Smart Production Planning and Control; Concept for improving Planning Quality with Production Feedback Data

Mina Rahmani[1], Øyvind A. M. Syversen[1], Anita Romsdal[1], Fabio Sgarbossa[1], Jan Ola Strandhagen[1]

[1] NTNU, NO-7491 Trondheim, Norway
mina.rahmani@ntnu.no

Abstract. Planning quality depends on the use of correct, accurate, realistic, and reliable planning data. Industry 4.0 has facilitated large-scale data collection from a variety of sources, including production feedback data. The hierarchical nature of traditional production planning and control (PPC) limits the ability to use such data to improve planning quality. This paper explores how planning quality can be improved through the application of production feedback data into tactical production planning. The paper shows that while current tactical planning is mainly based on static master data, some of the master data for planning should instead be dynamically determined based on analysis of production feedback data. The paper develops a conceptual model for how production feedback data can be linked to tactical planning, illustrates how production feedback data can be applied in tactical planning, and proposes a method for how companies can integrate production feedback data into their tactical planning. Future work includes application and testing of the proposed concept in real-life cases and studies to better understand the specific relationship between the accuracy of master data and the performance of production plans.

Keywords: Smart Production Planning and Control, Planning Data, Master Data.

1 Introduction

Industry 4.0 encapsulates the trend of digitalization of operations in order to achieve more intelligent manufacturing processes [1]. As companies apply emerging digitalization technologies in all aspects of their operations, companies are experiencing an explosion in the generation of, and access to, data both from internal operations and the external environment [2]. And with this comes unprecedented opportunities for the application of data from a more diverse range of sources also into production planning and control (PPC), a concept which has been aptly named smart PPC. Smart PPC aims not only to support human decision-making but also to automate PPC tasks and make way for more integrated, dynamic, and real-time PPC [3].

Traditionally, PPC has been based on a hierarchical approach, where material flow and capacity are coordinated and aggregated across planning levels [4]. Planning quality depends on correct, accurate, realistic, and reliable planning data since this forms the basis for the input parameters used for planning [5, 6]. Thus, the quality of a plan is only as good as the input data used.

On the tactical planning level, the input parameters for PPC typically consist of static master data from the company's enterprise resource planning (ERP) system such as product identification numbers, bill of materials (BOM), processing times, lead times, and batch sizes. This is combined with dynamic data such as customer orders, forecasts, and inventory levels to determine a plan of products to be produced in given volumes on given days to satisfy customer demand. In addition, most production companies gather large amounts of data from operations and machines on the shopfloor. However, the hierarchical nature of traditional PPC currently limits the ability to include this type of dynamic production data as feedback into higher planning levels [7].

The purpose of this paper is to explore *how planning quality can be improved through the application of production feedback data into tactical production planning*. The paper posits that while current tactical planning is mainly based on static master data, some of the master data for planning should instead be dynamically determined based on analysis of production feedback data.

The paper has three main contributions: 1) development of a conceptual model for how production feedback data can be linked to tactical planning, 2) illustration of how production feedback data can be applied in tactical planning, and 3) development of a method for how companies can integrate production feedback data into their tactical planning.

The scope of the study is on PPC, with a main focus on master data for tactical planning, particularly material requirements planning (MRP). The concept is developed with a main focus on a mass production environment, with production of standard products, in batches with fixed process steps and routings, in a make-to-stock (MTS) production environment.

The paper is organized as follows. In section 2, the theoretical background of the study is outlined. This is subsequently used in section 3 to develop a concept and a method for the application of production feedback data into tactical planning. Finally, section 4 presents the study's conclusions and suggestions for further research.

2 Theoretical Background

2.1 Production Planning and Control (PPC)

The purpose of the PPC function is to ensure availability of materials and other variable resources needed to supply the goods and services that fulfil customer demand [8]. PPC is typically based on a hierarchical approach with different planning levels and time horizons. The PPC framework by Vollmann, Berry [9] is the basis for most traditional planning systems in production today [10]. In this generic framework, the planning levels are divided into strategic (long-term), tactical (medium-term), and operational (short-term). The strategic level provides a broad and aggregated view of production operations. Here, sales and operations planning (S&OP) reconciles demand and capacity into an aggregate plan which forms the basis for the master production schedule

(MPS) [10]. The MPS is then analyzed through rough-cut capacity planning to discover potential capacity problems and critical resources [11].

