Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 93 (2020) 192–197

www.elsevier.com/locate/procedia

53rd CIRP Conference on Manufacturing Systems

# Production planning for collaborating resources in cyber-physical production systems

Michaela Krä [a]*, Ludwig Vogt [a], Christian Härdtlein [b], Stefan Schiele [a], Johannes Schilp [a,b]

[a] *Chair of Digital Manufacturing, Faculty of Applied Computer Science, Augsburg University, Eichleitnerstr. 30, 86159 Augsburg, Germany*
[b] *Fraunhofer Research Institution for Casting, Composite and Processing Technology – IGCV, Provinostr. 52, 86153 Augsburg, Germany*

* Corresponding author. Tel.: +49 821 598-4393; fax: +49 821 598-143372. *E-mail address:* michaela.krae@informatik.uni-augsburg.de

**Abstract**

The increasing demand of flexibility in cyber-physical production systems results from a growing number of product variants and customer specific products. Resources, like robots and humans, offer different skills modelled on the production planning level. Skill based task allocation requires normally that a task is executed by one resource providing all necessary skills for this task. This paper describes an approach in production planning how teams of several resources proposing diverse skills can be combined in order to accomplish a task in collaboration. The composition of the team aims at combining resources with complementary and supportive skills.


Peer-review under responsibility of the scientific committee of the 53rd CIRP Conference on Manufacturing Systems

*Keywords:* Production planning; Flexible manufacturing system (FMS); Emergent task allocation

## 1. Introduction

In times of increasing costs for resources, their workload is a key performance indicator standing in the centre of attention in manufacturing systems. Establishing the possibility to accomplish tasks in collaboration, would present a chance to augment the capacity utilisation of resources. Nowadays, this approach is not yet common as planning and control systems are in general not able to consider assigning tasks to more than one resource. Taking into account the challenges arising in the context of Industry 4.0 and its implementation in manufacturing systems taking a closer look on collaborating resources and their use in cyber-physical production systems (CPPS) seems appropriate. [1,2]

CPPS, i.e. a smart factory centered on cyber-physical systems, offer possibilities to restructure traditional processes regarding manufacturing organisation [3,4]. More product variants and the increasing demand of customer specific products result in challenges in production systems that demand among other requirements higher flexibility concerning task fulfilment [5,6]. Decentralisation and digitisation are key concepts for the implementation of Industry 4.0 and both offer possibility for collaboration on resource level, thus a way of creating flexibility [7].

The target of this paper is to show how the composition of teams in a flexible and autonomous way can optimize the manufacturing workflow. This approach relies on augmenting the options of the task allocation step in production planning by providing the possibility to form teams of resources that collaborate for a defined task.

In chapter 2, relevant work concerning production planning, skill based modelling of resources, task assignment and collaborating teams in production is analysed. An overview of the developed skill definition, collaboration algorithm and a short introduction into the applied Java framework is presented in chapter 3. Chapter 4 describes the test scenario and shows the results of the performed tests. It provides insight into the building of teams and its effects on the production schedule. To finish, the paper is summed up in chapter 5 and an outlook on future research topics is provided.

2212-8271 © 2020 The Authors. Published by Elsevier B.V.

Peer-review under responsibility of the scientific committee of the 53rd CIRP Conference on Manufacturing Systems
10.1016/j.procir.2020.03.030

## 2. State of the art

In a first step, relevant literature is evaluated. The considered topics comprise production planning, modelling of resources and task allocation in general as well as in the context of CPPS. It can be seen that resources collaborating only for a defined time to fulfill a task and their role and integration in manufacturing systems are missing. The question that can be derived when analyzing the state of the art is how non-predefined teams of resources can help to optimize processes in manufacturing systems and to rise resource workload.

### *2.1. Production planning*

The overall goal of production planning and control (PPC) in manufacturing systems consists in meeting deadlines, reducing through-put time and stock, increasing workload as well as fulfilling quality criteria, i.e. attain the logistic target values [8]. Generating a valuable production plan is the central mission of production planning and is based on task allocation (cf. chapter 2.3) with priority rules [9]. The planning steps present the preparation for production control, i.e. the coordination of task fulfilment by one or more resources [10].

