

9th International Conference on Digital Enterprise Technology - DET 2016 – “Intelligent Manufacturing in the Knowledge Economy Era

A flexible simulation support for production planning and control in small and medium enterprises

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Abstract

For efficient, effective and economical production operation management in a manufacturing unit of an organization, it is essential to integrate the production planning and control system into an enterprise resource planning. Today's planning systems suffer from a low range in planning data which results in unrealistic delivery times. One of the root causes is that production is influenced by uncertainties such as machine breakdowns, quality issues and the scheduling principle. Hence, it is necessary to model and simulate production planning and controls (PPC) with information dynamics in order to analyze the risks that are caused by multiple uncertainties. In this context, a new approach to simulate PPC systems is exposed in this paper, which aims at visualizing the production process and comparing key performance indicators (KPIs) as well as optimizing PPC parameters under different uncertainties in order to deal with potential risk consuming time and effort. Firstly, a production system simulation is created to quickly obtain different KPIs (e.g. on time delivery rate, quality, cost, machine utilization, WIP) under different uncertainties, which can be flexibly set by users. Secondly, an optimization experiment is conducted to optimize the parameters of PPC with regard to the different KPIs. An industrial case study is used to demonstrate the applicability and the validity of the proposed approach.

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Peer-review under responsibility of the scientific committee of the 5th CIRP Global Web Conference Research and Innovation for Future Production

Keywords: Production Planning and Control, On-time delivery, Modeling and simulation, Simulation-based optimization

1. Introduction

PPC addresses a fundamental function of productivity, management and resource utilization [1]. A survey among companies of machine and plant engineering illustrates that today's planning systems suffer from low quality and low range in planning data, which results in unrealistic delivery times [2]. It leads to the dilemma of PPC, namely it is to achieve high process efficiency, low throughput times and good planning confidence in spite of a turbulent environment with uncertainties such as dynamic factory changes, constraints, short product lifecycles, an increasing variety and a growing individualization of demand [3].

In most cases, production planning is addressed manually by practitioners, even in modern production with sophisticated automated systems. This manual process is time-consuming,

sub-optimal (as only few alternatives are considered) and completely dependent on the planner's expertise [4]. Additionally, it is well known that in the make-to-order sector an order spends up to 90% of the total time in production waiting in front of or between work centers and only 10% in actual transformation work on the machines. [5].

All above discussed challenges require that the company is able to act in its flexible PPC which can response to unpredicted situations. It is necessary to model and simulate PPC with information dynamics in order to analyze the risks which are caused by multiple uncertainties. In this context, the produced approach focuses on a flexible simulation system of medium-term of PPC with integrated internal production systems and system variants (e.g. scheduling policies, machine breakdown, quality issues, processing time fluctuation) as well as external customer forecast orders. The main objective is to

build a flexible simulation system for medium-term PPC analysis based on the forecast and different uncertainties so that the companies can design a more feasible production plan in shorter time and update it flexibly to fulfil their production target. Furthermore, it provides the chance to make transparent design processes so that the production planning staff can reduce their workloads by using this simulation system. In chapter 2, the current state of the art in literature regarding this topic is presented. The developed method is elaborated in chapter 3. Finally, chapter 4 concludes with a summary.

