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Data-based identification of throughput time potentials in production departments

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Abstract

Logistics performance becomes an ever more important strategic factor for manufacturing companies to obtain a competitive advantage. Yet, numerous companies fail to meet their own corporate goals or customer requirements. One of the most important objectives in logistics is speed in terms of short delivery times which are mainly determined by the production throughput times. Derivation of effective improvement measures requires a profound understanding of logistic cause-effect relationships. At a time of increasing digitalization, an increasing amount of feedback data is available that offers great potentials to discover novel insights. Yet, the vast amount of data can also be overwhelming and result in unsystematic and ineffective analysis of less meaningful data. Therefore, in this paper a systematic procedure is presented that allows data-based identification of throughput time potentials in production departments. The quantitative analysis framework is based on a generic driver tree structuring the influencing factors on throughput time. The approach will boost the understanding about logistics relations and will particularly help SMEs to focus on the most relevant influencing factors and data. Furthermore, it provides a basis for future more advanced information systems that will help companies to continuously improve their logistics performance and adapt their supply chains to ever-changing conditions.

Keywords

Throughput time; Logistics; Production controlling; Data analysis

1. Introduction

Logistics performance plays a highly important strategic role for manufacturing companies to successfully compete in today's difficult economic environment [1]. Studies show that companies striving towards consistent optimization of their supply chain regarding logistic key performance indicators (KPIs) can verifiably increase market success [2]. Besides on-time delivery particularly short delivery times are considered an essential target affecting customer satisfaction [2,3]. In order to continuously improve logistics performance, a systematic production controlling is required continuously collecting, analyzing and interpreting relevant feedback data within the closed loop of production planning and control (PPC) [4]. Digitalization of production processes and an increasing data availability offer tremendous improvement potentials regarding decision support systems in the context of production controlling. Yet, production controlling still is a mostly manual activity as companies are not willing to rely on automatically generated planning results [5]. At the same time, companies often lack the understanding of the manifold and multi-causal logistical interactions in supply chains [6,7]. Hence, there is a high risk of unsystematic data analyses and ineffective improvement measures. Current trends therefore aim at applying simulation, artificial intelligence (AI) and machine learning algorithms to identify cause-effect relations [8,9,10]. But due to the

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low transparency of these methods and the chance of identifying pseudo-correlations, the risk of misleading data interpretation remains. A profound understanding of the most relevant cause-effect relationships in logistics thus is the necessary basis to effectively detect improvement potentials in logistics. Therefore, the bottleneck-oriented analysis approach has been developed applying logistic models [11]. Yet, the approach is limited to the application of production operating curves and requires a lot of expert knowledge as guidelines are missing which influencing factors to include in the analysis.

This paper shows that if the primary drivers of the logistics KPIs have been identified, comprehensive analyses can be conducted only based on a limited amount of meaningful data. Using the example of production throughput time, it is presented how generally valid driver trees can be derived based on logistic models in section 2. Subsequently, it is presented how the bottleneck-oriented analysis approach can be integrated in a systematic procedure and how the driver tree helps structuring the analysis for non-experts in section 3. An industrial case study demonstrates how the most significant levers for throughput time reduction can be identified using generally valid logistic models and simple analysis methods.

2. Influencing factors on throughput times

In the following, a brief overview about the different definitions and time shares of throughput times is provided before the main influencing factors are derived based on the theory of the logistics operating curves. Based on these fundamentals, a driver tree for order throughput times is derived setting the guidelines for effective data analysis.

2.1 Throughput time definition

Throughput time is a KPI that is measurable in the production stages along the supply chain. It can be recorded on different levels (see Figure 1). In general, it is distinguished between two types of throughput times: order throughput times and throughput times at operation level. The order throughput time comprises the time span from order release to the end of production of a production order (PO). Depending on the order fulfillment strategy, one PO may consist of several manufacturing orders in a pre-production stage supplying components for a subsequent assembly order in the end-production stage. Within each production stage, POs are being processed in different operations. According to the throughput element [12], the throughput time on operation level consists of an inter-operation time between the completion of the predecessor operation and the beginning of the next operation and the operation time. The inter-operation time comprises a share of waiting time post-processing, the time required for transportation to the next work system, and a waiting time pre-processing. Particularly in shop production the share of productive operation time is mostly marginal compared to interoperation times.

