Data-driven detection of moving bottlenecks in multi-variant production lines

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Abstract: Because bottlenecks limit the throughput of production systems, it is important to correctly detect and control them. This task is especially demanding in high-speed dynamic production environments within asynchronous production lines. A change in conditions often shifts the bottleneck from one process to another. This paper proposes a data-driven concept for the detection of dynamic bottlenecks in multi-variant production lines. We build on and contribute to the literature of bottleneck detection methods. We propose a novel concept that dynamically and automatically detects bottlenecks using cycle time data from shop-floor machines. The cycle time distribution of produced batches is translated into the cumulative probability function, which is used to detect the moving bottlenecks.

Keywords: Line Design and Balancing; Intelligent Diagnostic Methodologies; Numerical Analysis

1. INTRODUCTION

To achieve flow efficiency, it is important to detect and control bottlenecks in production. In the case where the bottleneck keeps shifting from one process to another, it can be difficult to create a "lean" production system (Roser et al., 2002; Goldratt and Cox, 1984). Therefore, lean manufacturers—including Toyota— actively work to identify and control bottlenecks (Roser et al., 2001).

The trend in manufacturing is towards increasing both technical and operational process complexity. Operational complexity is shaped by a high number of product variants, volatile customer demands in combination with short lead times, and the need for a high utilization of production resources (i.e. cost-efficient production). This complexity is especially high for production processes where the scalability of the technical equipment (and the resulting financial effects) hinders the establishment of a single-product production line. In a high-volume, multi-variant production line, the bottleneck is likely to move rapidly between processes.

Regardless of the number of product variants produced on a multi-step production line, an important design parameter is the (customer) "takt time". The customer takt time in a lean production system is defined as the available time for production in a period divided by the amount of a certain product variant demanded by the customer in the same period (Rother and Shook, 2003). If, and only if, the cycle time of each process is synchronized and close to the takt time, a flow production without any storage is possible.

If production processes are *not* synchronized (e.g. due to batch processes), a true flow production is not possible, as consecutive processes have to await the slowest one in line — which is the current bottleneck. It imposes limits to the overall throughput and requires additional buffers in the line, which accumulate waste throughout the processes and increase *lead times*. Based on the customer takt time, every production process should be technically designed to produce a product variant as close to the customer takt time as possible, not faster, but especially not slower. However, the practicability of takt time in multi-variant production lines has limits. For example, technical and financial challenges of synchronizing different product variants and volumes are an issue. Moreover, unplanned breakdowns and downtimes make the production processes miss their cycle time targets.

We apply a design science research method to propose a solution to the problem of bottleneck detection in multi-variant production lines. Accordingly, we structure the paper as follows. In section 2, we review the literature and define the problem. In section 3, we describe the research approach. In section 4, we develop the solution. In section 5, we discuss the solution and conclude.

2. LITERATURE REVIEW

Different researchers have suggested different methods to detect bottlenecks. Reviewing the literature, we find three distinctly different approaches to bottleneck detection: pen-and-paper-based value stream mapping, physical walks along the production lines, and computerized methods.

Bottleneck detection research usually starts with the notion that "throughput is the most relevant metric to evaluate the efficiency of production" (Yu and Matta, 2016), and the idea that a few machines limit the overall throughput of production processes (Liu and Lin, 1994; Li, 2009; Betterton and Silver, 2012). These machines are the *capacity constraints*, also described as *bottlenecks* (Roser et al., 2002; Roser et al., 2015; Goldratt and Cox, 1984). For broad literature reviews of bottleneck definitions, see Betterton and Silver (2012), Yu and Matta (2016) and Roser et al. (2015).

2.1 Value Stream Mapping for bottleneck detection

A common systematic approach for identifying bottlenecks is *value stream mapping* (VSM) (Sunk et al., 2017, Dennis, 2007). VSM is a "highly accepted" method (Sunk et al.,

2017) for improving production processes (Dal Forno et al., 2014). VSM is often described as a classical "pen-and-paper" method (Liker and Meier, 2006), which maps the "value-adding, non-value-adding, and value preserving activities that are required to create a product" (Sunk et al., 2017). Starting from a manually recorded current state map, an ideal state map is proposed (Sunk et al., 2017; Rother and Shook, 2003). A key element of VSM approaches is its focus on customer takt time.

