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Towards Robustness Of Production Planning And Control Against Supply Chain Disruptions

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Abstract

Just-in-time supply chains have become increasingly popular in past decades. However, these are particularly vulnerable when logistic routes are blocked, manufacturing capacities are limited or customs are under strain, as has been seen in the last few years. The principle of just-in-time delivery requires a coordinated production and material flow along the entire supply chain. Challenges in the supply chain can lead to various disruptions, so that certain manufacturing jobs must be changed, postponed or cancelled, which will then impact supply down the line up to the consumer. Nowadays, many planning and control processes in the event of a disturbance are based on the procedural knowledge of employees and undertaken manually by those. The procedures to mitigate the negative effects of disturbances are often quite complex and time-critical, making disturbance management highly challenging.

In this paper, we introduce a real-world use case where we automate the–currently manual–reschedule of a production plan containing unavailable jobs. First, we analyse existing literature regarding the classification of disturbances encountered in similar use cases. We show how we automate existing manual disturbance management and argue that employing stochastic optimization allows us to not only promote future jobs but to on-the-fly create entirely new plans that are optimized regarding throughput, energy consumption, material waste and operator productivity. Building on this routine, we propose to create a Bayesian estimator to determine the probabilities of delivery times whose predictions we can then reintegrate into our optimizer to create less fragile schedules. Overall, the goals of this approach are to increase robustness in production planning and control.

Keywords

Production Disturbances; Disturbance Management; Production Planning and Control; Automated Production Planning; Supply Chain Management; Robustness

1. Introduction

Over the last decades, companies have been faced with challenges in a competitive environment characterised by globalisation, increasing product variety and growing market dynamics [1]. These new market requirements force them to focus on their essential core competences and to outsource other activities. In this context, the management of logistic processes in particular has become considerably more important in recent years [2]. Logistic objectives such as delivery times, on-time delivery, service level, throughput times, inventories, capacity utilisation and delay costs are critical to the success of an enterprise [3]. Due to the increasing inter-company cooperations e.g. as a result of outsourcing, logistics have to deal more and more with cross-company delivery problems, leading to new challenges and the discipline of supply chain management.

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Changing customer demands, a dynamic environment and quality problems are requiring companies to adapt themselves and their business and manufacturing processes faster to new boundary conditions leading to reschedules in supply as well as to turbulences along the entire value chain and supplier networks [4]. This leads to disturbances on various levels, not least due to the high complexity of such systems [2]. Disturbances occur both at the management level and at the level of production and assembly processes [5].

To counter disturbances at production level, it is necessary to optimally synchronize production planning and control. The main task of production planning and control is the coordination of all production and assembly processes to achieve the logistical targets [6]. In production planning, the current production plan is established for a certain planning time fence. All material and resource requirements are derived from that. Production control regulates the execution of the planned schedule, accounting for all unavoidable disturbances such as employee absences, machine disruptions, delivery delays or quality issues and production losses [7–9]. A detailed overview of several classification systems for production disturbances is presented in section 2.1. In section 3, we give an overview over various approaches in literature towards handling disturbances automatically.

In this paper, we present a real-world use case of a large multinational company (cf. section 4), in which a production plan, which covers a fixed horizon of ten days, is devaluated by material flow disturbances. The disturbance makes the production of one or more jobs within the fixed planning horizon impossible, so the production plan has to be changed. The main causes of these disturbances are short-term delivery problems or failures, material discrepancies in the enterprise resource planning (ERP) system or breakdowns in the company's own preproduction. The potential reasons for these are manifold and less relevant for this work as we focus on resolving the effect rather than preventing disturbances. Nor could the disturbance be solved at the logistical level, since e.g. a larger warehouse is not a realistic option for modern cost-sensitive operations. Given the existing options, in this case disturbances can only be reacted to at the level of production planning and control.

Recent studies show that, especially in production planning and control, many activities are based on the experience and process knowledge of the responsible employees [10]. Part of these manual steps are e.g. rescheduling in the event of a malfunction as well as the identification and selection of suitable strategies to resolve the situation [11]. In our use case, the production plan was fixed completely manually so far.

