CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2021

2nd Conference on Production Systems and Logistics

Requirements for Human-Centric Informational Complexity Management in Production in the Context of the Matrix Fusion Factory

Jörg Siegert[1,2], Thilo Schlegel[1,2], Liliana Zarco[1], Thomas Bauernhansl[1,2]
[1]Institute of Industrial Manufacturing and Management IFF, University of Stuttgart, Nobelstr. 12, Stuttgart, 70569, Germany
[2]Fraunhofer Institute for Manufacturing Engineering and Automation IPA, Nobelstr. 12, Stuttgart, 70569, Germany

Abstract

For four years now, the concept of the Matrix Fusion Factory MFF has been developed and studied. The MFF dissolves the separation between digital and real entities and focuses on value creation in production. The MFF is based on two prerequisites: first, an organizational structure for assessing value creation in factories whose modular hardware and software structures are constantly reconfigured; and second, the fragmentation logic presupposes increasing complexity, which in turn requires methods for evaluating and reducing complexity. This paper focuses on the reduction and management of informational complexity since different ways of information management (i.e. capturing, selecting, compressing, and providing information) lead to different effects on the production system, especially if the information is processed by humans. Therefore, the central assessment approach for information management must be value creation. Thus, this paper discusses the impact of information management on value creation and how information management can support value creation. In particular, it is clarified how informational complexity in production can be reduced without distorting the underlying information and the implications for technology and organization are discussed.

Keywords

Matrix Production; Complexity Management; Information Management; Matrix Fusion Factory; Decision Making; Information Logistics

1. Introduction and Motivation

Ultra-flexible, mobile, and highly modularized manufacturing systems consisting of constantly reconfigured hardware and software module networks offer numerous additional degrees of freedom due to their modularity and mobility. To enable optimal value creation, these degrees of freedom require methods and approaches to deal with the enormous increase in complexity. [1–9]

The basic requirement for creating value in production is to complete customer orders with assured quality. Especially in ultra-flexible factories, where the entire manufacturing system is in a constant state of change, the order becomes the only constant that cannot be changed by the manufacturing system [2, 10–13]. Therefore, the MFF considers the factory as a service provider for the respective order. The goal is to optimally adapt the manufacturing system to the order.

The completion of the customer's order is the basis of value creation, with the fundamental objective being maximum added value through a minimum use of resources. The MFF therefore aims at minimizing the use of parts and factory resources to complete an order. Prerequisites for the minimum use of production

DOI: https://doi.org/10.15488/11287

resources are scalability of the resources themselves and sufficient degrees of freedom to adapt to the order. The MFF considers machines as context-related, temporary networks of scalable hardware and software modules, thus generating additional degrees of freedom [2].

According to Milling, a system is complex if the number of possible links within a system is no longer manageable and the causalities among them cannot be recognised anymore [14]. According to Kluth et al. complexity involves the four complexity dimensions variety, heterogeneity, dynamics, and non-transparency [3]. According to Siegert et al., complexity in modular and flexible production systems depends on the number of degrees of freedom of its subsystems and components [1]. These degrees of freedom include, above all, the spatial, time and informational forms, interconnections and changes of all entities of a system. However, even if complexity may not be quantified, the varying states of complexity of a production system can be described and differentiated from each other [1]. According to Weaver complexity can be -classified as organised and unorganised complexity [15]. Ferretti defines a system's complexity as ontological complexity, the existing lack of order, or as epistemological complexity, i.e. the overstraining of human perceptual capacities because of a wide variety and diversity of existing interdependencies [16].

Both extreme ontological and (perceived) epistemological complexity lead to an overload of information. Therefore, the concept of minimizing the use of resources is also applicable to information. In line with the other production resources, it must be decided how much and which information is required to fulfil a task. The effect of distorted information must therefore be considered.

Each decision and each process in a manufacturing system is based on information [17–19]. In particular, the above-mentioned degrees of freedom can only be used to add value by modelling information [20]. Value creation is therefore dependent on the right information in the right place at the right time [21, 22]. For this reason, information, its provision, and its processing require special consideration in the MFF.