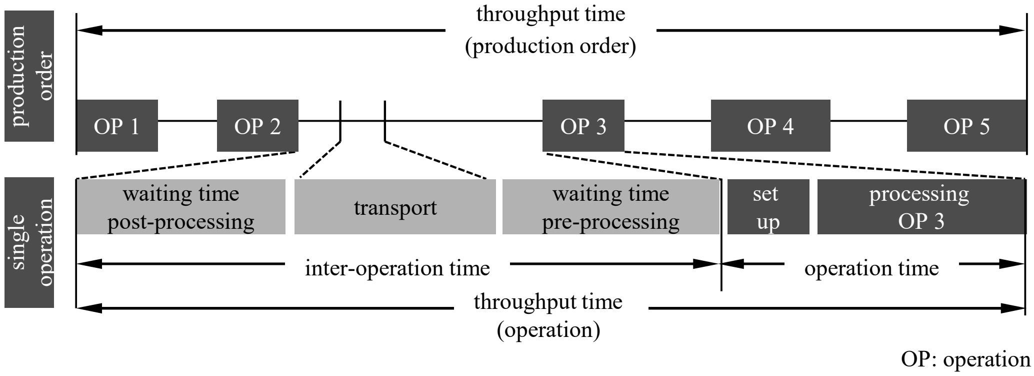

Figure 1: The throughput element (in accordance with [12] and [13])

2.2 Production operating curves

The most important control variable determining throughput times is the work in process (WIP) in production departments and thus the WIP level at the particular work systems. The higher the WIP level the longer the waiting queues and consequently the resulting throughput times. However, a low WIP level may cause losses in capacity utilization. This planning dilemma can be resolved by the theory of the production operating curves (see Figure 2), quantifying the relation between WIP, capacity utilization (or output rate) and throughput time of a work system [14]. In an idealized state the output rate, respectively capacity utilization, of a work system increases proportionally with an increasing mean WIP level until it reaches the maximum utilization. The WIP level at which the utilization is just the maximum without queues forming is called ideal minimum WIP ($iWIP_{min}$). That means that neither a PO waits for processing nor the work system waits for its next PO. Up to this point there are no queues and throughput times hence equal the sum of the minimum transition time and the operation time. A further increase in the mean WIP does not lead to a further increase in capacity utilization, but rather causes longer queues and thus longer throughput times. In reality work systems are subject to varying workloads or capacities and other forms of disturbances (e.g. lateness of incoming orders). Hence, real operating curves are curve-shaped with the ideal characteristic curves as natural thresholds. For every work system there is an operating state where utilization losses are marginal at a reasonable WIP level (intermediate state). Higher WIP levels result in an overload state without notable utilization increases but rising throughput times. Throughput times at these work systems could easily be reduced by reducing the WIP level. In contrast, lower WIP levels cause an underload state with significant utilization losses but short throughput times.

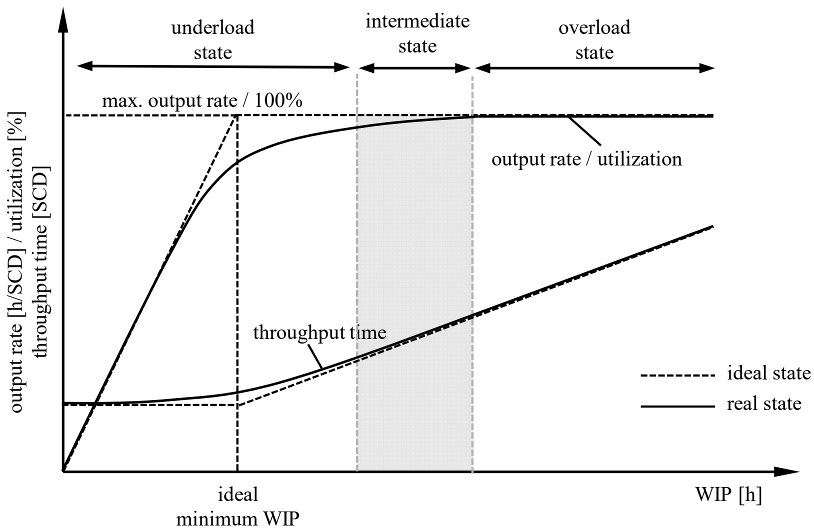

Figure 2: Exemplary production operating curves of a work system

The shapes of the operating curves are specific for each work system. Besides the available maximum capacity, the main influencing factor is the position of $iWIP_{min}$, which in turn is determined by the order workload (in target hours) and their variance in particular. Furthermore, especially the spread of workload and the available capacity flexibility have an impact on the gradient of the curves. In order to be able to compare the WIP levels of several work systems, the relative WIP level, as the ration between the absolute mean WIP level of each work system and its ideal minimum WIP level is used. The relative WIP is a suitable indicator to evaluate the operating point of work systems. While work systems with a very high relative WIP (>>300%) are likely to operate in an overload state with long waiting queues and long throughput times, very low relative WIP levels (<200%) indicate underload states. [11]