Manual disturbance management is often quite complex, time-consuming and relies on the procedural knowledge of employees. In this paper, we present our own approach for automating and subsequently improving this process with various techniques from the wider field of artificial intelligence (cf. section 5). We start by replicating the existing manual processes in software, albeit substantially faster. We discuss that–with the help of stochastic optimisation–we are able to solve the problem more effectively by foregoing a mere repositioning of scheduled jobs to on-the-fly create completely new production plans for the fixed horizon that are optimized in terms of throughput, energy consumption, material waste, and operator productivity. In a next step (cf. section 6), we propose to not only react to disturbances that have already occurred, but also to predict or prevent them by generating new alternative solutions (e.g. finding new suppliers, readjusting slightly different parts or simply fulfilling different orders first). For this, we discuss the use of Bayesian Neural Networks.

2. Production disturbances and robustness

In this section, based on a detailed literature review, several classification systems of production disturbances are provided. We then introduce the term "robustness" both in general and in the context of production systems, as this is a formalisation of the properties of systems that can deal with such disturbances.

2.1. Production disturbances

Production disturbances are unexpected and undesirable events that cause a production system not to function as planned. Equipment or software failures, media errors, waiting times for materials, subsequent interruptions in the production flow of stations/machines, lack of personnel, loss of speed, scrap or quality problems, planning errors and adjustments are factors that are often classified as disturbances by manufacturing companies. The occurrence of disturbances directly affects the productivity of production systems, as more time and resources than planned are required to produce the same outcome. Reducing production disturbances contributes to stable and more reliable production systems and is critical to maintaining the competitiveness of manufacturing companies [12]. Literature offers a wide range of disturbance classifications. The main classification systems are summarised in Table 1.

Table 1: An overview of classification systems for disturbances found in literature

Classification basis	References	Categories	Explanation and/or examples
Manner of occurrence	[13]	Unpredictable	Unexpected, appears suddenly during execution of production processes, abrupt changes in the expected and planned production specifications, e.g. urgent order, modification of order, machine breakdown
		Predictable	Can be predicted during execution of production processes due to undesirable situations caused by deviations from expected and planned requirements or deviations from equipment specifications, e.g. equipment breakdown
Origin of disturbances	[14,15]	Internal	Undesirable events triggered by resources and/or operations of production systems, e.g. machine breakdown, unavailability of labour, quality inspection, layout re-configuration
		External	Undesirable events caused by the environment in which the production system is evolving, e.g. disturbances due to the company's relationship with its customers or suppliers (e.g. delivery difficulties of raw materials in terms of time, quality and price, delay, cancellation, introduction of rush orders)
Type of affected entities	[16]	Resources	Machine breakdowns, change or lack of resources (raw materials or tools)
		Operations or work order	Overflow and change request (increase/decrease in operating times)
	[17]	Production	Each class is divided into inventory, capacity, and dual/multiple suppliers' issues
		Supply	
		Transportation	
	[18,19]	Supply	Delays, quality problems
		Resources	Machine breakdown, tool breakage, labour problems
		Production	Scraps management, quality problems, production time, product reject
		Customers	Rush orders, order modification, order cancelation
Nature of effect caused to aggressed production system entities	[20]	Unavailability of aggressed entity/relation	Sudden (unpredictable) event that disables an entity in production system, entity switches from Normal functioning mode to the Stop mode, or disturbance that has attacked an interentities relation causes the impossibility of interaction or communication between the two entities
		Degradation of aggressed entity/relation	Corresponds to an event that causes the alteration or non-satisfaction of one or more properties/requirements of a production system entity, aggressed entity becomes unable to perform its function according to pre-set objectives
Causes of disturbances	[21]	Component failures	Breakdowns in sensors and mechanical limit switches
		Design	Disturbances which would have been avoided had the design been conceived differently, e.g. flaws in software design, mechanical blocking due to software design, collisions because of poor coordination of system component functions, materials inadequately chosen given a robot's loading capacity, and errors caused by assembling system parts
		Human error	Includes those errors committed by the operators who run the system
		External Factors	Likely to interfere with organization performance, e.g. delays in deliveries, delays in testing machinery and equipment, and mistakes in installation of machinery and equipment

As shown in Table 1, the individual categories always depend on different characteristics of the disturbances. Furthermore, some classification systems map disturbances along the entire supply chain, while others only focus on the disturbances within a production system.

