Robert Schmitt · Günther Schuh *Editors*

Advances in Production Research

Proceedings of the 8th Congress of the German Academic Association for Production Technology (WGP), Aachen, November 19–20, 2018

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Contents

Future Machines and Data

Systematic Data Analysis in Production Controlling Systems to Increase Logistics Performance

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Abstract. Logistics performance becomes an ever more important strategic factor for manufacturing companies. A continuous production controlling supports in identifying weak points and deriving effective counter measures improving logistics performance sustainably. In this paper a framework for production controlling is presented, which allows data based identification of the root-causes of low logistics performance. It illustrates how systematic data analyses can be performed based on causal trees structuring the complex and multi-causal logistical interdependencies in a company's internal supply chain. Step by step analysis guidelines will especially enable SMEs in particular to benefit from increasing data availability and quality and will build the basis for advanced IT-based support systems.

Keywords: Logistics · Production planning · Production controlling

1 Introduction

Manufacturers have to encounter the challenges of global markets. Limited differentiation potentials of products through functionality, quality or price elevate the importance of logistics performance as a major factor of competitiveness [1] that significantly influences customers' purchasing decisions [2]. Studies show that enterprises striving towards a consistent optimisation of their supply chain regarding logistic objectives can verifiably increase market success [3]. Despite the great importance of high logistics performance, many companies have considerable deficits in achieving their own and market-related logistical targets [4]. Especially manufacturing companies in the individual and small-series production are facing increasing challenges regarding on-time delivery and delivery time [5].

Production controlling aims at countering this deficit through continuous collection, analysis and interpretation of relevant feedback data within the closed loop of production planning and control (PPC) [6]. Within the business control system, production controlling thus aims to increase transparency within the company's internal supply chain by means of IT-supported data collection and processing [7]. The focus of production controlling is on evaluation and regulation of the production system configuration rather than on controlling single production orders [8].

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Digitalisation of production processes and the associated increase in data availability and quality offer tremendous improvement potentials regarding decision support systems in the context of PPC and production controlling. Yet, most companies still perform PPC and controlling activities manually as they do not rely on automatically generated planning results [9]. At the same time, companies often lack the understanding of the manifold and multi-causal interactions in logistics systems [10]. This leads to unsystematic data analysis and wrong interpretations of key performance indicators. Hence, there is a high risk of defining ineffective measures not countering the real root-causes of present problems or even resulting in an even worse logistics performance due to inconsistent logistic objectives and target settings or incorrect or inconsistent settings of PPC parameters (see [10]). So far, there is a lack of assistance systems adequately supporting enterprises in data analysis and decision making within the framework of production controlling [11].

This paper addresses existing shortcomings and presents a framework building the basis for an advanced production controlling system particularly focusing on small and medium sized enterprises (SMEs). Based on generally valid cause-effect-relationships in logistics systems, the most relevant indicators that need to be tracked and monitored along the internal supply chain are proposed. Furthermore, it is shown how to use this information to systematically identify weaknesses and improvement potentials using logistic models and selected further analysis methods. Firstly, this will result in an enhanced understanding of existing logistical interdependencies and thus enable SMEs to derive effective measures sustainably improving logistics performance. Additionally, it sets the guidelines for cross-data interpretation, which build the foundation for future algorithms of IT-based decision support systems.

2 Fundamentals of Production Controlling

In this chapter, the basics of production controlling are presented. This includes general requirements for production controlling, the general controlling process as well as the most important logistic target figures that need to be controlled.

Production Controlling. Today, controlling is a tool used by corporate management to support operational planning, control and monitoring functions [12]. The tasks of controlling include retrieval, preparation and analysis and distribution of data within the company [13]. Within the framework of production controlling, as a subsystem of corporate controlling, not only financial, but also logistical key figures of production must be taken into account [14]. For this purpose, production controlling must be able to record the effects of logistical decisions in the area of PPC on the company's performance and cost objectives [15]. Hence, production controlling, as defined in this paper, could also be called logistic production controlling and does explicitly not include controlling of technical manufacturing processes. The general controlling process is illustrated in Fig. 1 [16].

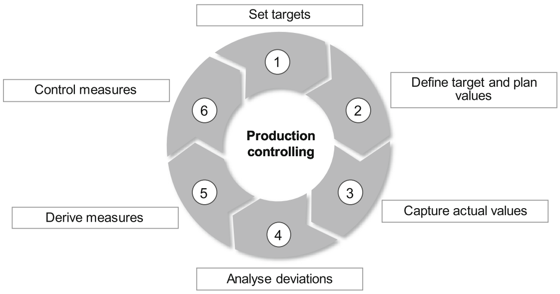

Fig. 1. The controlling process

In order to derive suitable measures, it is crucial to carefully analyse the real reasons for occurring deviations. Therefore, this paper will especially emphasise analysis of the root-causes of deviations in the following. For that purpose, relevant targets that need to be controlled are proposed in a first place.