2.3 Derivation and structuring of the main influencing factors on order throughput times

Based on the throughput element and the theory of the production operating curves presented above, generally valid influencing factors on the mean throughput time of POs can be derived and structured in a logical driver tree (see Figure 3). In accordance with section 2.1, on a first level there are two main drivers on order throughput times: the general production and product structure, and the throughput times of the single operations during order processing. Regarding the production / product structure, particularly the number of process steps and / or the number of production stages define the shortest possible throughput time of a PO. The number of operations and production stages in turn, are determined by product complexity, the in-house production depth, and the position of possible order decoupling points (storage stages). Another influencing factor on the mean order throughput time in a production department concerning production / product structure is the variant-creation point. A late variant-creation for instance allows producing in bigger lot sizes upstream the variant creation point and thus minimizes necessary set-up processes. A further subdivision of the identified drivers is not made, since this is hardly possible on a generic level and requires company-specific analyses.

According to the throughput element, throughput times generally comprise two time shares: operation time, and inter-operation time. Operation times define how long a work system is blocked with an order. Firstly, this depends on the workload of the orders (measured in target hours), which is determined by the setup time, the lot size and the process time per unit. How fast order workloads can be processed further depends on the available capacity (measured in hours per shop calendar day). The capacity of a work system results from the number of parallel and substitutable work stations or employees, the working hours per shop calendar day (SCD) and idle times due to technical or organizational downtimes (e.g. errors or maintenance).

Inter-operation times arise from required minimum transition times due to transportation or technological-induced idle times (e.g. cool down after oven processes) and queuing times caused by the WIP level. As shown in the production operation curves, the WIP level is directly related to the planned operating point and therefore to the planned throughput time. The planned operating point should be the result of a logistic positioning in accordance with the underlying logistics targets. Viable throughput times at the desired operating point depend on the shape of the throughput time curve, which is affected by the maximum output rate, the mean order workload and the variance of order workloads, the input variance and the available capacity flexibility, as well as the capacity structure (e.g. two workstations and single-shift operation vs. one workstation and two-shift operation). If the actual throughput times deviate from the planned throughput times, backlog occurs that causes increasing (or decreasing) waiting queues. Furthermore, the WIP level is significantly influenced by the choice of production control methods. Workload-oriented order release procedures for instance, such as the ConWIP procedure, can be applied to keep the WIP and thus the throughput times at a constant level [15].