In addition, disturbances that have occurred can be differentiated according to their temporal impact, which can range from hours to weeks. Short-term disturbances are abrupt, suddenly occurring and lead to strong deviations between planning and realisation. Examples are machine breakdowns or order modifications. Medium-term disturbances are consequential errors from disturbances in the short-term range or due to inaccurate representations of the real plant and order data. The modification of the production plan or the use of non-adapted control strategies usually cause long-term disturbances [22].

According to [23], disturbances can be divided into deterministic and stochastic disturbances. Deterministic disturbances interrupt the production process in a planned manner, such as preventive and planned maintenance. Stochastic disturbances cause unanticipated interruptions in production systems.

Along with these, other disturbance categories can be found, such as primary and secondary disturbances [24]. In [15,21,25–31] further classification systems can be found. Some of these are along the lines of those shown in Table 1, some are an extension by adding new classes, some aim at specific levels of production or are sector-specific. Furthermore, our research has shown that there is no existing disturbance classification based on the impact on production planning or production control.

2.2. Robustness

Different meanings of the term "robustness" exist in literature depending on the context. In general, robustness describes the ability of a system to maintain its functionality in reference to changes of internal or external variables. Robustness is reflected in the degree to which a system is insensitive to effects that were not explicitly considered in its design [32]. Tomforde et al. [32] distinguish between active and passive robustness and present a quantification method to measure robustness. The term "robust" usually refers to a fundamental design concept that allows the system to work correctly under a wide range of disturbances. In the context of production, robustness refers to manufacturing tolerances, scheduling systems or production processes. The robustness of a production plan describes its ability to be executable and achieve satisfactory results despite changing environmental conditions and disturbances typical in production systems. A production process is robust if it is insensitive to undesirable influencing variables, if production takes place on schedule and if quality is met while maintaining the planned economic effort [33,34].

3. Disturbance management in literature

Production planning and control has gradually shifted from low level internal decision making to incorporating the entire supply chain [35]. Combined with JIT production this raises the need of supply chain risk management [36]. Existing research in this area can be split into two main sectors, reactive, where disturbances are handled after they occurred (cf. section 5), and proactive, where potential future risks are identified (cf. section 6).

Li et al. [37] proposed a framework which employs machine learning techniques to identify when rescheduling is needed before performing optimization and tested the approach on simulated use cases. Starting from an existing schedule with unavailable jobs Wang et al. [38] use a branch-and-price algorithm to find an alternative to the original schedule while allowing to fully reject single jobs. Bierwirth and Mattfeld [39] employed genetic algorithms for a similar non-deterministic and dynamic job shop problem, where –instead of disturbances removing existing jobs–newly arriving jobs require a rescheduling.

On the proactive side, the possibility of using higher statistics to predict possible supply risks has been explored by several authors, such as Wang et al. [40] or He et al. [41]. Brintrup et al. [42] performed an analysis of which features prove useful to predict supply disturbances while highlighting the importance of domain knowledge for this process. They also built a point estimate prediction system for estimating delivery probabilities. Baryannis et al. [43] explored the performance trade-offs necessary to use more explainable models like decision trees. Recently, Hosseini and Ivanov [44] employed Bayesian Neural Networks to model supply chain disruptions caused by a pandemic.

4. Case study

In this paper, we present a real-world case study from a multinational manufacturing company. Our use case involves large-scale production using several parallel assembly lines. A few variants of a basic product are produced on one assembly line with a constant cycle time each. This is ensured by the number of employees per assembly line: If a product has more features, i.e. more assembly steps, more employees are used and vice versa. In assembly, work is done in two-shift operation. The number of employees is highest at the beginning of each shift and decreases over the course of the shift. This means that at the beginning of each shift, the product variants with the most features are processed and the less complex variants are assembled at the end of the shift. This is the strictest form of flow production called continuous flow production, which is bound both spatially and temporally. It is characterised by a continuous transport flow on a conveyor belt [45].

For this case study, we only consider disturbances linked to material availability. The procurement of raw and auxiliary materials or semifinished products is synchronized with the production plan by using the just-in-time principle (JIT). There is a fixed production plan for the next ten days, which is determined with the help of a scheduling optimizer. On each new day, the plan is extended by one day through another scheduling run (rolling horizon production planning). We consider a disturbance in material availability that results in a planned job that cannot be produced and lies within the fixed planning horizon. Following [14], this kind of disturbance can have both internal and external triggers. It can occur at short notice if, e.g. during the setup of one or more workstations on the assembly line, it is discovered that a material is missing for which there should be stock according to the ERP system (internal disturbance). The discrepancy in material availability can also become apparent in the medium term due to delivery problems by the supplier (external disturbance) or due to a breakdown in the company's own preproduction (internal disturbance). However, both can also occur at short notice.