In the tactical level, the MPS is combined with BOM and inventory data to determine the requirements for components and parts and to generate production and purchase orders in a process known as MRP. The MRP logic is an iteration of three main steps: netting against available inventory, planned order calculation, and BOM explosion for gross requirement calculations of components [12]. The primary objective of MRP is to determine what to order, in which quantities, and at what time – both from purchasing and production [10]. Before the MRP is executed, capacity requirements planning (CRP) is performed to check that the required capacity is available.

On the operational level the plan from the tactical level is scheduled and executed in the form of production and purchase orders. This level is also concerned with monitoring of operations, dispatching, expediting, inspecting, evaluating, and taking corrective actions [8].

In general, there are two main challenges related to traditional production planning decisions that need to be addressed. First, the planning of the production quantities, production dates, and capacity requirements are done in separate steps. As a result, there is no guarantee that the products will be ready by their due dates [13]. Second, the generated plans throughout the planning processes are not updated, leading to differences between the actual and expected plans. The main reasons for the discrepancies could be inaccurate planning assumptions, unanticipated events such as machine breakdown, raw material shortages, operators' illness, and the lack of data to update the plans [13].

Although many companies have made large investments in technologies to automate production processes, many of the PPC decisions still rely on experts' experience [3], and they are often performed with the support of spreadsheet solutions. This type of manual planning has a number of limitations and weaknesses, especially for planning tasks of high mathematical complexity such as lateness minimization, effective solution generation, factory utilization, and inventory minimization [14]. It is therefore necessary to investigate how technological advances impact planning decisions, especially regarding the balance between automated and manual, experience-based planning [15].

2.2 Information Systems and Data Capture

Most organizations worldwide have adopted ERP systems to integrate the complete range of their processes and functions and present a holistic view of the business from a single information and information technology (IT) architecture [16]. This is accomplished by combining numerous core business processes into an integrated database that allows for one-time data entry and easy access to a single aspect of information [17, 18]. ERP systems use three categories of data: master data, business records, and system-generated transactions. Master data is used to create business records – and both are necessary to generate transactions [18].

The quality of master data is one of the key factors influencing how well production planning and execution in an organization operate [19]. Master data identify and describe all the important business objects, e.g., business partners, employees, articles, BOM, equipment, and accounts. Typically, master data are created once, used many times and not frequently updated [19, 20], which means that master data used for e.g. MRP or scheduling might not accurately reflect the current state of the shopfloor [21].

Along with Industry 4.0 the world has seen an explosion in the creation of data sets from production. Such production feedback data consists of information concerning the current statuses of active production jobs, utilized work stations, and set-up and processing durations for process steps [22]. The data capture on the shopfloor takes place both automatically through systems such as manufacturing execution systems (MES), supervisory control and data acquisition (SCADA), production activity control (PAC) and production data acquisition (PDA) systems, and through manual reporting by shopfloor staff. The captured data is used for detailed scheduling, and control and monitoring of production in order to update short-term production plans, handle unexpected events, and monitor resource efficiency and production job statuses [23].

The investigations into the use of production feedback data into PPC has increased over the past decade. Schäfers, Mütze [24] created an integrated concept for acquisition and utilization of production feedback data using radio frequency identification (RFID) technology to support PPC. This study mainly focused on applications for scheduling, capacity planning, and production control. Other studies have focused on improvement of the integrity and consistency of production feedback data for uses in advanced planning and scheduling (APS) systems and production control [22, 23, 25]. However, more research is needed into the usefulness of production feedback data for master data and tactical planning.

2.3 Planning Quality

Planning quality is a commonly used term to indicate how good production planning is [26]. Planning quality can be understood as a key indicator for the planner to assess the reliability of the production plan in the planning phase and to continuously improve the operational reliability of production plans in forthcoming phases [27, 28]. Lingitz and Sihn [28] further define high planning quality as production planning where there are no deviations, or at least deviations within an acceptable range, between the production plan created in advance and the actual execution on the shopfloor. The deviations can be caused by uncertainties such as inaccurate or incomplete planning data, unforeseeable external events, or inappropriate PPC systems. Planning quality can also be assessed with regards to planning accuracy and plan stability [26].