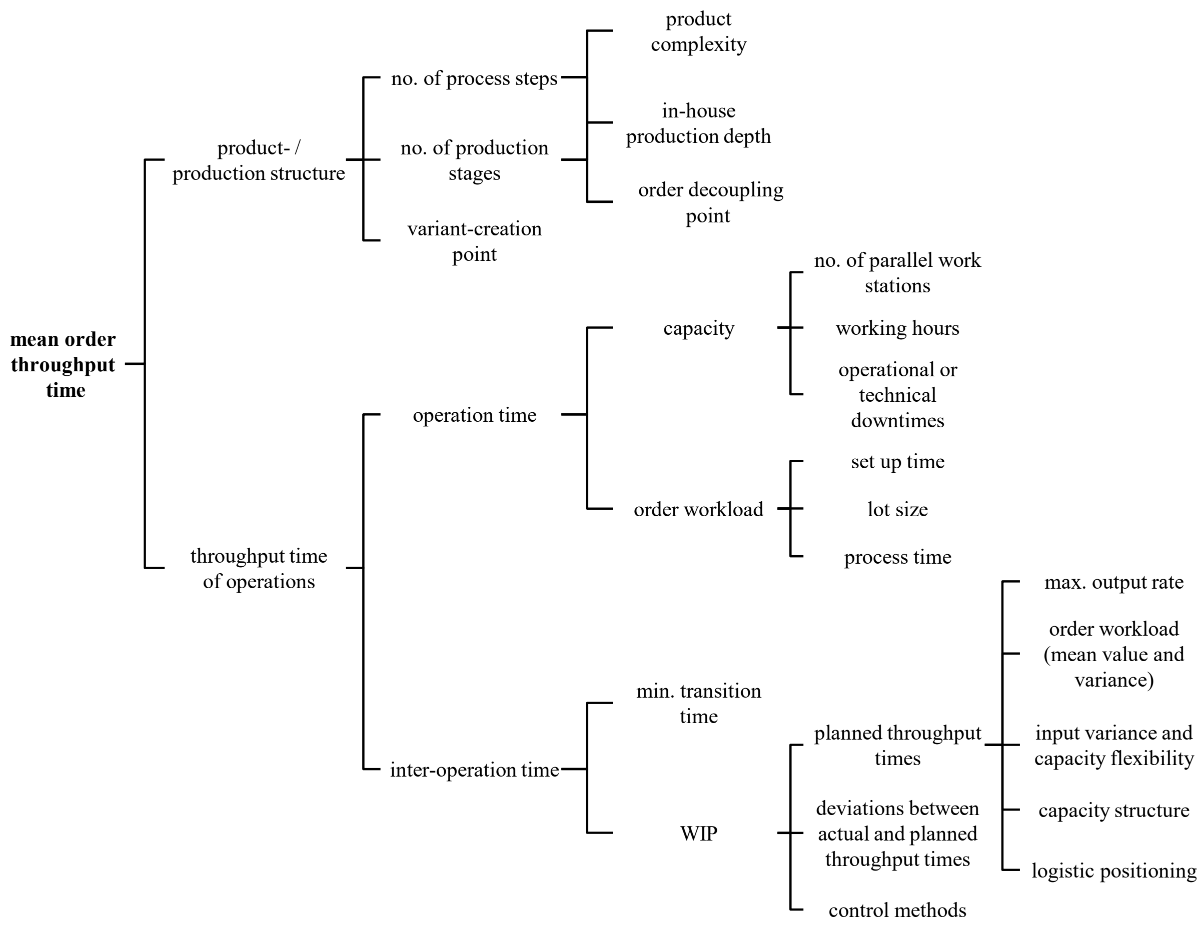

Figure 3: Order throughput time driver tree

3. Analysis approach

The general driver tree helps structuring throughput time analyses as well as focusing on the most relevant parameters and data required to identify the main levers for throughput time reduction. The comprehensive analysis procedure consists of four steps as illustrated in Figure 4. In a first step, a high level throughput analysis is conducted based on order generation, order release, and order completion dates to identify systematic planning errors and to initially localize problem areas. Furthermore, the system state is examined mainly using throughput diagrams.

The second analysis step focuses the production structure to account for the upper branch of the driver tree. A main task here is to map the actual order throughput for the most relevant product families, which can oftentimes be obtained from operation event logs and simple predecessor-successor analyses. From there, for instance, information about the amount of operations per PO can be obtained which indicates if reduction of process steps offers significant throughput time potentials. This could also be the starting point for additional analyses (value stream analysis, variant trees, etc.) not solely using feedback data in order to create more detailed insights.

After having evaluated the general production structure, data analyses on work system level are performed in step three mostly following the general steps of a bottleneck-oriented logistics analysis (see [11]) in order to identify throughput time potentials for single process steps. The general ideal is that the distribution of order throughput times usually follows the Pareto principle, meaning that a limited number of work systems are responsible for the most significant percentage of the total order throughput time. Consequently, in a first step, analysis focuses on the throughput time determining bottlenecks. A very helpful tool to identify the most critical work systems and the main throughput time drivers is the logistical resource portfolio [16].

A detailed process and operation analysis follows in step 4 in order to detect the real root-causes for high operation or inter-operation times. From a logistical point of view, this primarily comprises identification of potentials for $iWIP_{min}$ reduction to decrease inter-operation times applying production operating curves. However, further company and process specific data and KPIs can be analyzed to examine process stability or quality for instance decreasing the maximum output rate. The developed driver tree helps deciding which further influencing factors might be of high relevance and should therefore be evaluated. Once, the main throughput time drivers have been identified, applicable measures can be derived. The general procedure is demonstrated in an industrial case study after briefly deriving data requirements in the following.

