International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:5, No:10, 2011

Dynamically Monitoring Production

Methods for Identifying Structural Changes relevant to Logistics

Marco Kennemann, Steffen C. Eickemeyer, Peter Nyhuis

***Abstract*—**Due to the growing dynamic and complexity within the market environment production enterprises in particular are faced with new logistic challenges. Moreover, it is here in this dynamic environment that the Logistic Operating Curve Theory also reaches its limits as a method for describing the correlations between the logistic objectives. In order to convert this theory into a method for dynamically monitoring productions this paper will introduce methods for reliably and quickly identifying structural changes relevant to logistics.

***Keywords*—**Dynamics, Logistic Operating Curves, Production Logistics, Production Planning and Control

I. Introduction

DUE to the recent economical up and downs, manufacturing enterprises find themselves confronted with significant challenges, particularly with regards to logistics. Optimally positioning themselves within the conflicting field of logistic objectives (such as WIP, utilization, throughput times and schedule reliability) is usually only inadequately possible. The Logistic Operating Curves, an approach based on modelling theory and developed at the Institute of Production Systems and Logistics (IFA), can be used to describe the interactions between these logistic objectives [1]. However, the dynamic influence of the market or structural changes that are then reflected in strongly fluctuating lot-sizes and thus varying work content, make implementing this mean based approach more difficult [2]. In order to undertake a sufficiently precise Logistic Positioning, long periods of analysis and stable processing states are required (see [3]), however, given the existing structural changes, conditions such as these cannot be met. A technique that converts the Logistic Operating Curves into a method for dynamically monitoring production is thus being developed within the context of the collaborative research centre 489 “Processing Chains for the Production of Precision Forged High Performance Components”, funded by the German Research Foundation (DFG).

Marco Kennemann is research associate at the Institute of Production Systems and Logistics, Leibniz University of Hanover, Garbsen, 30823 Germany (corresponding author to provide phone: 0049-511-762-18187; fax: 0049-511-762-3814; e-mail: kennemann@ifa.uni-hannover.de).

Steffen C. Eickemeyer is research associate at the Institute of Production Systems and Logistics, Leibniz University of Hanover, Garbsen, 30823 Germany (corresponding author to provide phone: 0049-511-762-18188; fax: 0049-511-762-3814; e-mail: eickemeyer@ifa.uni-hannover.de).

Prof. Peter Nyhuis is director of the Institute of Production Systems and Logistics, Leibniz University of Hanover, Garbsen, 30823 Germany (e-mail: nyhuis@ifa.uni-hannover.de).

Currently, there is no model that allows logistics to be continually monitored and improvement measures to be derived. In order to recognize when a new Logistic Positioning is necessary, dynamic processing states that are not caused by natural variance but rather structural changes in processes have to be reliably and quickly identified. From a logistics perspective, significant changes in the mean or standard deviation of the work content are critical since these directly influence the ideal minimal WIP required for the production and thus the shape of the Logistic Operating Curves. In the following paper, the possibility of transferring the methodology of quality control charts to monitoring the work content will be examined based on simulated work content structures. Since work content distributions are not subject to any strict planned or target values, existing statistical quality control approaches cannot be directly adapted. A new approach using dynamic quality control charts and dynamic CUSUM control charts (CUSUM: cumulated sum) is thus developed and examined here with regards to its suitability for identifying structural changes.

II. Standard Control Charts for Monitoring the Means and Standard Deviation

A. Fundamental Assumptions of Standardized Control Charts

Standardized control charts that are utilized for monitoring industrial manufacturing processes come in different forms [4]. In practice, normally distributed quality characteristics, which, in a stable (undisrupted) state do not exhibit variability in their distribution or mean, are assumed [5]. Structural changes in the work content can be identified by changes in the standard deviation of the work content (WC_s), the mean work content (WC_m) or a combination of both. Normally distributed data form the ideal conditions, however, these are only rarely found on the shop floor [3]. Chambers and Wheeler [6] have shown in simulation studies that moderate deviations from the normal distribution fail to have any noteworthy influence on the function of the control charts. With deviating distributions the number of ‘false alarms’ can increase, whereby this increase turns out to be reasonably low [6]. As a result, the research conducted in this project was initially conducted using approximately normal, simulation-generated work content distributions.