Planning quality is influenced by the cognitive strengths and weaknesses possessed by human production planners [14]. The limitations to manual planning presented in section 2.1 can thus also impose negative effects on the planning quality if the ability of the planner is insufficient in terms of translating the real-life capabilities of the company into production plans.

The quality of planning, and thus also the success of PPC, is further highly dependent on the quality of the master data used in planning. Quality can be reduced due to the static nature of master data utilized for scheduling, which might for instance not accurately reflect the current state of the shopfloor [21].

In general, planners do not frequently change master data in planning systems such as ERP [19]. Consequently, the current state of the shopfloor is not incorporated into the planning system and can lead to discrepancies between master data and the actual shopfloor situation. One study in a medium-sized mechanical engineering enterprise found that deviations between production plans and the actual execution on the shopfloor could be as high as 75 % if the production plans were generated three days ahead [29]. This illustrates the importance of companies having updated master data in the system. A company should be able to swiftly adapt plans based on data from the shopfloor to avoid consequences such as higher than necessary inventory levels, longer lead times, or bad adherence to promised delivery dates [22].

The quality of the master data is also susceptible to errors from the planners or other users. Lindström, Persson [30] showed that several of the most prevalent data quality problems in production planning could be caused by human errors, such as negligence causing changing task needs, inexperience causing data production errors, and user's ignorance, inexperience or inattention causing inaccurate data entries.

2.4 Smart Production Planning and Control

With technological developments, Industry 4.0 has opened a trend toward creating self-controlled operations and integrated systems. Industry 4.0 can be defined as "an integrated, adapted, optimized, service-oriented and interoperable manufacturing process in which algorithms, big data, and high technologies are included " [31]. Industry 4.0 technologies such as the internet of things (IoT), big data analytics (BDA), and cyber-physical systems (CPS) lead to the creation of enormous amounts of data and have the potential to revolutionize production operations [32].

Building on the Industry 4.0 framework, smart PPC has emerged where Industry 4.0 technologies and capabilities are integrated into PPC to improve the performance of the production system by enabling real-time, data-driven decision-making and continuous learning with input from a more diverse range of data sources [10]. Smart PPC should, in general, perform better than traditional PPC since it uses a huge variety of endogenous data from the production system and external data from its environment [10].

Beyond studies on smart PPC reported in scientific literature, there is a plethora of commercial actors offering smart PPC and manufacturing solutions. The German software company Seeburger AG claims that real-time data captured from production lines can be used in their business integration suite to optimize planning by minimizing setup times, maximizing machine utilization and ensuring that delivery times are met [33]. The supply chain software supplier Flexis AG posits that their system through real-time data can foster more accurate short- and mid-term planning, providing competitive advantage through improved planning capabilities [34]. These are just two examples of commercial actors claiming that their solutions support planning tasks with the help of data specifically captured from production lines. The main limitation of such offerings is that while the suppliers promise improved production planning, their claims are not yet supported by academic research or empirical evidence.

2.5 Research Opportunities

The presentation of the theoretical background underpinning this study highlighted some pertinent challenges and interesting opportunities for research on smart PPC. First, Industry 4.0 has facilitated large-scale data collection from a variety of sources, including production feedback data. Second, there is a need for more research on the potential utilization of such production feedback data into tactical planning beyond the conceptual level. Third, research shows that it is vital for companies to have robust and reliable master data due to its direct effect on planning quality. Fourth, the fact that master data is generally updated on an infrequent basis lead to discrepancies between the master data and the situation on the shopfloor. Finally, there is a need for a systematic approach for identifying production data that can be fed back into the master data for planning. While some master data does not vary over time, some of the master data for planning should instead be dynamically determined based on analysis of production feedback data.

3 Concept for application of production feedback data in tactical production planning

In 2020, Oluyisola, Sgarbossa [10] explored the potential of smart PPC to improve the performance of the production system through the use of more dynamic and reactive data from the production system. Building on the works of Garetti and Taisch [35] and Bonney [36], the authors adapted the established Vollmann, Berry [9] PPC framework by adding feedback loops that are witnessed in real life production systems – with particular focus on the tactical and operational PPC levels where such loops are more frequent and important [36]. However, the proposed framework only conceptually links lower planning levels and PPC process with higher levels through feedback loops on performance, notably material use performance, capacity use performance, purchasing performance, and system performance. Thus, the framework does not specify the type of data and how the data from lower levels can be used in higher-level planning processes.