Logistic Target System. The overall objective in production logistics is logistics efficiency. Hence, companies aim to achieve high logistics performance at low logistics costs. Logistics performance expresses itself in short delivery lead times and a high due date compliance. Logistics costs can be expressed in terms of production and capital commitment costs. From the corporate view, logistics costs mainly result from work in process (WIP) and capacity utilization [17]. In analogy, the target system for storage systems comprises low inventory and low storage costs, which define the logistics cost, while logistics performance is mainly defined by the means of the service level [18].

Based on this overall logistic target system, targets for each department across a company's internal supply chain, generally consisting of procurement, a preliminary production stage, an interim storage (or buffer), an end production stage and dispatch, can be derived. As dispatch is the last step in the internal value chain, the performance measures towards the end customer are measured in this process. The *delivery time* to the customer equals the sum of *throughput times* of the order-specific processes in the internal value chain. The delivery due date compliance achieved, results from the lateness of the single processes. The timeliness in processes with a storage or buffering function is evaluated using the target figures *service level* (storage) or *due date compliance* (buffer). According to the definition of due date compliance, orders are considered on time if they are finished up to the date of demand. Negative effects of materials being provided too early are taken into account via the resulting stock level. In order to evaluate the scheduling situation in production processes, however, the target *schedule reliability* is applied. In that case, orders are only considered on time if they are finished within an interval of the accepted lateness. *Delivery capability* is another important indicator regarding the scheduling situation. While due date compliance and schedule reliability are computed by comparing actual to planned finishing dates, delivery capability compares actual to the desired delivery date of the customer. Figure 2 sums up the resulting target systems across a company's internal supply chain [19].

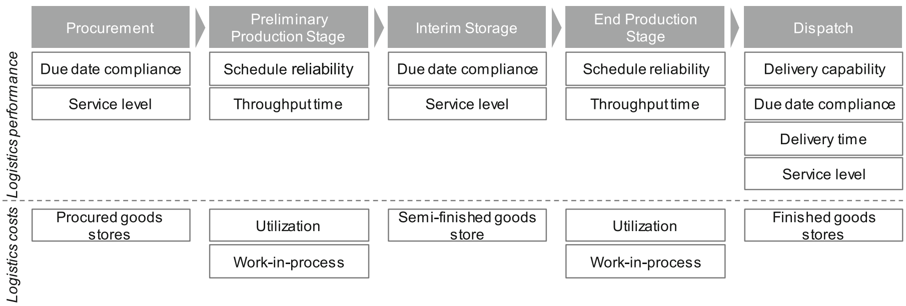

Fig. 2. Logistics objectives in the company's internal supply chain

3 Cause-Effect-Relationships and Relevant KPIs

In order to analyse the real root-causes of target deviations, general logistical interdependencies must be known. For that purpose, this chapter provides a brief introduction into general influencing factors on the attainment of logistical targets before an approach for structuring these factors into generally valid cause-effect-relationships is presented.

Influencing Factors on the Attainment of Logistical Targets. The attainment of logistical goals depends on a large number of influencing factor**s.** First, the objectives itself affect each other and are partly contradicting. A high service level, for instance, requires a correspondingly high stock level, which causes high inventory costs. The required stock level to achieve the desired service level in turn depends on the schedule reliability and the throughput times of upstream processes. Throughput times in production processes mainly result from the WIP in the production stage. This illustrates that there is a rather complex interplay between the logistic target figures within each core process but also between the target figures across the entire value chain.

Second, PPC configuration has a significant influence on target achievement. With the production control model, LÖDDING has already displayed how production control measures affect the logistical targets by identifying and structuring actuating and control variables [19]. The order release process, for instance, directly determines the WIP in a production stage and thus the realisable throughput times and capacity utilisation. SCHMIDT and SCHÄFERS extended the model and developed an integrative model of PPC showing the interrelations between control variables determined by PPC tasks, affected actuating variables and logistics objectives [20].

The third group of influencing factors are subsumed under organisational boundaries, building the general framework of the value chain and limiting the scope of action of PPC. The supply chain design regarding the position of the order penetration point, for instance, strongly determines achievable delivery times. Another example of this category is capacity flexibility determining to which extend production control can react to changing workload levels.

Additionally, there are environmental factors that cannot or that can only hardly be affected by the company. These primarily comprise customer and employee behaviour, technical errors, supplier reliability, as well as market and political developments. Figure 3 sums up the relevant categories of influencing factors that need to be considered.

