Available online at www.sciencedirect.com
ScienceDirect
Procedia CIRP 52 (2016) 210 – 215
www.elsevier.com/locate/procedia

Changeable, Agile, Reconfigurable & Virtual Production

Increasing the traceability through targeted data acquisition for given product process combinations

Christina Reuter[1], Felix Brambring[1] and Thomas Hempel[1]*

[1]*Laboratory for Machine Tools and Production Engineering (WZL) of RWTH Aachen University,Steinbachstr. 19, 52074 Aachen, Germany*

* Corresponding author. Tel.: +49 241 80 20 394 ; fax: +0-000-000-0000. *E-mail address:* {c.reuter, f.brambring,t.hempel}@wzl.rwth-aachen.de

Abstract

Today's manufacturing companies are faced with the challenge to achieve a high adherence to delivery dates under volatile market demands and to achieve a high efficiency of the order to delivery process. This challenging situation can only be handled with the help of an optimal alignment of the production, the production planning as well as the production controlling processes. Sufficient and high quality information from the production are the major basis for successfully mastering the tasks of production planning and control. With the help of the approach proposed in this paper, companies can start setting up a targeted data acquisition concept for their product process combination. It helps them, amongst other things, preventing production problems and responding rapidly to fluctuating customer needs.

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016

Keywords: data acquisition; production control; traceability

1. Introduction

In order to stay competitive, many manufacturing companies, especially small and medium sized enterprises (SME), face the challenge to transform their production and the corresponding production planning and control (PPC) processes for the upcoming Internet of Things (IoT) Era. Often they are missing the necessary competencies or are failing to perform this step from a benefit-oriented resource perspective. Since their time and cost budget is a constraint, SME need to focus particularly on relevant data types, data acquisition points and technologies that will be beneficial for their manufacturing processes. State of the art approaches are lacking in supporting SME sustainably, systematically and company-specific on their way to IoT from a PPC-perspective[1]. With the help of this paper, companies can start setting up targeted data acquisition concept for their product process combination. Through this, they will be able to satisfy fluctuating customer needs and keep a high adherence to delivery dates.

2. Data acquisition from production and data Processing

2.1. Data analytics as an enabler for improving the Production Planning and Control

The data analytics process is a typical approach in the area of business analytics [2]. In Figure 1 this process is shown adapted to analyzing production data, through stating the objective of each step for using production data.

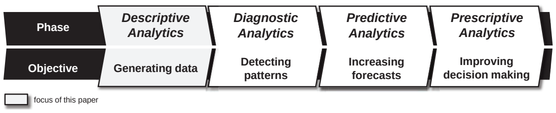

Figure 1: Data analytics process (in dependence on [2])

The steps of the production oriented data analytics process are described in the following. The first step is the phase of the descriptive analytics. Generating data on the shopfloor and in IT-Systems is the major purpose of this phase. The better the data quality is in respect to correctness and

Peer-review under responsibility of the scientific committee of the Changeable, Agile, Reconfigurable & Virtual Production Conference 2016
doi:10.1016/j.procir.2016.07.039

granularity of the generated data, the better the traceability will be. According to DIN ISO 9000 *traceability* is the ability to identify and trace the history, distribution, location, and application of products, parts, materials, and services. A traceability system records and follows the trail as products, parts, materials, and services come from suppliers and are processed and ultimately distributed as final products and services [3]. In this paper, traceability is considered as the capability to track current and trace the previous status of production, e.g. tracking various orders during their production process or receiving the current capacity status of a working machine. Good traceability is the basic requirement for improving the capability to plan and control a production under volatile production and market conditions such as technical disturbances, rush orders, changes of the customer order, organizational disturbances, incorrect planning times or incorrect transition times. From the technological perspective, there exist many ways for increasing the traceability. Just to name a few: Barcode on orders and materials, data matrix labelling, radio-frequency identification (RFID) of orders or production materials, camera technology, near field communication (NFC) or real-time locating system (RTLS) for tracing materials [4]. The focus of this paper will be on this phase of the data analytics process.