As mentioned in section 2, the quality of planning processes, especially MRP and CRP, is highly dependent on the master data used in planning. However, due to the static nature of master data, the current state of the shopfloor is typically not reflected in these tactical planning processes [21], leading to a potentially large deviation between the planned production and the actual execution of the plan on the shopfloor. Therefore, exploiting production feedback data from the shopfloor to analyze and update master data can potentially improve the quality of the material and capacity plans. To reflect this, the framework of Oluyisola, Sgarbossa [10] was adapted and extended by showing how data captured on the shopfloor level should be fed into master data rather than directly into the tactical level planning processes. This better reflects the need to process, combine and analyze such feedback data before it is used in planning processes. The proposed concept is illustrated in **Fig. 1**.

The concept was developed through workshops and discussions among researchers, building on existing concepts and frameworks, as well as decades of experience from working on PPC issues in collaboration with industrial companies in a variety of production environments and industrial sectors.

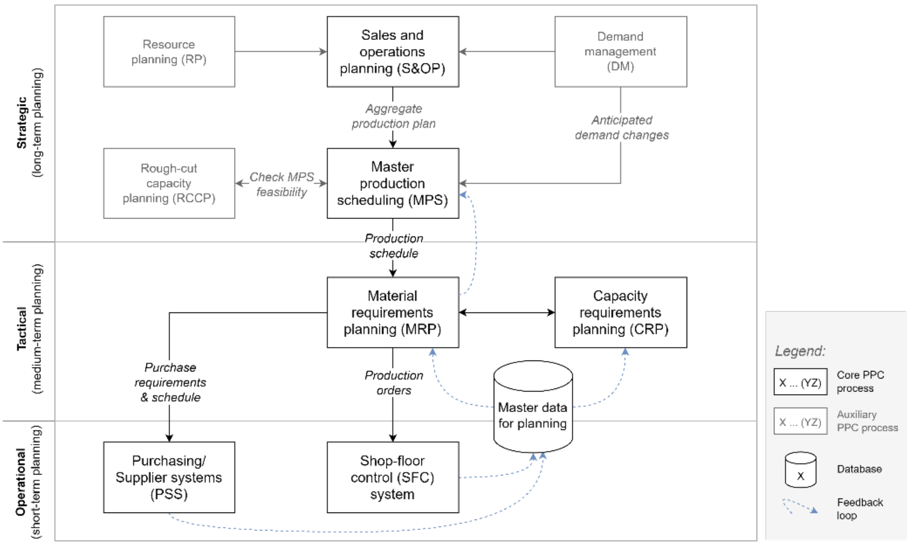

Fig. 1. Conceptual model for application of production feedback data into tactical production planning [based on 10]

3.1 Linking Master Data with Production Feedback Data

The model in **Fig. 1** conceptually illustrates feedback loops where data captured on the shopfloor is fed into master data for planning. The feedback data can be analyzed to provide decision makers with a better understanding of the input data used in tactical planning. As highlighted in section 2.5, some types of master data should potentially be dynamic because the values can vary over time. Thus, companies should analyze production feedback data to determine which master data should remain static and which data should be dynamically determined. Further, feedback data can be used to determine and validate the static master data.

Fig. 2. conceptual model for application of production feedback data into MRP is based on Strandhagen, Romsdal [37] and illustrates how the net requirements calculation of the MRP process is based on both static and dynamic information. The figure's starting point is the traditional generation of the MPS based on customer orders and forecasts. Further, dynamic information on scheduled receipts, inventory levels, and work in process are taken into consideration in the calculation of the net requirement. Then, two master data boxes represent the use of production feedback data to: 1) validate static master data, and 2) dynamically determine master data that is variable. Both

types of master data are then used to calculate the net requirements. The output of the net requirements calculation is a set of purchase and production orders.

