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Approach for an Adaptive Control Loop between Supply Network and Manufacturing

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Abstract

The development of control loops in manufacturing has been increasingly getting attention by the scientific community. Most presented approaches, however, are exclusively focused on control loops within manufacturing, e.g. between manufacturing control and shop floor. They usually do not include any external factors, for example, from the supply network. To address this issue and to further contribute towards existing approaches, the work herein presented shows the requirements and an initial concept of a control loop between supply network and manufacturing. The findings of this work enable a more effective and efficient reaction by incorporating external factors into the control system and, therefore, a closer integration between supply network and manufacturing.

Keywords: Supply Network; Production Planning and Control; Manufacturing Control; Closed-loop Control

1. Introduction

Manufacturing industry faces enormous challenges worldwide. The complexity of supply networks is increasing due to their global distribution, changing structures and fast changing demands. This is enforced by the change from a seller's market to a buyer's market and decreasing manufacturing volumes with a simultaneously increasing number of variants [1, 2]. The market environment in which manufacturing companies operate is, therefore, becoming increasingly complex, volatile, uncertain and ambiguous [3]. In order to achieve a high level of delivery reliability and thus meet the growing importance for customer satisfaction, it is essential for manufacturing companies to react quickly to events in the supply network [4–6].

Consequently, new partnerships are established to address these challenges. For example, German automobile manufacturer Volkswagen has announced a collaboration with cloud computing provider Amazon to develop a cloud-based platform for the efficient networking of all machines, plants, factories and, in the future, also suppliers [7]. The focus is put on new perspectives for comprehensive process optimization in the overall production process. The basis for this is the vision of a horizontal and vertical integration of the supply network, i.e. the integration of all relevant events, with significant expected cost savings [1]. Due to the high level of automation, the semiconductor industry, for example, has been working on the integration of the supply network since the early 2000s [8].

Current technological developments in digitalization, such as cyber-physical systems, big data, machine learning and artificial intelligence, are driving the development towards autonomy, especially in complex systems [9]. Approaches to transfer control engineering principles to production planning and control (PPC) for the creation of robust processes are also receiving increasing attention [5].

As a contribution to the integration of supply network and manufacturing, this paper presents an adaptive, learning control loop for efficient operative reaction to events of the supply network in manufacturing contributing to the approach of supply chain event management [10, 11].

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2. State of the Art

2.1. Closed-Loop Control

Closed-loop control, also referred to as feedback control, is a process in which the controlled variable *x* is continuously or sequentially measured, compared to the reference variable *w* and influenced by the manipulated variable *y* in order to adapt it to the reference variable [12, 13]. One or several disturbance variables *z* can also be implemented. A distinction can be made between continuous feedback control and sampling control as well as between non-adaptive and adaptive control [13]. The principle of closed-loop control has been successfully used for many years in manufacturing processes and has also received a great deal of attention in PPC [5, 14]. Here, the principle of the control loop is transferred to the elements of the PPC to achieve a continuous adaptation of manufacturing.

2.2. Control Loops in Manufacturing

An overview and classification of existing approaches for control loops in PPC is given in [15]. Table 1 shows a characteristic concept for each category supplemented by an industry standard concept for process control.

Table 1. Classification of control loops in manufacturing.

Category according to [15]	Characteristic representative
(1) Control of Inventory	Wiendahl [16]
(2) Control of Capacity	Begemann [17]
(3) Control of Load	Scholz-Reiter et al. [18]
(4) Control by Rescheduling	Brackel [19]
(5) Knowledge-based Control	Philipp et al. [20]
(6) n.a.	Sachs et al. [21]

According to [15], categories one to three are closely related by the manufacturing system's load as their controlled variable. However, they can be distinguished by the method of determining the load. This is achieved by either measuring the inventory level, which can be controlled by order releases (1), or by capacity adjustments (2), or by a complex setup of multiple controlled and manipulated variables (3). Since categories four and five build on a terminated production plan, their control activities are only performed in case of deviations. The controller type can be distinguished between rescheduling the entire production plan (4) and knowledge-based and predefined procedures to react in current manufacturing situation (5). This is complemented by an approach from discrete, model-based process control (6).

2.3. Machine Learning

If a decision problem cannot be solved mathematically in an exact manner, in complexity theory of computer science it is called non-deterministic polynomial-time hard (NP-hard) [22]. In PPC, this is already the case for problems involving more than two machines or non-predefined order sequences [23]. In practice, heuristic methods are therefore mainly used for optimization in PPC [22, 23].