As described above, disturbance management regarding an occurred and not prevented disturbance is carried out completely manually by a production planner. Depending on the point of occurrence of the disturbance, the production plan must be adjusted in the short term or changed in the medium term. The planner executes the following process.

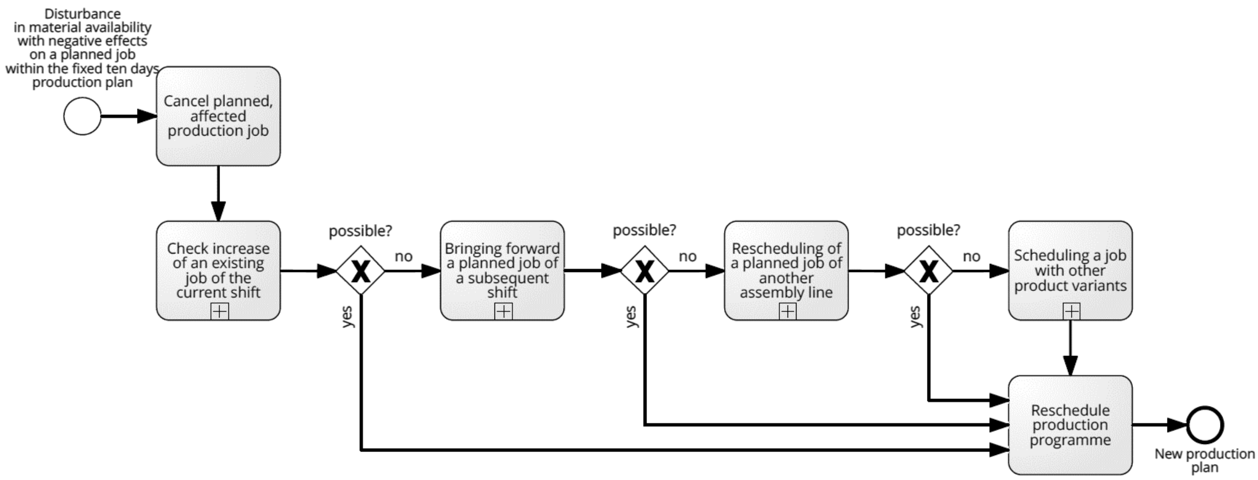

Figure 1: Process of manual fixing of a production plan in case of a disturbance in material availability

As shown in Figure 1, the rescheduling of the production plan is a step-by-step approach. Each step has further sub-processes in which the planner checks the availability of a sufficient number of employees, of critical parts of the bill of materials, of short range, design and finishing parts as well as preproduction capacities. If there is more than one possible solution, then the option with the earliest demand in the market is selected. The aim of rescheduling is to optimally close gaps in the production plan in order to maintain adherence to schedules and to prevent or minimise production losses. Another crucial factor is to avoid that workers are not busy or have to be sent home.

5. Improving reactive disturbance handling

The current disturbance handling process of the case study, described in section 4, is primarily carried out manually. Due to the time and staff required to execute certain production jobs and some strict requirements, as not to cause a break in production, only very few alternative viable production plans exist. These might not be optimal and currently primarily selected because they fulfil the constraints and do not lose out on production capacity. Typically, the number of viable solutions is in the low hundreds. However, highly trained and experienced planners know which jobs are likely suited from their grasp at the overall picture and therefore do not need to evaluate too many solutions following the time-intensive process of Figure 1.

In a first step, we thus automate important parts of the process to speed up and improve disturbance handling. Using data about each product, such as material requirements, the number of employees needed and current market demand, all of which is readily available in the existing ERP systems, we can find the best alternative for replacing the disturbed job in the original production plan. Additionally, instead of simply using the first possible solution like in the manual step-by-step process, we can perform an exhaustive search evaluating all viable solutions, therefore, achieving human-competitive or better results. A description of the cost function used to evaluate an individual solution can be found in section 5.1. The algorithm can perform all the previously manual work, although we allow the expert user to choose between equally good or similar plans in the hope, they have a better grasp at the big picture and select even more smartly from the possible options. However, currently the available options only allow the swap of two jobs or the expanse of one. We often encounter that other operations or a different order might provide a better overall plan. Section 5.2 describes how stochastic optimization can be used to create entirely new schedules for the fixed planning horizon while still fulfilling the known demand and utilizing the existing and expected parts. With the described capabilities of automatically fixing disturbances, we can consider this scheduling/control mechanism to be weakly robust, returning the system into an acceptance state.