The underlying research questions are therefore:

- What is the role of information and information distortion concerning value creation in production? Especially considering the concept of a minimum use of production resources?
- How to determine the admissible value/degree of information
- distortion?
- What requirements does this place on organizational and technical structures? How can these requirements be addressed?

This paper uses the paradigm of the Matrix Fusion Factory to show how value creation can be optimized by incorporating relevant production aspects. In the following, the role of information and information distortion in the concept of a minimum use of resources is described and how to determine the permissible degree of information distortion. Then, the role of the decision maker is considered from a human and machine perspective before explaining the organizational structures of the MFF.

2. Determining permissible information distortion

Distorting information means selecting, presenting, or weighting information in such a way that the underlying facts described by the information are framed in a certain way. This usually results from omitting or not considering some additional information by oneself or others. That does not necessarily mean reducing the content of truth of the various pieces of information per se or creating false information. Thus, it is not necessarily the information itself that is distorted, but the picture that is gained from the information [23–28]. Information distortion is therefore a cognitive bias [25–28] which in extreme cases may also lead to false knowledge.

Any way of aggregating information therefore leads to a distortion of the underlying facts [27]. However, since humans [29] or computers are unable to solve tasks unless information is aggregated, this is an essential step [30]. Therefore, it is not necessary to clarify whether information may be distorted but rather to which extent this is permissible.

This poses the problem of how to identify potentially distorted information. Checking the content of truth of individual pieces of information is certainly not the sole solution because the truth of individual pieces of information may be unchanged. It is only possible to detect the absence or incorrect weighting of individual pieces of information causing a distortion, if the overall picture generated can be matched some other way. This can be achieved by comparing it either with the real facts or with other images with validated truth content.

The relevant production target variable is quality-assured added value. In production, information is usually condensed to aid decision making. For this purpose, complex facts are simplified, or important interrelationships are highlighted. Whether the impression of a fact has been "mapped correctly" can therefore be determined by the impact of the decision made. If the decision or the resulting action adds value, the distortion of information was permissible or at least not detrimental. However, if the decision has a negative effect on value creation, the distortion was not permissible. The basis for assessing permissible information distortion is therefore its effect on value creation.

This leads to a further examination of the decision-making process, its influences and the resulting actions within the production system.

Understanding mental processes, such as perception, memory, reasoning, and motor response, as they affect interactions among humans and other elements of a system in general, is an independent discipline called cognitive ergonomics [31].

According to Endsley, in cognitive ergonomics decision making and the subsequent performance of the decided course of action can be traced down to the situation awareness of the decision-maker [29, 31, 32]. Endsley [33] defines situation awareness as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future". Dominguez defines situation awareness as the "continuous extraction of environmental information, integration of this information with previous knowledge to form a coherent mental picture, and the use of that picture in directing further perception and anticipating future events" [34].

Consequently Endsley's model [29, 32] (see Figure 1) is set into three levels of situation assessment, each level being a necessary precursor to the next higher level. This model follows a chain of information processing, from perception, through interpretation, to prediction. The three levels of situation awareness are as follows: Perception of the elements in the environment: this stage is the first step to achieve the situation awareness which is related to the human's perception of information in a given time and space. Comprehension of the current situation: comprehension is essential to understand the significance of the elements perceived and to gain a

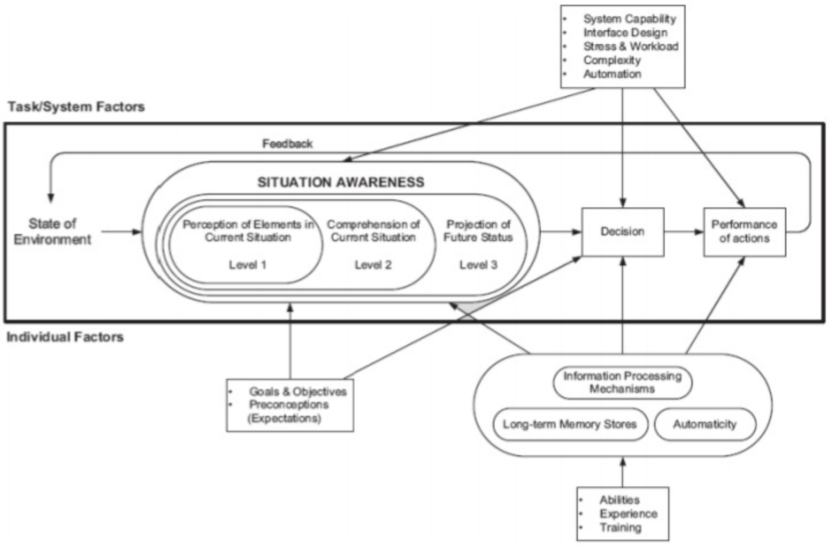

Figure 1 Model of situation awareness levels [29]