Machine learning (ML) aims at generating knowledge from data by developing a complex heuristic model from training data. This makes ML a key technology for the development of intelligent systems, which are often referred to as artificial intelligence [24]. The automated development of models from data is also the main difference to earlier approaches of artificial intelligence, which were based on manually constructed knowledge bases [24, 25]. As ML allows generalization to unknown data, it differs from mathematical optimization [26].

The use of ML is therefore particularly worthwhile when, due to the complexity of the problem, not all potentially possible situations and all changes over time can be anticipated. This is also the case when it is unclear what the algorithmic solution to the problem must look like [27]. Experience has shown that ML is much more suitable than conventional methods of data analysis, especially for more than 15 dimensions in the data sets [28].

ML methods can be categorized per type of feedback into unsupervised, supervised and reinforcement learning (cf. Fig. 1). In practice, however, the first two cannot always be clearly distinguished [24, 27]. Each of the methods is suitable for different learning tasks.

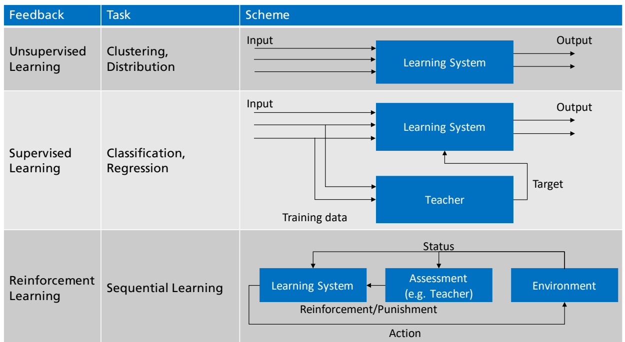

Fig. 1. Methods of machine learning (adapted from [24, 27]).

In the manufacturing environment, ML is already used, among others, for pattern recognition, process control, fault detection and classification, and predictive maintenance [29]. Furthermore, adaptive control based on reinforcement learning is used for order dispatching [30], process control [31] as well as in robotics [32, 33]. An overview of suitable algorithms is given by [34].

2.4. Architecture to Apply Machine Learning

Transaction data in PPC is generated in large quantities by sensors and IT systems in a diverse and heterogeneously structured manner and must be processed and analyzed in minimal computing time [5, 35]. In addition, reliability of the data must be ensured, as they are crucial for the success of the company. These challenges are also known as the 5V of big data (variety, volume, velocity, veracity, value) [35, 36]. If ML procedures are used in PPC, these challenges must be considered.

Lambda architecture is a well-known concept for addressing such challenges in data analytics [37]. It structures data processing into three layers. They are defined as batch, speed and serving layers, which differ in particular in their latency during data processing [37, 38]. This is due to the technical impossibility to evaluate all historical data in acceptable computing time after the occurrence of events. For this reason, the large amounts of data that are made available through the serving layer are pre-processed in the batch layer. Because of their close connection, batch and serving layer are often referred together as batch layer [37–39]. These layers are always supplemented by speedy near-real-time analysis efficiently and quickly carry out analysis of data when a decision must be made because of an event. Exemplary implementations of a lambda architecture with diverse software components [38] and performance analysis [39] can be found in the literature.

Transferred to ML, models are developed and trained in the batch layer using algorithms. These models are applied to events in the speed layer in near real-time computing time.

3. Analysis of Control Loops in Manufacturing

To analyze control loops in manufacturing, requirements must first be defined. Then existing concepts are compared and analyzed based on these requirements.

3.1. Requirements

The following requirements were synthesized from the introduction and state of the art. First, the control loop must be suitable for the **application**, meaning it must allow control of manufacturing with the aim of improving key performance indicators regarding the supply network (e.g. delivery reliability) and taking its influences into account. The necessity of this requirement results from the motivation to transfer control engineering principles [5] to the interface between supply network and PPC. For this purpose, it is also necessary to consider **external events** from the supply network in the control loop and that appropriate measures can be taken in response to the former. Therefore, the control loop must be designed in the sense of an **adaptive** control [13] in such a way that its data-driven model is not only oriented to predefined situations, but also dynamically adapts with unknown data. The **learning capability** [40] follows on from this and should enable the controller to develop new decisions from data sets. For this, it is necessary that data-based decisions can be abstracted and transferred to unknown data sets. In combination with a high **degree of automation** [41], the learning capability allows for controlling and adapting all result variables to changed environmental conditions enabling to correct defined and undefined errors. The system limits can thus be continuously extended. For this purpose, the controller must be able to determine **multi-dimensional parameters** and their dependencies as manipulated variables. The complexity of the problems in PPC [23] alone determines this complex controller design with multi-dimensional manipulated variables.

