma techniques and the Lean Manufacturing principles. Despite growing popularity and impressive outcomes, the Lean Six Sigma model does not always offer the expected results (Dragulanescu and Popescu, 2015). Sagnak and Kazancoglu, (2016) discussed the integration of green lean approach, and identified the limitations of green lean approach. The Six Sigma approach was applied in order to overcome these limitations. Ali and Deif (2014) presented a dynamic model to evaluate the degree of leanness in manufacturing firms. Their model was based on system dynamics approach and presented a "leanness score" for the manufacturing system. Ringen, Aschehoug, Holtskog and Ingvaldsen (2014) explored the relationship between quality and lean as integrated parts of a holistic production system.

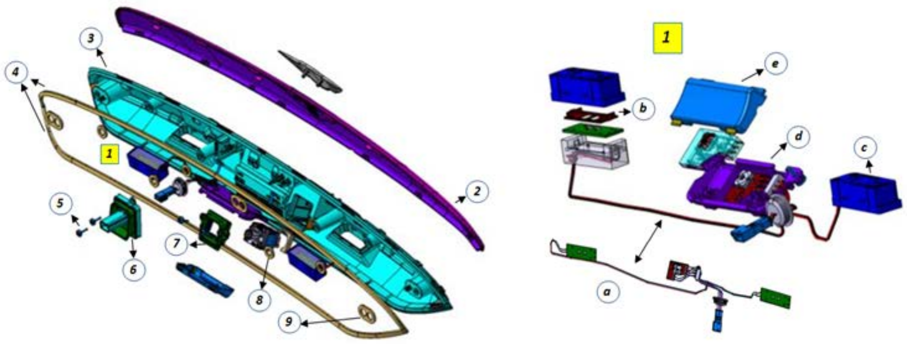
The success of Six Sigma improvement process depends on many factors of social, technical and financial character. Mehrabi (2012) considered the evolutionary review of the benefits and challenges of Six Sigma projects and recognized the key and influential elements of the successful approach of Six Sigma method. The study of Arumugam, Antony and Kumar (2013) investigated the impact of two organizational antecedents, (1) Six Sigma resources (technical) and (2) team psychological safety (social), on the success of Six Sigma process improvement projects. Their study empirically established the notion that technical and social supports jointly impacted the success of initiatives such as Six Sigma. Arumugam, Antony and Linderman (2016) examined the interrelationship between Six Sigma project goals, adherence to the Six Sigma method, and knowledge creation. It was found that adherence to the Six Sigma method becomes more beneficial for projects that create a lot of knowledge. Some of the Six Sigma projects failed due to insufficient data and human errors. Hwang (2006) discussed the DMAIC phases to improve the mentioned situation and to avoid the time and cost for sourcing data.

2. Materials and methodology

2.1 Case study description

The case study is focused on the production of components for automotive industry. It is focused on an assembly/production line, which is used for mounting the rear trunk lighting of the license plate – a lightbar (figure no. 1).

The production line consists of seven workstations, served by six workers. In terms of functionality, the line consists of pre-production and assembly section. Pre-production function is directed to the preparation of parts for the assembly of the final product. It has three workstations, welding pins, potting and stove, all served by two workers. The assembly of the final product is performed at four workstations (two screw stations, crimping and test station), served by four workers. The operations at the workplace pre-production are performed on two pieces simultaneously, at the assembly workplace on four pieces at the same time. Position of a storage buffer with a capacity of 400 units in between the pre-production and assembly workplace allows that the processes must not be fully synchronized. Working place operates on three working shifts, if necessary, the production takes place over the weekend. This part of production cycle reaches a higher number of rejects and waste time caused by higher unplanned stopping or slowing production. Stopping production is conditioned by wrong machine settings, material shortages or machine break. The slowdown is usually caused by training of a new operator on a job, respectively new operators, and by an insufficient number of operators on the line (shift). Stops and slowdown in production are caused mainly due to the assembly operation, which is the bottleneck of a production. Therefore, the idle times and the costs of poor process account only for this particular workplace.