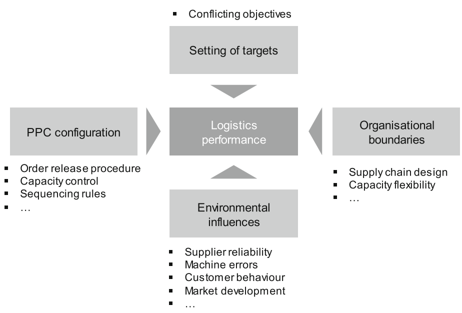

Fig. 3. General influencing factors on logistics performance

Structuring Approach. The complex interactions in a company's internal supply chain have been analysed and systemised in the form of causal trees. A poor performance in terms of schedule reliability in the end production stage, for example, can, on a first level, either be caused by deviations between the actual completion sequence and the planned completion sequence or by backlog. Moreover, orders can already be started either early or late. Possible reasons for backlog, deviations from the planned processing sequence or input lateness are structured in further levels of the tree until no further subdivision is feasible. Such trees have been developed for each logistic target figure. The single causal trees are interconnected as deviations from one target figure may influence other target figures as well. For example, one reason for a late start of a production order can be missing materials because of a low service level of the interim storage. In that way, the developed causal trees form a consistent causal network along the internal supply chain (Fig. 4).

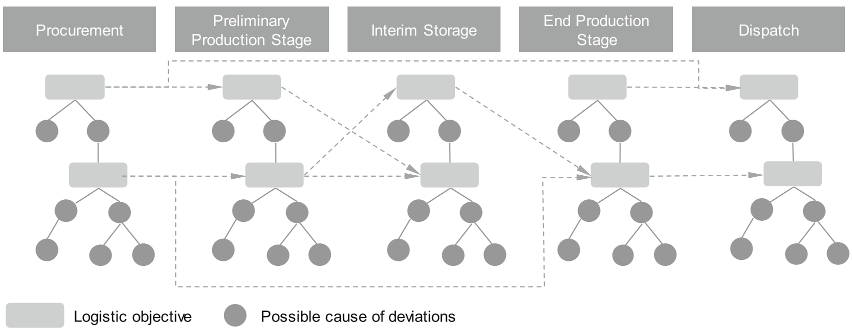

Fig. 4. The general concept of the developed causal network

These causal trees increase the logistical understanding of employees in SMEs in particular to enable them to identify weak points without external guidance. Furthermore, they are the basis for further quantitative analyses.

Derivation of Relevant KPIs. Based on the causal trees, relevant data and key performance indicators that need to be tracked can be derived. This is demonstrated for the causal tree of a low service level. A low service level may occur due to a low target service level, due to a planned stock level that is lower than required to achieve the target service level or due to deviations of the actual stock level from the planned stock level. As the stock level equals the sum of lot stock and safety stock, possible reasons for the planned stock level being too low are a low planned lot stock level, resulting from small incoming lot sizes or a low planned safety stock level. Safety stock is required to compensate for deviations from actual to planned inward and outgoing stock movements. Deviations to consider are especially late deliveries and varying demand rates. If these variations are not considered properly, losses in service level occur. Furthermore, a low planned safety stock level might also be due to calculation errors. Reasons for the actual stock level being lower than the planned stock level can be exceptional (short-term) events, such as promotional campaigns, which have not been considered or changes in the general framework conditions. These can either be a long-term increase of the demand rate or long-term supply shortages. In these cases, planned stock levels need to be adjusted to the new conditions [19].

In accordance with the first level of the tree, two main KPIs need to be available: the planned mean stock level, and the actual mean stock level. Whereas the actual stock level can directly be retrieved from the enterprise resource (ERP) system, the planned mean stock level equals the sum of the mean planned lot stock and the planned safety stock. The lot stock equals half the lot size of incoming orders. The planned safety stock is usually part of the master data of each article. According to the causal tree, information about occurring deviations from plan, which in fact are input lateness as well as demand rate variations, are required to evaluate, if the planned safety stock is sufficient. To compute those KPIs, warehouse movement data as well as planned arrival dates are required. As these are the same data required to assess the causes for low actual mean stock levels, no further information is required. Figure 5 sums up the causal relations and the resulting data requirements.

Similarly, data requirements and suitable KPIs for the analysis of the root causes for a poor performance regarding the other logistic target figures have been derived and aggregated in a catalogue of KPIs. These should be tracked in order to facilitate identification of weak points in the company's internal supply chain. Table 1 illustrates the top-level indicators. There are overall performance indicators that should be applied in order to identify general weaknesses within the supply chain. Throughput time and lateness indicators of this category refer to the entire order flow. Hence, they are measured at the end of a production stage. Especially if lateness KPIs are not tracked for single workstations, the order flow related indicators need to be taken into account to identify improvement potentials. Information about the backlog of a production stage are indicators for possible capacity or planning problems causing lateness. However, as the lateness distribution itself already allows prioritisation of possible causes for the resulting lateness [19], backlog indicators are not necessarily required but could be helpful to simplify root cause analysis. Besides those overall performance KPIs, information regarding the single workstations in production and assembly processes are required for detailed analysis and identification of bottlenecks and weak points within the production process. Here again, some KPIs are not necessarily required, but would simplify further analysis if accessible. The last category of indicators addresses storages, which are found in procurement as well as in production and dispatch. Besides KPIs regarding the stock level, especially information concerning