### *2.2. Modelling of resources*

One method of responding to shorter product life cycles and smaller lot sizes consists in a skill based modelling of the orders and available resources. With this approach, the order or the tasks of an order are not assigned to a specific station respectively machine. Instead, the skills of the order are compared with the skills of the resources and allocated accordingly. For the modelling of the skills different concepts are proposed in literature. Malec et al. [11] also propose a bilateral skill definition which contains a top-down modelling of the production goals and a bottom up description of the machine skills. Björkelund et al. [12] extend the previous described dual approaches to the Product Process Resource (PPR) concept. Based on this work, Aleksandrov et al. [13] developed a skill based framework for assets in reconfigurable manufacturing systems which takes the lifecycle perspective of the assets into account. In addition to the utilization during the execution, their skill concept can be used for operative planning and mid to long term asset management. Backhaus et al. [14] use the skill definition of the PPR model to simplify the programming of reconfigured production tasks with a focus on robotic applications.

Hammerstingl [15] focused in the research project AKOMI on the skills required in assembly processes and categorized them into basic skills and composite skills. Because currently the main applications for mobile resources in production systems are logistics and assembly processes, the modelling of resources and their skills in this concept is inspired by the work of Hammerstingl [15].

### *2.3. Task allocation*

Over the last decades, many approaches for the task allocation problem were scientifically discussed, but only few of those methods achieved relevance in practice. The use of priority rules can be seen as the most established strategy for automated task allocation. Regarding the trade-off between allocation speed and solution quality, priority rules perform mostly satisfying for numerous target values, although an optimal solution should never be expected. [16]

As shown in literature, there is no general assignment rule that equally addresses all kinds of target values. Furthermore, only tendencies for the relation between a certain rule and specific target criteria can be formulated [18,17]. This is why priority rules must be chosen with care considering the initial situation and the objectives pursued. The selection of rules for a flexible production system becomes additionally complicated, when cooperations between resources have to be taken into account. Such cooperations will bound a higher capacity of the available resources to one single task, which might inhibit the processing speed of others. The question arises, how strongly this affects the generated result of different priority rules. A strategy to handle the negative side effects (cf. chapter 2.1) must be found. Even though a high number of priority rules has been proposed for the task allocation to single resources, there is still a lack of rules that integrate the multi-resource-case within an effective algorithm for the whole allocation problem.

More advanced approaches avoid the manual construction of rules. In the paper of Hildebrandt et al [19] a genetic algorithm is used to create better priority rules. It is shown that more complex rulesets of up to 70 criterions can clearly improve the resulting schedule. Heger [20] applies a machine learning approach to a similar problem. In general, genetic algorithms and machine learning are amongst the methods which can be used to directly generate single schedules [21]. However, long computing times disqualify such procedures in practice, where fast reaction to sudden disruptions is demanded. Both Hildebrandt et al [19] and Heger [20] avoid this disadvantage by limiting these long computing times to the formulation of fitting priority rules, which then can be applied fast in production. Afterwards, the rules found can be applied quickly in production. Till now, such more advanced methods were not used in scheduling cooperations.

### *2.4. Collaboration*

The advances in human-robot collaboration (HRC) and CPPS have increased the number of possible collaboration tasks in production and therefore the interest in collaboration planning systems. Past work has mainly focused on the collaboration planning between robot arms and human workers in assembly tasks. Takata et al. [22] present a system which intercepts all changes from the initial planning with human workers which can be impracticable in fast changing scenarios. In [23] the allocation is based on a capability comparison between workers and robots. Skills are drafted from a study and the generic description of human and robotic capabilities. Because they use 25 individually rated indicators for the comparison the transferability to new applications can be costly and time consuming. Other publications like [24] and [25] focus on the task allocation in assembly cells which was transferred to a common model from Nikolakis et al. [26]. Their methodology proposes a two level breakdown of the order and a subdivision in tasks. The model is able to allocate tasks to teams of collaborating resources but it is necessary that these teams are defined in advance and modelled as one resource.

## 3. Concept of planning for collaborating resources

An overview about frequently used terms regarding task assignment and their meaning in this paper is given. Afterwards, the developed program with the implemented task assigning procedure and the selectable production planning rules are described.

While the order breakdown in this paper is similar to [9], the concept is able to plan not-defined collaborations. Instead of requiring that collaborations are previously established, it searches for the best possible teams of resources among the available resources to meet the skill demand of a task. The goal is to optimize the manufacturing workflow.