Legend:			
1	Cable harness	2	Light cover
a	PCB led + PCB switch + Connector	3	Structure Lightbar
b	Gasket lens	4	Up and down gasket
c	Semi-transparent lens	5	Screw
d	Housing switch	6	Gasket connector overmolded
e	Microswitch	8	Gasket cylindrical pin
		9	Gasket oval pin

Figure no. 1: Decomposition of the final product

2.2 Problem definition

The aim of this paper is to analyse the total cost of poor quality due to poor production quality and poor organizational quality of processes related to assembly of above mentioned final product – a lightbar for automobile.

Input data consists of actual (historical) data collected from production over a period of 23 working days. The analysis is carried out in two ways depending on the purpose of use. The first, retrospective method specifies total cost of poor quality of the production, deeply analyses rejects rate in time series analysis and sigma level analysis. Second, prognostic approach carries out the calculation of the total cost of poor quality using Monte Carlo simulation and the individual costs are analysed in terms of probability. Both approaches are shown schematically in figure no. 2.

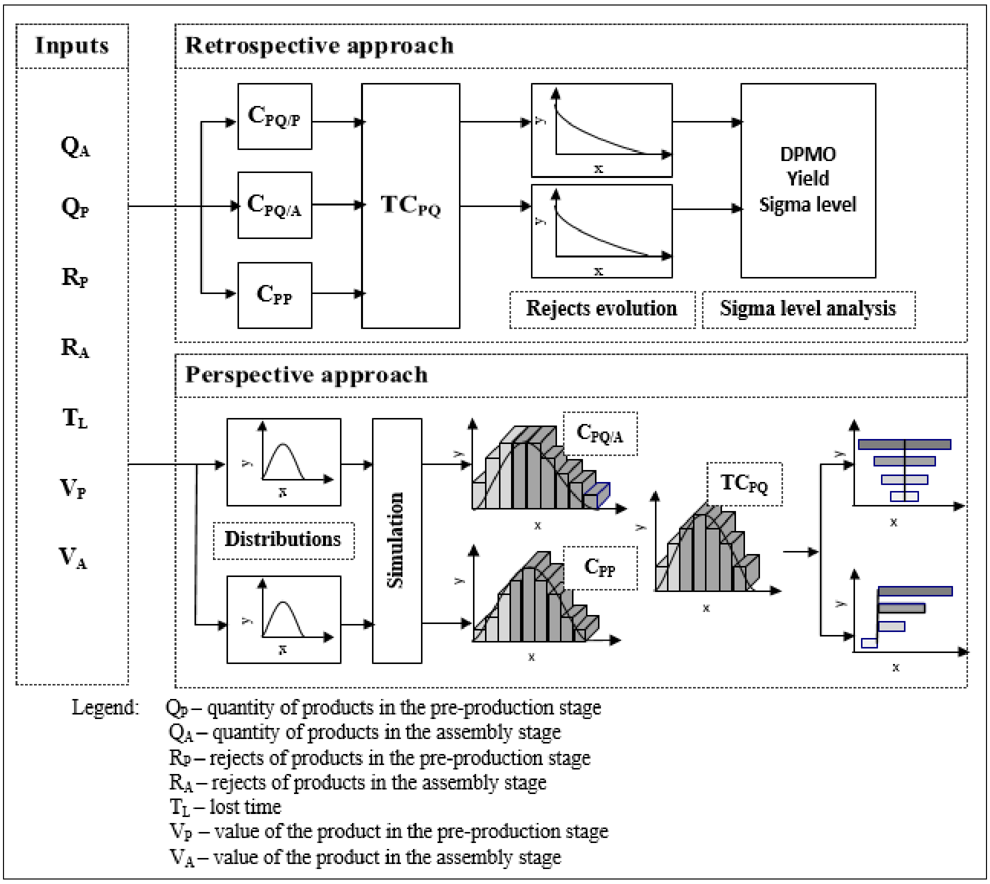


Figure no. 2: Scheme on cost analysis of poor quality

2.3 Methodology of cost calculation

Cost Analysis caused by poor quality and poor organization of production process is based on a partial evaluation of the costs of rejects and costs of unused disposable time. Thus, the costs associated with poor quality were in this case study of the dual nature:

- Expenses incurred due to a poor production quality (rejects). Rejects signify insufficient production that needs to be replenished. The company incurs costs in an amount of intermediate product on the certain level of completion. In this case, the first part of semi-finished products is discarded after pre-production stage. The average value of rejects at this stage of the production process is EUR 5.5. The other part of the rejects is discarded after an assembly stage. At this level of development, the average value of one reject is EUR 15. The production value, which should be replaced by rejected products, represents the cost of poor product quality. Costs calculation takes into account a fact, that 2 pieces are being processed simultaneously.