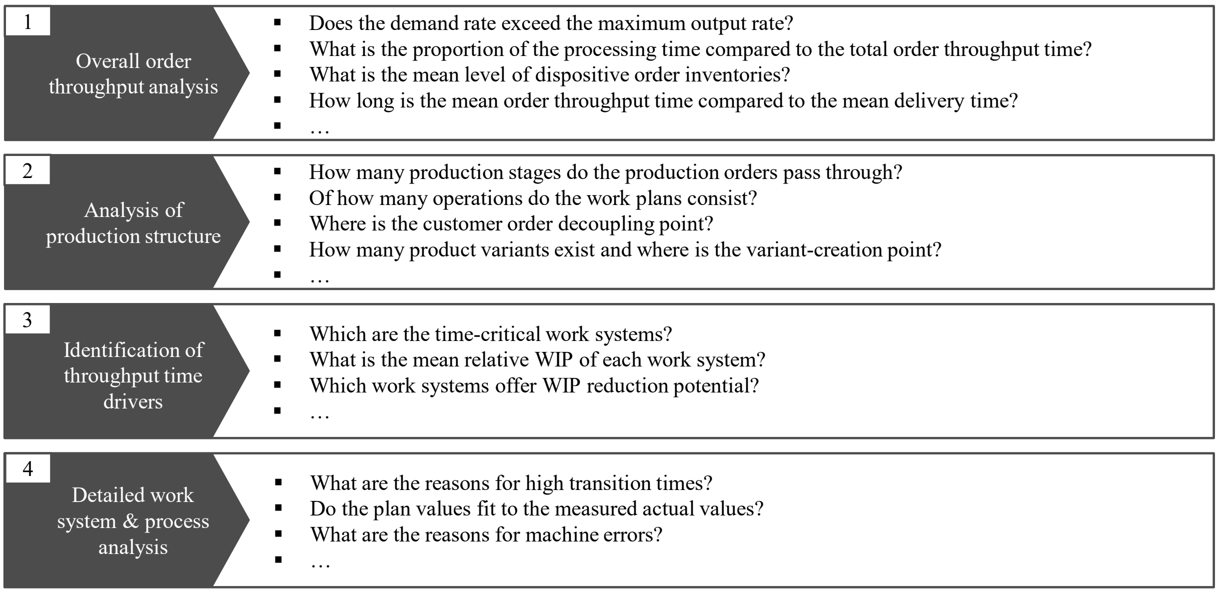

Figure 4: Throughput time analysis procedure

3.1 Data requirements

Knowledge about which relations to analyze and which analyses to perform significantly reduces analysis and interpretation effort as most analysis steps can be conducted using only a limited amount of data. Contrary to the trend towards big data analyses, only well-founded correlations need to be examined already allowing a valid delimitation of the essential potentials. Table 1 provides an overview of the minimum data-requirements for each analysis step. It turns out that only a relatively small amount of data is required that can usually be easily retrieved from ERP systems. This data basis should be the starting point for each throughput time analysis. Nevertheless, use-case specific extensions of the data basis by adding further process or product parameters (e.g. product or order characteristics) is possible and may provide additional insights through correlation analyses or other analysis methods. As statistical analyses are performed based on mean values and standard deviations, it is crucial that the applied data basis represents a typical period of operation and includes a sufficient amount of observations in order to derive statistically valid conclusions. Furthermore, validity checks are required as otherwise implausible or faulty feedback data might be evaluated. Therefore, process experts should always be consulted to discuss available data.

Table 1: Minimum data-requirements for each analysis step

Data requirements	Step 1	Step 2	Step 3	Step 4
order no.	x	x	x	x
date order generation	x			
date order release	x		x	x
date order completion	x		x	x
order processing time	x		x	x
date order procurement	x (MtO only)			
delivery date procurement order	x (MtO only)			
delivery date to customer	x (MtO only)			
operation no.		x	x	x
work system no.		x	x	x
start of operation			x	x
end of operation			x	x
setup time			x	x
no. parallel work stations			x	x
capacity / max. output rate			x	x
further order / product data	use-case specific			

3.2 Analysis procedure – Case study

In the following, the general analysis procedure is demonstrated based on an industrial case study conducted at a mechanical engineering company producing customer specific machines following an MtO-strategy. Data of a representative six month period have been analyzed comprising 3,114 POs. The overall throughput analysis revealed that a large amount of the delivery time is caused by a certain manufacturing department (mean order throughput time: 25 SCD) as to why this production department has been chosen for further throughput time analysis. Ready to sell parts as well as components for subsequent assembly stages are produced in a shop production. An analysis of the order throughput revealed that the manufacturing stage is operating in a steady state and the demand rate and output rate are harmonized (see Figure 5). However, the mean WIP is rather high and in average the proportion of operation time accounts for only about 6% of the total order throughput time. This indicates that WIP reduction offers the highest potential to reduce throughput times. In average, the planned throughput time further match the actual throughput time and no systematic backlog occurs.