3.2. Comparison and Analysis

In the following step, the defined requirements are used to compare the concepts classified in section 2.2. Table 2 shows the resulting comparison and assessment of the individual concepts. The rating for each requirement ranges from not in scope (0) to very well suited (++++).

Table 2. Assessment of concepts for control loops in manufacturing.

Requirement	[16]	[17]	[18]	[19]	[20]	[21]
Application	+	++	++	++	++	0
External Events	0	0	0	0	0	0
Adaptivity	++	++	++	++	++	++
Learning Capability	+	+	+	+	+	+
Degree of Automation	+	+	+	+	+	++
Multi-dim. Parameters	+	++	+++	++++	++	++

These concepts focus primarily on the internal optimization of manufacturing and not on the integration with the supply network. Consequently, external events are not considered. The concepts are also designed adaptively for known parameters only and not as learning systems. Furthermore, the degree of automation is mainly less and only a few concepts intensively consider multi-dimensional parameters as manipulated variables.

4. Concept

The requirements are implemented with the concept of the adaptive control loop for an integrated supply network (ACSN). The ACSN is a discrete, event-based, adaptive and learning control loop that integrates the supply network with the PPC (cf. Fig. 2, blue control loop). This complements existing approaches for control loops in manufacturing (cf. Fig. 2, green control loop) to form a cascade control, whereas state of the art forms the inner control loop and the ACSN the outer control loop.

The ACSN consists of a controller as well as manufacturing control and manufacturing as controlled system. More precisely, the controller interacts with sequence deviation [42] in manufacturing control. Additionally, operating and machine data acquisition serves as the measuring element.

The reference variable for the control loop is the production plan, which - adapted by the controlling element - also serves as manipulated variable. This influences the controlled variable, namely the expected delivery dates of the manufacturing orders. However, since different use cases can aim at different objectives (cf. section 5) the controlled variable can be replaced. Events from supply network, such as deviations between forecasts and actual customer behavior, are considered. These events can either be detected when they occur using established technologies such as statistical process control [43] or be predicted in advance [44]. For effective processing, events are then classified [45], before incorporating them into the controlling element's decisions.

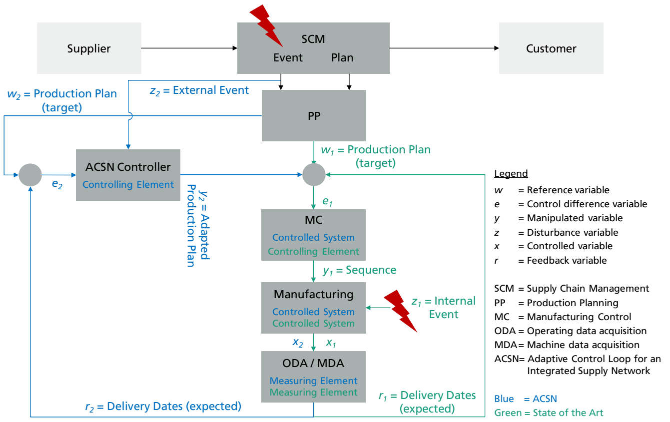

Fig. 2. Adaptive control loop for an integrated supply network.

The ACSN becomes adaptive and learning fusing reinforcement learning in the controlling element. The status information (cf. Fig. 1) is reflected in the controlled variable. If the deviation between planned and expected delivery date is smaller, this is used as reinforcement during learning. If the deviation becomes larger, this is used as so-called punishment. This approach makes it possible to adjust even complex manipulated variables with many dependencies automatically and with better results with increasing duration.

To be able to work with the heterogeneous data from supply network and PPC, the concept can be implemented based on the lambda architecture (cf. Fig. 3). Input data for this are then the production plan (reference variable), the adjusted production plan (manipulated variable), the expected delivery dates (controlled variable) and events from supply network (disturbance variable). Subsequently, these data are used to train a model in the batch layer with reinforcement learning. This takes place periodically, for example at night or on weekends. In the speed layer, shown here via the controlling element, the model is applied to the data set when an event occurs to decide on corrective measures such as order prioritization and thus adjust the production plan (especially after manufacturing has started).