Cost of poor product quality:

$C_{PQ/P} = Q_P$ x V_P (1)

$C_{PQ/A} = Q_A$ x V_A (2)

where:

$C_{PQ/P}$ – cost of poor product quality in the pre-production stage,

$C_{PQ/A}$ – cost of poor product quality in the assembly stage,

Q_P – quantity of products in the pre-production stage,

Q_A – quantity of products in the assembly stage,

V_P – value of the product in the pre-production stage,

V_A – value of the product in the assembly stage.

- Costs due to a poor organization of the process. These costs are related to unplanned downtime of workplaces, respectively with the slowdown in activity for reasons that were specified in Chapter 3. The costs associated with poor quality process mean the value for lack of production not being produced, because of an unused time capacity of particular workplaces. Since the time delays were usually caused by problems at the assembly station, this place has to be considered as the bottleneck of the production process. Therefore, lack of production has the same value as the output at the assembly station. The calculation takes into account the fact that the assembly workstation has 4 simultaneous working positions, that is four pieces at the same time, and thus the cost of poor process are multiplied by 4 (see formula no. 3).

Cost of poor process:

$C_{PP} = (T_L/T_A)$ x V_A x n (3)

where:

C_{PP} – cost of poor process,

T_L – lost time,

T_A – average assembly time

n – number of parts assembled simultaneously.

Total cost of poor quality is the sum of both: costs of poor product quality and cost of poor process quality.

Total cost of poor quality:

$TC = C_{PQ/P} + C_{PQ/A} + C_{PP}$ (4)

Calculation of the cost of poor quality based on historical data

Calculation of the cost of poor quality is based on data obtained by monitoring a selected stage of the production process. Input data are represented by output volume, the number of rejects and idle time. (Table no. 1)

Table no. 1: Input data

Day	Pre-production			Assembly			Lost time [min]
	Output [pcs]	Rejects [pcs]	Rejects [%]	Output [pcs]	Rejects [pcs]	Rejects [%]	
1	1,203	158	13.13	1,022	33	3.23	134.0
2	1,185	176	14.85	1,036	25	2.41	115.2
3	1,010	75	7.43	1,111	40	3.60	130.2
4	1,039	70	6.74	924	51	5.52	205.2
5	953	38	3.99	966	3	0.31	195.0
6	919	41	4.46	949	1	0.11	208.0
7	1,032	39	3.78	1,103	4	0.36	174.0
8	950	50	5.26	928	4	0.43	70.0
9	1,095	9	0.82	1,133	16	1.41	60.0
10	1,134	32	2.82	1,034	6	0.58	130.0
11	1,014	29	2.86	1,012	13	1.28	135.0
12	890	15	1.69	1,049	0	0.00	90.0
13	1,065	21	1.97	923	2	0.22	199.0
14	1,086	16	1.47	1,025	2	0.20	142.0
15	998	15	1.50	741	10	1.35	275.0
16	1,010	12	1.19	1,039	8	0.77	145.0
17	1,056	23	2.18	1,081	13	1.20	110.0
18	795	9	1.13	842	7	0.83	620.0
19	1,010	12	1.19	1,039	8	0.77	130.0
20	1,134	32	2.82	1,015	6	0.59	35.0
21	955	11	1.15	672	4	0.60	315.0
22	993	16	1.61	967	7	0.72	180.0
23	781	8	1.02	778	4	0.51	475.0
Σ	23,307	907		22,389	267		4,272.6

Time resources of workplaces are defined by the nominal time fund reduced by the planned breaks. Effective time fund reflects the organization of production, which is continuous, and consist of 3 shifts. Planned breaks relate to each work shift equally. (Table no. 2) Available production time per day is calculated according to following relations:

$$T_{nom/day} = 24\text{ h x }60\text{ min} = 1\ 440\text{ min} \tag{5}$$

$$T_{ef/day} = T_{nom/day} - 3T_{SB/shift} = 1\ 245\text{ min} \tag{6}$$

where:

$T_{nom/day}$ – nominal daily time fund

$T_{ef/day}$ – effective daily time fund

$T_{SB/shift}$ – scheduled breaks per work shift

Table no. 2: Scheduled breaks

Reasoning breaks	Average scheduled time losses per work shift [min]
Meeting at the beginning of a shift	5
Lunch break	30
Testing MASTER PIECES	5
Restock of a material	10
Final cleaning	5
Preventive maintenance, changing a reference	10
Total average scheduled losses for one shift	**65**

3. Results and discussions

3.1 Poor quality and poor process cost calculation results

Costing the poor quality is based on specific historical data by monitoring the production process over 1 month (23 working days). (Table no. 3) Data refer to the number of rejects in the pre-production unit, assembly time and recorded time losses. For the purposes of relevant calculation, the losses caused by slow-down production were estimated as complete production stop, based on the percentage estimate of a given slowdown (e.g. in the calculation, 100 min of slowdown in production down to 50% was assumed as 50 min. of lost time). Table no. 1 presents a summary of the input data for production after the above-mentioned adjustment in the time losses.

Table no. 3: Poor quality cost

	Unit	Pre-production	Assembly
Output	pcs	23,307	22,389
Defects	pcs	907	267
Net output	pcs	22,400	22,122
Average value of the unit	EUR	5.5	15.0
Cost of poor product quality	EUR	4,988.5	4,005.0
		8,993.5	
Average lead time	min/pcs	2.2	4.3
Total cost of poor product quality	EUR	8,993.5	
Disposable time	min	28, 635.0	
Lost time	min	4,272.6	
Cost of poor process	EUR	59,617.7	
Total cost of poor quality	EUR	68,611.2	

3.2 Analysis of the rejects evolution within a time series

Input data on the quality of production generate the time series and one of the analytical reflections for research can be trend analysis within the flow chart. The time series in terms of rejects trend are shown in figure no.3. A trend line course for the stage of pre-production and assembly has logarithmic character. It is obvious, from the graph that the rejects trend has descending direction and the process shows signs of a gradual stabilization.

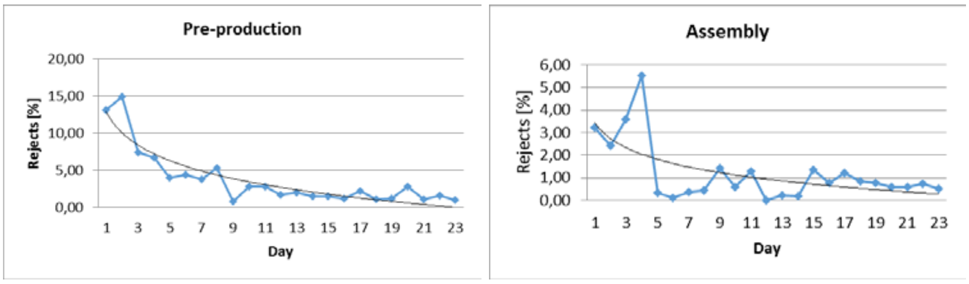


Figure no. 3: Time series plot of the rejects in the pre-production and assembly stage

3.3 Sigma level analysis

Due to the discontinuous nature of the output, a process capability was not measured with parameters Cp and Cpk, but on the basis of data – the number of units and the number of rejects. Next, for both phases of the production process, capability level was assessed through sigma level. Sigma level presents a level of quality production process. Due to the evaluation of a sigma level of a process, indicators as Defects per unit (DPU) and Defect per million opportunities for error (DPMO), valuation and yield sigma level are calculated. Process sigma level was calculated using the Process Sigma Calculator. The result was assumed on 1.5 σ a shift. The resulting values of quality indicators for pre-production, assembly and entire process are presented in table no. 4. The overall level of yield is given by the pre-production stage yield $Yield_P$ and assembly stage yield $Yield_A$.

DPU = Total of defects/Total of units (7)

DPMO = (Total of defects /Total of units) x 1 000 000 (8)

$Yield_{TOTAL} = Yield_P \times Yield_A$ (9)

where:

DPU – defect per unit,

DPMO – defect per million opportunities for error,

$Yield_P$ – Yield (pre-production stage),

$Yield_A$ – Yield (assembly stage),

$Yield_{TOTAL}$ – Yield overall.