2. State of the art

Regarding this topic, several approaches have been discussed in the research community. Alvandi presents a simulation-based approach to model energy and material flow and considers the hierarchical structure of energy and material consumers within the system. An evaluation of the improvement strategies on energy and material efficiency was investigated [6]. Stricker identifies and evaluates the appropriate enablers for robustness for specific production systems. Multi-objective decision support models are created to evaluate the best enablers for the levels of production network, plant and shop-floor [7]. Volling builds a framework comprising separate interlinked quantitative models for order promising and master production scheduling and evaluates their potential using simulation [8]. Lee illustrates how simulation-based shop-floor planning and control can be extended to enterprise-level activities (top floor). Nevertheless it only focuses on the transformation between shop floor and top floor [9]. Chakravorty finds the performance of Drum-Buffer-Rope (DBR) to be very sensitive to changes in the levels of free goods (FG) released into the operation based on the simulation of a job shop operation. Contrary to the way FG have been treated in the past, schedulers using DBR need to be cognizant of how orders of these items are accepted and scheduled [10]. Duffie focuses on classical control theoretical modelling of transient behaviour and fundamental dynamics of production planning and control, which generally is considered to include scheduling, sequencing, loading and controlling [11]. Gyulai presents a planning and control methodology, which is based on adaptive calculations. Besides, historical data is used as direct input of discrete-event simulations to determine the proper control policies of human operator allocation for the different scenarios [12]. Auer describes an integrated planning solution for the harmonization of sales, purchasing, supply chain and production planning along the planning cascade. By harmonizing, cost savings and additional value potential is realized [13]. Georgiadis develops a system dynamics model to support the decision-making on time-buffer policies [14]. Baldea defines several necessary directions for future development as well as a complement of promising application [15]. Leng proposes an optimal allocation mechanism based on the Theory of Constraints in face of meeting peak demand in a certain period for the whole system. A genetic algorithm has been selected for solving the optimization model [16]. Seitz clarifies the advantages of cyber-physical system (CPS) in view of production planning,

controlling and monitoring. The order processing is improved through logistics models with CPS [17]. Chen inspects the effectiveness of three manufacturing rules (line balance, on-time delivery, bottleneck utilization) in terms of three important performance metrics (effective WIP (work-in-process), on-time delivery, bottleneck loading). Guidelines for manufacturing rule selection are provided [18]. Grundstein presents a quantitative, three-dimensional evaluation system. It allows for a complete quantitative evaluation of autonomous control in production systems. [19]. Suwa introduce new approaches to online scheduling based on a concept of cumulative delay. This approach can reduce frequent schedule revisions and avoid overreacting to disturbances and simplify the monitoring process of a schedule status [20]. Golmohammadi provides a number of simulation scenarios of a master production schedule and the drum-buffer rope (DBR) scheduling method. The optimization techniques are used to find optimal and/or satisfactory solutions for input variables in the simulation experiment [21]. Yan presents an algorithm whose complexity is unrelated to the batch size to obtain the starting time of a batch production. A heuristic method based on a genetic algorithm is constructed to solve the splitting and scheduling problems simultaneously [22].

Overall, existing approaches are providing PPC improvement through optimized algorithms in modelling and simulation. However, they take the production system framework and production process uncertainties into account insufficiently. Secondly, these approaches are not flexible enough and cannot be easily adapted to different segments of industries.

3. Methodology

The presented approach helps to overcome this gap mainly in two steps. In a first step, a PPC simulation system is created which integrates internal production systems and system uncertainties as well as external customer forecast orders. It can quickly obtain the KPIs (on time delivery rate, quality, cost, machine utilization, WIP) under the different uncertainties. In the first step, the hierarchy of the system, structure of the data base, the initiation of the concept module, and the flexible simulation system are developed.

Secondly, the preliminary optimization experiment to find out the optimized PPC parameters in order to achieve better KPI results under the specific situation are produced.

3.1. Hierarchy of the system

According to the VDI-3633 procedure, the establishment of simulation system starts from preparation phase. The whole structure includes four elements, which are basic production system, customer order forecast, uncertainties, KPIs. Customer order forecast as one of the key inputs mainly consists of product name, order quantity, due date and customer code. Regarding the uncertainties, the machine break down indicator (MTTF, MTTR), scheduling policies (first in first service, earliest due date, shortest processing time), quality issues (rework rate, scrap rate) and customer issues (rush order) are included. The KPIs present the simulated

results, for instance, on-time delivery rate, quality rate, inventory, cost information.

On the basis of the analysis above, the hierarchy of the system is integrated by three different levels which are defined

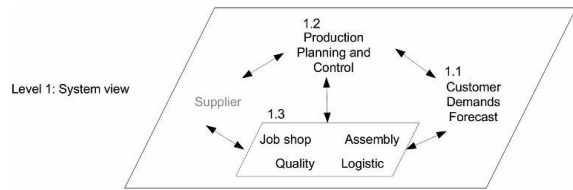


Fig. 1. System views of modelling and simulation

as system view, process view and unit process. In the first level, system view is initially created (cf. Figure 1).