B. Mean and Standard Deviation Control Charts

The mean and standard deviation control charts commonly used in the industrial practice can be traced back to Shewhart’s traditional control charts [7]. The methodology of these control charts is based on statistical hypotheses tests. Based on these hypotheses and assuming normally distributed data, it is verified whether or not the sample mean μ or the sample standard deviation σ corresponds to a given process level μ_0 or permissible standard deviation σ_0 (see (1)). In applying so-called 'two-sided' control charts, both deviations above and below target values are detected. In order to verify the hypotheses from (1) the test statistics, the arithmetic sample mean $\bar{x}$ as well as the sample variance S^2 or the standard deviation σ according to (2), are used (see [5]).

TABLE I
FORMULARY FOR MEAN AND STANDARD DEVIATION CONTROL CHARTS

	testing hypothesis	
mean control chart	H_0: $\mu = \mu_0$ vs. H_1: $\mu \neq \mu_0$	**(1)**
standard deviation control chart	H_0: $\sigma = \sigma 0$ vs. H_1: $\sigma \neq \sigma_0$	
H_o: mean μ and standard deviation σ equal the rated values μ_o and σ_0 of the process		
H_1: mean μ and standard deviation σ differ significantly from the rated values μ_0 and σ_o		
	test statistic	
mean control chart	$\mu = \overline{X} = \frac{1}{n}\sum_{i=1}^{n} x_i$	**(2)**
standard deviation control chart	$S = \sqrt{S^2} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2}$	
μ: arithmetic mean		
S: estimator of the standard deviation σ		
x_i: ith value in a sample with i = 1,…,n		
n: sample size		

The control limits are thus defined so that, for a undisrupted process, a percentage of $(1-\alpha)\cdot 100\%$ of all realizations on average is within a defined tolerance interval [5]. Control limits are frequently sub-divided into 'warning limits' (WL) and 'intervention limits' (IL). Warning limits are then defined based on a significance level of α=5% and intervention limits on a significance level of α=1% (see [8]). Instead of 99% or 95% control limits, so-called '3-sigma limits' are frequently applied. These correspond with a α-level of only 0.27% (see [9]). Generally speaking, when test variables exceed the corresponding control limits the H_0 hypothesis from (1) is rejected in favour of the alternative hypothesis and consequently assessed as a process not in control. Extensive information about configuring relevant control limits can be found in [5, 8, 9].

C. CUSUM Tests: Control Charts with Memory

The CUSUM approach (cumulative sum) is also referred to as so-called 'control charts with memory'. The memory of these cards is based on the property that the underlying test variable is derived from the current value and a number of previous values, thus establishing a relationship between the current processing situation and earlier ones. Methods such as this are frequently applied in order to reveal structural changes in the manufacturing. As a control variable, CUSUM uses the cumulated sum of the differences (C_i) calculated from a current observation x_i and the process level or target value (see (4)) [8]. Alternatively, within the frame of the time sequence analysis, the difference of the 1 step ahead prediction is defined as the cumulated sum [10]. For controlled (undisrupted) processes the observations are randomly distributed around the processing level, so that the sum of these differences (CUSUM) is also distributed around zero. This assumption is at the same time summed up under the H_0 hypothesis (see (3)). In other words, when there are structural changes, the sum of the residue significantly and increasingly deviates from zero (see [8]).