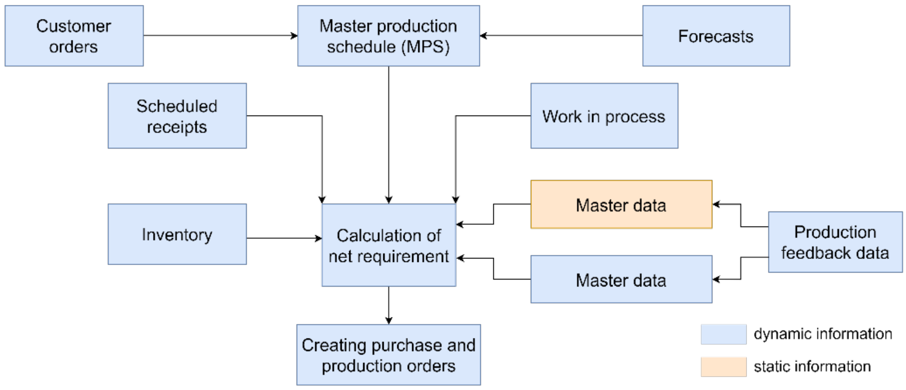

Fig. 2. Conceptual model for application of production feedback data into MRP [based on 37]

The quantity coefficient expressed in the BOM, i.e., the required quantities of items to produce a finished product, illustrates the difference between static and dynamic master data [13]. If the historic feedback data shows that the quantity is constant over time, between different batch sizes, between machines, etc., the coefficient can be a static parameter in the master data. However, if the data shows that it is not constant, it could be relevant for planners to determine the quantity dynamically using current data from the production line and use this input to the plan for the upcoming period.

To further illustrate the potential link between master data and production feedback data, a list of common master data was compiled. The list was collected from scientific and ERP system literature, mainly based on Kurbel [13] and Jakubiak [19]. The list was subsequently analyzed in workshops and discussions among the authors to identify the master data most relevant for tactical planning. Master data without a clear link to MRP or CRP (e.g., physical characteristics of parts and necessary operator skills) or to production operations (e.g., organizational data, replenishment time for parts, and machine cost rates) was excluded. Next, the list of master data relevant for tactical planning was used as inspiration for brainstorming in workshops and discussions to identify examples of data typically captured on the shopfloor which could be linked to each of the master data types. For each master data, examples of relevant production feedback data were identified, along with the formulas for how the master data could be calculated based on the production feedback data and examples of the application. The result is presented in **Table 1**.

Table 1. Examples of links between master data for tactical planning and production feedback data

Category	Master data for planning	Examples of relevant production feedback data	Formulas and examples of application in tactical planning
Part or component	Scrap rate per part	Number of parts consumed per batch. Number of scrapped parts per batch.	Formula: number of scrapped parts / number of parts consumed. Used in calculation of net requirement for parts.
Product	Quantity coefficient per product	Number of units produced per batch. Number of input units or number of raw materials consumed per batch.	Formula: number of input units / number of units produced. Used to determine the number of parts or input units in the BOM.
	Scrap rate per product	Number of units produced per batch. Number of scrapped units per batch.	Formula: number of scrapped units / number of units produced. Used in calculation of gross requirement for units.
Resource	Processing time per unit	Start and end time per batch (i.e., production run). Number of units produced per batch. Start and end times of stops (within batch).	Formula: batch time (end time – start time) – total stop times (end time – start time, per stop) / number of produced units. Used in CRP and scheduling.
	Changeover time per resource	End time of previous batch and start time of next batch.	Formula: sum of time for activities for switching from one batch to another. Used in CRP (assumes non-sequence dependent changeover times) and scheduling.
	Scrap rate per resource	Number of units produced per resource. Number of scrapped units per resource.	Formula: number of scrapped units per resource / number of units produced per resource. Used in calculation of CRP and scheduling.

In the table, the *part* category refers to all elements of the finished product, including the finished product itself and all additional elements required to make the finished product [13]. The *product* category provides insight into the parts which constitute a product and their relationships. The *resource* category refers to the machines and tools in the production facility used to produce parts or products and where data is potentially generated and captured [13]. The *quantity coefficient per product* is defined as the required quantities of items to produce a finished product [13]. *Scrap rate* expresses the percentage of scrapped defective units that will not enter the rework process [38] and is identified per material, product, and resource. *Processing time* expresses the required time to process a product, while *changeover time* is the time required to prepare a resource for changing from producing the last unit of a former batch to producing the first unit of the new batch [39].

It should be noted that although capacity is a key parameter used in planning, it is not included in the master data overview. This is because capacity is not an objective value that can be captured from the production system but rather a subjective decision by the company, for instance the duration and number of shifts per day.

