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Short Communication

Big Data Analytics Based on Logistical Models

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Abstract

Over the past years, a change of feedback data in terms of quantity, quality, and timeliness could be observed in production. The generation of high resolution production feedback data enables producing companies to apply big data analytics in order to create competitive advantages. This paper describes how logistical models can be used to conduct big data analytics. It will be explained how such logistic-oriented big data analyses can be applied to improve the logistical performance of producing companies. The results will be illustrated with the help of a best practice project.

Keywords: Big data, analytics, logistical models, competitive advantage

JEL Classification codes: D20, L22

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Production companies currently find themselves in a competition market that can be characterized by an increasing variant diversity, shortening product lifecycles, and economic uncertainty. As a result, orders fluctuate strongly. This dynamic leads to steadily increasing expectations regarding logistics, which have to be met by enterprises in order to remain successful in the market (Schönsleben, 2012; Schuh & Stich, 2013). At the same time, it is difficult for producing companies to recognize the interdependencies between the logistic objectives, as well as the possibilities for influencing them due to the variety and complexity of processes (Wiendahl, 2002). Specific logistical models are therefore needed to make these connections describable. Moreover, feedback data in the right quantity, quality, and timeliness is needed as input for these models.

The generation of high resolution feedback data, as well as the application of logistical models, enables producing companies to conduct big data analytics in order to create competitive advantages in the field of logistics. This paper explains how big data analytics and logistical models can be combined and how producing companies can improve their logistical performance in doing so. At first, a short overview of the theoretical background will be presented. After that, the combination of logistical models and big data analytics will be explained in detail. The results will be illustrated with the help of a best practice project.

Literature Review

In order to develop a common understanding, at first all relevant fundamentals will be presented and explained. In particular, the term *big data analytics* will be defined. Furthermore, two basic logistical models, namely the *lateness histogram* and the *throughput diagram*, will be presented.

Big Data Analytics

As part of the high-tech strategy of the German government, Industry 4.0 found its way into producing companies. It pursues the goal to create an environment where humans, machines, and objects can be linked intelligently, horizontally, vertically, and in real-time. Networks of working, transport, and stock systems should work self-organized (Russwurm, 2013). The advancement of information and communication technologies plays an important role (Bauer, Schlund, Marrenbach, & Ganschar, 2014). Major fields of action are the Smart Factory, cyber-physical systems, cyber-physical production systems, the Internet of Things and, in particular, big data analytics (Nyhuis, Mayer, & Kuprat, 2014).

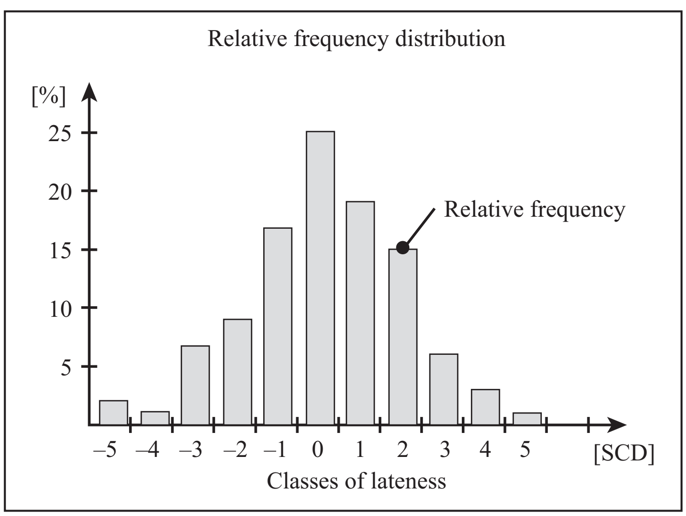
Within the Industry 4.0 environment, big data analytics represent the processing of vast amounts of high resolution production feedback data. It helps to generate meaningful information regarding the production status that can be used to improve the logistical performance and, hence, to gain competitive advantages. Generally, advanced tools or models (e.g., logistical models) are applied to conduct big data analytics.