TABLE II
FORMULARY FOR THE CUSUM-TEST

testing hypothesis	
H_0: $C_i = 0$ vs. H_1: $C_i \neq 0$	**(3)**
test statistic	
$\text{CUSUM} = C_i = \sum_{i=1}^{n}(x_i - x_{\text{process level}})$	**(4)**
C_i: cumulated sum of differences (cusum)	
x_i: ith value in a sample with i = 1,…,n	
$x_{\text{process level}}$: estimated mean based on former periods	

In order to verify the hypotheses from (3), control limits are required. Here too, within the frame of this verification process different approaches to constructing the control limits are described in publications. Monitoring the CUSUM can for example be conducted via a so-called 'V-mask' (see [11]), a method that can be traced back to Barnard [12]. Alternatively, supplementary test variables can be introduced and used as a basis for monitoring. For this, Faes [8] describes the use of so-called 'tolerance parameters' which can be implemented for monitoring decision limits. From the field of time sequence analyses the method developed by Brown, Durbin und Evans [10] for designing relevant warning limits can be referred to.

III. ADAPTING CONTROL CHARTS TO DYNAMIC STATES

One of the basic conditions for implementing quality charts is the assumption of a controlled and steady process. A controlled process is characterized by uniform variance, equivalent means, agreement between the target and actual means as well as normally distributed processing data (see [13]). At the same time, these conditions form the primary limits for directly transferring the standardized methodology of control charts to monitoring dynamic work contents. On the one hand, when considering dynamic states no strict target values can be provided, on the other hand, the statistical limits aligned with these are no longer applicable when conditions are dynamic. Research at IFA has extensively pursued this problem. Following, techniques for extending the initially described control chart approach to dynamic processing states will be introduced.

A. Dynamic Mean and Dynamic Standard Deviation Control Charts

In order to adapt the control charts to dynamic conditions, the test variables from (2) are first adjusted. To do so, a method for calculating rotating test variables is selected: The mean work content (WC_m) and the standard deviation of the work content (WC_s) are continually calculated over a fixed window (k) (see (5)).

TABLE III
FORMULARY FOR DYNAMIC MEAN AND STANDARD DEVIATION CONTROL CHARTS

	test statistic		
dynamic mean control chart	$\mu(i;k)_{roll} = \frac{1}{k}\sum_{f_1=i}^{f_2=i-k+1} x(i)$	with k=20	**(5)**
dynamic standard deviation control chart	$s(i;k)_{roll} = \sqrt{\frac{1}{k-1}\sum_{f_1=i}^{f_2=i-k+1}\left(x(i)-\mu(i;k)_{roll}\right)^2}$	with k=20	

$\mu(i;k)_{roll}$: cyclically calculated mean with i, i-1, i-2, …, i-k+1
$s(i;k)_{roll}$: cyclically calculated estimaor of the standard deviation with i, i-1, …, i-k+1
x(i): aktual value i
k: sample size for cyclical calcutlation of the test statistics

As depicted in Fig. 1, it is important to select an appropriately sized window. If the length of the window selected is too small, the smallest random changes or outliers can enormously impact the test variables when there is a dynamic state and consequently, frequently lead to undesired false alarms. Selecting too large of a rotating window results in strongly smoothing the test variables and may delay reactions to actually existing structural changes. Since research at IFA has shown that a rotating data span of k= 20 observations is sufficient, this is the length of the window chosen.

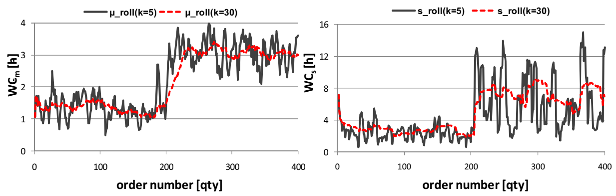


Fig. 1 Rotating Calculations of Means and Sample Estimates of Variance

In addition to dynamically calculating the test variables, the control limits also have to be adapted to the new conditions. In doing so the dynamic control limits must fulfil the following characteristics: On the one hand, a continual adjustment to continuous changes has to occur. On the other hand, the control limits have to demonstrate a certain inertia so that sudden structural changes can nevertheless be registered. To do so, based on the current situation (Observation x_i) a rotating process level of n=100 values is applied. Dynamic control limits are defined in accordance with [5] and [8] and summarized in (6) and (7), whereby, the standard control charts form the basis for these control limits.