The VSM method currently faces a "diminishing gradient" of effectiveness (Sunk et al., 2017). Because the "low hanging fruits" have already been picked in many factories, the identification and elimination of waste and inefficiencies has become more complex (Abdulmalek and Rajgopal, 2007). Moreover, classical VSM can hardly be used for products with a high number of product variants (Singh et al., 2011) or products with a complex bill of materials (Braglia et al., 2006). Based on their findings, Braglia et al. (2006) proposed supplementary VSM tools as a future field of research; these tools are able to cope with the variances of production processes by employing statistical methods.

In their literature review of VSM, Dal Forno et al. (2014), included 57 publications from 1999 to 2013. The papers were classified into 11 problem categories describing the limits of VSM. Related to multi-variant production lines, three of these are of special importance: "process measurements", "map obsolescence" and "high product mix". Together, these problems occurred in 74% of the analysed contributions. Under these circumstances, the mapped value streams did "not represent the process' real situation, because each day the process behaves in a different way" (Dal Forno et al., 2014).

These limitations of VSM are partly due to the "pen-and-paper" approach, in which a lot of manufacturers fail to apply the VSM repeatedly and regularly (Dal Forno et al., 2014). Dal Forno et al. (2014) concluded from their findings that only stable processes should be mapped, or if a process is complex or not stable, it should be mapped more frequently. Facing the efforts required for a manual collection, they concluded that new opportunities for applying the VSM could be gained if the timely effort for the measurement of the relevant production data could be reduced.

Besides the usual results of a VSM (long change over times, stock, chaotic material flows, etc.), a less known tool in the VSM literature can localize the bottlenecks of the value stream of a product: the takt diagram (Rother and Shook, 2003; Singh et al., 2011). In a takt diagram, the measured process cycle times are displayed and compared to each other and to the customer takt time. The highest bar exceeding the customer takt time is the (current) bottleneck. The result is a snapshot of the process on the day of mapping. Moreover, the resulting VSM of one product is representing the VSM of all the products of the previously defined family of products at "all times".

The mentioned characteristics of VSM and the takt diagram make both inappropriate for analysing bottlenecks in the more dynamic environments (i.e. the dynamic relocation of bottlenecks) of aligned, multi-variant production lines. In this paper, we present a method for statistical analyses of multi-variant production lines, using automatically collected data to enable a frequent and simple dynamic takt and bottleneck analysis.

2.2 The bottleneck walk and related methods

Based on the categorization of Yu and Matta (2016), the listed methods of bottleneck detection can, even though they compare different parameters, be procedurally compared to the bottleneck walk of Roser et al. (2015). An exception, within the ones described by Yu and Matta (2016) is the one proposed by Betterton and Silver (2012). The bottle neck walk, developed by Christoph Roser and colleagues (Roser et al., 2011; Roser et al., 2002, Roser et al., 2015) over the last 15 years, is called an *active period method*.

The bottleneck walk is based on several assumptions and is time intensive: Roser et al. focused on the detection of timely shifting bottlenecks by walking along the production process. During the walk, the inventory level along the production line is noted down at each station. "Repeating a string of observations multiple times" is recommended to receive a full picture of the timely shifting bottlenecks. Hence, Roser et al. (2015) solved the problem of having only one snapshot of the conditions by repeating the bottleneck walks several times (i.e. "distributed over several days"). Through repeating the bottleneck walks more often, it is assumed that all possible bottlenecks, especially timely shifting ones, are detected. However, this cumbersome process makes the approach time intensive. Roser (2002, 2015) stressed that it is important to not only focus on the value adding steps but also on non-value adding processes to detect bottlenecks.

