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Parameter Drift in Risk-Based Statistical Control Charts

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Abstract

The quality control and approval in the supply chains of automotive industry is vital. Though statistical control charts are widely used tools for this quality (conformity) control, they have some shortcomings: the control charts are designed on reliability base instead of risk base; they do not take the consequences of decisions deriving from them. The data is obtained from measurements that are subject of uncertainty but this measurement uncertainty is ignored in the conformity control even if it is known from the calibrations. In addition there could be changing parameters; their values alter after the control in the subsequent phases of the production, e.g. the geometrical parameters of castings after heat treatment. This paper proposes a solution that minimises the risk of the decision and gives the optimal decision rules with the help of simulation of the whole process. The application determines the optimal bounds of the acceptance region and the control rules of the chosen chart considering the cost of decision errors, measurement uncertainty, the production process parameters and their probable transition or alteration.

Keywords: Statistical process control (SPC), decision risk, measurement uncertainty, deformation, simulation;

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1. Introduction

Since Walter A. Shewhart (1931) introduced the control charts they have been widespread in the industrial conformity control without any significant modification. The traditional control charts and subsequent cumulative sum (CUSUM), exponentially weighted moving average (EWMA) and moving average (MA) charts inspect the stability of a process and show whether control of this process required or not. These charts and the applications based on them work on reliability base and do not take the measurement uncertainty and the possible alteration of observed value after the inspection into account. Thus the probability calculation of the incorrect (process) control and risk of decision errors could be wrong and the product could become nonconform in subsequent production phases or at the customer.

In this paper the authors will show on the example of conformity control of moulded pivot bearings how the consideration of measurement uncertainty, the cost of decision outcomes and the drift of parameter values can be combined into one process control method to maximise the profit regarding conformity decisions.

2. Background of the Study

There are two different disciplines close to each other but not overlapping in the practice. Both theories, the statistical process/conformity control and the measurement uncertainty, deal with the inspections of products or processes. Statistical process control suggests decisions based on inspection results, measurement uncertainty theories investigate the goodness of these results, the combination of these disciplines has not been established before.

2.1. Statistical Process Control

In statistical process control (SPC) a process is said to be controlled when, through use of past experience, one can predict at least approximately the probability that the observed values of a product characteristic will fall within given limits (Shewhart, 1931; Besterfield, 1994). SPC is an optimisation philosophy concerned with continuous process improvements, using a collection of (statistical) tools for data and process analysis, making inferences about process behaviour and decision-making. The goal of SPC is the elimination of variability in the process (Montgomery, 1996) (Schippers, 1998) being aimed at detection of assignable causes of variation, hence at reduction of the overall variability of the control parameters. In addition, Reis and Saraiva (2006) suggested that measurements do play a central role in SPC. The growing availability and increasing complexity of measurement systems often raises practical problems that require the adaptation of the classical SPC frameworks in order to accommodate for them (Dale & Shaw, 1987; Thomas, 1987; Wood, 1994). Current SPC methodologies do not explicitly take into consideration measurement uncertainty information. Thus, the imprecise data rule out the implementation of conventional statistical process control (SPC) techniques and tools. So the validity of conventional SPC approaches is questionable (Massotte & Bataille, 2000) and some alternate approach is required.

In statistical process control the distribution of observed values is assumed normal in most of the cases. Though traditional control charts work even if the normality criteria is violated (Montgomery, 1996) if the sample size below 4 or individual value chart is applied the non-normality could increase the decision errors significantly (particularly type I errors) (Schilling & Nelson, 1976). However, the MA and EWMA charts are insensitive for normality and the other charts can be modified to compensate the effect of sensitivity (Table 1) (Chen & Yang, 2002; Chen & Hsieh, 2007; Haridy & El-Shabrawy, 1996; Kao & Ho, 2007; Maravelakis, Panaretos, & Psarakis, 2005; Serel & Moskowitz, 2008; Yu & Wu, 2004), none of these charts take into account the measurement uncertainty and the consequence of the wrong decision. It is not enough to reduce the number of decision error type I or type II, the risk of

the decision must be minimized. The method proposed in the third section gives a solution for these problems, it takes the decision errors from the non-normality and the measurement error and the consequences of these decision errors into account.