5. Application and Expected Benefits

Since the concept of ACSN is still under research and development, only preliminary experiments have been conducted to date. However, to elaborate the expected benefits of the approach, two applications based on the concept and the preliminary findings have been discussed in expert workshops.

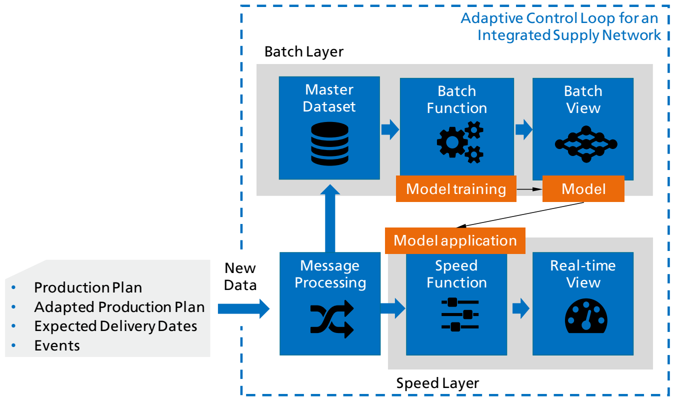

Fig. 3. Implementation of the adaptivity and learning capability of the control loop according to the lambda architecture.

5.1. Preliminary Experiments

For preliminary experiments, the ACSN was implemented in a simplified form and combined with a simulation model of a semiconductor production as its globally distributed and complex supply network with complex manufacturing suitably reflects an application for the ACSN [6, 46].

In the simplified implementation of the ACSN the information flows are not fully automated and in the controlling element a simplified classification by supervised learning is used instead of reinforcement learning. The simulation model is based on MIMAC Set 1, which is widely used in literature and describes a simplified semiconductor manufacturing process with two products and corresponding routings [47]. Resulting simulation runs can be divided in three sections (cf. Fig. 4). First a settling phase of about one month, in which production starts up. Second, a phase in which work in progress and capacity utilization converge to their limits. This also reduces delivery reliability, as queues now form at machines. Thirdly, a stable phase in which delivery reliability in particular also stabilizes.

As shown in Figure 4, the corrective measures taken by the ACSN have a positive effect on delivery reliability, which has been increased by one to six percent. Furthermore, in the most imporant stable phase delivery reliability settles at around 70 percent, while only around 66 percent without the ACSN. The concept of the ACSN therefore works in principle and an improvement in delivery reliability can be achieved.

However, further research and development (cf. section 6) is necessary to transfer the concept and preliminary experiments to practice and to allow for validation in a real manufacturing environment.

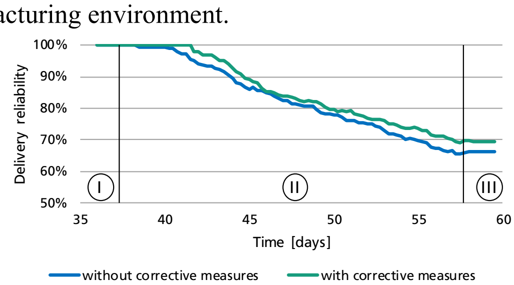

Fig. 4. Delivery reliability in preliminary experiment.

5.2. Application for Logistic Objectives

The first scenario aims at the already mentioned improvement of delivery reliability in semiconductor manufacturing. The complex manufacturing process in this industry results in a lead time of up to three months [6]. However, with an increasing time horizon, planning accuracy decreases significantly [48]. For example, according to [49] research at Intel has shown a significant deviation between forecasts and actual demand. Within a time period of ten years they have only matched for 35 minutes. Deviations between forecasts and actual demands result in many events that require appropriate responses.

Benefits of the ACSN in this scenario have been discussed in an expert workshop with a semiconductor manufacturer. Experts from the areas of supply network planning, PPC and manufacturing were involved. It is expected that by automating the entire process, the ACSN will enable a faster response to events from supply network and thus a more efficient process. The improvement in delivery reliability in the single-digit percentage range as shown by the preliminary experiments (cf. section 5.1) was considered realistic and promising. In addition, the ACSN will make the decision on corrective measures in PPC more robust by avoiding errors that occur when manual interventions are made in PPC. For example, due to its complexity, manufacturing can behave unexpectedly when manual interventions are made; under- or over-steering is also possible if parameters are manually incorrectly adjusted [6, 42]. With the expected improved delivery reliability customer satisfaction increases, which is of great importance with regard to the buyer's market. In addition, the deeper integration of supply network and manufacturing and the subsequent increase in delivery reliability allows safety stocks to be reduced, which is expected to lead to significant cost reductions [43].

