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Dynamics In Production Processes

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Abstract**—**An increasingly dynamic and complex environment poses huge challenges to production enterprises, especially with regards to logistics. The Logistic Operating Curve Theory, developed at the Institute of Production Systems and Logistics (IFA) of the Leibniz University of Hanover, is a recognized approach to describing logistic interactions, nevertheless, it reaches its limits when it comes to the dynamic aspects. In order to facilitate a timely and optimal Logistic Positioning a method is developed for quickly and reliably identifying dynamic processing states.

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

I. Introduction

GLOBAL competition and considerable economic fluctuations pose huge challenges for manufacturing enterprises also with regards to logistics. The Logistic Operating Curves, a method based on modeling theory, describe the interactions between the logistic objectives such as Work in Process (WIP), utilization, throughput time and schedule reliability [1]. The dynamic influences of the market or structural changes that are expressed in strongly fluctuating batch sizes and consequently, work contents, complicate implementing this method though. Since they are based on average values, the Logistic Operating Curves Theory requires long periods of analysis and stable processing states in order to be able to execute a sufficiently precise Logistic Positioning [2]. Dynamic processing states (cf. [3], [4]), however, comply with neither of these conditions.

Within the frame of the collaborative research centre 489 “Processing Chains for the Production of Precision Forged High Performance Components”, sponsored by the German Research Society (DFG), an approach was thus developed that allows the application of the Logistic Operating Curves Theory to also be extended to dynamic processing states. Currently, there are no models that support continuously monitoring dynamic processes and deriving decisions for improving logistics within them.

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In order to identify when a new Logistic Positioning is required, dynamic processing states that are not caused by natural variance in the process, but rather by structural changes first have to be reliably and quickly identified.

As a result of structural changes a process can experience significant alterations and shifts in its mean values as well as deviation in the relevant key parameters. Within the frame of the statistical process monitoring and control the mean values and variance parameters are predominantly drawn upon to identify deviations [5], [6]. In the following paper, the use of control charts and statistical ‘two sample tests’ for identifying simulation generated structural changes in the work content distributions will be examined.

II. Logistic Operating Curves Theory

The Logistic Operating Curves Theory, which is implemented in the operational practice and has become a recognized concept, is based on the quantitative description of the function correlations between the logistic objectives: throughput time, WIP, utilization and schedule reliability. Because the Logistic Operating Curves clearly depict the discord between the targets and the impact of the prioritization becomes clear (cf. Fig. 1) they are well suited for conducting a Logistic Positioning within the field of conflict between the logistic objectives. The central variables for the ideal Logistic Operating Curves are the maximum output rate ($ROUT_{max}$) and the ideal minimum WIP ($WIPI_{,min}$) on a workstation. The ideal minimum WIP is primarily influenced by the mean and standard deviation of the work content (WC_m, WC_s). Since the input parameters for the model are generally data which is influenced by the production planning and control (PPC) functions, it seems obvious to draw upon the Logistic Operating Curves as a basis for a continual process model and to orient these on the logistic factors.

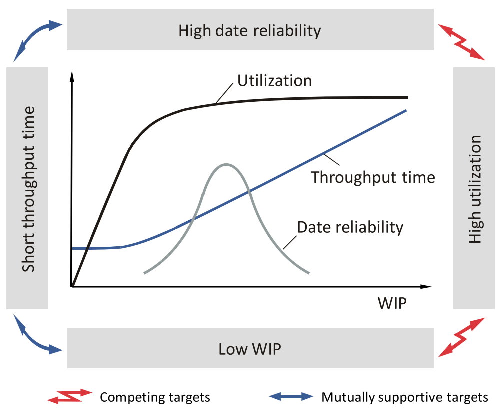

Fig. 1: Field of Conflict between the Logistic Objectives [2]