2.3 The inter-departure time variance method

The "inter-departure time variance" method (ITV) of Betterton and Silver (2012) is based on the analysis of the variance of the inter-departure times of each unit produced at each station along a production line: The one with the lowest ITV is the bottleneck. They show in their paper that the proposed method "performs as well or better than other published bottleneck detection methods". However, Betterton and Silver (2012) also admitted that the IVT method cannot sufficiently locate the bottleneck. Hence, they highlight the need for future research; that is, on the impact of the buffer level on the method's capability.

Note that the IVT method differs from the other bottleneck detection methods, as it is no longer based on manually collected data, but on automatically collected data. This data-driven approach is further supported by the results of Yu and Matta (2016), who highlighted the advantages of data-driven bottleneck detection. Yu and Matta (2016) presented a software framework to statistically prove the reliability of the bottleneck detection method. This was needed because the existing methods did not rely on a comprehensive real-time collection of data, but rather on snapshots.

2.4 Proposed design to solve the problems

In this paper, we aim to overcome the challenges related to the different approaches above by taking the best from each of them. Our proposed conceptual method relies on a comprehensive automatically updated database of process data to locate where, when and why bottlenecks occur. Accordingly, our method enables a clear-time production step, as well as a product variant-specific analysis of bottlenecks along the production line.

Furthermore, we do not measure interdependent metrics, such as the IVT, but we take the *cycle time* as an independent, deceiving metric of each process. Thereby, we not only build on the approaches of Roser et al. (2015) and Betterton and Silver (2012) but also expand and improve them to be applicable to all manufacturing processes, as recommended by Roser et al. (2015). In addition, none of the reviewed bottleneck-detection methods are product specific and therefore do not reveal information about what exact product variant is causing the bottleneck.

A promising development that can help overcome the limitations of data collection is the so-called digital shadow of a product, which is defined as the "sufficiently precise image of the processes within (…) the production (…) which are needed for a real-time capable evaluation basis" (Bauernhansl et al., 2016). If the digital shadow of each individual product contains the cycle time at each station along the value stream, the classical time-invariant snapshot as well as comprehensive data about timely changing conditions for each product produced can be attained.

The proposed methodology aims to reduce the throughput time in a production line. The value-added part of the throughput time can be composed of the cycle times of the single production steps (Rother and Shook, 2003). The distribution of the cycle time at a single production resource is usually approximated with Weibull's probability density function (Tirkel and Parmet, 2017). Employing this approximation ensures, by its means of standardization, the comparability of different cycle-time distributions. Besides, the corresponding cumulative probability function is given in a mathematically contained way. This function reveals the probability that a certain parameter is at or below a certain threshold. The assumption is used within the proposed concept to illustrate the mechanisms of evaluation.

3. RESEARCH APPROACH

We use the research method of design science research (van Aken et al., 2016). Based on the specific task of an industrial partner to increase the efficiency of a multi-variant production line, a data-driven concept for the detection of dynamically relocating bottlenecks was developed. The concept was generalized to be applicable to any kind of multi-variant production line. The human agency impact of the proposed method is low, as the whole processes of data collection and analysis can be fully automated.

The design proposition of the concept can be stated as follows: On multi-variant, multi-step production lines, inefficiencies such as bottlenecks and asynchronicities can currently only be specified based on experience or on expensive manual and frequent elaborations. The proposed concept focuses on the analysis of a time- and product-based variant-dynamic value stream and can be used to precisely localize improvement potentials by analysing the automatically collected cycle times by means of statistical analysis.

4. SOLUTION DEVELOPMENT

4.1 Data collection and preparation

A first step is to automate the collection of machine data. We propose that for every produced product and thus for every product variant and at every time, the cycle time should be collected at each station along the value stream and linked to the individual product. The result is a digital product shadow containing all the cycle times along the value stream. It is important to highlight here that this includes both value-adding and non-value-adding steps of the value stream, such as transport and storage. In doing so, we create the database for a comprehensive dynamic takt/bottleneck analysis.