Table no. 4: Quality process indicators

	DPMO	Yield [%]	Sigma level
Pre-production stage	38,915	96.11	3.26
Assembly stage	11,925	98.81	3.76
Process overall	50,371	94.96	3.14

3.4 Cost analysis of poor quality based on probability characteristics and simulation

Previous approach for calculating the cost of poor quality was provided with real data. This was a retrospective cost calculation, values were known from historical records and the cost of poor quality were calculated relatively reliable. Average values of selected input parameters as the value of semi-finished products, production time or assembly duration time were used for calculations. This approach is relatively common in practice, and its application is described in a number of case studies, e.g. in terms of services company would Dragulanescu and Popescu (2015) in the field of education by Mehrabi (2012) or by Pugna, Negrea and Miclea (2016) in an assembly process. Other applications of probability characteristics and simulation of scientific work appear in the field of dealing with little quality. In terms of assessing process capability in the Six Sigma program when data follows the gamma distribution problem is solved by Hsu, Pearn and Wu (2008). Similarly, the Six Sigma performance for non-normal processes, using mathematical optimization models, addressed Aldowaisan, Nourelfath and Hassan (2015). But in both cases there was no simulation activities. Monte Carlo simulations offer additional opportunities for analysis and use of data particularly in forecasting.

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Where it is necessary to forecast the amount of the cost of poor quality for the next period, then calculation and analysis of the cost of poor quality should be determined based on the probabilistic characteristics of the input parameters. In the case study, probabilistic characteristics were defined for the input parameters based on historical data. Costing was accomplished by Monte Carlo simulation and the resulting costs are analysed in terms of probability. As selection of the distribution and its characteristics vastly affects simulation results, it is in terms of accuracy significant for calculations. Therefore, a distribution function has to reflect reality as closely as possible. Case study presents the forecasting and the analysis of costs of poor quality assuming that the probability characteristics of the input variables result from the obvious development that was used as a model for estimating the future costs.

3.5 Defining the probability characteristics of the input variables

Based on the recognized facts, distributions for the input variables were defined (table no. 5). For the variables, which course is known from historical data, a probability distribution was defined by the function “Fit” (the best fit to our historical data). The distribution of the remaining variables was defined based on the experience, respectively estimates of real progress.

Table no. 5: Distribution functions for input variables

Variable	Distribution	Characteristics
Scheduled breaks	Triangular	Mean 65; Min. 60; Max. 70
Output/day (pre-production)	Poisson (fit)	
Defects/day (pre-production)	Geometric (fit)	
Output/day (assembly)	Negative Binominal (fit)	
Defects/day (assembly)	Geometric (fit)	
Lead time in assembly	Triangular	Mean 4.3; Min. 4; Max. 4.6

An example of distribution defined by the triangular distribution based on the known data, and the geometric distribution using the function Fit is presented in figure no. 4.

Calculation of the cost of poor process is based on probabilistic characteristics. Unused time fund (Lost Time) is determined as the difference between the effective time fund and standard time required for creating the final output in the observed period (formula 10). For standard time, the average assembly time is considered and the calculation takes into account the simultaneous processing of products in four workplaces. The average daily output value was considered for the calculation, and the distribution was defined according to real progress during the reporting period using the Fit function.

$$T_L = T_{ef} - T_P = T_{nom} - T_{SB} - T_P \tag{10}$$

$$T_P = Q_A/T_A \tag{11}$$

where:

T_L – lost time,

T_{nom} – standard time fund for monitoring period,

T_{ef} – effective time fund for monitoring period,

T_{SB} – scheduled breaks for monitoring period,

T_P – time production for monitoring period.

Considered times, other than the standard time fund, are based on the probabilistic nature, see table no. 5. Average installation time appears twice in the calculation (once in the calculation of T_P, and once when calculating C_{PP}). In order to avoid in calculation double uncertainty regarding to assembly time, and thus increasing the variability of output, it is considered only as an assumption in calculating T_P. In the calculation of C_{PP}, as the value the constant number 4.3 min is considered. Calculation of cost of poor quality is based on formulas (1-4). Prognosis was performed by Monte Carlo simulation.