picture of their relationships. Projection of future status: this level of situation awareness is associated with the ability to project the future of the elements in the environment. Accuracy of the projection is highly dependent upon the accuracy of perception and comprehension.

In the context of decision making, information distortion can therefore be understood as the wrong perception of information or the wrong supply of information, or the wrong comprehension of the current situation and therefore a wrong picture of the relationships of the perceived elements. This will lead to a wrong projection of a future status and subsequently to a poor decision and taking a suboptimal decision.

According to Endsley's model, the parameters influencing the situation awareness and therefore inducing information distortion can be divided into individual factors and task/system factors.

Individual factors can be influenced by training and experience. This is underlined by the conclusion of Carley and Lin that information distortion can at least to some extent be combated by training [27] and ties in with IFF's definition of competence [17]: "Competencies represent the entirety of abilities, skills and existing knowledge to adequately apprehend, analyse, evaluate, make decisions, and act correctly in complex, dynamic and sometimes chaotic situations, taking into account relevant goals." This definition strongly emphasises the evaluation of the situation to take the correct action. Therefore, systematically correct action calls for the analysis and evaluation of the situation and for decision-making. Unsystematically correct action, i.e., action that is not in line with the decision but nevertheless adds value, makes the system unpredictable in the long term if it occurs frequently and should therefore be avoided. If unsystematically correct action is taken frequently, decision making processes or decisive entities should be checked for their suitability.

Task/System factors are largely influenced by complexity and the resulting stress and mental workload. Mental workload reflects the amount of mental resources required to perform a set of concurrent tasks [35]. Manufacturing systems are therefore prone to diminishing the situation awareness and to inducing information distortion of the individuals since they typically have a high level of complexity, many different capabilities, are highly automated, and are usually operating under cost and time pressure, therefore creating a high stress and high workload environment for their employees to work in. This impedes the situation awareness of the decision makers and leads to information distortion. This is underlined by the findings of Chaxel, Wiggins et al., that the mere belief of having limited time to make a decision is influencing and aggregating information distortion [23]. In addition, according to Carley and Lin, technology based distortion is typically more debilitating than personnel induced information distortion [27]. Especially as far as big data approaches are concerned, this leads to the consideration of how to reduce the content of the various dimensions of the 5V model [36] without unduly distorting it.

In short, to ensure correct actions and therefore value creation, the individual factors and the task/system factors must thus be brought into balance (see Figure 2). This paper focuses on the organizational and technical requirements for adjusting the task and system factors to the individual factors to avoid information distortion.

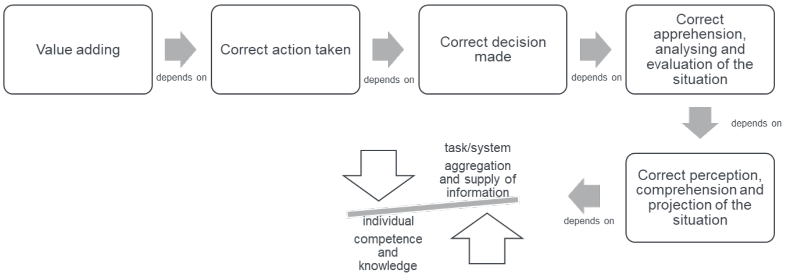

Figure 2 Value adding and balancing factors

3. Determining optimal degrees of freedom

In manufacturing systems, decisions are made by different actors or entities. Decisions can therefore be divided into decisions made by machines and decisions made by humans, depending on the type of entity making the decision. On a higher level, the process leading to the making of a complex decision is similar both for humans and machines, regardless of their different data processing capacities and speeds. Both need to consider the facts of the matter on the basis of information, weigh this information, determine possible courses of action, prioritize these courses according to the anticipated effects, and then decide on one of the courses of action [37, 38]. The fundamental difference between decisions made by machines and by humans apart from the suitability for different situations and areas of application is therefore from the industrial management point of view the assumption of responsibility [17].