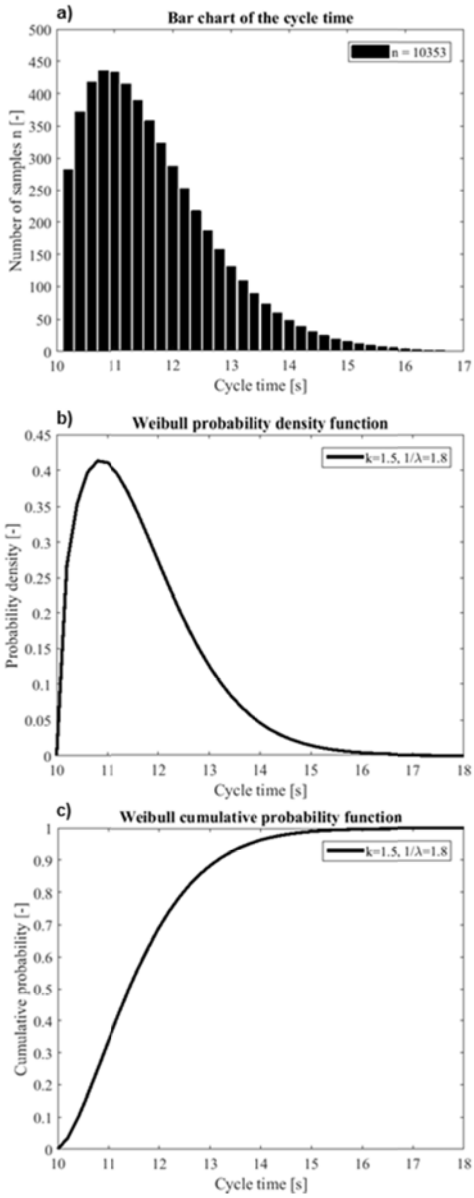

Fig. 1 a) Simulative bar chart of the cycle time at a single production step of a specific product variant for one batch produced (with a total number of samples n = 10'353); b) Weibull curve fit of the given cycle time distribution to receive the probability density function; and c) integration of the probability density function to receive the cumulative probability function.

In the second step, the data are prepared for analysis. First, the cycle time distribution of a specific product variant v_i at a certain production step s_i over a given period (e.g. a batch, a shift or a day) is presented, based on simulative data, as shown in the bar chart in figure 1a). The cycle times are displayed on the abscissa, whereas the number of samples on the ordinate and thereby the absolute frequency is given. Based on the accumulated data, a curve fit for the Weibull function with the shaping parameter k and $^1/_\lambda$ can be elaborated, in the same way as figure 1b). The resulting equation can then be integrated to receive the (Weibull) cumulative probability function, which can then be plotted the same way as figure 1c).

4.2 Mechanism of evaluation

In the following section, we describe how one can interpret and use the results of the proposed method to detect moving bottle necks in multi-variant production lines.

Figure 2a) displays the “design guideline”; that is, the customer takt time as an absolute scale of evaluation. The intersection of the vertical takt time with the cumulative probability function provides insight about the percentage of the number of products of product variants v_i, which are produced faster or at the costumer takt time (here: ~89%). This analysis enables the first productivity assessment of a single production step s_i: Is the process capable of producing within the planned threshold of the takt time?

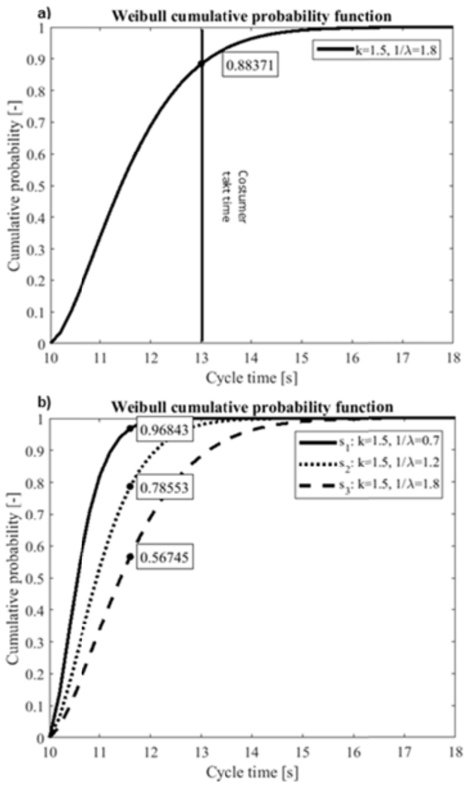

Fig. 2 a) First mechanism of evaluation: Comparison of the cumulative probability function to the costumer tact time; b) second measure of evaluation: A comparison of the cumulative probability functions relative to each other.