The allocation algorithm must settle two fundamental decisions repeatedly. Firstly, every order has to be prioritized using a specific ruleset. Simple and commonly known examples for this kind of rule would be the “First-In-First-Out”-Principle, “Earliest Due Date” or “Shortest Manufacturing Time”. The second decision regards to the available resources, which qualify for the task that needs to be scheduled. Again, different criterions could be chosen, such as workload, transport distance or the best fitting resource in context of skills. Such straightforward rules, which apply only one single criterion, are called “elementary rules”. However, these rules are unlikely to achieve sufficient schedules in a complex production setting. [16]

To fit real world problems, rules are combined. This can happen in various ways, e.g. by addition, multiplication or division of criterions or priorities. This task is particularly difficult if there are no guidelines for the formulation of new rules, which is currently the case when planning with cooperating resources.

### *3.1. General definitions*

Similar to the modelling of resources (cf. chapter 2.2) the definitions used in this paper are derivatives from [15] and [27] because of their proximity to the application field. The following notations visualized in figure 1 are used in this work:

- Job: First level of order breakdown.
- Task: Second level of order breakdown.
- Resource: A production resource defines a device which produces benefit and offers utility. A resource can be an individual machine like a CNC mill or an AGV, a worker or a production tool. There is no differentiation between the various resources except their skills. Every resource has its specific skillset based on its capabilities due to equipment and technical specifications.
- Skill: A skill is defined as a solution-neutral capability offered by a resource [9]. It is not associated with either resources or products rather than an abstract process description. To enrich the skill definition features are added to its notation.

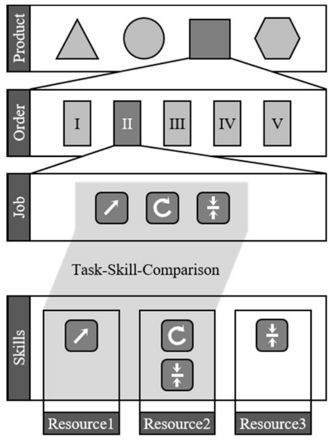


Figure 1. Relation between key terms.

The structure of the features is designed to be individually expendable for each application.
- Cooperation: Two or more resources with the same or different skills collaborate to accomplish a task. It is not differentiated between the ways of interaction of human-robot teams: coexistence, cooperation or collaboration.[28]

### *3.2. Task assignment and identification of teams for collaborations*

As part of the FORobotics project, a Java add-on for a PPC system was built that imports all orders and available resources from a database. After collecting the data, the resources are assigned to the jobs based on a skill comparison and a chosen priority production scheduling rule (cf. chapter 3.3). The orders and resources are imported via JSON files through an application programming interface (API) from a PPC system (cf. figure 2). After parsing the imported files, orders are split into their jobs. Subsequently, a comparison between the necessary skills and the available resources is conducted. The skill comparison includes the capacity evaluation because the capacity of each resource is also modelled via its skills (cf. figure 3) and can be defined in different units, e.g. quantity, dimensions, weight.

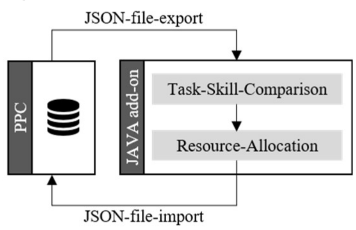


Figure 2. Overview of systems

All resources $r_n$ or teams with up to three resources $r_{n,1}$, $r_{n,2}$, $r_{n,3}$ which fulfill the following criteria are stored in a “resource-job” list:

$$QR_{t_M} = \{r_n \mid NSK_{t_M} \in OSK_{t_n}\}$$

$$QC_{t_M} = \{r_{n,1,2,3} \mid NSK_{t_M} \in (OSK_{n,1} \cup OSK_{n,2} \cup OSK_{n,3})\}$$

where $NSK_{t_M}$ are the needed skills for task $t_M$ and $OSK_{t_n}$ the offered skills of resource $r_n$. $QR_{t_M}$ contains all resources which are qualified for task $t_M$, and $QC_{t_M}$ contains all possible teams which are qualified for task $t_M$.