Greater degrees of freedom in the manufacturing system mean more possible courses of action and more scopes for action. In general, this means that the number of suboptimal courses and scopes for action increases disproportionately as the degrees of freedom increase. This is problematic because the possibility of making wrong or suboptimal decisions may not only have a negative effect on value creation but may also unnecessarily increase epistemological complexity. The decision maker (whether human or machine) is confronted with a multitude of decision options, from which the few relevant options must first be laboriously filtered out before the most suitable one can be determined [28, 39, 40].

Especially in the context of the dynamics of the production environment, this preceding step significantly increases epistemological complexity [1] which creates a much greater risk of making a wrong decision and ultimately taking an incorrect course of action. Polman suggests that this is even more the case if a decision is made for a third party [28]. This leads to the question of how to restrict the degrees of freedom in order to reduce the risk of making wrong decisions.

Basically, it can be said that too much complexity must always be avoided, otherwise the chain of action consisting of analysis and evaluation cannot be run through systematically [17, 29, 32, 33]. In addition, evaluating possible courses of action calls for an assessment of the consequences of the decision made. Therefore, only those degrees of freedom should be implemented whose benefits and consequences can be estimated by the decision-maker with a certain amount of confidence.

This leads to the following insight:

1. Additional degrees of freedom make a positive contribution to value creation if the type and number of resulting decision options do not disproportionately raise the risk of wrong decisions.
2. The question of the degrees of freedom required, or of the manageability by the decisive entity, always depends on the entity’s competence.
3. The degree of overload can be strongly influenced by the way in which information is provided.

It has become apparent that, particularly for point 3, a large proportion of the fundamental logistical principles and main objectives can be transferred to handling information: the 5Rs of information logistics are therefore structured as follows: the right information (right choice), in the right quantity (right aggregation), at the right place, at the right time for the right decision-making entity [41, 42].

4. Organizational requirements for socio-technical systems

The requirements described above necessitate a socio-technical organizational structure that makes it possible to integrate people in terms of information and behavior so that they are cognitively addressed optimally and socially integrated. Only then they are able to make the right decisions at the right time and possess the necessary freedom and motivation to translate their decisions into correct action. This is confirmed by different studies in the field of cognitive ergonomics which state that mental workload can vary between low (i.e., underload) and very high levels (i.e., overload) [43, 44].

These two extremes are classified as inappropriate and can lead to imperfect or inaccurate perceptions, as well as to low levels of attention and capacity, and to insufficient time for a proper information processing [43–51]. High levels of mental workload occur when task demands exceed performer capacity [52]. [53]

Therefore, a location- and time-dependent resource allocation of data, knowledge, competencies, and performed actions is necessary. Additionally, requirements increase with the scope of the decision to be made. In the factory context, the smaller the quality control loop the better [54]. This also applies to decision-making control loops. Consequently, decisions affecting the direct creation of value should also be made close to the point where the value is added, since the information picture at this point is largely original and undistorted. This is underlined by the findings of Carley and Lin who state that regardless of information distortion performance is enhanced if there is a match between the complexity of organizational design an task environment [27].

In addition, the ability of the decision-making entity to recognize when it is overstretched, needs help, or can no longer assume responsibility should be considered. In the latter case, escalation management within a hierarchy chain is required. At the same time, the reverse case should also be taken into account. If the production-related person is capable of assuming responsibility for the right decision, he or she should be able and allowed to make it. This, in turn, requires the right of access to further information if the employee considers it useful for the decision. This increases the effectiveness and efficiency of value creation and is in line with the concept of minimizing the use of resources, since the information control loops should be kept as small as possible in the respective context. This also increases the employee's self-efficacy and enhances motivation and willingness to perform.

This context-related shifting of decision points along organizational structures is modelled in the MFF by means of flexible, heterarchical quality control loops.