Table 1. Categorisation of single variable control charts

	Control charts (if sampling by variables)			
	Reliability centered		Risk-based	
	Sample size and sampling intervals are constant	Sample size and sampling intervals are variable	Sample size and sampling intervals are constant	Sample size and sampling intervals are variable
Normality is assumed	x-bar, s, R, CUSUM, EWMA, MA	CUSUM, x-bar, s, EWMA, MA, T ²	-	-
Normality is not assumed	x-bar, R, CUSUM, EWMA, MA	x-bar, CUSUM, EWMA, MA	-	-

2.2. Measurement uncertainty

How can we take the measurement uncertainty into consideration? The Guide to the Expression of Uncertainty in Measurement (GUM) (BIPM et al., 1993) proposes methods to evaluate and express this uncertainty in a uniform way. However, GUM does not give any suggestions, how to decide about the conformity of a product or a process on the basis of uncertainty. Following the GUM many studies discussing this problem have been published. Forbes (Forbes, 2006) approaches the conformance assessment as a Bayesian-decision, where the costs of wrong decisions are taken into account. Pendrill (2006) emphasizes that the impact of decisions should be kept to the fore at the specification of maximum permissible errors. To have correct risk calculation the measurement uncertainty must be treated in a probabilistic approach (Rossi & Crenna, 2006).

Measurement uncertainty can be expressed in two ways (BIPM et al., 1993). On the one hand the measurement uncertainty can be expressed as a probability distribution of measurement results described by the value of standard deviation (standard uncertainty). If the measurement result is obtained from the values of a number of other quantities the standard deviation called combined standard uncertainty. On the other hand, the uncertainty can be described as an interval. The length of the interval calculated as a multiplication of the combined standard uncertainty and a *k* coverage factor. The value of *k* is determined by the confidence level and the type of the probability distribution function, but it is often specified as 2 or 3 (BIPM et al., 1993; Ellison & Williams, 2007; ILAC, 2009; ISO, 1998). This approach assumes the symmetry of the probability distribution, but this assumption is not valid in every case (Rossi & Crenna, 2006), that is why 2 different (*K_L* and *K_U*) values are used in this paper instead of a joint *k* and these new altered coverage factors were determined not by the reliability but by the risk of decisions (Fig. 1).

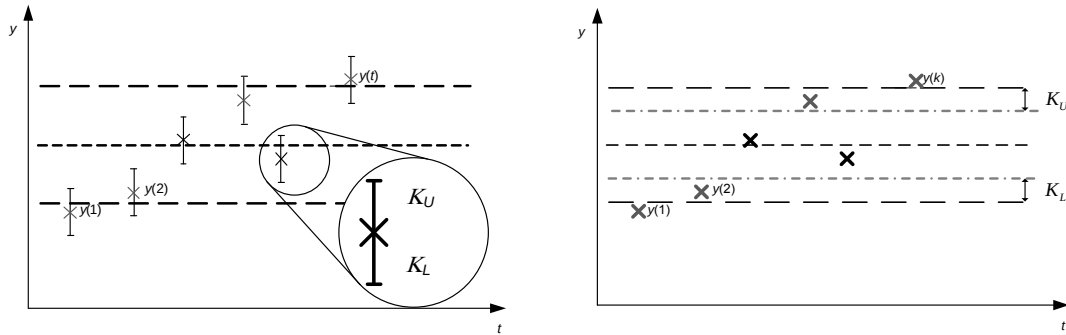


Fig. 1 Decision-making of conformity based on measuring intervals instead of measuring points (left side) and the alteration of limits as an equivalent solution (right side)

3. Methods

Simulations have been run to determine the optimal alteration of specification limits. The probability distribution of measured values (and its parameters) can be determined from the initial inspections. The measurement uncertainty can be obtained from the calibrations, previous experience and the documentation of measuring instrument. The x real values are estimated as the difference of y measured values and m measurement error. The probability distribution of x real values (and its parameters) comes from the deconvolution of distribution of y measured values using the knowledge about the probability distribution (and its parameters) of measurement uncertainty.

Because of the measurement uncertainty four cases can be distinguished as a combination of real conformity and the decision itself (Table 2). If control is not required, but unnecessary control is done based on the measured value, decision error type I is made. If the real value of observed characteristic is nonconforming but it is undetected because of the measurement uncertainty decision error type II is made. Appropriate decisions are made if a nonconform process gets controlled or conform process runs.

Table 2. Profits influenced by the decisions and the facts

		Decision	
		Control is not performed (1)	Control is performed (0)
Fact	Control is not required(1)	$\pi_{11}=r_{11} - c_{11}$ Appropriate acceptance	$\pi_{10}=r_{10} - c_{10}$ Inappropriate control
	Control is required (0)	$\pi_{01}=r_{01} - c_{01}$ Inappropriate acceptance	$\pi_{00}=r_{00} - c_{00}$ Appropriate control

The c_{ij} costs, assigned to the 4 cases of decision outcomes, depend on the number of executed measurement, the cost of production of service or product and the actions in accordance with the decisions. In order to calculate the unrealized profit an alternative decision is made the r_{ij} revenues must also be taken into account beside the costs. So $\pi_{ij}=r_{ij}-c_{ij}$ proportional profits are used to calculate the $\Sigma\Pi$ total profit in reference to decisions. The q_{ij} number of elements belongs to certain cases calculated in the simulation.

$$\Sigma\Pi = q_{11} \cdot \pi_{11} + q_{10} \cdot \pi_{10} + q_{01} \cdot \pi_{01} + q_{00} \cdot \pi_{00} \quad (1)$$

To maximize the expected profit let the decision rules be modified: the process will be treated as conform if $LCL + K_L \leq y \leq UCL - K_U$ where K_L and K_U the correction components belong to the LCL and UCL lower and upper control limits. The value of correction components are calculated in the simulation. These correction components are not coefficients; they give directly the extent of the alteration of control limits. If the risk of decision error type II is low the value of correction component can be negative. In this case the control limits do not become stricter rather wider. Our Monte Carlo simulation searches the value of K_L and K_U that determines the maximum of total profit in reference to decisions.