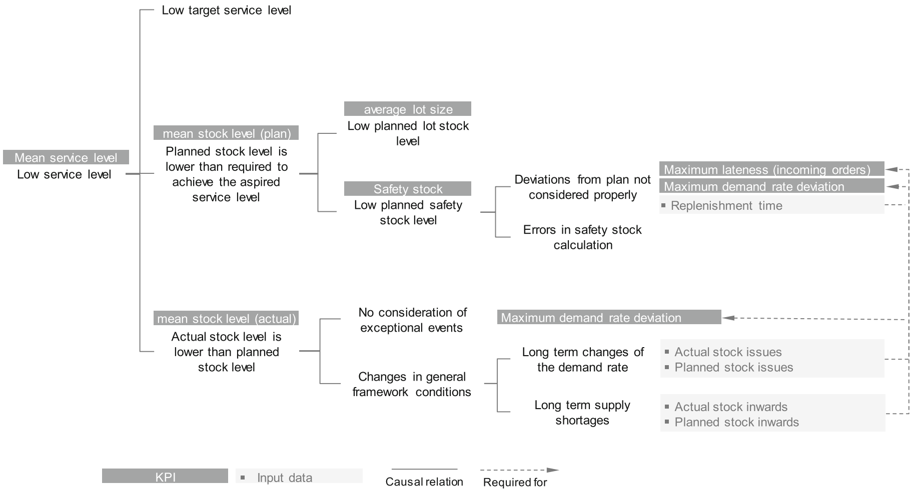

Fig. 5. Causal tree for a low service level and derived data requirements

occurring deviations from plan are required. Besides the listed KPIs there are many other possible KPIs that could be used in root cause analysis, such as KPIs for quality issues or employee availability. However, the provided list already allows localisation of the actual problem. Further, company-specific KPIs can be applied for even more detailed analysis (e.g. causes for machine errors).

Table 1. Most relevant KPIs for logistics analysis

Overall Performance KPI (for entire production stage)		
Throughput time	**Lateness**	**Backlog**
▪ Mean order throughput time ▪ Share of idle time	▪ Mean output lateness ▪ Mean input lateness ▪ Standard deviation of output lateness ▪ Standard deviation of input lateness	▪ Mean Backlog* ▪ Standard deviation of backlog*
Production/Assembly Processes (for each workstation)		
Throughput time	**Lateness**	**Inventory**
▪ Mean throughput time ▪ Mean operating time ▪ Standard deviation of the operating time ▪ Mean flow rate*	▪ Mean output lateness ▪ Mean input lateness ▪ Mean relative lateness* ▪ Standard deviation of output lateness ▪ Standard deviation of input lateness	▪ Mean WIP ▪ Relative WIP
Output value	**Backlog**	**Sequencing**
▪ Mean output value* ▪ Overall equipment effectiveness*	▪ Mean Backlog* ▪ Standard deviation of backlog*	▪ Sequencing reliability*
Storage (for each article/group of articles)		
Inventory	**Lateness**	**Demand**
▪ Stock turnover rate ▪ Mean stock level ▪ Relative stock level* ▪ Mean lot Stock ▪ Mean safety stock	▪ Maximum positive lateness of incoming orders	▪ Mean demand rate ▪ Maximum demand rate

*not necessarily required

4 Systematic Data Analysis

With the relevant KPIs being identified and causal trees indicating the relationships between the KPIs, systematic data analysis is possible. Detailed procedure guidelines starting from problem identification over root-cause-analysis to derivation of measures have been developed. According to the controlling process, deviations are identified by continuously monitoring the logistics target values and comparing actual values to the defined target values. Once a deviation is detected, the first step is to localise the most critical workstations (in production stages) or group of articles (in storages) mainly causing the deviations by analysing the above listed KPIs. By comparing the share of throughput times, for example, the workstations, which do affect the resulting overall throughput time of a production stage the most, are identified. Further analyses should focus on those bottlenecks. The required analysis steps for root-cause identification are directly derived from the causal trees. Based on the structure of the trees, step by step analysis instructions have been developed determining which analyses to perform at each fork (decision point) of the trees. The proposed analyses are mainly based on well-approved logistic models and supportive further analysis methods such as correlation analysis or time series. The developed instructions contain information about the type of analysis, required input data to perform the analysis and hints regarding result interpretation. They hence enable employees to draw the right conclusions from the KPIs proposed above and may serve as specifications regarding which queries and analyses to integrate in IT-based support systems. The general procedure for root-cause identification is demonstrated in the following based on two simple examples.

When analysing the root causes of long throughput times, the basic relations described in the production operating curves can be used as shown in Fig. 6. The relative WIP, which is the ratio between the actual mean WIP and the ideal minimum WIP [18], indicates throughput time potentials. If the planned relative WIP is significantly higher than about 250%–500%, the planned throughput time can usually be reduced. This also already indicates that a suitable measure would be limiting the WIP level. If the throughput time ratio of the work station in question is very high, but WIP level cannot be further reduced without expecting utilisation losses, reducing the operating time is the sole possibility for throughput time reduction.