3.2 Method for Application of Concept

A step-by-step method for the application of the concept in companies was developed in workshops and discussions among researchers, with inspiration from the control model methodology for the improvement of production and logistics [40, 41]. The proposed method consists of four main steps: mapping, analysis, design, and implementation. The steps can be carried out in parallel and cycles rather than strictly in a linear sequence. This allows for findings from one phase to guide e.g., supplementary data collection and analyses in previous steps. The method requires involvement and collaboration throughout different company functions, involving production managers, planners, shopfloor operators, IT, forecasting, sales, marketing, etc.

Below, each step is briefly described regarding objectives, main activities, and results.

Step 1; mapping. The objective of step 1 is to collect data to create a structured description and understanding of the company's production processes, current operations, and planning and control. This includes a detailed overview of the company's inherent data capture and its capabilities. The mapping should identify production data that is currently captured, as well as how, from where, and how often the data is captured. The company should also create an overview of production data that they are not currently capturing, but which could be useful for planning. Alongside the mapping of production data, a comprehensive list of the master data currently used for planning should be created.

Step 2; analysis. The objective for the analysis phase is to analyze the data collected in step 1. The step should; 1) identify which production data is relevant to use as feedback into master data for planning, and 2) determine which master data for planning should be static and which should be dynamic.

The lists of master data for planning and production feedback data from step 1 serve as starting points for the analyses. First, potential links between master data for planning and production data should be identified, where master data with no clear link to production planning is excluded. Next, for each type of master data, relevant production feedback data should be identified (for example, see **Table 1**). The result is an overview of links between master data and production feedback data.

Once the relevant production feedback data has been identified, it should be determined whether each data type should be static or dynamically determined in each planning cycle. For this, historic production data should be analyzed to identify if or how the data varies over time and whether it is random or it can be accurately predicted. Data that does not appear to vary over time can be classified as static parameters in the master data and the analyses can be used to validate the values used for instance in the ERP system. Data that is found to vary over time should be classified as dynamic parameters, where historic production feedback data is analyzed to accurately determine values in each planning cycle.

Step 3; design. In this step, the company should determine, standardize, and describe how production feedback data should be used in planning in the future. This includes specifying which production feedback data to capture, how often and where, and how it should be processed. Further, it should provide planners with a description of how to use production feedback data in planning, including the frequencies with which static master data should be analyzed or validated, which analyses to carry out to determine the static input parameters in each planning process, and thresholds that should trigger reassessment of the classification of static and dynamic planning parameters. In addition, it should be specified how production feedback data should be cleaned and potentially combined with other data before it is used for planning purposes.

Step 4; implementation. The final step is implementation of the solution designed in step 3. This will involve planners, IT staff, shopfloor operators and production managers. The new solution should be implemented into the company's planning processes, the company's ERP system and other planning tools used by planners.

4 Conclusions and Directions for Further Research

This paper explored the opportunities for applying production feedback data into tactical production planning, with a main focus on MRP. The developed conceptual model for how production feedback data can be linked to MRP goes beyond previous studies by specifying how this data can contribute to more dynamically determined key input data to the MRP process. In addition, the feedback data can be used to verify and continuously monitor static master data to ensure that planning is based on accurate, realistic, reliable, and current data. The feedback data can in such a way contribute to higher planning quality. In addition, use of more up-to-date data reflecting the situation on the shopfloor reduces discrepancies between planning and execution, which can lead to better plan stability. On the other hand, the continuous monitoring of production feedback data can also enable a company to swiftly adapt plans to shopfloor events and conditions. The proposed concept further challenges the established view of master data as something stable and invariable, thus contributing to overcoming the ‘set it and forget it’ challenge of a lot of IT systems. The emergence of Industry 4.0 provides new opportunities for re-examining the use of data in tactical planning, potentially improving the accuracy of planning data by using actual data from the production line rather than simply static master data.

In **Table 1**, the paper illustrates how production feedback data can be applied in tactical planning by linking master data for planning with relevant data from the shopfloor. This list is not exhaustive and will vary by company depending on the characteristics of their products and production system, as well as their infrastructure for data capture.

The proposed method assists companies in implementing the use of production feedback data into their planning. This highlights the importance of analyzing the company's available historic production feedback data in order to identify which data to capture on the shopfloor. Companies can, for instance, differentiate between essential, important, and optional feedback points for data capture [24]. Further, companies must determine whether data should be monitored continuously to assess the accuracy of the static master data or if the data only needs to be verified or recalculated at regular intervals. And for master data that should be dynamically determined in each planning cycle, the company should ensure the necessary data and tools for analysis are available to planners.