TABLE IV
CONTROL LIMITS FOR DYNAMIC MEAN AND STANDARD DEVIATION CONTROL CHARTS

	control limit	
mean control chart	$L_{u,l} = \mu_0(i;n)_{roll} \pm t_{1-\frac{\alpha}{2};k-1} \cdot \frac{s_0(i;n)_{roll}}{\sqrt{k}}$	**(6)**
standard deviation control chart	$L_u = \sqrt{\frac{\chi^2_{(1-\frac{\alpha}{2};k-1)}}{k-1}} \cdot s_0(i;n)_{roll}$ $L_l = \sqrt{\frac{\chi^2_{(\frac{\alpha}{2};k-1)}}{k-1}} \cdot s_0(i;n)_{roll}$	**(7)**

with $L_{u,l}$: upper/lower limit
k=20 and n = 100
dynamic mean value $\mu_0(i;n)_{roll} = \frac{1}{n}\sum_{f_1=i}^{f_2=i-n+1} x(i)$
dynamic standard deviation $s_0(i;n)_{roll} = \sqrt{\frac{1}{n-1}\sum_{f_1=i}^{f_2=i-n+1}\left(x(i)-\mu_0(i;n)_{roll}\right)^2}$
t: percentile of the normal distribution with k-1 degrees of freedom and the level of significance α
$\chi^2_{(\alpha;\,k-1)}$: chi-square-distribution with k-1 degrees of freedom

B. Dynamic CUSUM Control Charts

In calculating a traditional CUSUM control chart, all of the underlying observations are integrated into calculating the $CUSUM_s$. The number of the addends thus increases with every new observation. In a dynamic field this can occasionally lead to the approach being largely inert. As a result, the test variable is henceforth calculated dynamically by means of a rotating window of n=100 realizations. Moreover, the method (see (4)) initially only takes into consideration the monitoring of changes in levels. This procedure can however also be transferred to monitoring the WC_s. In this case the differences between the current deviation s based on k=20 values and the process variability of the work content are added (see (8)) when calculating the CUSUM. In order to differentiate these approaches the designator $CUSUM_\mu$ was introduced for monitoring the WC_m and $CUSUM_s$ for monitoring the WC_s. Furthermore, the V-mask method is applied in a slightly modified form for monitoring the CUSUM (see Fig. 2) and an independent definition of the control limits is developed (see (9)).

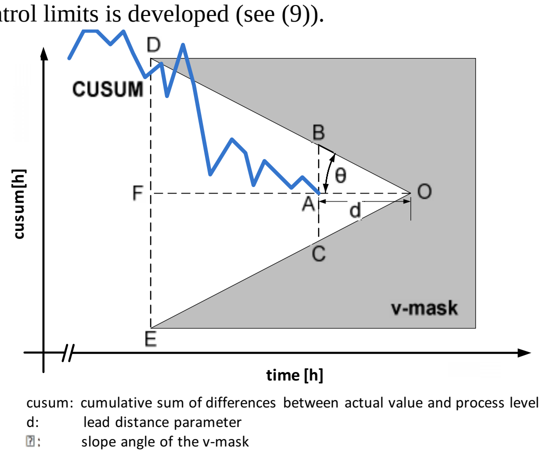


Fig. 2 V-Mask Diagram (based on [11])

The method based on (9) describes an independent approach to deriving dynamic control limits. The control limits are first oriented on the average CUSUM of the last 100 or 20 observations ($\bar{C}_\mu(n=100)$; $\bar{C}_\mu(k=20)$; $\bar{C}_s(n=100)$; $\bar{C}_s(k=20)$). Weighting these terms differently can ensure that current only-temporary changes or outliers do not lead to an overrating. In addition to this consideration of the means, a so-called 'safety margin' is defined. Within the frame of monitoring the levels, this safety margin considers 3-times the process level ($3*\mu_0(100)$) and is also supplemented by 6-times the work content variability ($6*s_0(100)$). In comparison, when monitoring the $CUSUM_s$ only 6-times the deviation of the process variability is considered.