Customer demand forecast contains information about customer requirements of goods. It includes the order information, such as the product number, product name, the quantity and the due date for delivery. This information is the starting point and basis for the production plan and execution. The second part production planning and control provides the guideline how to execute the production in an efficient way, which integrates the consideration of different principles of scheduling, dispatch, inspection, quality management, and inventory management. The third part is about production, namely job shop and assembly. Besides production, the quality and logistics aspects should be also considered in this production system. Since this paper is mainly focusing on the internal production planning and control, the supplier aspect is not integrated into this system.

The second level is process view which means machining, assembly, quality check etc. Every station is considered as one entity. For instance, if the first process is turning, all relevant information of this process such as processing time, quality rate are considered. In this paper the machining process is mainly focused.

The third level is unit process view which includes more details of one process, namely it consists of start loading, production, unloading and finish. Later on, this differentiation is helpful for making time measurement analysis such as calculating value adding and non-value adding.

3.2. Structure of the data base of the system

A data flow diagram (DFD) is a graphical representation of the "flow" of data through an information system, modelling its process aspects. A DFD is often used as a preliminary step to create an overview of the system, which can later be elaborated. DFDs can also be used for the visualization of data processing. Figure 2 shows the information flow in the simulation system. The customer will create the demand forecast in the very beginning. During this period, the customer can still update the demand forecast once there are some information changes. The order is created accordingly. This information will be forwarded to the production planning and control module. After the scheduling principle is selected, all the information will be formed as demand information and transferred to the production basic system, which will start to produce by job machine, logistics, assembly and quality

control. The production status information will be summarized and send back to the production planning and control, then it will be further forwarded to the customer in the end.

To transfer the real working conditions into the simulation system, the data dictionary that refers to items such as data

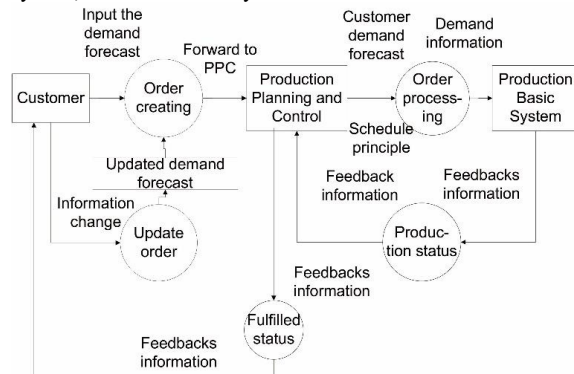


Fig. 2. Overview of data flow

structure, data flow, data storage and processing logic is applied. Through data dictionary, the external entities are defined and described in the system that is necessary to improve the analysis.

With the customer module, for example, the items of data, namely, customer ID, order number, product ID, quantity, due date are considered. All of them are set to integer types in this module. Afterwards the data structure which reflects the combination of the relationship between data items is carried out. Further on, a data structure in the system transmission path and data storage is worked out. Regarding data processing, all the data is transferred on the basis of process. For instance, the job shop starts production and provides feedbacks information once it receives the demand information. Therefore, the information input is demand information, and the corresponding output is feedback information.

3.3. Initiation of the conceptual model

The conceptual model is a simplified model of the real system. In this paper, the conceptual model consists of agents and fixed parameters as well as variables. For instance, the transportation between processes in the reality is simplified to a "conveyor" agent with defined parameters or variables such as length, space between entities, speed in Figure 3.