The study's contributions are not only useful for improving planning quality. The insights from analyzing production feedback data can also provide companies with a starting point for improvement efforts to reduce or control variation on the shopfloor.

Although the concept was developed with a specific production environment in mind, the approach can also have merit in other production environments. For instance, for production environments with flexible routing and sequences, data from the shopfloor can provide better insights on routings and sequence-dependent changeover times.

Future work includes application and testing of the proposed concept in real-life cases. Future research should also be conducted to better understand the specific relationship between the accuracy of master data and the performance of production plans. This could be done using a model-based approach with sensitivity analysis to identify how different types of production feedback data affect planning quality. Another interesting avenue for further research is to investigate how production feedback data can be used in dynamic production scheduling to identify and manage unexpected events.

Acknowledgements. The research presented in this paper was conducted as part of the DigiMat project, with financial support from NTNU, the participating companies, and the Research Council of Norway.

References

1. Zhou, K., T. Liu, and L. Zhou, *Industry 4.0: Towards future industrial opportunities and challenges*. 2015. 2147-2152.
2. Oluyisola, O.E., *Towards Smart Production Planning and Control: Frameworks and case studies investigating the enhancement of production planning and control using internet-of-things, data analytics and machine learning*. 2021: NTNU.
3. Rahmani, M., et al., *Towards smart production planning and control; a conceptual framework linking planning environment characteristics with the need for smart production planning and control.* Annual Reviews in Control, 2022.
4. Arica, E. and D.J. Powell, *A framework for ICT-enabled real-time production planning and control.* Advances in Manufacturing, 2014. **2**(2): p. 158-164.
5. Van Nieuwenhuyse, I., et al., *Advanced resource planning as a decision support module for ERP.* Computers in Industry, 2011. **62**(1): p. 1-8.

6. Hees, A. and G. Reinhart, *Approach for production planning in reconfigurable manufacturing systems.* Procedia Cirp, 2015. **33**: p. 70-75.
7. Meyer, G.G., J. Wortmann, and N.B. Szirbik, *Production monitoring and control with intelligent products.* International Journal of Production Research, 2011. **49**(5): p. 1303-1317.
8. Slack, N., A. Brandon-Jones, and R. Johnston, *Operations Management (7th edition)*. 2013: Pearson.
9. Vollmann, T.E., et al., *Manufacturing Planning and Control for Supply Chain Management.* 2005, New York: McGraw-Hill.
10. Oluyisola, O.E., F. Sgarbossa, and J.O. Strandhagen, *Smart production planning and control: concept, use-cases and sustainability implications.* Sustainability, 2020. **12**(9): p. 3791.
11. Jacobs, F.R., et al., *Manufacturing planning and control for supply chain management: APICS/CPIM Certification Edition*. 2011: McGraw-Hill Education.
12. Higgins, P., P. Le Roy, and L. Tierney, *Manufacturing planning and control: Beyond MRP II*. 1996: Springer Science & Business Media.
13. Kurbel, K.E., *Enterprise resource planning and supply chain management.* Functions, Business Processes and Software for Manufacturing Companies. Progress in IS. Springer, Dordrecht, 2013.
14. De Man, J.C. and J.O. Strandhagen, *Spreadsheet application still dominates enterprise resource planning and advanced planning systems.* Ifac-Papersonline, 2018. **51**(11): p. 1224-1229.
15. De Man, J.C., et al., *Planning and control frameworks of the future.* International Journal of Mechatronics and Manufacturing Systems, 2020. **13**(3): p. 199-209.
16. Klaus, H., M. Rosemann, and G.G. Gable, *What is ERP?* Information Systems Frontiers, 2000. **2**(2): p. 141-162.
17. Häkkinen, L. and O.P. Hilmola, *ERP evaluation during the shakedown phase: lessons from an after-sales division.* Information systems journal, 2008. **18**(1): p. 73-100.
18. Sagegg, O.J. and E. Alfnes, *ERP systems for manufacturing supply chains: applications, configuration, and performance*. 2020: CRC Press.
19. Jakubiak, M., *The Concept of Minimizing Master Data in The Production Planning Process on The Example of ERP Software.* 2021.
20. Knolmayer, G.F. and M. Röthlin. *Quality of material master data and its effect on the usefulness of distributed ERP systems*. in *Advances in Conceptual Modeling-Theory and Practice: ER 2006 Workshops BP-UML, CoMoGIS, COSS, ECDM, OIS, QoIS, SemWAT, Tucson, AZ, USA, November 6-9, 2006. Proceedings 25*. 2006. Springer.
21. Geiger, F. and G. Reinhart, *Knowledge-based machine scheduling under consideration of uncertainties in master data.* Production Engineering, 2016. **10**: p. 197-207.
22. Schuh, G., et al., *Achieving higher scheduling accuracy in production control by implementing integrity rules for production feedback data.* Procedia CIRP, 2014. **19**: p. 142-147.
23. Reuter, C. and F. Brambring, *Improving Data Consistency in Production Control.* Procedia CIRP, 2016. **41**: p. 51-56.