TABLE V
CONTROL LIMITS FOR THE DYNAMIC CUSUM-TEST

$CUSUM_\mu$		**$CUSUM_s$**		
test statistic				
$CUSUM_\mu := C_\mu(n) = \sum_{f_1=i}^{f_2=i-n+1}(x(i) - \mu_0(i;n)_{roll})$		$CUSUM_s := C_s(n) = \sum_{f_1=i}^{f_2=i-n+1}(s(i;k)_{roll} - s_0(i;n)_{roll})$		**(8)**
control limit				
weighted mean of $CUSUM_\mu$	safety distance	weighted mean of $CUSUM_s$	safety distance	
$\left(\frac{3\cdot\bar{C}_\mu(n)+\bar{C}_\mu\mu(k)}{4}\right)$	$\pm(3\mu_0(i;n)_{roll}+6s_0(i;n)_{roll})$	$\left(\frac{3\cdot\bar{C}_s(n)+\bar{C}_s(k)}{4}\right)$	$\pm 6s_0(i;n)_{roll}$	**(9)**
with $x(i)$: aktual value i $\mu(i;n)_{roll}$: cyclically calculated mean of the sample with n=100 $s(i;k)_{roll}$: cyclically calculated actual standard deviation of the sample with k=20 $s_0(i;k)_{roll}$: cyclically calculated standard deviation of the sample with n=100 $\bar{C}_{\mu/s}(n;k)$: sliding CUSUM-mean calculated with the last n=100 and k=20 CUSUM-values				
parameter v-mask				
$\theta = 26.6°$ AB, AC = $5*s_0(i;n)_{roll}$ AF = 15 values		$\theta = 21.8°$ AB, AC = $1.5*s_0(i;n)_{roll}$ AF = 15 values		**(10)**

The V-mask (see schematic depiction in Fig. 2), a control mechanism whose origin can be traced back to Bernard [12], is used as an additional supplement. A V-mask is thus positioned within the CUSUM chart so that the line AO runs parallel to the X-axis or the horizontal axis. The vertex of the V mask, point O, indicates forward in the direction of the x-axis and point A marks the last (current) observation. If all of the previous CUSUMs lay within the limits of the V-mask the process is considered in statistical control. In comparison, a significant change in the analyzed process is indicated by the intersection of the CUSUM and the v-building axis of the V-mask [11]. Generally, the design of the V-mask is determined by the "lead distance" d and the angle θ (see Fig. 2). These can for example be adapted empirically by developing different masks based on previous data. Within the frame of the $CUSUM_\mu$ test the parameters of the V-mask are tightly defined based on Oakland [11] (slope angle $\theta = 26.6°$, decision interval AB and AC with $5*s_0(n=100)$). In the $CUSUM_s$ test, the control parameters are set more closely in order to reveal smaller differences in the variability (slope angle $\theta = 21.8°$, decision interval AB and AC with $1.5*s_0(100)$). The definition of the test variables $CUSUM_\mu$ and $CUSUM_s$ as well as the derivation of the applied control limits are presented in (8) and (9).

IV. ANALYSIS AND EVALUATION

A. Data Simulation

The analysis is conducted based on simulated work contents. For this purpose, the LOCCS 1.56 tool, developed at IFA, was used to generate two (approximately) normally distributed data series (Distribution A and Distribution B, see Fig. 3) and aggregated into a total distribution.