3.4. Creation of the simulation system

Based on the conceptual model, the simulation program is further developed by considering the several factors such as input/output data, data transformation and uncertainties.

conveyor- Conveyor

Name: Showname

Entityclass:

Lengths: = Specified explicitly
 Defined by path

Length =

Space: =

Speed: =

Fig. 3. Conceptual model of transportation

The scheduling policies are taken as one example to illustrate how to model the uncertainties in the initiative phase. It is well known that scheduling is a decision process that is used on a regular basis in many manufacturing and services industries. It deals with the allocation of resources to tasks over given time periods and its goal is to optimize one or more objectives. For a production facility that is capable of manufacturing multiple products, production scheduling aims to identify the order (sequence) in which the products should be manufactured, the assignment of tasks to equipment and exact timing of the operations, which maximize profit while meeting the demand (quantity) of each product in a given time frame. Here, three principles are considered as uncertainties, namely first come first service (FCFS), shortest processing time (SPT), earliest due date first (EDD). The notation is illustrated as followed,

n jobs have to be processed on m machines, each job can be worked on by at most one machine at a time and each machine can work on at most one job at a time. p_{ij} is processing time of job j on machine i (includes setup times of the machine and transportation times of the job), d_j is time at which the processing of job j is due to be completed. w_j describes the urgency or importance of job j . The scheduling principle and rush order are realized based on the value of w_j in the system as formula (1) showed.

$$w_j = \begin{cases} 1, & FCFS \\ \text{Max } w_j - d_j, & EDD \\ \text{Max } w_j - p_{ij}, & SPT \\ \text{Max } w_j & \text{rush order} \end{cases} \quad (1)$$

The maximum w_j is set to be value 21,000,000. According to FCFS, jobs are executed in the order of their arrival. w_j is equal to one for all jobs j . The EDD schedules the jobs in increasing order of their due dates. This priority rule is carried out by using maximum w_j minus completion due date. For instance, the due date is on March 15th, 2016, and then the priority w_j is 21,000,000 minus 2,016,0315, namely 838,685. The SPT schedules the jobs in increasing order of their processing times. The priority rule is represented by using maximum w_j minus processing time. For the rush order, the priority is set to be maximum value of w_j .

The scheduling policies are transferred into modelling by identifying w_j of each part and the priority is further transparently transmitted in the whole system. Next to the priority, the other properties such as product ID, due date can also be tracked in the simulation system in Figure 4.

According to the formal modelling, a production planning and control simulation system are built by four segments, respectively data input window, process execution window, KPIs results window and statistics of work in process (WIP).

The data input window consists of customer forecast information such as lot number, product number, quantity, due date, part cost and processing time. The uncertainties can be easily set by users (e.g. process time fluctuation, machine/resource breakdown, rework rate, scrap rate, batch size, scheduling policies, parts per arrival). Secondly, in the process execution window, the dynamics status can be observed by users and the production execution process is transparent and visualized. Furthermore, in the KPI window on-time delivery rate, quality, cost are analyzed at the same time. For all

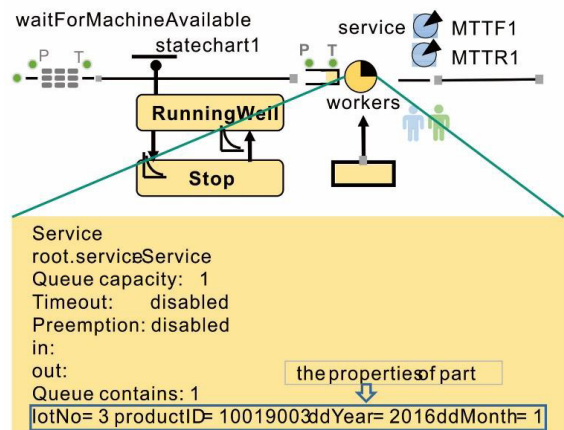


Fig. 4. Transparent information in system

KPIs it is possible to make comparisons based on the different uncertainties. Since its cost is crucial in the production, the WIP information is recorded in the WIP window while implementing the simulation.

Based on the simulation system, it is able to evaluate the impact of different uncertainties. Here the on-time delivery rate is set as the target and the scheduling policies as the uncertainty. The system is able to evaluate fast which scheduling policy is optimal in the specific situation.