The second step, the diagnostic analytics, is about pattern recognition within the generated data. Typical recurring patterns in data of a production surrounding are e.g. repetitive machine sequences or seasonal variations within a production cycle. Identified repetitive machine sequences could be used for adjusting the machine layout by implementing line segments in order to cut throughput times. By taking into account seasonal variations, material disposition can order early enough so that no shortages in material supply will occur.

In the third step, the predictive analytics, the ability to build forecasts with the help of the previously identified patterns is in the focus. In a production surrounding, forecasts enable e.g. predictions about potential capacity bottlenecks. By intervening as predicted, a bottleneck-reduced production can be achieved.

The fourth and last phase of the data analytics process are the prescriptive analytics. The major goal of this phase is the generation of decision support for managerial problems that occur during production. Instead of having to use gut feeling, prescriptive analytics use the processed data from the steps before and quantifies possible decisions. Last but not least it rates them with the help of a target function.

As described above, the focus of this paper is on the descriptive analytics phase. In order to follow a targeted approach in having all necessary feedback data in the required accuracy and frequency, the data needs of the production planning and control have to be identified. Therefore, in the following subchapter the Aachen production planning and control model will be presented to give a framework for major actions and their data needs for a PPC.

2.2. Aachen PPC model as a framework for actions

The goals of the Aachen Production Planning and Control model are oriented on the typical logistic objectives, that most producing companies are following [5]. The goals are:

- High adherence to delivery dates
- High and smoothed capacity utilization
- Short throughput times
- Low work in progress
- High flexibility [6]

The complete Aachen PPC model is shown in the following Figure 2. Since this paper can only go briefly into the topic of improving the traceability through targeted data acquisition, the focused tasks which have data needs will be the in-plant production planning and control tasks. These core tasks are also the most relevant ones for achieving a high logistic objective fulfillment, because they are linked directly with the production shopfloor.

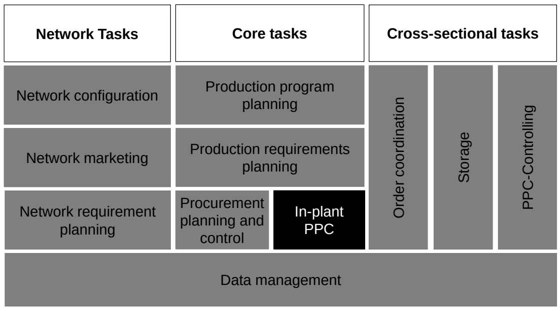

Figure 2: Aachen PPC model [5]

The major tasks of the in-plant production planning and control are described briefly in the following. The four tasks, order generation, order release, sequencing and capacity control will later be used in the proposed approach, to derive their data needs.

Order generation ensures the planned values for the input and output of the production as well as the planned sequence. The order release defines the period of time in which the orders are needed for production and sets the actual input for the production. Capacity control identifies and determines how much time a machine is running and how long each worker is engaged on each machine. Sequencing, however, determines the process order of each machine [7].

In the following section the product process matrix will be introduced. It will be used to categorize product process combinations.

2.3. Categories of product process combinations

Production processes can be distinguished by many characteristics. The automotive mass production of Toyota will differ strongly in terms of characteristics and challenges from the production of a low volume, very specialized machine building company. Hayes and Wheelwright [8] introduced the product process matrix in order to offer a simple framework to distinguish such differences as described above. Their product process matrix is stated in the following Figure 3.

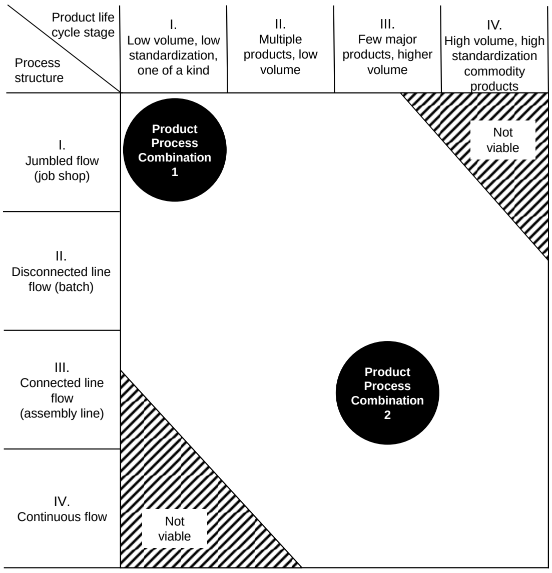

Figure 3: product process matrix [8]