In the MFF, information is provided in such a way that people can grasp the relevant facts quickly and correctly. It must therefore represent the facts correctly and, if possible, coherently. This particularly applies to the quality of the information. Contradicting information, or information that appears to contradict each other, leads to cognitive dissonance and leads to suboptimal decisions. Information must either be aligned, for example on different levels of aggregation, or must point these levels out. To avoid cognitive dissonance, it is important to ensure that information is not excessively distorted. The MFF embeds the information and the human being into the information supply by using the Standardized Coordinate System [20]. The manufacturing system is recorded by cameras and other sensors, merged with information from planning and control and the resulting information is then fed back into the real factory via projectors mounted on the hall ceiling (see Figure 3). This superposition of the digital and real world enables context-related information to be provided on the shopfloor in real time, thus supporting prompt decision-making adapted to the situation at hand. In addition, by overlapping the real factory with the digital image, cognitive dissonance is avoided because differing information is recognized immediately, enabling its cause to be ascertained. Furthermore, by interacting with the cameras on the hall ceiling, (e.g., via gestures), additional information can also be requested at any time, even when the system is in operation. The degree to which information is aggregated can be altered or the consequences of decisions can be simulated (e.g., when planning AGV routes).The MFF is increasingly using game engines which can quickly visualize even complex facts, simulate the consequences of actions and thus reduce the complexity of

Figure 3 Matrix Fusion Factory

decision-making [55–58]. The integration of information into the physical shopfloor means that effects can be viewed directly in the real system, thus enabling, for example, collisions to be predicted and avoided. In addition, the display of information via projectors also fits in with the concept of a minimum use of resources, since information and light are only coupled and projected where they are needed.

In the standardized coordinate system, all recorded data is classified according to time, place and position. It is then processed and, if it makes sense, merged or placed in relation to each other [20]. This also includes the information generated by the standardized coordinate system and projected into the shopfloor. The information provided by the projectors is simultaneously recorded again by the cameras in the context of, and together with, the real production. The MFF thus consists of a physical and a digital part of the manufacturing system, which together form the real manufacturing system on the shopfloor. This real-time fusion of real and digital facts, which also gives the MFF its name and enables correct action to be taken, can be used to identify distorted information or unmethodical actions before they lead to impairment of the entities or of value creation. This is true, whether the individual distorts the supplied information, the supplied information is distorted, or both. The state of the real manufacturing system can be retrieved in the standardized coordinate system for any point in time. Therefore, causes can be inferred by identifying the respective time and place. In an ideal case, the triggering action can be corrected in good time and the cause of the error eliminated before a negative effect can occur.

5. Technological requirements

The MFF strives to minimize the use of resources in value creation. To this end, only the number of resources deemed necessary to complete an order and optimize value creation are provided. Oversizing modular production resources is regarded as waste. For example, it makes no sense to use a six-axis robot if only three axes are required; the three remaining modules can be used to add value elsewhere.

In particular, the transformation enablers according to Nyhuis (scalability, modularity, mobility, compatibility and universality) [59] are prerequisites for the adaptability of a manufacturing system made up of groups of hardware and software modules. Classical production systems often consider transformation enablers primarily in a hardware context. A distinctive feature of the MFF is that the transformation enablers are also considered in the context of groups of software modules. Especially game engines have been able to demonstrate their capabilities in this regard [57].

However, transformation enablers are not sufficiently capable of determining how and to which extent an adjustment must be made to optimize value creation. This is in part due to the fact, that the effect of adjustments on the workload and capability of the individual decision-making entity is not considered.

To determine how the manufacturing system of ultra-flexible factories must be adapted to orders in a way that adds value, the information contained within the production system must be mapped in an up-to-date and accurate manner. Due to the system's dynamics and complexity, a map of this information can only be accurately generated if the system is able to describe itself in sufficient detail, at least in part. This presupposes the system's basic ability to describe itself.

For this the system must possess executable processes to describe itself and its parts which is especially important when new module groups with new process capabilities are assembled. The self-descriptive capability of the manufacturing system, including its process capabilities, is a prerequisite for achieving an optimal match between the order and the manufacturing system [1, 10, 11].