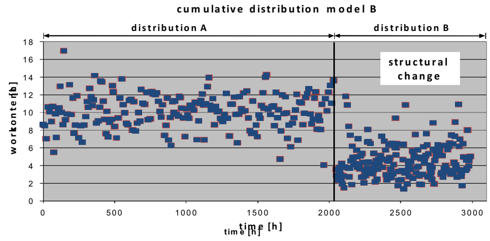
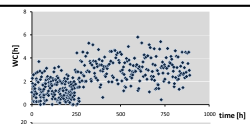
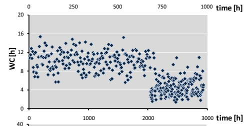
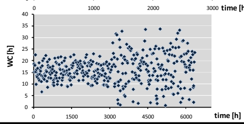
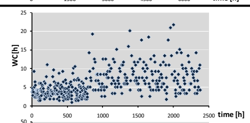
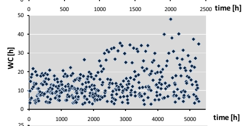
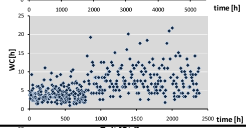
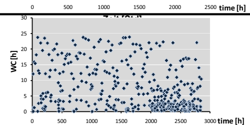
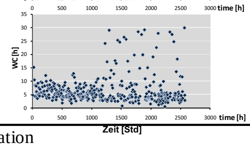


Fig. 3 Simulation of Structural Changes based on the Example of Distribution Model B

TABLE VI
DISTRIBUTION CHARACTERISTICS FOR SIMULATED MODELS

model		distribution A		distribution B		work content distribution
		μ_A	σ_A	μ_B	σ_B	
I	A	1,4	0,8	3,1	1,0	
I	B	10,2	2,0	4,5	1,9	
I	C	15,2	3,4	16,5	7,6	
II	D	4,0	1,9	7,9	3,8	
II	E	10,8	4,8	15,6	9,4	
II	F	8,5	2,7	11,9	7,5	
III	G	9,8	7,5	4,4	5,0	
III	H	5,8	2,2	7,0	6,8	

μ: mean value σ: standard deviation
model group I: predominantly normal distributed models with major changes
model group II: predominantly asymmetric distributed models with major changes
model group III: asymmetric distributed models with minor changes

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:5, No:10, 2011

Each data series consists of 200 orders. The evaluation of the testing methods introduced here, will be subsequently presented based on different distribution models (Models A to H). The test models are summarized in Table VI along with the underlying distribution parameters. The difference between the data series are identified either by a change of the WC_m, the WC_s or a combination of both. Furthermore, within the test models varying degrees of structural changes are detected. Distribution Model B is exemplarily depicted in Fig 3.

B. *Experiment Results*

In the evaluation and, in particular, the assessment of the tests introduced here, the following aspects are to be included:

- the relative order of magnitude of the work contents' structural changes,
- the type of the structural change: changes in the level, variability or a combination of both distribution characteristics,
- the actual shape of the data distribution before and after the structural break: normally distributed, symmetric data models, or distributions skewed to the right with an extremely long tail.

Considering these assessment criteria, it can be assumed that the different tests could lead to deviating results. The results thus should always be evaluated in view of the respective model distributions. Table VII summarizes the results of the experiments in the form of a test matrix. The results of each method as well as the number or range of false alarms are allocated to each of the distribution models. Following that Fig. 4 depicts the dynamic means and standard deviation control charts as well as the corresponding CUSUM charts based on the example of Distribution Model B.