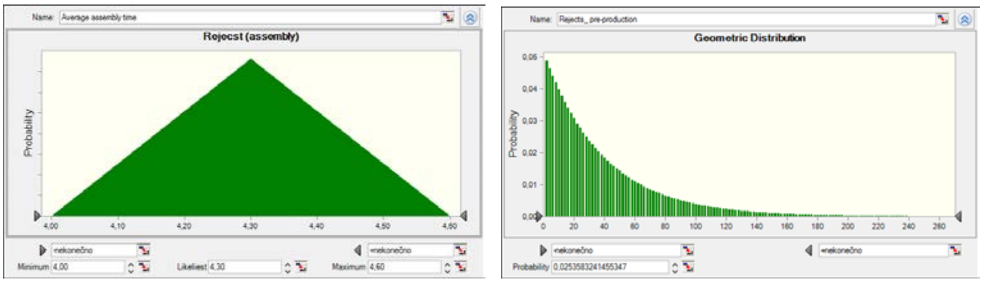

Figure no. 4: Example of definition of the triangular (left) and the geometric (right) distribution

3.6 Results of the analysis of the cost of poor quality based on simulation

The simulation was accomplished by defining the probability characteristics for entering the input variables and relationships for each cost calculation. In figure no. 5-7, there are presented simulation outputs – forecast charts for individual costs. Figure no. 5 shows the cumulative cost of poor production quality. According to simulation, the average value of the cost makes EUR 8,703.26, which is very close to the values calculated based on historical data (EUR 8,993.5). At the same time, the graph allows the analysis of the probability when exceeding this value. The probability of exceeding the calculated value of cost proceed at 38.65% (figure no. 5), which agrees also with historical data. That fact declares much higher incidence of rejects in the process of pre-production and also costs on rejects at this stage are lower.

On the contrary, the average value of cost of poor process declared by simulation output is significantly higher (EUR 64,203.66) as the calculation of historical data (figure no. 6). This reflects the fact, that for the lost time value reflects to both, the time recorded during the monitoring of the production process plus idle effective time overall. This result is projected in the graph of total costs (figure no.7), where the difference between the average value from simulation run and calculation according to the data is evident. There is also a high probability (64.95%), that the costs exceed the calculated value.