This technical self-description capability forms the basis of the socio-technical organizational structure. Since degrees of freedom always contribute effectively to value creation if the type and number of resulting decision options do not disproportionately increase the risk of wrong decisions, the complexity of the information map of the manufacturing system restricts the degrees of freedom that can be used to create value. This calls for a situation-specific representation of information depending on the deciding entity and the decision space available. The representation must be focused and sufficiently up to date to enable correct decisions to be made. These target variables conflict with each other, as shown in Figure 4 based on the target cross of production logistic variables.

The challenge in using computer-based information processing, also to support decisions made by humans, is the high degree of modeling effort required to represent complex systems. In recent years, the capabilities of machines and algorithms in terms of data processing, aggregation, and analysis have greatly improved. Especially the rapid development of artificial intelligence leads to a steady increase in performance [38, 60–62]. Nevertheless, complex simulation tasks often require costly or elaborate hardware equipment and extensive computation times, which conflicts with the requirements of near-real-time decision making. To enable the right decisions to be made at the right time, a balance between both objectives that is adapted to the situation must be achieved. Therefore, the accuracy of the model must be adjustable so that the decision maker is presented with a sufficiently complex picture of the facts within a sufficient period of time, thus allowing him or her to use the relevant information to make the right decision.

To this end, the MFF also uses computational decision-making processes such as machine-learning algorithms. These are mainly used to support human decision making by providing and preprocessing information, such as person-neutral detection of the viewing direction for optimal positioning and orientation of information projected onto the hall floor. Especially in dynamic and complex situations, the decision-making competence of humans is required. To avoid cognitive dissonance and improve the quality of decisions, in the MFF machine-processed information is integrated into the context of the real factory.

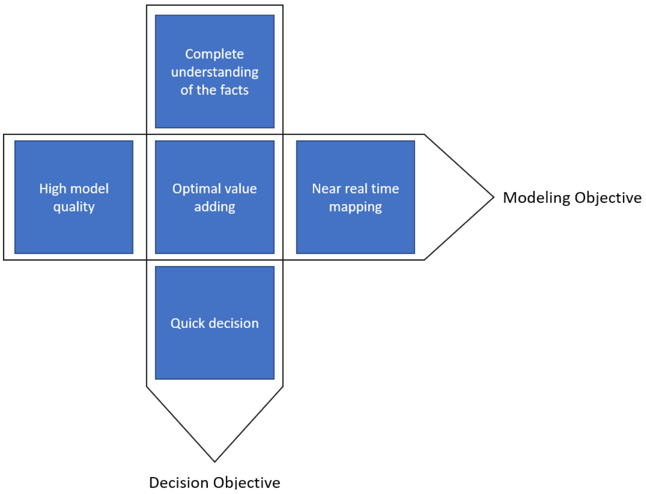

Figure 4 Target cross of information processing in production

This is in line with the position taken by the German Ethics Council, which points out the dubious quality of algorithm-based decision support systems and is concerned about effects on human self-efficacy [63]. In the MFF, therefore, the focus is on the ability of the person to adapt the representation of information to his or her needs and to understand and verify it. This improves the receptivity and quality of decisions and enables the person to be more involved in decision-making processes. The standardized coordinate system also makes it possible to document and assign decisions.

6. Conclusion and Future Works

The paper has demonstrated the role of information and information distortion in ultra-flexible factories, particularly with regard to the concept of minimizing the use of resources. It has also explained how permissible information distortion can be determined. Based on this, the role of human and machine decision making was considered, the requirements of complex information management were ascertained and presented, and the effects on the organizational structure and technology were derived. The target cross of production information was developed and introduced.

In the future, approaches will be investigated that improve model quality and reaction times in the context of the provision of information by machines. In addition, further cameras and sensors on different levels of the MFF will be included in the Standardized Coordinate System. The integration of additional data processing capabilities into a holistic information logistics approach will be examined. As part of this, the

5R approach is to be validated. Also, greater emphasis will be placed on the interaction between humans and technology. Exoskeletons also will be integrated into the MFF and the concepts presented in this paper will be transferred to human-exoskeleton interaction.

References

[1] J. Siegert, T. Schlegel, L. Zarco, B. Miljanovic, A. Meyke, and T. Bauernhansl, "Ultra-flexible Factories: An Approach to Manage Complexity," Procedia CIRP, vol. 93, pp. 329–334, 2020, doi: 10.1016/j.procir.2020.04.112.