5.3. Application for Energy Objectives

With the ongoing debate on climate change an increasing share of renewable energies becomes crucial to meet climate protection goals. Consequently, with the inherent volatility of renewable energies, energy supply will become more and more volatile [50]. Therefore, the second scenario aims at synchronizing volatile energy supply and demand by utilizing price signals as triggers in the ACSN in the sense of automated demand response [51].

Benefits of the ACSN in this scenario have been discussed in an expert workshop with a manufacturing company. Experts from the areas of energy procurement, PPC and manufacturing were involved. Again, it is expected that by automating the entire process, the ACSN will enable a faster response to events representing deviations in energy price signals and thus a more efficient process. In addition, the ACSN will make the decision on how to react to price deviations more robustly by reducing human decisions in a complex environment such as the energy system with multi-dimensional parameters. Furthermore, the potential for demand response is increased by lowering the entry barriers for companies by incorporating energy targets in the manufacturing control loop.

6. Summary and Outlook

The implementation of control loops linking supply network and manufacturing is a key aspect for meeting global challenges. However, existing approaches for control loops are not suitable for this integration. Therefore, a concept for an adaptive control loop for the integration of supply network and manufacturing was developed.

To extend knowledge in this research field, the authors are currently focusing on the following aspects. To be able to validate the concept in practice, suitable algorithms for the controlling element must be selected. Afterwards, the concept can be implemented and trained with data relevant for a real application. Prerequisites and limits can then be derived and, subsequently, the concept can be applied to further use cases.

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References

[1] Bauernhansl T, 2017. Die Vierte Industrielle Revolution: Der Weg in ein wertschaffendes Produktionsparadigma. In: B Vogel-Heuser, T Bauernhansl, M ten Hompel (eds.). *Handbuch Industrie 4.0: Bd. 4: Allgemeine Grundlagen*. Berlin: Springer Vieweg. pp. 1–31.

[2] Chien C-F, Dauzère-Pérès S, Ehm H *et al.*, 2008. Modeling and analysis of semiconductor manufacturing in a shrinking world. In: SJ Mason et al. (eds.). *2008 Winter Simulation Conference*: IEEE. pp. 2093–2099.

[3] Mack O, Khare A, 2016. Perspectives on a VUCA World. In: O Mack et al. (eds.). *Managing in a VUCA World*. Cham: Springer. pp. 3–19.

[4] Chopra S. *Supply Chain Management: Strategy, Planning, and Operation,* 7th edn. Boston, MA, USA: Pearson, 2018.

[5] Schuh G, Lödding H, Stich V *et al.*, 2011. High Resolution Production Management. In: C Brecher, F Klocke (eds.). *Wettbewerbsfaktor Produktionstechnik: 27. Aachener Werkzeugmaschinen Kolloquium, 26. - 27.05.2011*. Aachen: Shaker. pp. 61–80.

[6] Mönch L, Fowler JW, Mason SJ. *Production planning and control for semiconductor wafer fabrication facilities: Modeling, analysis, and systems*. New York, NY, USA: Springer, 2013.

[7] Volkswagen. Volkswagen and Amazon Web Services to develop Industrial Cloud. https://www.volkswagenag.com/en/news/2019/03/volkswagen-and-amazon-web-services-to-develop-industrial-cloud.html. Accessed 31 October 2019.

[8] Semiconductor Industry Association, 2001. The International Technology Roadmap for Semiconductors (2001 ITRS). https://s.fhg.de/itrs2001. Accessed 31 October 2019.

[9] Bauernhansl T. *Cognitive Production Systems - Technologies and Business Impacts.* NEXCON First International Virtual Congress on Smart Manufacturing. 28 February 2019. Stuttgart, 2019.

[10] Otto A. Supply Chain Event Management: Three Perspectives. *The International Journal of Logistics Management* 2003 *14*(2). pp. 1–13.

[11] Konovalenko I, Ludwig A. Event processing in supply chain management – The status quo and research outlook. *Computers in Industry* 2019 *105*. pp. 229–249.