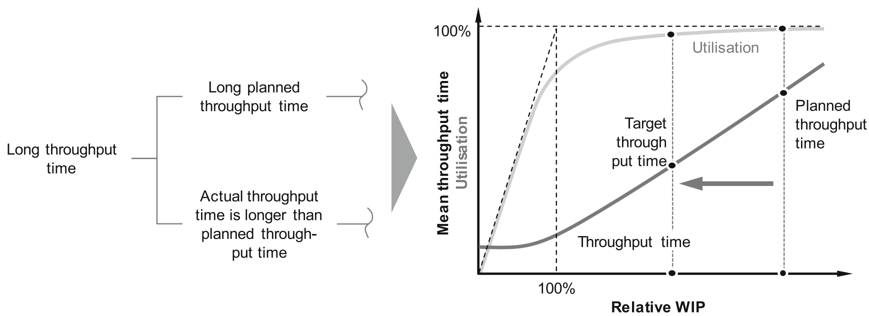

Fig. 6. Throughput time potential identification using production operating curves

Another example of how to use logistic models in root cause analysis is illustrated in Fig. 7. According to the causal tree for a low service level presented above, the first decision is, whether the low service level results from a planned stock level that does not match the desired target or if the actual stock level is lower than the planned level or from an already low target level. The service level operating curve is applied for analysis. Based on the target service level the required mean target stock level can be calculated. In Fig. 7 the actual mean stock level is significantly lower than the planned stock level. Hence, the respective branch of a low actual stock level needs to be further pursued. At the same time, the planned stock level is significantly higher than the target stock level. This value should be corrected to avoid unnecessary inventory costs, once the actual stock level approaches the planned stock level again.

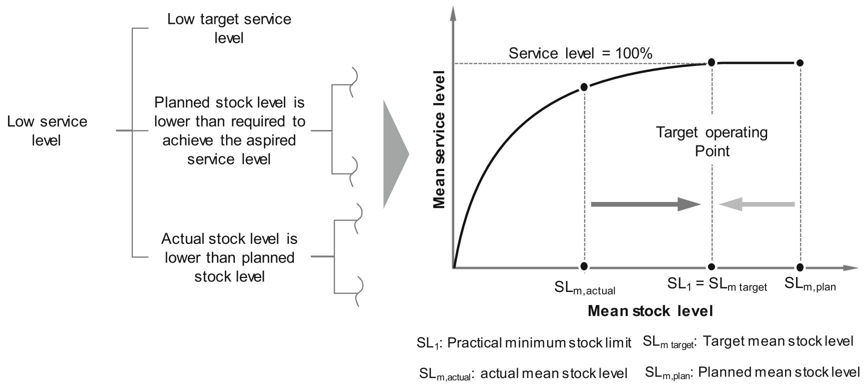

Fig. 7. Root cause identification for a low service level using the service level operating curve

The developed analysis procedures are being translated into flow charts. In combination with the detailed descriptions of each analysis step, comprehensive procedure guidelines for how to perform data analyses in the context of production controlling is provided, which can be used as the basis for intelligent algorithms applied by IT-based decision support systems. The analysis procedure is further complemented with a catalogue of suitable measures for each root-cause. In that way, the developed approach supports the entire controlling process.

5 Conclusion

In this paper an approach for systematic data analyses in the context of production controlling is presented. For the most important logistics objectives causal trees structuring the complex logistical interdependencies have been developed. Based on these causal trees relevant KPIs that should be tracked and monitored have been derived. Furthermore, the identified causal relations set the guidelines for systematic data analyses based on logistic models and further analysis methods. Concluding, a systematic and simple approach for production controlling has been developed supporting in terms of which data to analyse, which analyses to perform, and how to interpret analysis results to identify logistical weaknesses in the company's internal supply chain. Due to its simplicity, it will increase the understanding of employees about the complex logistical interdependencies. In times of ever more available feedback data, the structured approach will thus enable especially SMEs to perform exhaustive logistical analyses with the help of the guidelines provided. Based on the analyses results, effective measures can be derived countering the root-causes of present problems. The developed analyses guidelines are being translated into flow charts, which can be used as specifications for future IT-systems allowing automatic or semi-automatic data preparation and analysis. The rather simple and transparent approach would allow employees to comprehend the conducted analyses and would thus also positively affect user acceptance (e.g. compared to complex supply chain simulations). In that way, such a controlling system would help to ensure that the potential of higher data availability is also exploited in the future, as less expert know-how and manual tasks would be required.

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CAD-Model Based Contour Matching of Additively Manufactured Components Using Optical Methods

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Abstract. Additive processes offer the possibility to produce complex geometries that are not possible to manufacture with traditional methods such as turning, milling or electrical discharge machining. Due to the layered structure of the material during the production process, the process time in the Fused Deposition Modeling (FDM) or Fused Layer Manufacturing (FLM) process is primarily dependent on the layer thickness. However, a large layer thickness induces deviations from the ideal shape of the component and features such as bores or fits. In a new approach, the additive process time will be reduced by applying excess material with a large layer thickness close to the desired contour. In a subsequent machining step, the excess material is removed, and the target contour is produced. This paper presents the first stage of this approach in which the alignment of an additively manufactured component within the working area of a milling machine is estimated based on CAD-Model and optical methods.