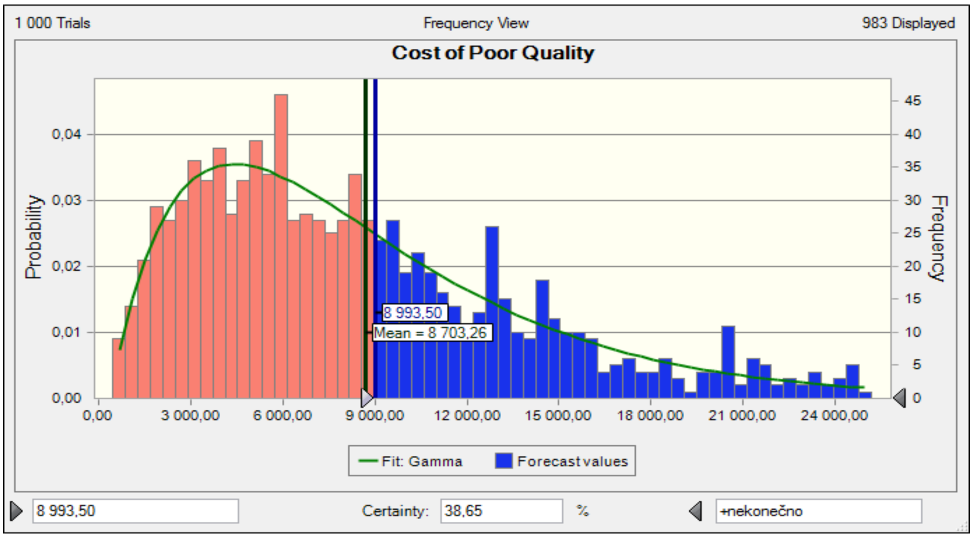

Figure no. 5: Cost of poor product quality

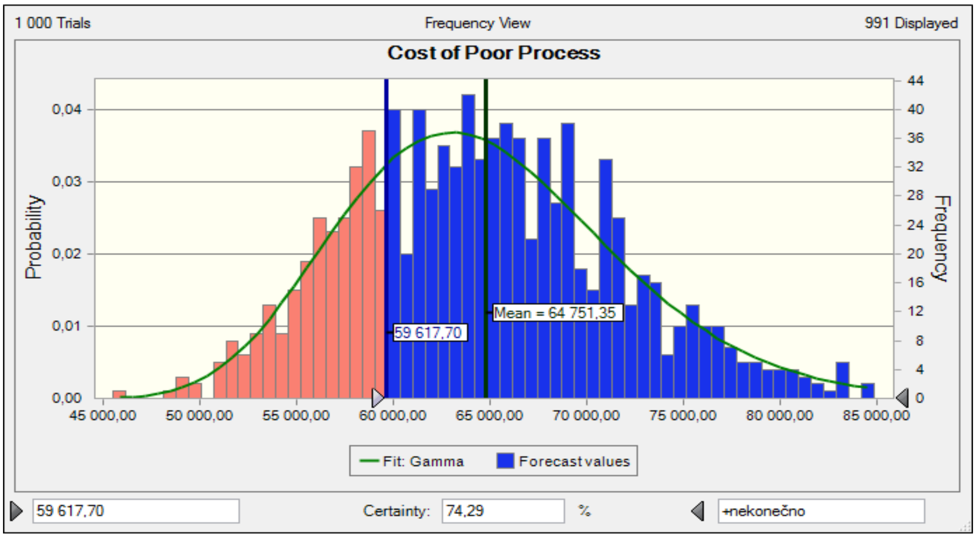

Figure no. 6: Cost of poor process

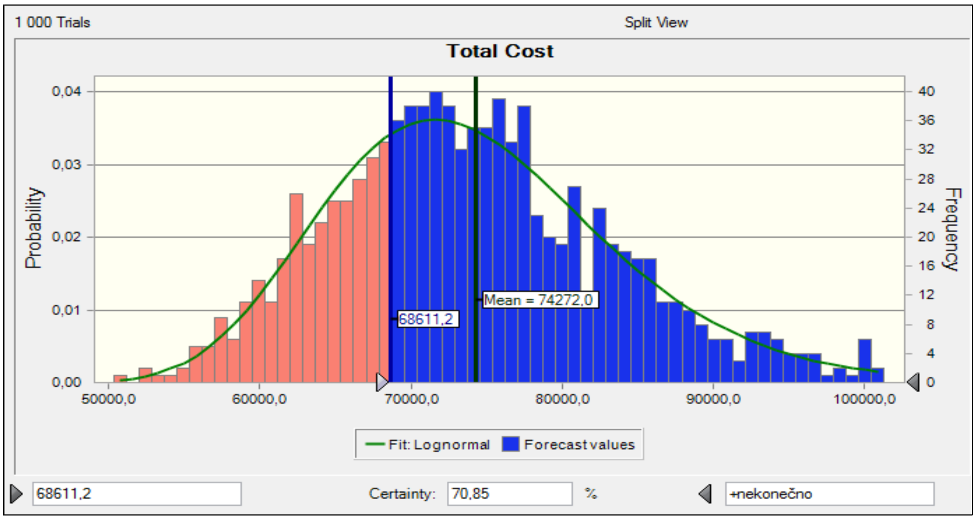

Figure no. 7: Total cost of poor quality

Effect of different assumptions on the overall output – Total Cost of Poor Quality- can be assessed on a Tornado chart (figure no. 8). Chart presents the changes in input factors ± 10% and their impact on overall costs. The strongest impact on the total cost has a continuous assembly time and lost time. These inputs and their variability may significantly affect the rate of utilization of the available time. Idle time fund reflects the cost of poor quality four times, as the assembly operations are carried out simultaneously on four pieces. In the presented case study, due to the high rate of idle time, these variables are dominant determinant of overall costs. Much less impact factor is a failure rate in pre-production stage and at the stage of assembly.