Basic Logistical Models

Nowadays, a vast amount of data is collected in producing companies. In order to describe the logistical performance, this data had to be structured, visualized, and analyzed. Methods of descriptive statistics and, in particular, histograms can be used for that purpose. A histogram creates transparency which is needed to optimize a production (Wiendahl, Nyhuis, Bertsch, & Grigutsch, 2012).

It can be distinguished between article, order, and resource data (Wiendahl et al., 2012). For every type of data, several attributes exist that can be described with the aid of key figures. For relevant articles, key figures are the safety stock or the replenishment time. Orders can be characterized by the lead time or the lateness. Resources can be described by the utilization or the work-in-process (WIP) (Bertsch, 2015).

Due to the vast amount of data collected in productions, the data analysis represents a great challenge. The histogram divides the data into classes in order to face this challenge (Ruge, Birk, & Wermuth, 2014). Subsequently, the absolute and relative frequency of each class can be determined. The frequency describes how many measured values lie in each class. In order to visualize the collected data, the generated frequency distribution can be transferred into a histogram. As shown in Figure 1, the frequencies of each class are plotted as vertical bars (Ruge et al., 2014).



Note. SCD = Shop calendar days.

Figure 1. Lateness histogram.

The Funnel Model (Figure 2) represents the basis for the Throughput Diagram. Similar to the flow systems found in process engineering, it describes the throughout behavior of a capacity unity through the input, WIP, and output. In this model, the funnel embodies the capacity unit and working station respectively. The WIP can be described as the sum of orders entering and leaving the working station, as well as orders that are already in the work station. The output rate can be determined by the opening of the funnel (Wiendahl, 1997;

Bechte, 1984; Lödding, 2013; Kivenko, 1981). Generally, the Funnel Model can be used to depict any unit of capacity, i.e., an individual workplace as well as a cost center or the entire production.

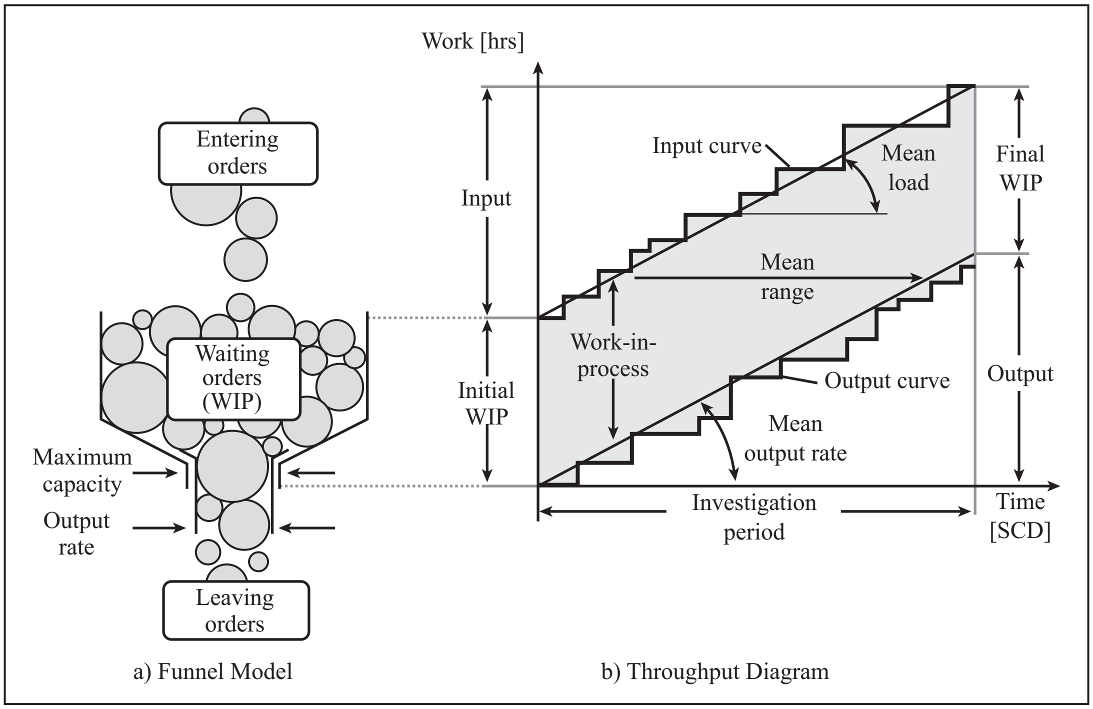


Figure 2. Funnel Model and throughput diagram for a workstation (Bechte, 1984).