On the rows of the matrix major stages through which a production process could be represented are stated. In the upmost row it is starting with a job shop production. Job shop productions are suitable for small lot sizes with a high variety of routings through the workstations. Setup times are a significant part of the production time and material flows are quite chaotic. Job shop productions offer a great flexibility and therefore are typical in companies with low volumes of non-standardized products. At the lower end of the matrix is a continuous flow production. As the name states, the product flows automatically through production with a fixed routing. Many fast-moving-consumer goods (FMCG) and chemical companies use that production layout. In between the two described extremal production process types are the disconnected line flow as well as the connected line flow. Many companies with specialized products try to produce within disconnected flow lines (product batches a produced on a limited number of identifiable routings through production). Connected flow lines are typical for automotive assembly [9].
The columns represent different product categories starting with a great variety associated with highly specialized machine manufacturing on the left-hand side to standardized FMCG on the right-hand side [8].

There exist many more characteristics for distinguishing production processes (c.f. e.g. [10] or [11]), but for this paper the level of Hayes and Wheelwright is detailed enough. As stated also in the matrix, in this paper only the two following production process and product combinations are taken into the focus:

- Product Process Combination 1: *Job Shop production & low volume, low standardization*
- Product Process Combination 2: *Assembly line production & few major products & higher volume*

3. Existing approaches

In this chapter, two relevant approaches are described and assessed, in order to derive the academic void. The first one is the approach for high resolution production management, the second one proposes a framework for information and communication technology (ICT) enabled real-time production planning and control.

3.1. Approach 1: High Resolution Production Management

The approach of High Resolution Production Management (HRPM) by Schuh et al. [12] was introduced in 2011. To enhance the capability to control a production system, the HRPM approach states that the production controller needs support through IT-systems. According to the paper, high resolution feedback data is one crucial aspect to enable that support. According to the paper, principles which should be followed in respect to generate high resolution feedback data are:

- increasing the frequency and accuracy of the feedback data,
- being able to zoom in or out of the data (depending on the case) and
- automatization (where possible) of the generation of feedback data.

The other parts of the approach mainly deal with more abstract levels of setting up a high resolution production management [12].

The approach of High Resolution Production Management by Schuh shows that the topic of the paper at hand is relevant. But the described approach is on a much more abstract level and does not address the topics of what data in what granularity is needed or how different product process combinations might need different implementation strategies.

3.2. Approach 2: A framework for ICT-enabled real-time production planning and control

The framework for ICT-enabled real-time production planning and control by Arica and Powell was published in 2014 [13]. The goal of the paper is to develop a conceptual framework for real-time production planning and control. In the paper, the authors analyze characteristics and shortcomings of existing systems. Based on this assessment, they propose a new framework for real-time production planning and control. In respect to data acquisition, the approach deals with technologies that could be used for generating real-time production feedback data, such as Enterprise Resource Planning (ERP), Advanced Planning and Scheduling (APS), Manufacturing Execution System (MES) or RFID. The authors emphasize the application of RFID as the most advanced and promising emerging real-time data capture technology that is currently available to manufacturers [13].

The approach also confirms the importance of the topic raised in the paper at hand, but it is again on a much more abstract level than the proposed approach in this paper. Different product process combinations and precise data needs from production are not discussed.

3.3. Critique of Literature

Existing approaches are drawing only a rough picture about a targeted data acquisition for increasing the traceability for given production structures. None of these approaches take different product process combinations into account, and how the varying circumstances are influencing data needs. Existing approaches often also don't have a guideline character and don't focus on production control and logistics. Furthermore, they are too abstract and do not give detailed hints what data from production has to be collected in order to improve the capability to track and trace production. These weaknesses show the research gap. The presented novel method in the following chapter will close that gap of existing approaches.