5.1. Comparing production plan costs

To evaluate and compare different alternatives a sensible cost function is needed:

$$c(p) = \sum_i^n w(p_i) + m(p_i) + s(p_i) + d(p_i) \quad (1)$$

where $p \in \mathbb{R}^{n,3}$ is a production plan, $c: \mathbb{R}^{n,3} \rightarrow \mathbb{R}$ and $w, m, s, d: \mathbb{R}^3 \rightarrow \mathbb{R}$. The cost function considers workers (w), material (m), setup (s) and demand (d), all of which individually inflict costs on a job. We optimize under the constraint that jobs in a plan have a decreasing demand in the number of workers over the course of a shift due to the fixed cycle times discussed in section 4. If a job would require more workers than a previous one or less workers than the next one, we assume that it should inflict a higher cost due to idling some workers for the duration of this job. Similarly, a job's usage of material that would be needed for another, later job within the fixed horizon (as not enough material is available to perform both despite expected deliveries arriving on time) should be punished. Switching between jobs causes setup costs due to changes in the machine configurations, transporting parts to stations etc. This is typically constant for a type of job, however, the less setup, the more production can take place overall. Lastly, we should always account for the actual demand. Some products might be needed earlier or later, in larger quantities or requested by higher priority customers. The parameters of those functions are largely application-specific and in our current implementation they are guided by expert knowledge.

Fully automated and unexplained decisions can often lead to distrust of computerized system by the employees using them, especially when they disagree with the final decision [46,47]. In the current setup, we involve the responsible stakeholders in the decision making by presenting the top solutions together with their itemized cost and allowing them to make their favourite pick. Together with historical information and expert statements about the parametrizations of those cost functions, this increases stakeholder’s trust in the solution quality.

5.2. Optimizing the production plan

As a next step, we expand the algorithmic capabilities to not only fix the plan but create a new optimal schedule: Instead of simply filling the timeslot of a single job that has become impossible due to a disturbance, we propose to reoptimize (while accounting for schedule nervousness) the entire production plan within the fixed horizon, allowing the reordering of jobs, expansion of jobs, as well as the addition of new jobs or the removal of jobs not affected by the disturbance. In addition to these new options in the assembly line, adjusting the company's preproduction plan as well as utilizing options for short-term deliveries could make further jobs available. While the current approach allows for evaluating all constraint-satisfying solutions in less than a second, optimizing the entire plan gives a vastly increased number of options for which an exhaustive search is no longer feasible for realistic real-world scenarios. For this reason, we deploy stochastic optimization methods such as the well-known genetic algorithm (GA), including specialised operators as in [48], utilizing the previously defined single-objective cost function. However, treating the costs multi-objectively or adding additional factors such as energy usage, material waste or operator idling is straight forward. With these powerful black-box optimizers, the production plan can not only be (hot-)fixed but improved. As a result, the production planning process will make another step towards stronger robustness and self-optimization. New solutions will likely exhibit more differences between the original and optimized production plan which could lead to distrust. However, with the explanations based on cost functions and expert information, stakeholders are deeply informed about the inner workings of the decision-making process. We plan to further explore explainability requirements and user needs in the future. Additionally, this optimizer could be expanded with additional data sources pertaining to uncertainties, i.e. of scheduled deliveries, in order to increase the robustness of the production plan by creating schedules that include jobs less likely to fail.

6. Estimating delivery uncertainties

While the fast handling of a disturbance is an important aspect of production planning and control, the actual goal is to avoid as many of these disturbances as possible. Each disturbance and fixing of the plan necessarily mean that a specific product is not manufactured. This might in turn lead to customer orders not to be fulfilled on time, or down-the-line production seeing further disturbances. We propose that our reactive approach at increasing the robustness of the production should be combined with a proactive component. If the likely occurrence of a disturbance was known in advance there could be two possible actions to prevent it from disrupting the production plan. Firstly, if it is known early enough, the initial scheduling could create a plan that is not affected by it. A second option would be to try to counteract the disturbance, e.g. by procuring parts from another supplier. The increased time available to react or proactively respond would improve overall planning agility.