Knowing all possible resources for every job allows calculating numerous parameters that characterize the overall situation given by the orders. Possible key figures influencing the assignment are due date, earliest start, manufacturing time, number of operations or flexibility. Each of those parameters can be addressed by an elementary priority rule. The orders will be sequenced and listed by such a rule or a set of rules and iteratively processed according to their priority. If one job has more than one suitable resource or cooperation, a second rule is needed for the allocation. Whenever this decision is necessary, all qualified resources or cooperations are assessed.

Each resource is analyzed for the earliest possible start it offers to the task, taking into account the associated journey and transport times to the place of procession. To support a balanced distribution of tasks among the resources, the workload of each resource is calculated, too. Another parameter is the flexibility of a resource, which is given by the number of tasks and teams it could be allocated to. Similar to the orders, all possible resources will be prioritized with a chosen rule regarding these parameters, which are repeatedly calculated for every single decision.

All mobile resources have the ability to collaboratively process certain jobs because of their integrated HRC technologies. Such cooperation is inevitably needed to execute some of the jobs contained, since their associated skills are not covered by one resource alone. Collaboration is only chosen if no single resource is suitable for a particular task. To meet the scheduling decisions after sequencing the orders, the resource that offers the earliest possible start is chosen for each task.

Since the robotic platforms can move autonomously, transport times between different locations must be considered. All physical transports within the system are independent jobs and given by the work plans. If a resource must move from one position to another, a new movement job will be created and fitted into the schedule.

### *3.3. Rules for collaborating teams*

The add-on has a framework to easily implement priority production scheduling rules. Since there exist many different rules in literature, it is not feasible to test every rule. Therefore, some central strategies were chosen [17]:

- “Shortest Manufacturing Time” (SMT): Orders are ranked higher if their minimal manufacturing time is small. This rule can be considered as well-known, it is supposed to generate good solutions regarding many target values.
- “Smallest Number of Cooperating Groups” (SNCG): An order is ranked higher if fewer cooperative teams are necessary for its fulfillment. This strategy moves cooperative tasks towards the end of the schedule.
- “Least Flexible Order First” (LFOF): The flexibility of an order is the amount of ways it can take through the production system, divided by the length of its work plan. If the least flexible orders are scheduled first, the more flexible ones can adapt to this occupation.

Initial tests have shown a partly complex or chaotic and therefore unrealistic production schedule which is why further rules have to be constantly set. Firstly, if a resource or a cooperating group of resources fulfills a job and qualifies for the successor of this job, the same resources will be assigned. Therefore, a chain of consecutive tasks will be processed by the same resource, as long as this resource is qualified. Secondly, if a cooperation contains resources that qualify for the successor of this cooperation, the following resource will be chosen from this cooperative group. This will prevent unnecessary shifts in resources between a job and its successor, which makes a schedule more comprehensible for human planners. Another advantage is the prevention of material rearrangements between resources that are not required.

## 4. Validation

To validate the concept, a test setting in the Software Plant Simulation was created that allows resources to cooperate in groups of up to three members. In order to evaluate the impact of cooperating resources, a number of different priority rules is applied to allocate the jobs. As will be shown, choosing the wrong priority rule can strongly affect the distinct target values. The following values are evaluated:

- Total duration of schedule [min]
- Average delay $AD$ [min] with number of delays $|dM|$, end of shift $ES$, order completion time $TC_M$, delay of order $d_M$:

$$d_M = TC_M - ES$$

$$AD = \frac{\sum_1^{dM} d_M}{|dM|} \qquad dM = \{M \mid d_M > 0\}$$

- Average manufacturing time per order [min]
- Workload [%]:

$$Workload = \frac{\sum_{N=1}^{R} WT_{r_N}}{D \times R}$$

with $R$ number of resources, $WTr_N$ the working time of each resource and $D$ the total duration of the planned schedule. The tested orders are supposed to fill a nine hour shift of the production system. Therefore, an order is considered as “delayed” if its start and completion do not happen within one single shift.

### *4.1. Implementation and test setting*

A set of ten orders with each containing one of five products is given for the test scenario. The orders are generated via a random order generator. Each of the five products has a work plan that differs in length, manufacturing time and necessary skills. The framework of the simulated production system consists of a production hall with an area of $4000m^2$ ($50m\ x\ 80m$) which contains a warehouse, a shipping station, quality assurance and several workstations. Deployed resources are six mobile platforms, three locally fixed stations and two workers. Additionally, some of the jobs have to take place at certain locations. The exact skillset of each resource results from their real life counterpart. As an example the skillset of one mobile robot is shown in Table 1.