[12] DIN EN 60027-6, 2008. Letter symbols to be used in electrical technology –Part 6: Control technology, Berlin. Beuth Verlag.
[13] DIN IEC 60050-351, 2013. International electrotechnical vocabulary – Part 351: Control technology, Berlin. Beuth Verlag.
[14] Moyne J, 2015. Run-to-Run Control in Semiconductor Manufacturing. In: J Baillieul, T Samad (eds.). *Encyclopedia of Systems and Control*. London: Springer.
[15] Niehues MR, Blum M, Teschemacher U *et al.* Adaptive job shop control based on permanent order sequencing. *Production Engineering* 2018 *12*(1). pp. 65–71.
[16] Wiendahl H-P. *Fertigungsregelung: Logistische Beherrschung von Fertigungsabläufen auf Basis des Trichtermodells*. München: Hanser, 1997.
[17] Begemann C. *Terminorientierte Kapazitätssteuerung in der Fertigung*. Hannover: PZH Produktionstechn. Zentrum, 2005.
[18] Scholz-Reiter B, Windt K, Liu H. A multiple-logistic-objective-optimized manufacturing planning and control system. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 2011 *225*(4). pp. 599–610.
[19] Brackel T. *Adaptive Steuerung flexibler Werkstattfertigungssysteme: Nutzung moderner Informations- und Kommunikationstechnologien zur effizienten Produktionssteuerung unter Echtzeitbedingungen*. Wiesbaden: Gabler, 2009.
[20] Philipp T, de Beer C, Windt K *et al.*, 2007. Evaluation of Autonomous Logistic Processes: Analysis of the Influence of Structural Complexity. In: K Windt, M Hülsmann (eds.). *Understanding autonomous cooperation and control in logistics: The impact of autonomy on management, information, communication and material flow*. Berlin: Springer. pp. 302–324.
[21] Sachs E, Guo R-S, Ha S *et al.*, 1990. On-line process optimization and control using the sequential design of experiments. In: *1990 Symposium on VLSI Technology*: IEEE. pp. 99–100.
[22] Pinedo ML. *Scheduling: Theory, Algorithms, and Systems,* 5th edn. Cham: Springer, 2016.
[23] Heger J. *Dynamische regelselektion in der Reihenfolgeplanung: Prognose von steuerungsparametern mit Gaußschen Prozessen*. Wiesbaden: Springer Vieweg, 2014.
[24] Döbel I, Leis M, Vogelsang MM et al. *Maschinelles Lernen: Eine Analyse zu Kompetenzen, Forschung und Anwendung*. München: Fraunhofer-Gesellschaft, 2018.
[25] Goodfellow I, Bengio Y, Courville A. *Deep learning*. Cambridge, MA, USA: MIT Press, 2016.
[26] Le Roux N, Bengio Y, Fitzgibbon A, 2012. Improving First and Second-Order Methods by Modeling Uncertainty. In: S Sra, S Nowozin, SJ Wright (eds.). *Optimization for machine learning*. Cambridge, MA, USA: MIT Press. pp. 403–430.
[27] Russell SJ, Norvig P. *Artificial intelligence: A modern approach,* 3rd edn. Upper Saddle River, NJ, USA: Prentice-Hall, 2010.
[28] Bauer H, Ranade P, Randon S. Big data and the opportunities it creates for semiconductor players. *McKinsey on Semiconductors* 2012(Autumn 2012). pp. 46–55.
[29] Susto GA, Pampuri S, Schirru A *et al.*, 2012. Automatic Control and Machine Learning for Semiconductor Manufacturing: Review and Challenges. In: *Proceedings of the 10th European Workshop on Advanced Control and Diagnosis (ACD 2012)*.
[30] Stricker N, Kuhnle A, Sturm R *et al.* Reinforcement learning for adaptive order dispatching in the semiconductor industry. *CIRP Annals - Manufacturing Technology* 2018 *67*(1). pp. 511–514.
[31] Liu K, Chen Y, Zhang T *et al.* A survey of run-to-run control for batch processes. *ISA transactions* 2018 *83*. pp. 107–125.
[32] Recht B. A Tour of Reinforcement Learning: The View from Continuous Control. *Annual Review of Control, Robotics, and Autonomous Systems* 2019 *2*(1). pp. 253–279.
[33] Jardine PT, Kogan M, Givigi SN *et al.* Adaptive predictive control of a differential drive robot tuned with reinforcement learning. *International Journal of Adaptive Control and Signal Processing* 2019 *33*(2). pp. 410–423.