One major source of disturbances we identified in section 2.1 is the unavailability of parts or raw materials, often caused by late or cancelled deliveries. In JIT production simply reacting once such a disturbance has already occurred leaves very little time for fixing the out-dated production plan. Even when using the system described in section 5 an earlier notice can help at creating more robust alternatives as the fitness landscape can be explored better or human intervention might make other parts in the fixed planning horizon available. For this reason, we propose to use statistical methods for estimating the probability distributions of delivery dates. With these models the probability of the delivery occurring between now and the desired date equals the integral under the distribution. This presents a great advantage over traditional point estimate methods that only tell us whether a delivery might occur at a specific time and date without any information about other points in time.

If a delivery would be predicted as likely to be late some manual actions could be performed. This includes simply checking back with the supplier, looking for alternative suppliers that can provide the required components on short notice, or using different, but compatible, materials/parts among other possible actions. While these actions can help at stabilising or saving a schedule, our focus for this paper lies on utilizing this information within our scheduling process, providing both alternative schedules as well as scheduling jobs in an order where they are more likely to be executable, i.e. by placing them at a time where they are likely to be available.

We plan to employ Bayesian Neural Networks, or other similar and potentially less complex methods providing useful posterior distributions, to estimate these delivery uncertainties or more specifically, their probabilities over time. For this we are collecting data of past deliveries, including ones that were on time, late or cancelled completely. As the usefulness of such data is highly dependent on the meaningfulness of its features, we are currently in the process of analysing which features contain useful information. One avenue we pursue is to probe scheduling and purchasing experts into how they determine a likely missed delivery in their own day-to-day work. Additionally, we analyse all available data with statistical methods such as feature importance analysis and variance inflation scoring.

7. Conclusion

The organisation in production networks and the increased use of JIT are forcing companies to coordinate their material flows along their supply chain. As shown, such complex production systems are vulnerable to a variety of disturbances. A key factor in dealing with production disturbances is a more robust production planning and control. In this paper, we have provided a comprehensive literature review on production disturbances and how they can be classified. We also found that there is currently no classification that distinguishes disturbances in terms of their impact on production planning and control. Thus, we plan on combining the presented classification approaches and develop a new concept to classify disturbances on planning and control level in future work.

We also presented a case study where the production plan of a multinational company becomes impossible due to disturbance in material availability. To automate the rescheduling of such plans we developed an algorithmic approach with several expansion stages. In the first stage, we automated the rescheduling steps, which are currently carried out completely manually, by optimising a weighted cost function. For the next stage, we discussed the usefulness of genetic algorithms, with the help of which it is possible not only to close gaps in production plans by simple measures, but also to create completely new production plans for the fixed planning horizon that are optimized with regard to further criteria. Most importantly, this scheduling solution allows more degrees of freedom than the automated user approach. As we described, this is a form of reactive disturbance management leading to more robust production systems. In a further expansion stage, we want to proactively handle disturbances in material availability or, at least, better identify potential future risks. To this end, we proposed the use of Bayesian machine learning to estimate the probability distributions of a delivery over time. This knowledge, in turn, can be integrated into our scheduling optimizer, which would lead to resilient and less vulnerable production plans and thus to an increased robustness of the whole production system.

To summarize, we found that despite a large variety of existing classification systems the case of production planning and control can still not be fully mapped. Furthermore, we were able to implement an artificial intelligence–based algorithmic automation achieving human competitive results in reactive handling of disturbances and proposed a proactive disturbance handling approach based on machine learned predictions.

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References

[1] Nyhuis, P., Mayer, J., Pielmeier, J., Berger, C., Engehausen, F., Hempel, T., Hünnekes, P. (Eds.), 2016. Aktuellen Herausforderungen der Produktionsplanung und -steuerung mittels Industrie 4.0 begegnen: Studienergebnisse. PZH Verlag, Garbsen.