Table 1. Skills of "Mobile Robot 1".

| Resource | Mobile Robot 1 |
|---|---|
| Skills | Navigate_0_0_1 |
| | Transport_20_5_2 |
| | Detect_1000_0_1 |
| | Secure_5_3 |
| | Interact_0_0_4 |

As described in chapter 3.2 the skills can be enriched with additional features. The features can be a product property like weight, a specified sensor, an output medium or a list of applicable grippers and so on. In our application the skills have up to three features recognizable by the separators "_".The general structure of a skill is "*Neutral skill_Feature 1_Feature 2_Feature n*" to illustrate this notation the skill "Transport_20_5_2" is shown in figure 3.

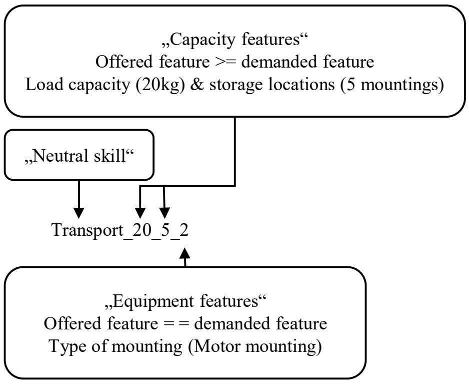


Figure 3. Skills and features for the "Transport" skill.

The ten work plans chosen can be considered as highly competitive. In this context, competition means that many tasks compete for the same resource or group of resources at the same time. A total of 162 operations has to be distributed among 12 resources and only one, two or four resources are qualified for each task. 16 of these operations demand a cooperating group. The competitive pressure between the orders increases the observable impact of different priority rules on the target values. If the orders were not competing but perfectly complementary, no priority rule would be needed at all, since the orders would never cross each other in their need for a certain resource.

### 4.2. Results and evaluation

As initially expected, the three rules perform differently towards the target criteria. No rule is superior to the others in all criteria. In general, the resulting workload of the resources is quite low. This is due to the strong competition between orders, deliberately caused by the formulation of the work plans. The rules lead to the results shown in table 2. There is no statistic component influencing the results as random effects are not considered why the outcome does not vary for the same rule setting.

It can be seen that SMT and SNCG perform very similar. This happens because an order with longer manufacturing time is more likely to contain cooperative tasks and therefore the obtained sequences are related but not completely the same.

Table 2. Results for the applied priority scheduling rules.

| | SMT | SNCG | LFOF |
|---|---|---|---|
| Total duration of schedule [min] | 888 | 852 | 724 |
| Average manufacturing time per order [min] | 337 | 321 | 393 |
| Number of delays [-] | 2 | 2 | 4 |
| Average delay [min] | 298 | 263 | 123 |
| Maximum delay [min] | 347 | 312 | 184 |
| Workload [%] | 27 | 28 | 33 |

In this setting, SNCG generates slightly better results than SMT, both achieve a faster average manufacturing time than LFOF and fewer orders are delayed. The smaller average manufacturing time clearly goes at the expense of the two delayed orders, which are extremely late. This is why the associated schedules are longer in duration. While few delayed orders are still in procession, most of the others were completed much earlier. This yields in a wide spread of different completion times, which are partly too early for some orders and much too late for others. According to literature, this behavior can be expected for the SMT-rule [29].

The LFOF-principle creates a more balanced schedule, reducing the average delay compared to the other two rules. In this test setting, LFOF distributes the tasks more evenly, which results in a faster and denser schedule of higher workload. However, delay is not avoided but spread over several orders.

Additionally to the three priority scheduling rules a combination of SNCG and LFOF is evaluated. The results are summed up in table 3.

Table 3. Results for the applied priority scheduling rules for SNCG+LFOF.

| | SNCG + LFOF |
|---|---|
| Total duration of schedule [min] | 707 |
| Average manufacturing time per order [min] | 404 |
| Number of delays [-] | 4 |
| Average delay [min] | 69 |
| Maximum delay [min] | 131 |
| Workload [%] | 34 |

In this test, the composite priority rule performs best regarding total schedule duration, maximum delay and workload. Orders of lowest flexibility and a low need for cooperation are scheduled first. Being aware of this, the comparatively good result of this rule is not a surprise. If fewer cooperations are needed in the early part of the schedule, the less flexible tasks can be processed first using a higher number of resources, since those are not yet needed in teams. In the later schedule part, the least flexible orders are mostly completed. The resources are now free to join groups and fulfill the last remaining tasks with a higher need for cooperation.