The throughput diagram can be built up by taking the events in the Funnel Model as the foundation (Figure 2). Orders entering production are chronologically plotted cumulatively according to their work content and form the input curve. In doing the same with completed orders, the output curve arises. In this model, the output date on a workstation corresponds per definition with the input date on the subsequent workstation. Moreover, the start of the input curve embodies the initial WIP of the working station during the investigation period. The throughput diagram can be used to describe primary production logistic objectives (utilization, WIP, throughput time, and lateness) of a working station. Moreover, it provides support in numerically calculating relevant key figures (Nyhuis, 2008; Nyhuis & Wiendahl, 2009).

The Potential of Logistical Models in Combination with Big Data Analytics

In the past, logistical models were mainly used to design and analyze production systems. However, due to low resolution production feedback data, long investigation periods were needed to generate valid results. Moreover, erroneous and non-existing feedback data respectively caused a reduction of the result quality.

Within the Industry 4.0 environment, the resolution of production feedback data can be increased to a high extent. The generation of high resolution production feedback data enables companies to represent actual operational states of production systems in real time, as well as to identify structurally relevant changes. In addition to designing and analyzing production systems, logistical models can also be used to conduct big data analytics and, hence, to support production planning and control processes (Nyhuis et al., 2014).

In order to support production planning processes by big data analytics, logistical models have to be supplied with high resolution master and movement data. For example, planned lead times are needed to schedule manufacturing orders realistically. Within the Industry 4.0 environment, actual lead times can be measured and analyzed continuously. The results can be used to increase the quality of planned lead times significantly, and eventually, to improve the logistical performance. Thus, the combination of logistical models and big data analytics increases the planning accuracy of production planning processes (Nyhuis et al., 2014).

As already mentioned above, up until now, long investigation periods were needed to apply logistical models accurately. Reasons for that are a low feedback data quality (actuality, correctness), and a low feedback data resolution (daily feedback of in fact continuous processes). Therefore, short-term controlling decisions cannot be supported by logistical models so far.

High resolution production feedback data make it possible to reduce the length of the investigation period. This has a direct influence on the ability to react on disturbances within the production. By processing the generated high resolution feedback date with logistical models, the necessity for structural changes can be identified in real time (Nyhuis et al., 2014). For instance, with the aid of the Throughput Diagram, an input increase in front of a workstation can be noticed immediately. Hence, the capacity can be adjusted in real time in order to keep the WIP on a constant level. It has to be pointed out that big data analytics support structural decisions regarding manufacturing control. However, decisions regarding single orders cannot be made.

The results of big data analytics, based on logistical models, can also be visualized quite easily. Visualizations support employees optimally in their fields of activities by presenting feedback data aggregately and depicting interdependencies between logistical objectives quantitatively. It provides the opportunity to represent production systems close to reality which supports decisions regarding production planning and control (Nyhuis et al., 2014).

Best Practice Project

The Institute of Production Systems and Logistics (IFA) applied the gained knowledge of the combination of logistical models and big data analytics in many industry consulting projects. A best practice project was conducted with a company that represents a supplier for the automotive industry. The company produces screws and valves for brake pipes and offers them in a high variant diversity. Moreover, it promises its customers very short a stable delivery times. However, this promise caused a lot of turbulences within the own production since the logistical performance was only on a medium level. Often, certain measures, such as additional shifts, had to be taken in order to meet the promised delivery times nonetheless. Hence, the goal of this project was to increase the logistical performance and the production planning and controlling processes, respectively, to reduce the turbulences within production.

The major part of this project was a big data analysis based on logistical models. In particular, data regarding lead times and order release were processed. The lead time distribution was visualized with the aid of a histogram (see Figure 3a). In contrast, the order release process was analyzed by applying the throughput diagram (see Figure 3b).