[2] Berlak, J., Berg, J., Stangl, M., Baumgart, L., 2020. Real-Time IoT-Based Production Planning and Control of Industrial Robots in an Automated Cyber-Physical Production System Under Dynamic Conditions: Lessons Learned from a Make-to-Order Usage Case, in: Moreno-Díaz, R., Pichler, F., Quesada-Arencibia, A. (Eds.), Computer Aided Systems Theory – EUROCAST 2019. Springer International Publishing, Cham.

[3] Lödding, H., 2012. A manufacturing control model. International Journal of Production Research 50 (22).

[4] Permin, E., Bertelsmeier, F., Blum, M., Bützler, J., Haag, S., Kuz, S., Özdemir, D., Stemmler, S., Thombansen, U., Schmitt, R., Brecher, C., Schlick, C., Abel, D., Poprawe, R., Loosen, P., Schulz, W., Schuh, G., 2016. Self-optimizing Production Systems. Procedia CIRP 41.

[5] Bokrantz, J., Skoogh, A., Ylipää, T., Stahre, J., 2016. Handling of production disturbances in the manufacturing industry. Journal of Manufacturing Technology Management 27 (8).

[6] Berlak, J., Hafner, S., Kuppelwieser, V.G., 2020. Digitalization's impacts on productivity: a model-based approach and evaluation in Germany's building construction industry. Production Planning & Control 32 (4).

[7] Wiendahl, H.-P., Wiendahl, H.-H., 2020. Betriebsorganisation für Ingenieure, 9th ed. Hanser, München.

[8] Eversheim, W., 1998. Organisation in der Produktionstechnik: Konstruktion, 3rd ed. Springer Berlin Heidelberg.

[9] Schuh, G., Stich, V., 2012. Produktionsplanung und -steuerung, 4th ed. Springer Berlin Heidelberg.

[10] Berger, C., Berlak, J., Reinhart, G., 2016. Service-based production planning and control of cyber-physical production systems. BLED 2016 Proceedings.

[11] Lödding, H. (Ed.), 2020. PPS-Report 2019: Studienergebnisse, 1st ed. TEWISS, Garbsen.

[12] Ito, A., Ylipää, T., Gullander, P., Bokrantz, J., Centerholt, V., Skoogh, A., 2021. Dealing with resistance to the use of Industry 4.0 technologies in production disturbance management. Journal of Manufacturing Technology Management 32 (9).

[13] Mirdamadi, S., 2009. Modélisation du processus de pilotage d'un atelier en temps réel à l'aide de la simulation en ligne couplée à l'exécution.

[14] Hopkin, P., 2018. Fundamentals of risk management: Understanding, evaluating and implementing effective risk management, 5th ed. Koganpage.

[15] Leitão, P., Restivo, F., 2004. Predictive disturbance management in manufacturing control systems. Proceedings of the IMS International Forum.

[16] M'Halla, A., 2010. Contribution à la gestion des perturbations dans les systèmes manufacturiers à contraintes de temps. Ecole Centrale de Lille; Ecole nationale d'ingénieurs de Tunis (Tunisie).

[17] Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M., 2016. Disruptions in supply chains and recovery policies: state-of-the art review. IFAC-PapersOnLine 49 (12).

[18] Vargas, A., Day, S., Boza, A., Ortiz, A., Ludäscher, B., Sacala, I.S., Moisescu, M.A., 2016. Decision-Making System and Operational Risk Framework for Hierarchical Production Planning. Journal of Control Engineering and Applied Informatics 18.

[19] Darmoul, S., Pierreval, H., Hajri–Gabouj, S., 2013. Handling disruptions in manufacturing systems: An immune perspective. Engineering Applications of Artificial Intelligence 26 (1).

[20] Bayar, N., Hajri-Gabouj, S., Darmoul, S., 2018. Knowledge-based disturbance propagation in manufacturing systems: A case study. International Conference on Advanced Systems and Electric Technologies.

[21] Cowling, P., Johansson, M., 2002. Using real time information for effective dynamic scheduling. European Journal of Operational Research 139 (2).

[22] Simon, D., 1995. Störungsmanagement, in: Reinhart, G., Milberg, J., Simon, D. (Eds.), Fertigungsregelung durch zielgrößenorientierte Planung und logistisches Störungsmanagement. Springer Berlin Heidelberg.

[23] van Brackel, T., 2009. Adaptive Steuerung flexibler Werkstattfertigungssysteme. Dissertation.