Logistic Operating Curves can generally be constructed for different conditions and compared with one another. The impact of interventions in the production process can thus be evaluated in view of logistic aspects. With a certainty of 95%, an accuracy of 20% (permissible deviation of expected and found values) and an underlying (normal) distribution, Nyhuis estimates the number of required feedback responses from the production to be 49 value pairs [2]. Furthermore, it is necessary that the input and output on a workstation are aligned with one another over the long term and thus that the observed workstation has adopted a steady state [1-2]. In the industrial practice e.g., in the forging industry which mostly has very long throughput times, a longer period can pass before this number of feedback responses are attained. However, because of the aforementioned conditions are necessary to apply the Logistic Operating Curves, they often reach their limits when the observational periods are short and processing states are fluctuating. As a result it is important to identify structural changes that subsequently allow a new Logistic Positioning as reliably and quickly as possible.

III. Identification of Structural Changes by means of Control Charts

Control charts are a very common instrument used in the industry to continually monitor and control manufacturing processes. The principle of control charts is based on the idea that systematic disruptions can be discovered and corrected through process correcting measures. Generally, relevant distribution parameters for the characteristic being monitored are used as control variables [7-9]. In this paper, the characteristic we will consider is the distribution of the work content, described by the mean and standard deviation of the work content (WC_m, WC_s). Unlike for example monitored standard tolerances, work contents do not follow any pre-determined target values. The structure of the work content can therefore change from one order to another, whereby the lack of clearly defined warning limits significantly complicates the control of the work content. Together with the assumed normal distribution of the work contents, the distribution form of this data is described by the expected value and variance. In order to monitor these distribution characteristics the traditional standard control charts (according to Shewart [7]) or a slightly modified variation are frequently implemented in the industrial practice.

At the Institute of Production Systems and Logistics, the control chart method was analyzed regarding its applicability among others within the frame of monitoring the work content. Implementing this method however proved to be unsuitable due to the dynamic characteristic of the work content. One of the fundamental prerequisites for applying control charts is a so-called “controllable process”. That means that the process has already been optimized and only random factors cause the deviations in the monitored parameter. In turn with a controlled or stationary process the mean and standard deviation of the monitored characteristic continually moves within known tolerance levels. Moreover, there is a strong agreement between the provided target values and those realized [10].

This is exactly where the difference between the work content data and the parameters that are traditionally controllable with control charts lies: Usually no target values are provided for the work content. The mean work content does not describe a concrete objective and thus does not contain any fixed planned values. Whereas when standard control charts are applied warning and action limits are initially set based on target parameters and subsequent samples are drawn and compared to these defined limits, this procedure cannot be transferred to the dynamic work content data. As a possible alternative to standard flow charts, research at the Institute of Production Systems and Logistics has developed methodical approaches proven to be well suited to monitoring the work content, particularly with regards to dynamic states.

IV. Using Two-Sample Tests for Identifying Structural Changes

The challenge in monitoring work content distributions is defining dynamic control variables or test procedures that continually adjust to the conditions. It thus seems obvious to implement the statistical method referred to as ‘two-sample tests’. Instead of strict control limits that can only be insufficiently provided when it comes to work contents, the tests compare samples with one another.

A current sample (e.g. 15 new work contents) can be tested for the identity of the distribution parameters with a saved sample (e.g. 15 work contents immediately preceding them). When the difference between the respective parameters is too large, the tested samples are characterized as unequal and thus identified as an indication of a structural change. The dynamic of the logistic data is considered in a manner that allows a current sample to be continually compared with a previous sample. Data that is significantly older is not considered, therefore false warnings due to “outdated” structures are decreased. In this context, continually means that as soon as the number of current realizations corresponds to the defined range of the sample, the test is repeatedly executed. Every ‘current sample’ thus becomes the ‘previous sample’ in the following test. The parametric two-sample test verifies the equivalence of both the means and standard deviations of the samples.