4. Approach for increasing the traceability through targeted data acquisition for given product process combinations

4.1. Overview

The approach (see figure 4) consists of two phases: The characterization and the configuration phase. The characterization phase is of static nature, which means that it only has to be performed once in order to generate its output, which is a necessary input for the second phase. The configuration phase has to be executed by every user of the approach, since it needs additional company-specific input.

The first step of the characterization phase is the derivation of data needs of tasks within the production planning and control. The second step deals with the identification of the interrelations between activities. This step is followed by an analysis of the influence of different product process combinations on the data needs. The fourth step of the characterization phase is the identification and classification of technologies for data acquisition from the shopfloor.

The second phase, the configuration phase, starts with the classification of the production of the user and the generation of the corresponding model. The built model is the base for the next two steps. The second step of the configuration phase comprises the targeted configuration of the production in respect to relevant data for the product process combination, data granularity and the data acquisition cycles. The last step will be the actual roll out of the configuration results in the transformation step. Due to the limitation of space, this paper is focusing on the first phase, the characterization phase. The second phase, the configuration phase, will be published in future papers. Therefore, the next subchapter will deal in more detail with the four steps of the characterization phase.

4.2. Characterization phase

Step 1: Derivation of the PPC data needs: As described in chapter 2.2, the PPC has various core tasks. In this paper, the focus is on the tasks order creation, order release, sequencing and capacity control. Each task consists of several smaller activities, which have data needs. In the first step of the characterization phase, the data needs for the single activities within the tasks of the PPC have to be derived.

Figure 4: Approach for increasing traceability through targeted data acquisition for given product process combinations.

To identify the entirety of the relevant single activities within the PPC, two parallel activities are performed: (1) identification of single activities based on theoretical PPC models such as the Aachen PPC model (c.f. chapter 2.2) and (2) reviewing documentations of typical ERP, PPC and APS systems in relevant industry sectors.

The first approach is followed through the derivation of data needs for the WIP control through reviewing the tasks within the Aachen PPC model. The capacity control "ascertains on short notice which measures are to be implemented for adjusting capacities. In particular, it determines overtime, shortened work hours and other special measures related to the flexibility of capacities."[7] In order to be able to execute e.g. work in progress control within the task of capacity control, frequent data about the WIP level have to be acquired from the queues and the actual work content at workstations (see Figure 5).

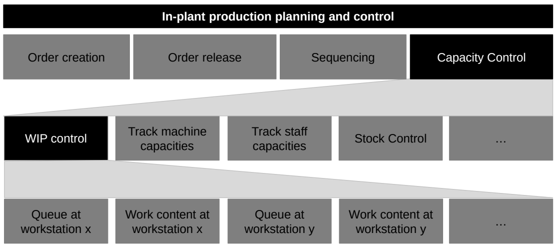

Figure 5: Exemplary derivation of data needs for the WIP control

The second approach is based on analyzing documentations of typical ERP, PPC and APS systems (e.g. SAP ERP, PSI Penta Adaptive, Inform felios) in the machinery and equipment industry to derive common single activities within the tasks of the PPC.

The result of the first phase is the identified entirety of relevant tasks and its data needs. In the second step, interrelations between these activities will be identified.

Step 2: Identification of interrelations between activities: The tasks of production planning and control are in many respects not independent of each other. Especially in the model for production control by Loedding these interrelations become apparent, since it shows the interactions of tasks of the PPC in the style of control theory [7]. One example of interrelations between the tasks of the PPC is described in the following: By following a setup-time optimized sequencing role, sequencing has an impact on the output rate and therefore the production's output. Order release impacts the WIP and thus also impacts the possible output [7].

Therefore, interrelations between single activities will be identified for activities in the second step of the proposed approach. This step is necessary, because different single activities might need the same kind of data, but in different numbers of request or in different degree of detail.