[24] Schwartz, F., 2004. Störungsmanagement in Produktionssystemen. Dissertation, Aaachen: Shaker.

[25] Katragjini, K., Vallada, E., Ruiz, R., 2013. Flow shop rescheduling under different types of disruption. International Journal of Production Research 51 (3).

[26] Bayar, N., Darmoul, S., Hajri-Gabouj, S., Pierreval, H., 2016. Using immune designed ontologies to monitor disruptions in manufacturing systems. Computers in Industry 81.

[27] Vieira, G.E., Herrmann, J.W., Lin, E., 2003. Rescheduling Manufacturing Systems: A Framework of Strategies, Policies, and Methods. Journal of Scheduling 6 (1).

[28] Paz Barroso, M., Wilson, J.R., 1999. HEDOMS - Human Error and Disturbance Occurrence in Manufacturing Systems: Toward the development of an analytical framework. Human Factors and Ergonomics in Manufacturing.

[29] Frizelle, G., McFarlane, D., Bongaerts, L., 1998. Disturbance measurement in manufacturing production systems. In: Proceedings of ASI '98, Bremen, Germany.

[30] Wandt, R., Friedewald, A., Lödding, H. Simulation aided disturbance management in one-of-a-kind production on the assembly site. IEEE International Conference on Industrial Engineering and Engineering Management 2012.

[31] Saadat, M., Tan, M., Owliya, M., 2008. Changes and disturbances in manufacturing systems: A comparison of emerging concepts. 2008 World Automation Congress.

[32] Tomforde, S., Kantert, J., Müller-Schloer, C., Bödelt, S., Sick, B., 2018. Comparing the effects of disturbances in self-adaptive systems-A generalised approach for the quantification of robustness. Transactions on Computational Collective Intelligence.

[33] Müller-Schloer, C., Schmeck, H., Ungerer, T. (Eds.), 2011. Organic Computing—A Paradigm Shift for Complex Systems. Springer, Basel.

[34] Scholl, A., 2001. Robuste Planung und Optimierung: Grundlagen-Konzepte und Methoden-experimentelle Untersuchungen.

[35] Olhager, J., 2013. Evolution of operations planning and control: from production to supply chains. International Journal of Production Research 51 (23-24).

[36] Jüttner, U., Peck, H., Christopher, M., 2003. Supply chain risk management: outlining an agenda for future research. International Journal of Logistics Research and Applications 6 (4).

[37] Li, Y., Carabelli, S., Fadda, E., Manerba, D., Tadei, R., Terzo, O., 2020. Machine learning and optimization for production rescheduling in Industry 4.0. The International Journal of Advanced Manufacturing Technology 110.

[38] Wang, D., Yin, Y., Cheng, T., 2018. Parallel-machine rescheduling with job unavailability and rejection. Omega.

[39] Bierwirth, C., Mattfeld, D.C., 1999. Production scheduling and rescheduling with genetic algorithms. Evolutionary computation 7 (1).

[40] Wang, G., Gunasekaran, A., Ngai, E.W., Papadopoulos, T., 2016. Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics.

[41] He, M., Ji, H., Wang, Q., Ren, C., Lougee, R., 2014. Big data fueled process management of supply risks: Sensing, prediction, evaluation and mitigation. Proceedings of the Winter Simulation.

[42] Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., McFarlane, D., 2020. Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. International Journal of Production Research 58 (11).

[43] Baryannis, G., Dani, S., Antoniou, G., 2019. Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. Future Generation Computer Systems 101.

[44] Hosseini, S., Ivanov, D., 2022. A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. International Journal of Production Research 60 (17).

[45] Fandel, G., Fistek, A., Stütz, S., 2011. Produktionsmanagement, 2nd ed. Springer Berlin Heidelberg.

[46] Muir, B.M., Moray, N., 1996. Trust in automation. Part II. Experimental studies of trust and human intervention in a process control simulation. Ergonomics 39 (3).

[47] Hoff, K.A., Bashir, M., 2015. Trust in automation: integrating empirical evidence on factors that influence trust. Human factors 57 (3).

[48] Viana, M.S., Morandin Junior, O., Contreras, R.C., 2020. A Modified Genetic Algorithm with Local Search Strategies and Multi-Crossover Operator for Job Shop Scheduling Problem. Sensors Basel 20 (18).

Biography

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