Keywords: 3D-Image processing · Computer Aided Manufacturing (CAM) Fused deposition

1 Introduction

Additive manufacturing provides the ability of designing and manufacturing work pieces with major engineering freedom by applying material in a layered structure [1]. Within the last 15 years additive technologies have become more important in the industrial manufacturing [2]. Because of the developed technological advantages over the last years additive manufacturing has become more and more an alternative process technology for short runs as well as highly individual production [3]. Therefore, additive manufacturing enables designers and engineers to develop new functional parts with higher complexity as well as lower material usage while keeping nearly the same mechanical characteristics. However, additively manufactured work pieces of 3D printing processes often do not fulfill tolerance requirements regarding the geometrical shape and surface finishing [4]. The tolerance deviations in most technologies,

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especially in Fused Deposition Modeling (FDM) or Fused Layer Manufacturing (FLM) processes, amounts to 0.1 mm and more. Reducing the layer height and/or the speed of the extruder's movement can increase the production quality but is accompanied by an increase in costs, as the production time raises. Hence, general work pieces manufactured in 3D printing processes need a finishing process in order to fulfill tolerance deviations.

Nowadays the difficulty lies in contour adjustment and referencing of the semi-finished component in the finishing process' mounting-area. This paper will present a method for determining the reference position of a workpiece as a prerequisite in post-processing of additively manufactured components created in 3D printing processes.

2 Overall Concept for Hybrid Process

Figure 1 depicts the overall concept of a hybrid (additive and subtractive) process, whereas Fig. 2 shows the computer vision processing pipeline for CAD-Model based contour matching. In a first step, the component is additively manufactured using G-code instructions based on an existing CAD model. Next an actual contour adjustment is performed by an edge detection of a 2D-image of the current surface to determine the orientation. The appropriate surface in the CAD model is selected by template matching, the barycenter of the surface as well as the orientation is computed and the real part is matched with the CAD model for further CAM analysis and code generation. Thereafter the work coordinate system can be matched with the CAM system or

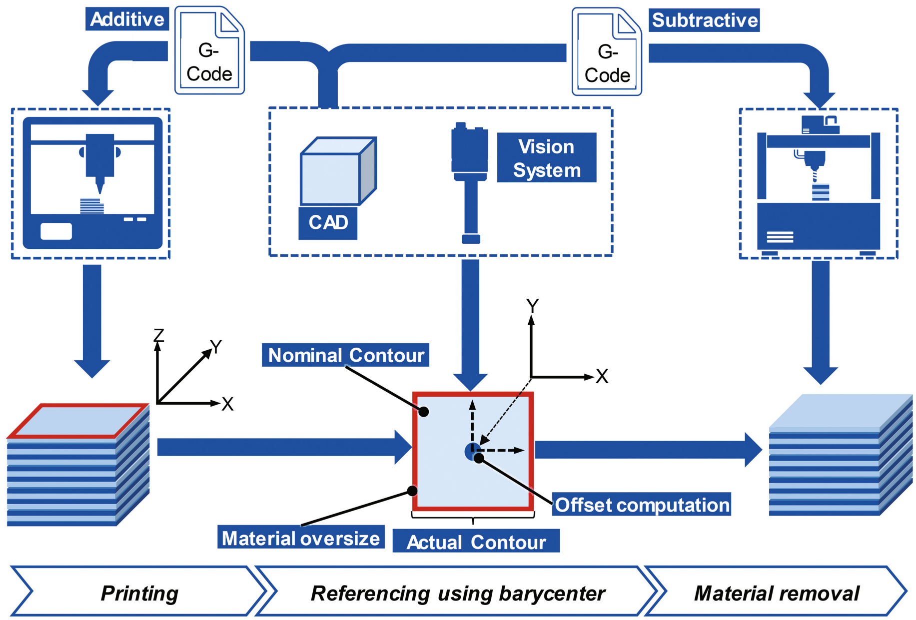

Fig. 1. Concept for removing excessive material in additive manufacturing parts

the offsets on the machine can be set accordingly to the required boundary conditions. Finally, the G-code for the selected part can be generated on the host and executed on the machine resulting in the removal of excess material.