Beside the comparison with an absolute scale (i.e. the customer takt time), the cumulative probability function can be compared in relation to each other, analysing the shifts or changes of the shape of the distributions. Figure 2b) displays a comparison of the cumulative probability functions relative to each other: The comparison provides insights about the efficiency of different batches produced, for example, at different production steps, relative to each other.

The described analysis can now not only be executed for one product variant v_i at one production step s_i but can also be extended to analyze multi-variant production lines. All the production steps of each product variant v_i (i.e. their corresponding value streams), can be compared, and all the product variants produced at a specific production step s_i can be compared to each other. In summary, the product variant v_i-specific and production step s_i-specific timely accumulated cumulative probability functions of the whole production line can be compared.

Cycle time distributions of various product variants at various production steps can vary due to internal as well as external influences. These variations within the proposed concept are represented by different shaping parameters k and $^1/_\lambda$ of the fitted Weibull function and consequently in the different shapes of the integrated function. The narrower the underlying distribution, the better. Consequently, the “optimal” cumulative probability function would have the shape of a step function, with the step at the planned cycle time (i.e. the customer takt time).

4.3 Analysis and results

The resulting curves can be compared relatively to each other in three dimensions through three analyses:

1. Dynamic bottleneck analysis along a value stream
2. Batch analysis
3. Single production step analysis

The first evaluation is basically an automated takt diagram-like analysis: The data of one specific product variant v_i along its value stream are compared. As different production steps (when producing one variant v_i) are compared, the variant-specific customer takt time can be applied as an absolute measure. Figure 3 shows the cumulative probability function for different production steps s_i along the value stream, as well as the corresponding customer tact time, and thereby combines the two presented mechanisms.

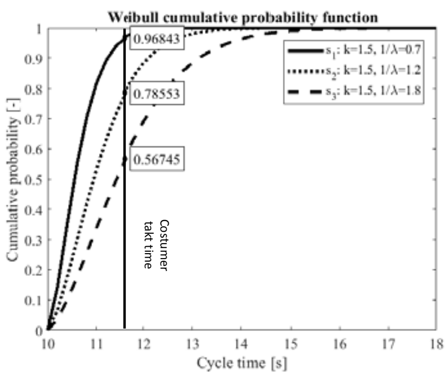

Fig. 3 Result of the value stream takt analysis: Probability function for three different production steps s_i along the value stream of a certain product variant v_i.

From figure 3, the following can be concluded: The value stream is not synchronized even though it might have been planned to be. This becomes evident when facing the intersections of the customer takt time with different cumulative probability functions: For production step s_3, for example, only 57 % of the products are produced faster or at the threshold, whereas for production step s_1, the probability is close to 100%. The step s_3 is clearly the bottleneck of the value stream, and hence it should be the first target for improvement.

Accordingly, the value stream takt analysis also reveals information about where to apply activities of improvement with a product variant-specific value stream, to obtain the greatest effect. The proposed dynamic bottleneck detection method is thereby more than a classical takt analysis, as it considers (due to the distribution) variation over time and uses this information to outline potential improvements.

The second evaluation uses the data of one process step for a single product variant produced, which is compared at different points in time (e.g. for each batch produced), relative to each other. Additionally, as the same product variant v_i is produced at a specific production step s_i, the costumer tact time can be used as an absolute measure. Hence, the variation over time reveals information about the stability of the process and can support a long-term continuous improvement process.

The third evaluation compares the data from different product variants v_i at one production step s_i. The customer takt time cannot directly be applied as an absolute measure. Therefore, the underlying cycle times are normalized with their product variant-specific costumer cycle times. These normalized cycle times can then again be accumulated and integrated to receive the expected cumulative probability function. Consequently, the ability of a production step s_i to produce different product variants v_i is evaluated and compared. Hence the single production process analysis reveals not only information about the capability of a process to produce different product variants but also about where to apply activities of improvement to receive the greatest benefit.