The approach is described in the following through some activities within the order release and the capacity control: To perform the order release method "load oriented order release" (Rule: Only release new orders into the production if the bottleneck of production offers enough capacity to process the order.) the production controller needs to know the capacity utilization of the workstations for this point of time. If the production controller performs WIP control (Rule: Keep the WIP level at a working station between defined action limits.) within the task of capacity control, he needs constant information about the capacity utilization of the workstation as well as information about entering and exiting orders at the focused workstation. Both activities are requiring the same kind of data (capacity utilization), but WIP control needs a higher frequency. This description leads to the following equation 1, with "freq_data_x" as the frequency of request for a kind of data x. "freq_data_x1" would be the frequency of data x required for new order release; "freq_data_x2" would be the frequency of data x for rechecking the capacity utilization for performing the WIP control. The overall required frequency "freq_data_x", which will then be set for all interrelated activities that are linked with the data, will be the minimum frequency.

$$freq\_data\_x = min\ (freq\_data\_x1;\ freq\_data\_x2;\ \ldots) \qquad (1)$$

The necessary degree of detail for any kind of feedback data x ("detail_data_x") is stated in equation 2. The maximum of all degrees of detail ("detail_data_x1" for degree of detail for activity 1; "detail_data_x2" for degree of detail for activity 2, …) determines the requirements on that kind of data.

$$detail\_data\_x = max\ (detail\_data\_x1;\ detail\_data\_x2;\ \ldots) \qquad (2)$$

The result of the second step are identified interrelations between single activities of the PPC. Furthermore the influence of these interrelations on the data need is stated.

Step 3: Influence of different product process combinations: As shown in chapter 2.3, this paper differentiates basically two product process combinations:

- Product Process Combination 1: *Job Shop production & low volume, low standardization*
- Product Process Combination 2: *Assembly line production & few major products & higher volume*

In a job shop environment, the production controller mainly has to react quickly to incidents, identify and resolve bottlenecks as well as to track and trace orders. In the assembly or production line setting, the production controller typically has to run the workstations at peak efficiency and meet material requirements [8].

In regard of the data needs, in a job shop production (Product Process combination 1) many more data has to be collected during the production process in order to be able to track and trace orders. To have an (almost) real-time feedback from production, at every working machine on the shopfloor data acquisition possibilities have to be provided, to collect data e.g. about the identification of the production order, its current completion status, the planned completion time etc. In an assembly line production (Product Process Combination 2) the tracking and tracing of an order is simpler, due to the fixed routing through production. Here it might be sufficient to collect data e.g. about the identification of the production order, its current completion status, the planned completion time etc. at the beginning of the assembly line and at the end of the process [14],[15]. The result of the third step are identified influences of different product process combinations on the data needs.

Step 4: Technologies for data acquisition: In the fourth step of the static characterization phase, technologies for data acquisition from the shopfloor are described in regard to their possible field of application and in regard to their technological capabilities.

Some parameters that are important to be taken into account while selecting suitable data acquisition systems in regard to the mentioned areas are e.g. the long-term stability and durability of the technology, its performance limits, its efficiency (price, including operating costs), the failure rate, bulk acquisition capability or data density [16].

Barcode on orders and materials, data matrix labelling, radio frequency identification of orders or production materials, camera technology, NFC or RTLS for tracing materials are typical solutions for acquiring feedback data from the shopfloor. These technologies have to be analyzed and categorized in detail, as the following example shows:

On the one hand, there are many studies that show the positive effects of RFID for generating production feedback data (e.g. [17]). On the other hand, RFID is unreliable in metallic surroundings, which are characteristic to many small and medium sized machinery and equipment manufacturers. If there are high demands on the data quality, it might be better to use data matrix labels (or a combination of RFID and data matrix) in that kind of surroundings to acquire correct data. In the proposed approach, each analyzed data acquisition technology will be summarized and categorized with the help of a morphological box. The boxes of the data acquisition technologies can then be matched with the related process requirements.

These morphological boxes for each relevant data acquisition technology are the result of the fourth phase of the proposed approach.