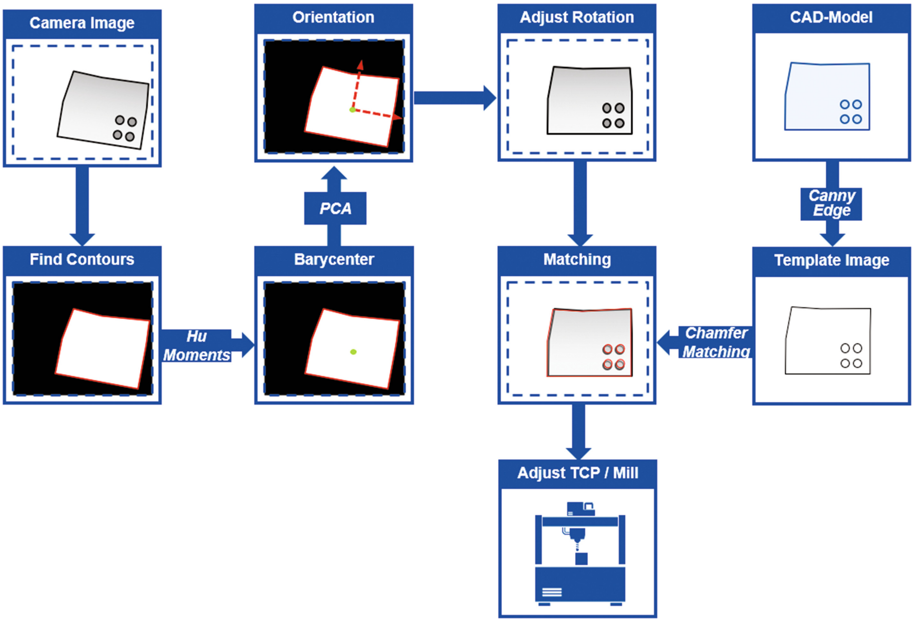

Fig. 2. Overview of computer vision processing steps

3 Mathematical Background

The calculation of necessary parameters and features of recorded camera images primarily requires an information extraction that is invariant to interfering factors or uses special computation. For the approach presented below, the Principal Component Analysis, Hu Moments and Template Matching are used as mathematical or Computer Vision methods to extract necessary information. These three methods are briefly introduced in this section.

Principal Component Analysis. The Principal Component Analysis (PCA) is a statistical method for calculating a main direction of a given multidimensional point cloud. This method is used to structure or prepare multivariate data sets in such a way that individual variables are related in the form of factors or linear combinations. In the Computer Vision area, the PCA is used to determine the orientation of an object in an image data set [5]. Since this is a statistical method, the image data must be prepared in such a way that there is a two-dimensional point cloud whose variables represent the X and Y positions. Based on an appropriate data record preparation, the following steps are performed:

1. Compute the two-dimensional mean vector $\overrightarrow{v_m} = \begin{pmatrix} \bar{x} \\ \bar{y} \end{pmatrix}$
2. Calculate the covariance matrix Cov(X) of the data set X
3. Derive the Eigenvectors $\overrightarrow{e_1}, \overrightarrow{e_2}$ and Eigenvalues e_1, e_2 of the covariance matrix Cov(X)
4. Choose the Eigenvector with the corresponding highest Eigenvalue as first component.

Hu Moments. In Computer Vision it is often necessary to derive properties of an image invariant of rotation, translation or perspective distortion. In this case, Hu moments are used to extract equal weighted averages from images that reflect the geometric properties of the image [6]. Hu moments can be applied to grayscale image information and are calculated as follows:

$$M_{ij} = \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{m} x^i y^j G(x, y) \tag{1}$$

whereas G(x,y) is the gray value located at pixel position x, y. Moments can be computed to any degree and combination of i and j. In order to obtain translation invariance, the so-called central moments are used:

$$\mu_{ij} = \sum\nolimits_{i=0}^{n} \sum\nolimits_{j=0}^{m} (x - \bar{x})^i (y - \bar{y})^j G(x, y) \tag{2}$$

Central moments form the base for computing properties of object within images like rotation or barycenter etc. Furthermore, moments are used as classifier for distinguishing different features of several detected objects.

Template Matching Template matching is a method applied in computer vision to detect or find a matching between a template image and a target image. The goal of template matching is to find the position of a (similar) template within the target image [7]. One possibility is to use the template as a filter kernel to achieve a correlation in the target image with the template by means through filtering. However, this method is only suitable if an exact template image (grayscale or color) shall be found in the target image. Another possibility is the fitting of templates in the target image using edge template matching. The templates consist of edges or contours of an object to be searched for, so that the search essentially consists of matching a geometry. In this case Chamfer Matching, as edge template matching, basically calculates the distances between the template and an excerpt of the target image [8]. Chamfer Matching is performed by the following steps using a grayscale target and an edge template image [9]:

1. Perform distance transform on target image to retrieve the transformed image $D_{dist}(x, y)$ using either Euclidean, City Block, Chess-Board or other distance metrics (dependent on requirements and computation power)
2. Translate the template image over the target image and compute the distances $d(u, v) = |T(u, v) - D_{dist}(x + u, y + v)|$ for a given position x, y on the target image and for each pixel of the template image, resulting in the distance matrix

$$M_{T,D} = \begin{pmatrix} d(0,0) & \cdots & d(0,V) \\ \vdots & \ddots & \vdots \\ d(U,0) & \cdots & d(U,V) \end{pmatrix}$$

3. Compute the chamfer score as average sum of all distances $D_{chamfer}(T,D) = \frac{1}{|M_{T,D}|} * \sum_{i=0}^{|M_{T,D}|} M_{T,D}(i)$ for several positions, resulting in a set of chamfer scores $D^1_{chamfer}, \ldots, D^n_{chamfer}$
4. Select the lowest chamfer score that is below a specific threshold $D_{chamfer} < D_{threshold}$
5. Region on position x and y associated with this chamfer score fits with the edge template image

Chamfer Matching is the most common used method in computer vision to detect skeletonized templates in images or camera recordings (e.g. gesture or hand recognition). Furthermore, it is a fast method for matching edge-based templates and finding candidate matches in the beginning of a recognition pipeline.