Based on the assumption of normally distributed and unrelated samples, it is possible to choose either the two-sample Gauss test or the two-sample t-test in order to test for equality of the means. When the samples are sufficiently large the Gauss test can be applied with the critical values of the normal distribution. For smaller samples such as those used in the analysis presented here, the mean (as the test variable) can no longer be characterized as normally distributed. In this case, the two-sample t-test with a t-distributed test function is drawn upon. The application of the t-test is facilitated by the fact that the sample variance of the work content is generally unknown and consequently can only be given as an estimated value. The t-test is also preferred in this case [11].

Parallel to shifts in the mean, a significant change in the variance indicates a change in the distribution structure of the work content. Instead of the t-test a two sample F-test is used to compare the sample variance. The quotient of the sample variance estimator, whose function with normally distributed variables follows an F-distribution, is used as the test function [11].

The test procedures each describe a bi-directional test, with which the equivalence of the expected values or the variance between two samples are tested under the H_0-hypothesis (Table I). The so-called p-value, which is defined as the degree of plausibility for the H_0-hypothesis is drawn upon as the test variable [12]. If the p-value is smaller than the selected significance level α, then the null hypothesis is rejected in favor of the alternative hypothesis ("structural interruption").

TABLE I
TESTING HYPOTHESIS OF THE T-TEST AND F-TEST

	H_0-hypothesis	versus	H_1-hypothesis
t-test	Mean values of the samples are equal $\mu_X = \mu_Y$		Mean values of the samples are **not** equal $\mu_X \neq \mu_Y$
F-test	Variances of the samples are equal $\sigma^2_X = \sigma^2_Y$		Variances of the samples are **not** equal $\sigma^2_X \neq \sigma^2_Y$

μ_X respectively σ^2_X: mean value respectively variance of the current sample
μ_Y respectively σ^2_Y: mean value respectively variance of the saved sample

V. Execution and Evaluation

A. Data Simulation

The analyses are conducted based on simulated approximately normally distributed work content. Strictly speaking this assumption is not fully met in the industrial practice. Research has shown though that moderate deviations from the normal distribution e.g., in connection with statistical control cards only lead to a minor distortion of the test results [13].

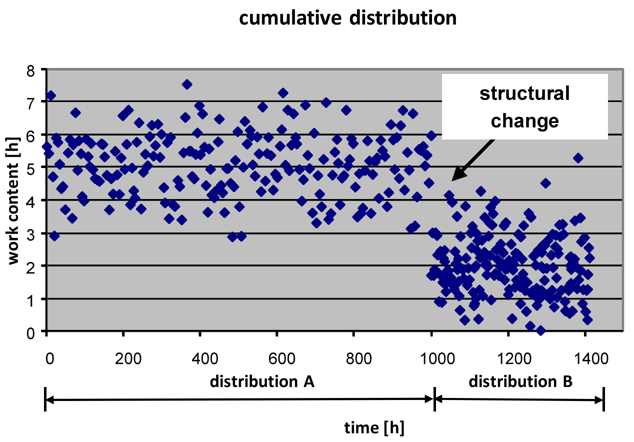

Fig. 2: Simulation of Structural Changes

Using LOCCS 1.56, a tool developed at the IFA, two normally distributed streams of data A and B were generated and merged together into one total distribution (cf. Fig. 2). Each data stream included 200 orders. The difference between the data streams are characterized by either a single change of the mean, the standard deviation of the work content or a combination of both.

Consequently, within the work content structural changes of varying degrees can be simulated and the appropriateness of different methods of identification can be tested. Generally speaking the distribution models in Table II are simulated so that the tests can be conducted. For testing the mean and standard deviation, three different distribution models were generated for each as well as an additional work content structure that represents a combination in the shift of the mean and change in the standard deviation (Model A-G). Distribution model C is exemplarily depicted in Fig. 3.