24. Schäfers, P., A. Mütze, and P. Nyhuis, *Integrated Concept for Acquisition and Utilization of Production Feedback Data to Support Production Planning and Control in the Age of Digitalization.* Procedia Manufacturing, 2019. **31**: p. 225-231.
25. Schuh, G., et al., *Increasing data integrity for improving decision making in production planning and control.* CIRP Annals, 2017. **66**(1): p. 425-428.
26. Lucht, T., et al., *Model-Based Approach for Assessing Planning Quality in Production Logistics.* IEEE Access, 2021. **9**: p. 115077-115089.
27. Ryback, T., et al., *Improving the planning quality in production planning and control with machine learning.* 2019.
28. Lingitz, L. and W. Sihn, *Concepts for improving the quality of production plans using machine learning.* ACTA IMEKO, 2020. **9**(1): p. 32.
29. Schuh, G., et al. *Cyber-physical production management*. in *Advances in Production Management Systems. Sustainable Production and Service Supply Chains: IFIP WG 5.7 International Conference, APMS 2013, State College, PA, USA, September 9-12, 2013, Proceedings, Part II*. 2013. Springer.
30. Lindström, V., et al., *Data quality issues in production planning and control – Linkages to smart PPC.* Computers in Industry, 2023. **147**: p. 103871.
31. Lu, Y., *Industry 4.0: A survey on technologies, applications and open research issues.* Journal of industrial information integration, 2017. **6**: p. 1-10.
32. Koh, L., G. Orzes, and F.J. Jia, *The fourth industrial revolution (Industry 4.0): technologies disruption on operations and supply chain management.* International Journal of Operations & Production Management, 2019. **39**(6/7/8): p. 817-828.
33. Holicki, R. *Using real-time data in smart manufacturing*. 2022 [cited 2023 01/05]; Available from: https://blog.seeburger.com/using-real-time-data-in-smart-manufacturing/.
34. Ostdick, N. *How real-time enhances planning and production*. 2017 [cited 2023 01/05]; Available from: https://blog.flexis.com/how-real-time-enhances-planning-and-production.
35. Garetti, M. and M. Taisch, *Neural networks in production planning and control.* Production Planning & Control, 1999. **10**(4): p. 324-339.
36. Bonney, M., *Reflections on production planning and control (PPC).* Gestão & produção, 2000. **7**: p. 181-207.
37. Strandhagen, J.O., A. Romsdal, and J.W. Strandhagen, *Produksjonslogistikk 4.0*. Vol. 1. 2021: Fagbokforlaget.
38. Chiu, S.W., C.-K. Ting, and Y.-S.P. Chiu, *Optimal production lot sizing with rework, scrap rate, and service level constraint.* Mathematical and computer modelling, 2007. **46**(3-4): p. 535-549.
39. Mali, Y.R. and K. Inamdar, *Changeover time reduction using SMED technique of lean manufacturing.* International Journal of Engineering Research and Applications, 2012. **2**(3): p. 2441-2445.
40. Alfnes, E., *Enterprise reengineering–a strategic framework and methodology*. 2005, Trondheim: Norwegian University of Science and Technology.
41. Alfnes, E. and J.O. Strandhagen, *Enterprise design for mass customisation: The control model methodology.* International journal of logistics, 2000. **3**(2): p. 111-125.