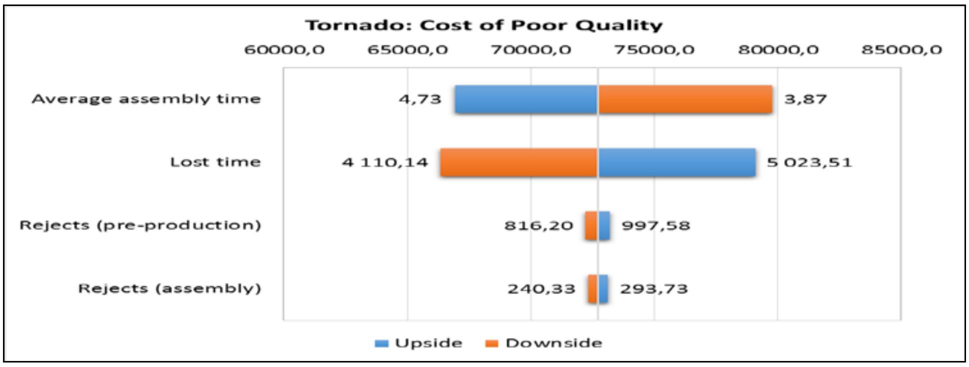

Figure no. 8: Tornado chart

The Sensitivity chart (figure no. 9) presents the contribution of the variables to the variability of output, showing only variables which contribution is greater than 0.1%. In this case, the variability of the total cost was considerably influenced by variability in the occurrence of rejects per day in the pre-production stage (49.6%) and in the phase of assembly (28.1%). The failure rate distribution function was derived from the actual course by Fit function, and it proves significantly higher variability than variables assembly time or volume output.

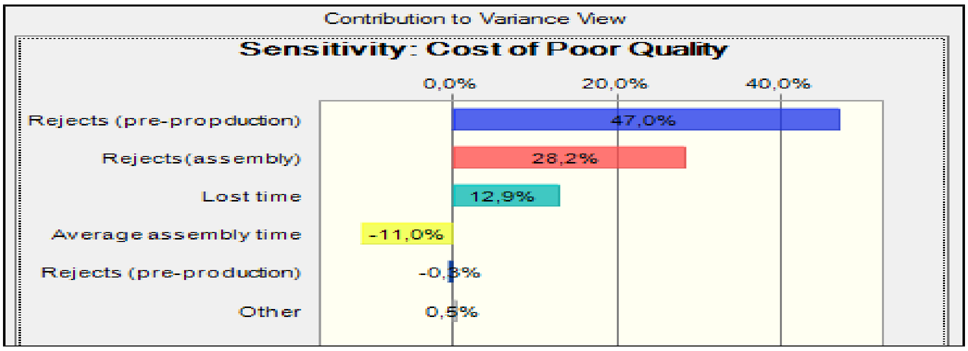

Figure no. 9: Sensitivity chart

Conclusions

This paper presents a model of analysis and calculation of the cost of poor quality using the software tool. Tracing the production process in terms of the cost of rejects and poor organizational process quality discovers a qualitative-economics view. The analysis presented in the article refers to a phase (Measure) within improvement process of the DMAIC method. Case study presents two approaches to determining the cost of poor quality. One approach from the retrospective view when the costs of poor quality and production process were calculated based on data from the previous period. The second method uses probabilistic characteristics of the input variables and is focused on perspective view on the cost of poor quality. Using simulation software in the second analytical approach allows incorporating the uncertainty of input variables and evaluating the resulting parameter from the perspective of uncertainty. The resulting costs values according to both approaches (calculated value in the first case and average value in the second case) were compared and evaluated in probabilistic terms. The contribution of all variables to the variability of output and the impact of the change on the overall costs was presented in both, Tornado and Sensitivity charts.

Retrospective analysis and calculation of the cost of poor quality is an important step in the process of detecting errors. Identification of weak points and the realization of their economic impact must be anticipated in improvement processes. Estimating the future development of costs of poor quality, knowing the effects of inputs uncertainty allows preventing the losses. If the variability of time or performance variables were known in advance, their relation to output would be known and their impact can be verified by means of the simulation. Use of software tools with a range of simulation techniques allows assessing the feasibility of expected or unintended impacts, in advance. Complex combining a number of uncertain variables and monitor their impact on one common target is difficult to implement without computer simulation. Knowing the variables that determine the achievement of objectives, and on the contrary, which one are most threatening for its variability, allows focusing on the right targets and eliminate wasting the resources on non-essential activities. Effective use of simulation software tools in the field of quality management has its important place, even its limits. Its indispensable role here still belongs to the experts who are solely familiar with processes. Correct estimate when defining the distribution of variables, sensitive assigning the uncertainty in simulation experiments, only in the necessary extent, those are prerequisites for the relevant simulation results and their benefits in improving quality.

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