## 5. Conclusion

Considering the current state of the art regarding task allocation in PPC, it can be stated that forming teams out of resources depending on the current orders and the subsequently required tasks presents an approach not yet established. Taking into account this possibility offers a way of facing challenges arising in CPPS as well as due to customer demand and more product variants.

The established concept for task allocation with collaborating resources was validated in a production scenario based on a simulation model. The evaluation shows that through-put time, delay and workload can be optimized. All general assertions about priority rules must be made with caution. The generated results are strongly dependant of the initial situation, i. e. orders and resources. In the given examples, one can see clearly that cooperating groups of resources must be scheduled with care. Jobs should be prioritized in a way that takes cooperation into account to achieve better results. Otherwise, it is more likely to generate comparatively poor solutions, demonstrated here by the SMT-rule which is supposed to perform well. The results for the SNCG + LFOF-rule show, that jobs of low flexibility and jobs with high need of cooperation should not be processed at the same time, if they compete for similar resources.

So far, the algorithm contains no specialized method to optimize vehicle routing problems, i. e. static values for transportation times are applied, but the transport and movement times can be improved by choosing other priority rules. Next steps consist furthermore in integrating the charging time of mobile resources and the splitting of related jobs in the case of a cooperation according to the divided job. This means that if three products are transported by two resources the related picking job has to be divided as well. The comparison between one resource and a team that can both fulfil a certain task concerning delay has not yet been implemented. The application needs to be analyzed regarding real time capability for the use in real world CPPS.

**Acknowledgements**

The presented results have been developed within the research project FORobotics (www.forobotics.de). The Bavarian Research Foundation funds this project.