The estimated probability distributions of the real process [with cumulative distribution function $F(x)$ or probability distribution function $f(x)$] and the measurement uncertainty [with $G(m)$ or $g(m)$], the p_{ij} profits of each decision outcome, the number of the samples n and the sample size m are the input variables of the simulation. The LCL and UCL control limits are calculated variables. The simulation gives the q_{ij} numbers of elements falling in into each decision outcome case as a function of K_L and K_U , and the calculated sum of profits. From this data the maximal profit and K_{Lopt} and K_{Uopt} optimal correction components belonging to it can be determined.

If the observed values drift or alter after the process control, this alteration can be taken into account during the simulation with its regression function. The outcomes of decisions considering the measurement uncertainty, the alteration of observed values and regardless of them can be contrasted to each other.

4. Results

The previously introduced method was tested on the statistical conformity control of aluminum alloy pivot bearings. This pivot bearing fixes the wheel bearing and all of the fittings directly connected to the wheel bearing in automobiles, this system connects the wheel to the suspension. One of the inspected parameter on this bearing is the deviation from the reference axis at the connection to the suspension. The target value is 0 with ± 0.7 mm tolerance. The initial inspection of the parameter showed that the probability distribution of the deviation from the reference axis can be estimated as a normal distribution with the mean $\mu=0.266$ and standard deviation $\sigma=0.1459$. However, the statistical process control is performed before the heat treatment; the deviation parameter alters during the heat treatment and quenching (after the SPC). The connection between the parameters measured before and after the heat treatment is assumed multiplicative. The deformation – alteration of the deviation from the reference axis – is a stochastic variable that also follows normal distribution with the parameters $\mu_{def}=1.03$ and $\sigma_{def}=0.4$. The measurement uncertainty of the positioning and measuring gauge have been estimated during the calibration and it is described with $\mu_m=0$ mean and $\sigma_m=0.0332$ standard deviation. The profits or losses of the four outcomes of the decision are $\pi_{11}=4.5$, $\pi_{10}=-9.75$, $\pi_{01}=-12.75$ and $\pi_{00}=-8.25$.

Table 3. Results of the alteration of control limits

Chart Type			Profit /loss (% of good decision)	Avoidable loss (% of original decision)
X-bar Chart	Absence of deformation	Original decision	24.64	32.95
		Considering measurement uncertainty and decision risk	16.52	
	Presence of deformation	Original decision	78.36	83.6
		Considering the deformation and decision risk	12.85	
		Original decision according to the recalculated control	18.44	30.37
		Considering the deformation and decision risk	12.84	
MA- Chart	Absence of deformation	Original decision	24.37	30.41
		Considering measurement uncertainty and decision risk	16.96	
	Presence of deformation	Original decision	84.54	84.49
		Considering the deformation and decision risk	13.11	
		Original decision according to the recalculated control	18.47	29.18
		Considering the deformation and decision risk	13.08	
EWMA- Chart	Absence of deformation	Original decision	24.63	29.96
		Considering measurement uncertainty and decision risk	17.25	
	Presence of deformation	Original decision	92.96	85.69
		Considering the deformation and decision risk	13.3	
		Original decision according to the recalculated control	18.16	28.85
		Considering the deformation and decision risk	12.92	

Three cases have been studied: the absence of deformation after SPC, the presence of deformation without the recalculation of the control charts and the case when control limits are recalculated after the deformation. In every case three charts are examined with and without the consideration of measurement uncertainty and decision risks (Table 3). The good decision is defined in this example as the decision that evaluate all the observations properly, that is there is no decision error type I or type II. The value of avoidable loss gives the rate of the difference between the good and the actual decision that can be averted, through taking the measurement uncertainty, decision risk and parameter value alteration into consideration, with the modification of control limit.

5. Conclusion

The results presented in this paper have shown that the reliability-centered approach in statistical process control does not give the best solution, the profitability of conformity decisions can be increased taking also the decision consequences into account. This new risk-based specification of control limits can be further enhanced with the consideration of measurement uncertainty and the possible drift of parameters. With the help of this method the loss between the ideal decision, when no decision error is made, and the actual decision based on classical SPC methods can reduced up to 30 percent.

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