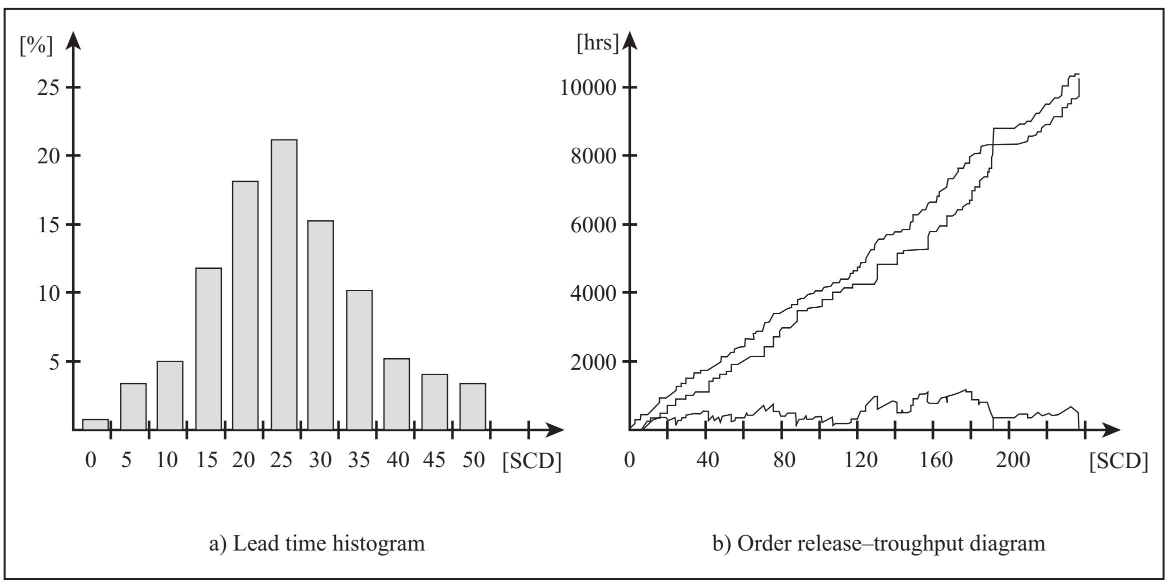


Figure 3. Lead time histogram and order release-throughput diagram.

Based on big data analytics, long—and more importantly—strongly varying lead times could be identified. The mean lead time was 26.3 shop calendar days (SCD), and the variation was 13.2 days. The main reason for that was unpredictable and, hence, unplannable transport times between the intermediate stock and working systems. Furthermore, the big data analysis disclosed a variation within the order release process. The input curve of the throughput diagram showed different gradients.

The long and strongly varying lead times, as well as the order release variation, had to be improved in order to increase the logistical performance of the production. Hence, different measures were developed to achieve this goal. Firstly, a new intermediate stock was implemented very close to the working systems. This measure eliminated most of the transport times which reduced the total lead time, as well as the lead time variation. Hence, lead time became more plannable which reduced the turbulences in production planning processes. Secondly, a planning table was implemented. This measure supports the controlling of the order release process and made it more stable. In conclusion, the implemented measures reduced the lead time and the lead time variation and improved the order release process which led to less turbulence and, therefore, to a higher logistical performance within the production. After the project, it was easier for the company to meet all of the customer requirements regarding delivery time.

Conclusion

This paper discussed how logistical models can be used to conduct big data analytics. Firstly, two basic logistical models, namely the histogram and the throughput diagram were explained in detail. Secondly, the potential of combining logistical models and big data analytics was explicated. Finally, a best practice project, in which logistical models and big data analytics were used to increase the logistical performance of a company, was presented.

The paper and the results of the best practice project have both shown that within an Industry 4.0 environment, logistical models and big data analytics can be combined to gain competitive advantages. By structuring, visualizing, and analyzing vast amount of data, the logistical performance of a company can be improved. Since the logistical performance represents an important distinguishing feature, the application of big data analytics helps companies to remain successful in the market in the long run. Further research has to clarify where logistical models can be applied as well in order to come closer to the Industry 4.0 vision of self-organized factories.

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