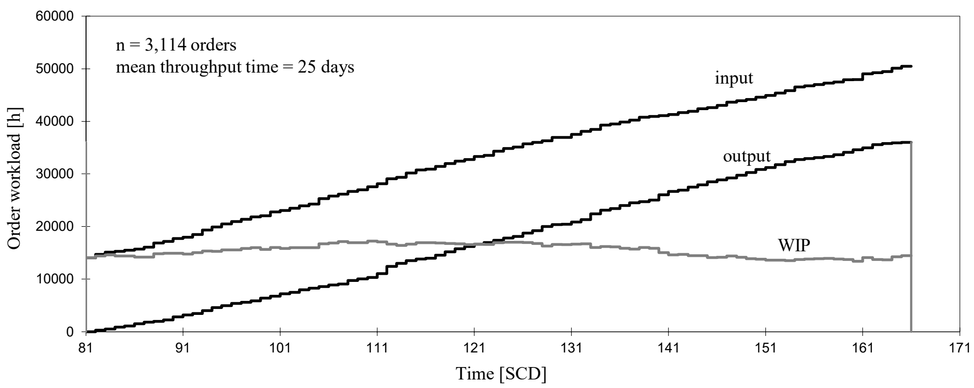

Figure 5: Throughput diagram of the manufacturing stage under examination

In step 2 the process structure was examined without questioning product design. The average number of operations per order was seven, also including storage and retrieval as well as transport operations. Focusing on the relevant value-adding operations, the number of operations decreases to approximately two per order. Hence, further analyses addressed the single work systems (WS) within the manufacturing department. In a first step, the logistical resource portfolio has been developed as illustrated in Figure 6. The portfolio indicates that WS 1 accounts for about 12% of the total throughput time within the examined period. As WS

1 further shows a very high relative WIP of about 1,050% it is very likely to operate in an overload state and to offer significant WIP reduction potential. For WS 2 in contrast, also showing a significant share of throughput time, the relative WIP equals only about 350% and throughput times probably cannot be decreased by reducing the WIP level without having to expect significant utilization losses.