4.4. Contribution to practice

The proposed concept enables an automated and comprehensive analysis and evaluation of dynamic production processes, especially focused on dynamically relocating bottlenecks. The value chain comparison outlined above fulfils the needs of a time-variant bottleneck detection method: Due to its characteristics of displaying the currently longest cycle time (lowest probability of achieving the costumer tact time) within the whole value stream, the method elaborates the bottleneck of the examined value stream. As the underlying analysis is time-period specific (e.g. a batch, a shift or a day), variations over time, also within a batch, can be evaluated through combining mechanism one and two, and hence a dynamic bottleneck analysis is enabled. Hence, the proposed method promises to solve the problem of timely shifting bottlenecks in dynamic environments.

The proposed concept is intended to make the time-consuming manual VSM or bottleneck detection approaches redundant, while it should increase the validity at the same time by considering not only one product variant at one time *but also all variants at all times*. The proposed concept will enable a comprehensive overview of the current state of the production in the "dimensions" batch, production step and value stream. Due to its automatically collected database, the accuracy (i.e. the quality of the underlying data) increases substantially; facing these facts, we expect the concept to drastically reduce the time needed for bottleneck detection.

Furthermore, the proposed concept increases the efficiency of the production improvement processes. The potential improvements (bottlenecks) are automatically localized and ranked. This simplifies the "business case" process of financial investments into fixing those bottlenecks. Finally, the effectiveness of any improvement can directly by deduced from a change in a cumulative probability distribution graph.

4.5 Limitations of the proposed method

The proposed method focuses only on cycle times to detect dynamically shifting bottlenecks. As mentioned, no human interaction (as in "pen-and-paper" techniques) is needed for data collection, which is also a limitation since it alienates the users from the data. Additionally, it is important to state that the proposed method requires a significant amount of production data (i.e. the number of products produced). For production lines with a batch size of one, the method is not suitable, as there is no cycle time variation per batch, and hence no data can be cumulated, integrated and compared.

It is important to note that the chosen curve fit (i.e. the assumption of the cycle time being Weibull-distributed) needs validation by testing the whole concept in simulative environments or, better yet, in real ones. However, from a mathematical point of view, distribution assumptions are not really a need when one real data is available: The bar chart of real cycle times can also be directly analysed to receive the corresponding cumulative probability function.

5. CONCLUSIONS

In this paper, we have proposed a concept for bottleneck detection for dynamic multi-variant, multi-step production lines. In a sense, we have suggested an automated and real-time version of a takt diagram. Hence, the proposed concept enables more than just a timely snapshot of production (as in most "pen-and-paper" approaches); it gives a comprehensive overview of the dynamically changing conditions of multi-variant production lines. The concept requires automatically collected data of individual products (i.e. process cycle times). These cycle times are then accumulated per batch and integrated over time to receive the cumulative probability function for each product variant at each production step along the value stream. We propose three ways of evaluating the resulting functions: A batch, single-production process and dynamic bottleneck analysis. A main advantage of the approach is its simplicity; complex simulation models and costly data collection are not needed.

5.1 Contribution and future research

This paper contributes to the literature on bottleneck detection, as it incorporates current developments – the digital shadow – with well-known and accepted methods for bottleneck detection. Furthermore, we propose a new method that overcomes the disadvantages of existing methods: The new method does not use just a "snapshot" of a production process, which needs generalization (in terms of time and product variants) as an input, but is instead based on real data. At the same time, the effort to receive the relevant information is drastically reduced. Thus, the proposed concept enables an analysis of the dynamic aspects of bottleneck localization.

The proposed concept needs validation and further development to work in a real environment. The graph s_1 in figure 3, for example, suggests that 97% of the produced products are produced faster than or at the takt time. Further research could investigate if this high percentage is a sign of waste, as the specific production step is too fast and hence over-engineered. Furthermore, the adequacy of the used statistics and mathematical analysis need to be proven with real data.

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