5. Conclusions and further research

In this paper, the approach for increasing the traceability through targeted data acquisition for given product process combinations was introduced. The approach consists of two major phases, the one-time characterization phase and the company-specific configuration phase. This paper was mainly focusing on the characterization phase, which consists of the steps “Derivation of the PPC data needs”, “Identification of the interrelations between activities”, “Influence of different product process combinations” and “Technologies for data acquisition”.

Conclusion of the research is, that companies can profit to a huge extent by focusing on beneficial data types and to take into account company specific product process combinations. Upcoming research efforts will be in the detailing and finalization of step two of the method. With the help of the presented approach, companies can start to set up a targeted data acquisition concept for their product process combination. It helps them amongst other things preventing production problems and responding rapidly to fluctuating customer needs.

6. Acknowledgments

The authors would like to thank the German Research Foundation DFG for the kind support within the Cluster of Excellence "Integrative Production Technology for High-Wage Countries".

REFERENCES

[1] C. Reuter and F. Brambring, “Improving Data Consistency in Production Control,” *Procedia CIRP*, vol. 41, pp. 51–56, 2016.

[2] J. R. Evans, *Business analytics: Methods, models, and decisions,* 1st ed. Boston: Pearson, 2013.

[3] Deutsches Institut für Normung, *Quality management systems: fundamentals und vocabulary (ISO 9000:2015)*, 2015th ed. Berlin: Beuth, 2015.

[4] S. Goswami, *Indoor location technologies*. New York: Springer, 2013.

[5] C. Brecher, Ed, *Integrative Production Technology for High-Wage Countries*. Berlin, Heidelberg: Springer-Verlag Berlin Heidelberg, 2012.

[6] P. Nyhuis and H.-P. Wiendahl, *Fundamentals of production logistics: Theory, tools and applications*. Berlin, London: Springer, 2009.

[7] H. Lödding, *Handbook of manufacturing control: Fundamentals, description, configuration*. Heidelberg: Springer, 2013.

[8] R. H. Hayes and S. C. Wheelwright, “Link manufacturing process and product life cycles,” *Harvard Business Review*, 1979.

[9] W. J. Hopp and M. L. Spearman, *Factory physics: Foundations of manufacturing management,* 2nd ed. Boston: Irwin/McGraw-Hill, 2001.

[10] W. H. ElMaraghy and R. J. Urbanic, “Modelling of Manufacturing Systems Complexity,” *CIRP Annals - Manufacturing Technology*, vol. 52, no. 1, pp. 363–366, 2003.

[11] K. Windt, T. Philipp, and F. Böse, “Complexity cube for the characterization of complex production systems,” *International Journal of Computer Integrated Manufacturing*, vol. 21, no. 2, pp. 195–200, 2008.

[12] C. Brecher and F. Klocke, *Wettbewerbsfaktor Produktionstechnik: Aachener Perspektiven ; [AWK, Aachener Werkzeugmaschinen-Kolloquium 2011, 26. bis 27. Mai ; Tagungsband]*. Aachen: Shaker, 2011.

[13] E. Arica and D. J. Powell, “A framework for ICT-enabled real-time production planning and control,” *Adv. Manuf,* vol. 2, no. 2, pp. 158–164, 2014.

[14] J. Kletti, *MES Manufacturing Execution System: Moderne informationstechnologie zur prozessfahigkeit der wertschopfung*. Berlin: Springer, 2006.

[15] H. Kühnle, *Produktionsmengen- und -terminplanung bei mehrstufiger Linienfertigung*. Berlin, Heidelberg: Springer, 1987.

[16] Reuter, C,Brambring, F,Hempel, T, “Approach of information provision for high resolution production control,” in *Proceedings of Abstract and Papers of 23rd International Conference on Production Research ICPR23: Operational Excellence towards sustainable development goals (SDG) trough Industry 4.0*, Manila: Central Book Supply, Inc, 2015.

[17] J. Brusey and D. C. McFarlane, “Effective RFID-based object tracking for manufacturing,” *International Journal of Computer Integrated Manufacturing*, vol. 22, no. 7, pp. 638–647, 2009.