TABLE VII
OVERVIEW OF EXPERIMENT RESULTS

	model	method: dynamic mean control chart α=5%	dynamic mean control chart α=1%	dynamic standard deviation control chart α=5%	dynamic standard deviation control chart α=1%	CUSUMμ control limits regarding (9)	CUSUMμ V-Mask	CUSUMs control limits regarding (9)	CUSUMs v-mask
I	A	201 / -	203 / -	201 / false warning: n = 190 - 200 n = 253 - 264	203 / -	205 / -	203 / false warning: n = 187 - 189	268 / -	-
I	B	204 / false warning: n = 386	206 /-	204 / false warning: n = 188 - 189	206 / -	208 / -	202 / -	246 / -	241 / -
I	C	- / false warning: n = 119 - 124 n = 192 - 199	- / -	204 / false warning: n = 126	210 / -	- / -	204 / -	219 / -	217 / -
II	D	206 / -	209 / -	205 / several false warnings	206 / false warning: n = 155 - 162 n = 354 - 361	209 / -	202 / false warning: n = 151 - 153 n = 348 - 353	- / -	211 / -
II	E	215 / false warning: n = 142 - 143	219 / -	214 / false warning: n = 250 - 364	219 / -	219 / -	221 / false warning: n=350	227 / -	- / -
II	F	211 / false warning: n = 287 - 288	216 / -	206 / false warning: n = 75 - 76 n = 155 - 165 n = 315 n = 342 - 347	208 / false warning: n = 342 - 344	221 /-	206 / false warning: n = 149 - 152 n = 286 - 287	217 / -	210 / -
III	G	220 / false warning: n = 363	224 / -	220 / false warning: n = 365 - 383	224 / false warning: n = 365 - 383	220 / -	- / -	248 / false warning: n = 380 - 384	- / false warning: n = 370 - 382
III	H	216 / false warning: n = 113 - 116 n = 134	- / -	209 / several false warnings	209 / several false warnings	218 / false warning: n = 108 - 114 n = 352 - 363	209 / false warning: n = 112 - 116 n = 286 - 287	218 / false warning: n = 102 - 116 n = 347 - 380	221/ false warning: n = 311 - 322 n = 346 - 368

Code: * / **
* order number when identifying structural changes
** value margin of false warnings
α: level of significance

In order to simplify evaluating the results, the analyzed models were divided into three classes. In Class I all of the models that are characterized by a significant structural change and for which the data structure is predominantly normal distributed are categorized. Models A, B and C are counted among these. Within these work content distributions the results for all of the tests considered were very good. This is demonstrated by the very quick detection of structural changes as well as a very low rate of false alarms. Due to the almost 'ideal' structure of the distributions even the smallest changes in the work content variability could be reliably identified for these models (see Model A and B).

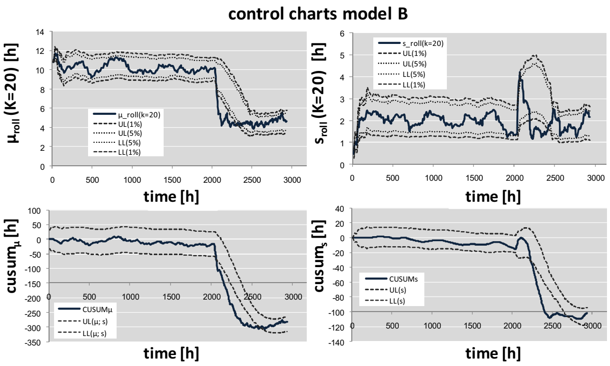


Fig. 4 Dynamic Means, Standard Deviations and CUSUM Control Charts (Example based n Model B)

Class II categorizes all of the models that have an asymmetric, right skewed distribution shape. The structural changes are however, clearly expressed. Test models D, E and F are allocated to this class. The methods introduced here also attain good results with these distribution models. The primary differences between this class and Class I is a slight increase in false alarms as well as a brief delay in reporting actually existing structural changes. If the results from all of the methods are considered and evaluated at the same time instead of considering individual experimental results, then undesired false alarms can also be differentiated from actual structural changes in these models relatively quickly and with a high degree of certainty. It should be noted here that right skewed distributions as presented and tested here are also observed in practice and also generally reflect real distribution forms of the work content. Based on these results it can be concluded that the test developed and applied here are relevant for the industrial practice.

Models G and H are classified under Class III. Within this category of models, the structural changes are less 'clearly' expressed. Furthermore, the work contents are characterized by an asymmetrical distribution form with an extremely long tail. Especially with these models, it is possible to reduce false alarms by combining a number of tests.

V. SUMMARY AND OUTLOOK

In conclusion, it can be said that the tests developed for controlling and monitoring the work contents under dynamic conditions can be successfully applied both to normally distributed as well as complex and skewed distribution forms. In this context, particularly right skewed distributions with so-called ‘long tails’ demonstrate a strong basis in the industrial practice. Complex structures such as these can however lead to delayed reports or to an undesired increase in false alarms. Simultaneously applying and evaluating different tests can counteract this effect.