3.5. Optimization experiments of the simulation system.

Through the simulation experiment it is realized to analyze fast the impact of uncertainties within a specific situation. However, in reality some input parameters are variable such as batch size and parts per arrival. The optimized values for these variables play a significant role for the planning staff of a company. Therefore the optimized experiment is created to solve this problem. The optimization process is built on top of the OptQuest Optimization Engine, which can automatically find the best parameters of a model, with respect to certain constraints.

4. Case Study

A case study at a Chinese medium size machining company, entitled Company W, is executed as pilot

experiment. The products are mainly aluminum products which are further delivered to customers. The abstract production flow chart in Figure 5 shows that the company prepares the raw materials parts according to the customer demand. The first step is turning and executes the quality check. The good parts will be further transported to the next process station based on two options. Product type one will be milled and tested, and then the product is finished. Accordingly the type two will execute cleaning and make further assembly. Then the finished product is accomplished after the quality test

The basic situation is that the machining department receives the forecast information of three types of products. The due date, processing time and quality rate as well as machine breakdown indicators are given. Then the outputs of the simulation shows that scheduling policy SPT is better

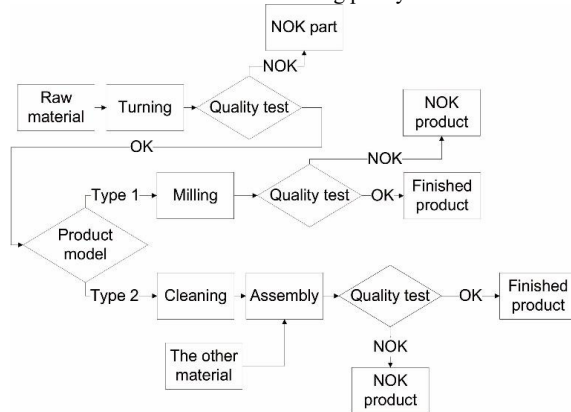


Fig. 5. Production process flow chart

than the others in this specific situation. With support of simulation, the planning staff save fifty per cent of the time (one hour reduces to thirty minutes) in comparison with the previous manual planning process in Table 1.

Table 1. Summary of on-time delivery performance

Schedule principle	Product 1			Product 2			Product 3		
	Total	On-Time	Not On-Time	Total	On-Time	Not On-Time	Total	On-Time	Not On-Time
FCFS	90	15	75	90	45	45	90	90	0
EDD	90	40	50	90	90	0	100	30	70
SPT	95	30	65	90	75	15	85	65	20

To achieve the better performance of on-time delivery, the optimization experiment provides the further support to the planning staff of the company. One scenario is investigated regarding the indicator on time delivery (OTD) as followed.

Objective function: Max. OTD (on-time delivery rate)
 s.t. $2 < \text{batch size} < 10$; $2 < \text{parts per arrival} < 10$

Based on the optimization results, it is shown that the optimized value of the batch size and the parts per arrival are both equaling three. The scheduling principle is EDD. In this situation, the production process can achieve the best performance of on-time delivery.

5. Summary

The presented paper is dealing with the issue of simulation support for production planning and control in small and medium enterprises with information dynamics in order to analyze the risks which are caused by multiple uncertainties. A production planning and control simulation system is built to analyze and evaluate the production performance according to defined KPIs. Taking uncertainty into account companies can design more feasible production plans in shorter time and fulfil their production requirements more flexible. A simulation study is conducted to quantify the potential risk of PPC under different uncertainties. It brings benefit with respect to customer service, particularly in the field of on-time delivery satisfaction. Further research includes the improvements of optimization experiments and the application in other production areas.