TABLE II
DISTRIBUTION PARAMETERS FOR SIMULATED WORK CONTENTS

test	distribution model	Distribution Parameters μ_A [h]	μ_B [h]	σ_A^2 [h^2]	σ_B^2 [h^2]	Limiting Value WC [h] LV_A	LV_B
	A	2	3	0,25	0,25	24	24
t-test	B	1	3	1	1	5	7
	C	3	2	1	1	24	24
t-test / F-test	D	10	2	1	0,25	24	24
	E	4	4	2	2,5	8	10
F-test	F	10	10	10	3,5	24	24
	G	5	5	2	5	8	24

WC: work content h: hour
μ_A / σ_A^2: mean value / variance of the work content before structural changes
μ_B / σ_B^2: mean value / variance of the work content after structural changes

The aim of monitoring the work contents is to be able to identify structural changes reliably and quickly as possible. In order to do this as quickly as possible the selected range of the sample should be as small as possible. Nevertheless, if the selected range is too small there is the danger that false warnings will increase due to random blips. Accordingly, a compromise between the actuality of the test results and their reliability has to be found.

B. Results

The simulated work content distributions from Table II form the basis of the two-sample tests. In each of the distributions a current sample n_x was alternatively examined for deviations with an older sample n_y. Samples with different sizes ranging from n=5 to n=30 were tested. Moreover, the test results were considered at different levels of significance α = 1%, 5% and 10%. This research is primarily concerned with the general suitability and reliability of continual two-sample tests. Parallel to this, the questions of an optimal sample size and the influence of the levels of significance were also pursued. Generally it should be kept in mind that in the industry the significance level is provided and is subsequently considered in the test decision.

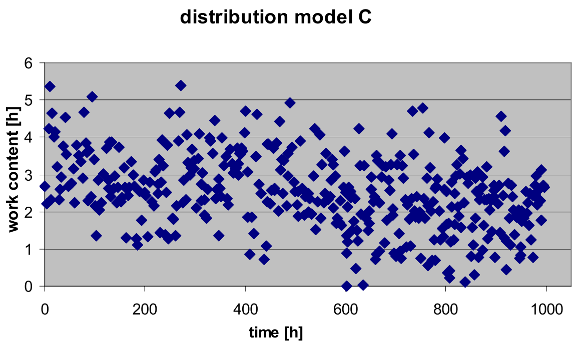

Fig. 3: Structural changes in model C

The results of the conducted tests are summarized in Table III. It can be clearly seen that in the distribution models A, B and D_1 the two-sample t-test reliably identified the structural changes of the mean value during the transition from distribution A to B (cf. Fig. 2). In all of the analyzed sample deviations and significance levels there was only one exception to this. However, when we consider all of the significance tests in model C the structural changes were not detected in approximately 28% of the tested cases. This result can be explained in that the changes to the processing state during the transition from distribution A to B are comparably minimal while the deviations are relatively high (cf. Fig. 3).