The CUSUM method (see (9)) presented here and the dynamic control charts thus primarily detect seldom occurring and chronologically further apart structural changes. The reason for this is the definition of the process level with a rolling window of n=100 observations. The size of the interval means that after there has been a change, the control limits first take on a new stationary state only after n=100 realizations. If there are renewed structural changes during the transition phase, the impact can overlap on the test variables and control limits thus complicating the identification of structural changes. One of the fundamental advantages of these methods though is their robustness to false alarms. In order to shorten the ‘reaction time’ to structural changes the data basis for calculating the rotating test variables could be reduced at the cost of increasing the number of false alarms. Alternatively, applying so-called ‘V-masks’ offers the possibility to monitor test variables already after k=15 realisations and thus also detect structural changes that occur chronologically closer to one another. By simultaneously applying the dynamic tests introduced in this paper the advantages of the individual approaches can be combined and the advantages reciprocally compensated for. False alarms can thus be practically considered by comparing the different test results in order to identify actual structural changes with a higher certainty.

The developed methods are suitable not only for monitoring work content distributions but also for other parameters that are relevant to logistics e.g., WIP. In order to facilitate a dynamic evaluation of the Logistic Positioning and corresponding measure derivation, part of the on-going research project is aimed at implementing the tests within a software demonstrator. Moreover, the next step in converting the Logistic Operating Curves into a method for dynamically controlling the production is the development of new parameters that can be monitored by means of the introduced tests and drawn upon for describing the dynamic process stated.

ACKNOWLEDGMENT

The authors would like to thank the German Research Foundation (DFG) for financially supporting this research within the context of the collaborative research centre 489 “Processing Chains for the Production of Precision Forged High Performance Components” in subproject C2.

REFERENCES

[1] P. Nyhuis, “Logistic Production Operating Curves - Basic Model of the Theory of Logistic Operating Curves,” Annals of the CIRP 55 2006 1, pp.441-444

[2] M. Kennemann, S. C. Eickemeyer, E. Schnurr, P. Nyhuis, “Produktionskennlinien im dynamischen Umfeld: Entwicklung eines logistischen Wirkmodells mittels simulationsgestützter Versuchsplanung,” In: ZWF-Zeitschrift für wirtschaftlichen Fabrikbetrieb, Hanser-Verlag, Volume 105 2010 10, pp. 865-869

[3] P. Nyhuis, H. P. Wiendahl, “Fundamentals of Production Logistics: Theory, Tools and Applications,” Berlin, 2008

[4] H. Rinne, H.-J. Mittag, “Statistische Methoden der Qualitätssicherung,” 2nd Edition Hanser-Verlag, Munich, 1991

[5] H.-J. Mittag, “Qualitätsregelkarten,” Hanser-Verlag, Munich, 1993

[6] D. J. Wheeler, D. S. Chambers, “Understanding statistical process controll,” SPC-Press, Knoxville, 1986

[7] W. A. Shewhart, “Economic Control of Quality of Manufactured Product,” New York, 1931

[8] G. Faes, “SPC-Statistische Prozesskontrolle: Eine praktische Einführung in die statistische Prozesskontrolle und deren Nutzung,” Books on Demand GmbH, Norderstedt, 2009

[9] T. P. Ryan, “Statistical Methods for Quality Improvement,” Yohn Wiley & Sons, New York 2000

[10] R. L. Brown, J. Durbin, J. M. Evans, “Techniques for testing the constancy of regression relationships over time,” Journal of the Royal Statistical Society, Series 37, 1975, pp. 149-163

[11] J. S. Oakland, “Statistical Process Control,” Butterworth-Heinemann-Verlag, Oxford, 2003

[12] G. A. Bernard, “Decision Interval V-masks for Use in Cumulative Sum Charts,” Applied Statistics , Vol. 1, p. 132

[13] E. Ludwig, “Modellgestützte Diagnose logistischer Produktionsabläufe,” Diss. Universität Hannover, Fortschritt-Berichte VDI Series 2, No. 362, Düsseldorf 1995