References

- [1] Mourtzis, D., Doukas, M. (2014): Design and planning of manufacturing networks for mass customization and personalization: Challenges and Outlook, In: Robust Manufacturing Conference, p. 1-13.
- [2] Hees, A., Reinhart, G. (2015): Approach for production planning in reconfigurable manufacturing systems. In: 9th CIRP ICME Conference, p. 70-75.
- [3] Schuh, G., Potente, T., Fuchs, S. (2011): Shifting Bottlenecks in Production Control. In: 4th International Conference on Changeable, Agile, Reconfigurable and Virtual Production, Montreal, Canada, p. 506-511.
- [4] Figueira, G., Amorim, P., Guimarães, L., Amorim-Lopes, M. (2015): A decision support system for the operational production planning and scheduling of an integrated pulp and paper mill, Computers and Chemical Engineering, p. 85-104.
- [5] Mula, J., Poler, R., Garcí'a-Sabater, J.P., Lario, F.C. (2006): Models for production planning under uncertainty: A review, International Journal of Production Economics, p. 271-285.
- [6] Alvandi, S., Bienert, G. (2015): Hierarchical modelling of complex material and energy flow in manufacturing systems. In: 22nd CIRP conference on Life Cycle Engineering, p. 92-97.
- [7] Stricker, N., Pfeiffer, A., Moser, E., Kadar, B., Lanza, G. (2015): Supporting multi-level and robust production planning and execution, CIRP Annals – Manufacturing Technology, p. 415-418.
- [8] Volling, T., Spengler, TS. (2011): Modeling and simulation of order-driven planning policies in build-to-order automobile production, International Journal of Production Economics, p. 183-193.
- [9] Lee, S., Son, Y.J., Wysk, R. (2007): Simulation-based planning and control: From shop floor to top floor, Journal of Manufacturing Systems, p. 85-98.
- [10] Chakravorty, SS., Atwater, JB. (2005): The impact of free goods on the performance of drum-buffer-rope scheduling systems, International Journal of Production Economics, p. 347-357.
- [11] Duffie, N., Chehade, A., Athavale, A. (2014): Control Theoretical Modeling of Transient Behavior of Production Planning and Control: A Review. In: Variety Management in Manufacturing. Proceedings of the 47th CIRP Conference on Manufacturing Systems, p. 20-25.
- [12] Gyulai, D., Kadar, B., Monosotri, L. (2015): Robust production planning and capacity control for flexible assembly lines. In: International Federation of Automatic Control, 48:3, p. 2312-2317
- [13] Auer, S., Mayrhofer, W., Sihn, W. (2012): Implementation of a Comprehensive Production Planning Approach in Special Purpose Vehicle Production. In: 45th CIRP Conference on Manufacturing Systems, p. 43-48.
- [14] Georgiadis, P., Politou, A. (2013): Dynamic Drum-Buffer-Rope approach for production planning and control in capacitated flow-shop manufacturing systems, Computers & Industrial Engineering, p. 689-703.

- [15] Baldea, B., Harjankoski, I. (2014): Integrated production scheduling and process control: A systematic review, *Computers and Chemical Engineering*, p. 377-390.
- [16] Leng, K., Wang, Y. (2012): Research on Capacity Allocation in a Supply Chain System Based on TOC. *Advances in EECM*, pp. 517-524.
- [17] Seitz, K., Nyhuis, P. (2015): Cyber-Physical Production Systems Combined with Logistic Models – A Learning Factory Concept for an Improved Production Planning and Control. In: the 5th Conference on Learning Factories, p. 92-97.
- [18] Chen, H.N., Cochran, J.K. (2005): Effectiveness of Manufacturing Rules on Driving Daily Production Plans, *Journal of Manufacturing Systems*, 24:4, p.339-351.
- [19] Grundstein, S., Schukraft, S., Scholz-Reiter, B., Freitag, M. (2015): Evaluation system for autonomous control methods in coupled planning and control systems. In: 9th CIRP ICME Conference, p. 121-126.
- [20] Suwa, H., Sandoh, H. (2013): Online Scheduling in Manufacturing - A Cumulative Delay Approach, Springer-Verlag, p. 93-101.
- [21] Golmohammidi, D. (2015): A Study of scheduling under the theory of constraints. In: *International Journal of Production Economics*, p. 38-50.
- [22] Yan, H.S., Wang, H.X., Zhang, X.D. (2013): Simultaneous batch splitting and scheduling on identical parallel production lines. In: *Journal of Information Sciences*, p. 501-519.