TABLE III
TABLE OF RESULTS FOR THE TWO-SAMPLE TESTS

model		sample size					
		n_x=n_y=5	n_x=n_y=10	n_x=10; n_y=20	n_x=n_y=15	n_x=n_y=20	n_x=n_y=30
A	α=1%	+/2	+/1	+,o/0	+/0	+/0	+/0
	α=5%	+/6	+/1	+,o/2	+/1	+/3	+/1
	α=10%	+/8	+/1	+,o/2	+,o/2	+/4	+,o/2
B	α=1%	+/1	+/0	+,o/0	-/0	+/0	+,o/0
	α=5%	+/4	+/0	+,o/0	o/0	+/0	+,o/0
	α=10%	+/6	+/0	+,o/1	o/0	+/0	+,o/0
C	α=1%	-/2	-/2	o/1	-/0	+/1	o/1
	α=5%	+/9	-/4	o/6	o/0	+/2	o/1
	α=10%	+/11	-/8	o/8	o/0	+/3	+,o/2
D_1	α=1%	+/0	+/1	+,o/0	+/1	+/0	+,o/0
	α=5%	+/3	+/1	+,o/1	+,o/1	+/2	+,o/1
	α=10%	+/8	+/2	+,o/3	+,o/2	+/3	+,o/2
D_2	α=1%	-/0	-/1	+,o/1	+,o/0	+/0	+,o/0
	α=5%	-/3	+/2	+,o/2	+,o/1	+/1	+,o/0
	α=10%	-/6	+/3	+,o/2	+,o/1	+/1	+,o/2
E	α=1%	-/0	-/0	o/0	-/0	-/0	o/0
	α=5%	-/3	-/2	o/1	o/0	+/2	+,o/0
	α=10%	-/3	-/4	o/1	o/1	+/4	+,o/0
F	α=1%	-/1	-/0	-/1	-/1	-/0	-/0
	α=5%	+/6	-/1	-/2	-/1	-/1	-/0
	α=10%	+/10	+/2	+/5	-/2	+/1	o/0
G	α=1%	-/2	+/0	+/0	+/1	+/0	+/0
	α=5%	-/7	+/1	+,o/1	+/2	+/3	+/0
	α=10%	+/11	+/4	+,o/5	+,o/3	+/5	+/0

Code: */** ~ reliability of the identifikation/ sum of false warnings
*: +: directly identified; o: late identified; -: not identified
D_1: t-Test; D_2: F-Test

The test results for Model C however could be considerably improved when a higher significance level is provided. Generally the results show that t-tests provide reliable warnings in most cases even when there are complex distribution structures with gradual changes instead of sudden ones.

Nevertheless, the test results from the sample test of the deviations (distributions D_2 to G) greatly diverge from the test results of the mean value. The evaluation of the trial results from Table III clearly shows that both the range of the samples as well as the significance levels strongly impact the percentage of reliably identified structural changes. The tests results are particularly positive when the current sample size $n_x = 10$ was selected and the historical sample n_y was more broadly designed with a data range of 20 values. A further fundamental advantage of this test design is that with a relatively small sample $n_x = 10$ a quick reference to the current processing situation can be ensured.

Furthermore the frequency of false warnings needs to be considered. As was to be expected, the significance level had a decisive influence on the error rate. On average the percentage of false warnings across all of the models, test methods and sample ranges increased by 1.18% with a α-level of 1% to a approximately 5.10 % (α = 5 %) and to approximately 9.04 % (α = 10 %). As a result the theoretical probability of a mistake (error type 1) and the tested error rate were very close to one another. However, the influence of the sample size was less systematically spread across the percentage of false warnings. Generally, the two-sample t-test tended to have fewer false warnings in the interval $10 < n < 15$.

VI. SUMMARY AND OUTLOOK

At the Institute of Production Systems and Logistics both control charts and statistical two-sample tests were analyzed with regards to their suitability for identifying logistically relevant structural changes. Due to the dynamic characteristics, the traditional control charts method developed by Shewhart [7] proved to be unsuitable in comparison to "continual" two-sample tests. In analyzing the mean value and deviations of structurally changed work content with two-sample tests it was found that structural changes within the context of the distribution structures used here were predominantly well identified. Warnings were reliably provided for clearly pronounced sudden changes in the distribution structure and even with less pronounced distribution structures (i.e., sliding distribution changes) the method was primarily able to identify them. However, it was determined that as a compromise between the highest possible scoring ratio and the least number of false warnings, a combination of the best sample size and test significance levels is required. These evaluations show that with a sample size of n_x=n_y=15 and a α-level of 5 %, a higher 'hit rate' can be attained with at the same time comparably fewer false warnings. Moreover, a differentiated sample analysis with n_x=10 und n_y=20 has the advantage that the structural changes can be discovered relatively quickly and reliably, while at the same time the false impact of individual blips within a sample

n_x can be reduced.

For an even quicker and more accurate identification of also smaller structural changes other test methods should be analyzed in the future as well as possibly implementing a combination of different methods and tests for identifying logistically relevant structural changed.

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