[34] Lewis FL, Vrabie D, Vamvoudakis KG. Reinforcement Learning and Feedback Control: Using Natural Decision Methods to Design Optimal Adaptive Controllers. *IEEE Control Systems* 2012 *32*(6). pp. 76–105.
[35] Bauer D, Maurer T, Henkel C et al. *Big-Data-Analytik: Datenbasierte Optimierung produzierender Unternehmen*. Stuttgart: Fraunhofer IPA, 2017.
[36] Demchenko Y, Laat C de, Membrey P, 2014 - 2014. Defining architecture components of the Big Data Ecosystem. In: *2014 International Conference on Collaboration Technologies and Systems (CTS)*: IEEE. pp. 104–112.
[37] Marz N, Warren J. *Big data: Principles and best practices of scalable real-time data systems*. Shelter Island, NY, USA: Manning, 2015.
[38] Kassner L, Gröger C, Königsberger J *et al.*, 2017. The Stuttgart IT Architecture for Manufacturing. In: S Hammoudi et al. (eds.). *Enterprise Information Systems*. Cham: Springer International Publishing. pp. 53–80.
[39] Kiran M, Murphy P, Monga I *et al.*, 2015. Lambda architecture for cost-effective batch and speed big data processing. In: *Proceedings of the 2015 IEEE International Conference on Big Data*: pp. 2785–2792.
[40] Anderson LW, Krathwohl DR. *A taxonomy for learning, teaching, and assessing*. New York, NY, USA: Addison Wesley Longman, 2001.
[41] Groche P, Hoppe F, Kessler T *et al.*, 2018. Industrial Working Environment 2025. In: M Liewald (ed.). *New developments in sheet metal forming: Conference proceedings of the International Conference on 'New Developments in Sheet Metal Forming' in Fellbach (near Stuttgart) - Germany, held on May 15th and 16th, 2018*. Stuttgart: Institute for Metal Forming Technology. pp. 125–136.
[42] Lödding H. *Handbook of manufacturing control: Fundamentals, description, configuration*. Heidelberg: Springer, 2013.
[43] Bauer D, Schlereth A, Maier F *et al.*, 2019. Automated Framework Based on Supply Chain Events. In: SemI40 Consortium (ed.). *A SemI40 Project Prospective: Industry4.0 from Evolution to Revolution*. pp. 36–41.
[44] Fernández E, Salomone E, Chiotti O. A model driven development approach based on a reference model for predicting disruptive events in a supply process. *Computers in Industry* 2012 *63*(5). pp. 482–499.
[45] Bauer D, Bauernhansl T, Sauer A. Enhanced Classification of Events for Manufacturing Companies in Supply Networks. *Procedia CIRP* 2019 *81*. pp. 87–92.
[46] Aelker J, Bauernhansl T, Ehm H. Managing Complexity in Supply Chains: A Discussion of Current Approaches on the Example of the Semiconductor Industry. *Procedia CIRP* 2013 *7*. pp. 79–84.
[47] Fowler JW, Trybula W, Lloyd P et al. *Measurement and Improvement of Manufacturing Capacity (MIMAC): Final Report*. Austin, TX, USA: SEMATECH, 1995.
[48] Schuh G, Potente T, Thomas C *et al.*, 2013. Cyber-Physical Production Management. In: V Prabhu (ed.). *Advances in Production Management Systems. Sustainable Production and Service Supply Chains: IFIP WG 5. 7 International Conference, APMS 2013, State College, PA, USA, September 9-12, 2013, Proceedings, Part II*. Berlin: Springer. pp. 477–484.
[49] Wilding R. The supply chain complexity triangle: Uncertainty generation in the supply chain. *International Journal of Physical Distribution & Logistics Management* 1998 *28*(8). pp. 599–616.
[50] Palensky P, Dietrich D. Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads. *IEEE Transactions on Industrial Informatics* 2011 *7*(3). pp. 381–388.
[51] Roesch M, Bauer D, Haupt L *et al.* Harnessing the Full Potential of Industrial Demand-Side Flexibility: An End-to-End Approach Connecting Machines with Markets through Service-Oriented IT Platforms. *Applied Sciences* 2019 *9*(18). pp. 3796.