**References**

[1] Scholz-Reiter, B., Rekersbrink, H., Görges, M., 2010. Dynamic flexible flow shop problems—Scheduling heuristics vs. autonomous control. CIRP Annals 59 (1), 465–468.
[2] References
[1] Scholz-Reiter, B., Rekersbrink, H., Görges, M., 2010. Dynamic flexible flow shop problems—Scheduling heuristics vs. autonomous control. CIRP Annals 59 (1), 465–468.
[2] Wiendahl, H.-H., Wiendahl, H.-P., Cieminski, G. von, 2005. Stolpersteine der PPS: Symptome - Ursachen - Lösungsansätze. wt Werkstatttechnik online 95 (9), 717–725.
[3] Lee, E.A., 2008. Cyber Physical Systems: Design Challenges. 11th IEEE Symposium on Object Oriented Real-Time Distributed Computing (ISORC), 363–369.
[4] VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (GMA), 2013. Cyber-Physical Systems: Chancen und Nutzen aus Sicht der Automation. Thesen und Handlungsfelder.
[5] Kolberg, D., Berger, C., Pirvu, B.-C., Franke, M., Michniewicz, J., 2016. CyProF - Insights from a Framework for Designing Cyber-Physical Systems in Production Environments. Procedia CIRP 57, 32–37.
[6] Reinhart, G. (Ed.), 2017. Handbuch Industrie 4.0: Geschäftsmodelle, Prozesse, Technik. Hanser, München, 1774 pp.
[7] Flämig, H., 2015. Autonome Fahrzeuge und autonomes Fahren im Bereich des Gütertransportes, in: Maurer, M., Gerdes, J.C., Lenz, B., Winner, H. (Eds.), Autonomes Fahren. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 377–398.
[8] Nyhuis, P., Wiendahl, H.-P., 2012. Logistische Kennlinien: Grundlagen, Werkzeuge und Anwendungen, 3. Aufl. 2012 ed. Springer, Berlin, Heidelberg.
[9] Schuh, G., Stich, V. (Eds.), 2012. Produktionsplanung und -steuerung 1: Grundlagen der PPS, 4. Aufl. ed. Springer, Berlin.
[10] Wiendahl, H.-P., 1997. Fertigungsregelung: Logistische Beherrschung von Fertigungsabläufen auf Basis des Trichtermodells. Hanser, München, 382 pp.
[11] Malec, J., Nilsson, A., Nilsson, K., Nowaczyk, S., 2007. Knowledge-Based Reconfiguration of Automation Systems, in: Proceedings of the 3rd IEEE International Conference on Automation Science and Engineering, Scottsdale, AZ, USA. 22.09.2007 - 25.09.2007. IEEE, pp. 170–175.
[12] Björkelund, A., Malec, J., Nilsson, K., Nugues, P., 2011. Knowledge and Skill Representations for Robotized Production, in: Proceedings of the 18th World Congress. The International Federation of Automatic Control, Milano, pp. 8999–9004.
[13] Aleksandrov, K., Schubert, V., Ovtcharova, J., 2014. Skill-Based Asset Management: A PLM-Approach for Reconfigurable Production Systems, in: Product Lifecycle Management for a Global Market. 11th IFIPWG 5.1 International Conference, PLM, Yokohama, pp. 465–474.
[14] Backhaus, J., Ulrich, M., Reinhart, G. Classification, Modelling and Mapping of Skills in Automated Production Systems, in: Proceedings of the 5th International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV 2013), Munich, Germany, pp. 85–89.
[15] Hammerstingl, V., Reinhart, G., 2018. Skills in Assembly.
[16] Pinedo, M.L., 2016. Scheduling: Theory, algorithms, and systems, Fifth Edition ed. Springer, Cham, Heidelberg, New York, Dordrecht, London.
[17] Nebl, T., 2011. Produktionswirtschaft, 7., vollst. überarb. und erw. Aufl. ed. Oldenbourg, München.
[18] Corsten, H., Gössinger, R., 2016. Produktionswirtschaft: Einführung in das industrielle Produktionsmanagement, 14., überarb. und erw. Aufl. ed. De Gruyter Oldenbourg, Berlin, Boston.
[19] Hildebrandt, T., Freitag, M., 2015. Bessere Prioritätsregeln für komplexe Produktionssysteme mittels multi-kriterieller simulationsbasierter Optimierung, in: Simulation in Production and Logistics. 16. ASIM Fachtagung Simulation in Produktion und Logistik, Dortmund. Fraunhofer IRB Verlag, Stuttgart.
[20] Heger, J., 2014. Dynamische Regelselektion in der Reihenfolgeplanung: Prognose von Steuerungsparametern mit Gaußschen Prozessen. Springer Vieweg, Wiesbaden.
[21] Brucker, P., Knust, S., 2012. Complex scheduling, 2nd ed. ed. Springer, Berlin, Heidelberg.
[22] Takata, S., Hirano, T., 2011. Human and robot allocation method for hybrid assembly systems. CIRP Annals 60 (1), 9–12.
[23] Ranz, F., Hummel, V., Sihn, W., 2017. Capability-based task allocation in human-robot collaboration, in: Procedia Manufacturing. 7th Conference on Learning Factories, pp. 182–189.
[24] Chen, F., Sekiyama, K., Sasaki, H., Huang, J., Sun, B., Fukuda, T., 2011. Assembly Strategy Modeling and Selection for Human and Robot Coordinated Cell Assembly, in: Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, CA, USA. IEEE, Piscataway.
[25] Duan, F., Gao, Q., Zhu, C., Kato, R., Arai, T., 2013. An Assembly-Skill-Transferring Method for Cellular Manufacturing System—Part I: Verification of the Proposed Method for Motor Skill, in: IEEE Transactions on Automation Science and Engineering, pp. 465–470.
[26] Nikolakis, N., Kousi, N., Michalos, G., Makris, S., 2018. Dynamic scheduling of shared human-robot manufacturing operations, in: Proceedings of the 51st Conference on Manufacturing Systems, pp. 9–14.
[27] Pfrommer, J., Schleipen, M., Beyerer, J., 2013. PPRS: Production skills and their relation to product, process, and resource, in: IEEE 18th Conference on Emerging Technologies & Factory Automation (ETFA), Cagliari, Italy. IEEE.
[28] Onnasch, L., Maier, X., Jürgensohn, T., 2016. Mensch-Roboter-Interaktion - Eine Taxonomie für alle Anwendungsfälle.
[29] Lödding, H., 2016. Verfahren der Fertigungssteuerung: Grundlagen, Beschreibung, Konfiguration, 3. Aufl. ed. Springer Vieweg, Berlin, Heidelberg.