Canny Edge Detection. To find templates in images or camera recordings using Chamfer Matching, a template image has to be preprocessed first to extract a pure skeletonized image. The Canny Edge Detector is a commonly used method for detecting edges in an image. For this the image is processed in several steps [10]:

1. Perform Gaussian Smoothing on grayscale image
2. Compute the partial differential derivatives $g_x(x,y)$ and $g_y(x,y)$ of the image in x and y direction using Sobel Filters
3. Compute the gradient of the image as $\Theta(x,y) = atan2(g_Y(x,y), g_x(x,y))$. As each pixel has only 8 neighboring pixels, the computed angle per pixel is mapped to 0°, 45°, 90° or 135°
4. Calculate the absolute edge strength using $G(x,y) = \sqrt{g_x(x,y)^2 + g_y(x,y)^2}$
5. Using $G(x,y)$ check for each pixel the left and right neighboring pixel value and set the value to $G(x,y) = \begin{cases} G(x-1,y), & \textit{if } G(x-1,y) > G(x,y) \\ G(x+1,y), & \textit{if } G(x+1,y) > G(x,y) \\ G(x,y), & \textit{otherwise} \end{cases}$
   This step is also called non-maximum suppression, as only pixels with maximum values are left along a potential edge. Pixel with non-maximum values are removed.
6. Hysteresis is applied as last step for determining from which edge strength a pixel is to be count to an edge using two threshold values $T_1 < T_2$. The image is scanned until a pixel value greater or equal T_2 is found. All pixel values of the corresponding edge that are greater or equal T_1 are marked as edge components.

4 Experimental Setup and Workflow

Orientation Detection. As a preparatory step of calculating the location of a workpiece, the orientation of the main components in relation to the surface of the CAD model used is determined (see Fig. 3). To do this, both image data and CAD surface data must first be converted to an equivalent format, as they are not comparable in their original form. As shown in Fig. 3 Canny edge detection is performed for both images to identify and use edges [11]. Additionally the general orientation of the image is computed using Principal Component Analysis of the thresholded image data itself. After this step, the main orientations in the image have been determined and a template matching can take place in the next step for cropping out the image to retrieve the region of interest.

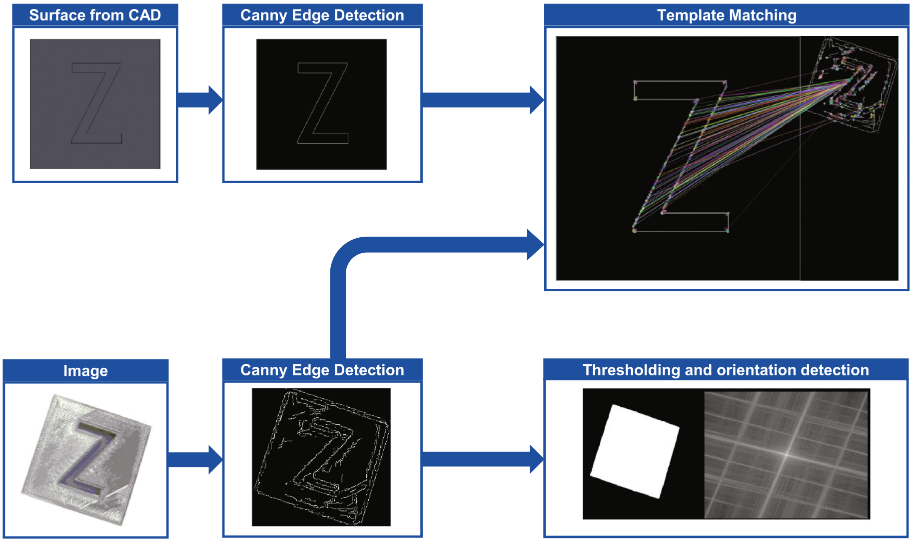

Fig. 3. Canny edge detection, template matching and PCA for determining main orientations.

Template Matching. To identify the views of interest in the streamed images the view has to be cropped to improve the overall performance of the algorithm. Since the orientations within the image have been found out, a template matching is performed in the next step to determine the important area of the image with the component to be localized. From the CAD data images of all 6 sides of the part are exported by a suitable interface in the CAD program. These images are rotated by the specific main orientations from the previous step before template matching is applied. If the template matching has found the most appropriate section the image is cropped.

Computation of Barycenter. After setting the appropriate orientation the next step is to compute the barycenter. This can be done by applying centralized Hu Moments on the grayscale image (see Fig. 4). The barycenter is then transformed using affine