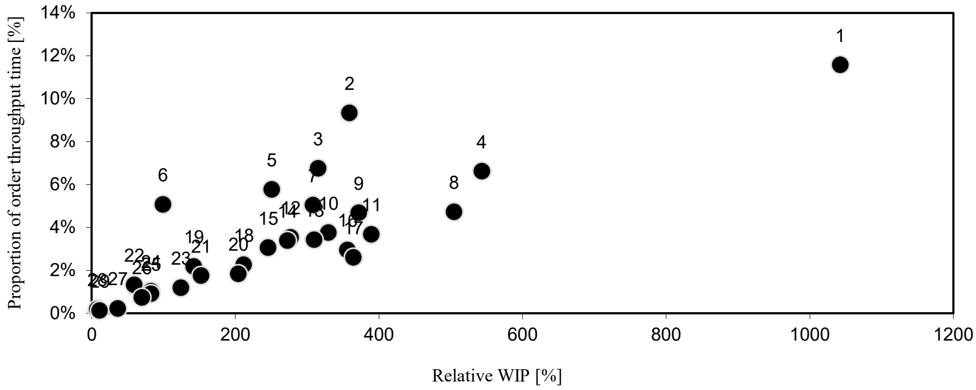

Figure 6: Logistical resource portfolio

In step 4 WS 1 and WS 2 have been analyzed in detail to identify appropriate levers for throughput time reduction using the theory of the production operating curves (see Figure 7). For WS 1 the detailed analysis revealed that a reduction of the relative WIP to about 500% would still allow a mean capacity utilization of more than 99% while reducing the mean throughput time from 10 SCD to 5 SCD. Further WIP reduction (and thus reduction of the planned throughput time) would theoretically be possible, but is not considered reasonable as relatively high setup time shares require optimization of setup processes parallel to main production time. For WS 2 a WIP reduction to 250% would result in a reduction of the mean throughput time from almost 8 SCD to 5 SCD. However, losses of capacity utilization of almost 2% would be expected. Additionally, WS 2 also requires setup optimization and thus a steady amount of waiting orders which is why a rather high WIP level is aspired. As minimum transition times are negligible for WS 2, according to the driver tree, another influencing factor causing a high WIP level and thus high throughput times is the order workload and the variance of the order workload in particular. Analysis of the order workload for WS 2 showed a relatively high variance with a variant coefficient of 1.12 resulting in an $iWIP_{min}$ of 42h. If it is possible to reduce the variance coefficient of the order workload (e.g. by splitting large order lot sizes) to only 0.9% the mean throughput time could be reduced to 5 SCD without any losses of capacity utilization. For further information regarding the underlying calculation rules and basic principles see [11]. Having a look at the driver tree, throughput times could also be decreased if the maximum output rate could be increased. Yet for both, WS 1 and WS 2 no significant losses of the maximum output rate due to unstable processes could be identified. Hence, the output rate could only be increased by increasing the capacity by investing in new machines, which was not considered feasible.

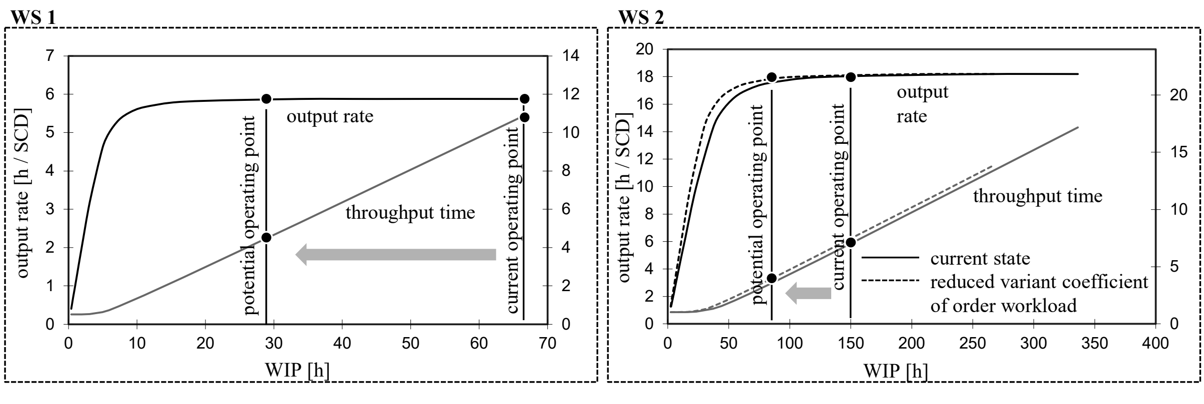

Figure 7: Derivation of throughput time potentials for WS 1 and WS 2 using production operating curves

Concluding, as WS 1 and WS 2 account for about 22% of the total throughput time in the production department, implementation of only the described two measures (WIP reduction at WS 1 and harmonization of the order workload at WS 2) would already result in a reduction of mean order throughput time of about 10%. The logistical resource portfolio indicates further critical work systems (WS 4, WS 3, and WS 8) that should be analyzed similarly. This allows a structured analysis procedure to identify potential levers for significant throughput time reduction only using the required data pointed out in Table 1. For more complex processes and identification of sources for failures for instance, further analysis of process and sensor data could create additional insights.

4. Conclusion

In this paper a systematic approach for data-based throughput time analysis has been presented. Based on well-established logistic models and generally valid cause-effect relations, a throughput time driver tree has been derived which helps companies focusing on the most relevant influencing factors on throughput times and sets the guidelines for the analysis procedure. It can be seen as an extension and systematization of the bottleneck-oriented logistics analysis enabling non-experts conducting the most relevant analyses own their own and adding further meaningful data available in their company. It has further been demonstrated that the most significant throughput time potentials can already be detected using only a limited amount of data. Similarly, detailed analysis procedures for the most relevant logistics KPI have been developed based on generally valid cause-effect relationships, which set the basis for the development of effective production controlling systems ideally supporting in identifying logistic weak points (find detailed analysis guidelines at www.quantilope-ifa.de). Increasing digitalization and available sensor data can create additional insights if used for further, use-case specific analyses. Therefore future research could focus on combining the generally valid analyses applying logistic models with further data-mining and AI approaches in order to include company specifics and previously unknown relations in the analysis of logistics performance.

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Biography

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