[2] J. Siegert, T. Schlegel, and T. Bauernhansl, "Matrix Fusion Factory," Procedia Manufacturing, vol. 23, pp. 177–182, 2018, doi: 10.1016/j.promfg.2018.04.013.

[3] A. Kluth, J. Jäger, A. Schatz, and T. Bauernhansl, "Method for a Systematic Evaluation of Advanced Complexity Management Maturity," Procedia CIRP, vol. 19, pp. 69–74, 2014, doi: 10.1016/j.procir.2014.05.041.

[4] Andreas Kluth, Jens Jäger, Anja Schatz, and Thomas Bauernhansl, "Evaluation of Complexity Management Systems – Systematical and Maturity-based Approach," Procedia CIRP, vol. 17, pp. 224–229, 2014, doi: 10.1016/j.procir.2014.01.083.

[5] H. ElMaraghy et al., "Product variety management," CIRP Annals, vol. 62, no. 2, pp. 629–652, 2013, doi: 10.1016/j.cirp.2013.05.007.

[6] S. Mattsson, E. Ekstrand, and M. Tarrar, "Understanding disturbance handling in complex assembly: analysis of complexity index method results," Procedia Manufacturing, vol. 25, pp. 213–222, 2018, doi: 10.1016/j.promfg.2018.06.076.

[7] B. Brinzer and K. Schneider, "Complexity assessment in production: linking complexity drivers and effects," Procedia CIRP, vol. 93, pp. 694–699, 2020, doi: 10.1016/j.procir.2020.04.014.

[8] V. Modrak, D. Marton, and S. Bednar, "The Influence of Mass Customization Strategy on Configuration Complexity of Assembly Systems," Procedia CIRP, vol. 33, pp. 538–543, 2015, doi: 10.1016/j.procir.2015.06.071.

[9] B. Alkan, D. A. Vera, M. Ahmad, B. Ahmad, and R. Harrison, "Complexity in manufacturing systems and its measures: a literature review," EJIE, vol. 12, no. 1, p. 116, 2018, doi: 10.1504/EJIE.2018.089883.

[10] T. Schlegel, J. Siegert, and T. Bauernhansl, "Metrological Production Control for Ultra-flexible Factories," Procedia CIRP, vol. 81, pp. 1313–1318, 2019, doi: 10.1016/j.procir.2019.04.019.

[11] T. Schlegel, J. Siegert, T. Mahr, L. Zarco, F. Herbrig, and T. Bauernhansl, "Metrological PPC: Determination of added-value driven module process graphs," Procedia CIRP, vol. 93, pp. 634–639, 2020, doi: 10.1016/j.procir.2020.04.123.

[12] J. Siegert, T. Schlegel, L. Zarco, and T. Bauernhansl, "Order-Oriented Learning Factories: Why and How Learning Factories Have to Adapt," Procedia Manufacturing, vol. 45, pp. 460–465, 2020, doi: 10.1016/j.promfg.2020.04.053.

[13] T. Bauernhansl et al., "Semantic Structuring of Elements and Capabilities in Ultra-flexible Factories," Procedia CIRP, vol. 93, pp. 335–340, 2020, doi: 10.1016/j.procir.2020.04.010.

[14] P. Milling, Systemtheoretische Grundlagen zur Planung der Unternehmenspolitik. Zugl.: Mannheim, Univ., Habil.-Schr. Berlin: Duncker & Humblot, 1981.

[15] W. Weaver, "Science and complexity," American scientist, vol. 36, no. 4, pp. 536–544, 1948.

[16] V. Ferretti, Back to Ptolemaism: To Protect the Human Individual from Abuses of Social Constructs: Print-on-Demand, 2012.

[17] J. Siegert, T. Schlegel, and T. Bauernhansl, “Verifiable Competencies for Production Technology,” Procedia Manufacturing, vol. 45, pp. 466–472, 2020, doi: 10.1016/j.promfg.2020.04.054.

[18] P. Mandal and K. Bagchi, “Strategic role of information, knowledge and technology in manufacturing industry performance,” Industrial Management & Data Systems, vol. 116, no. 6, pp. 1259–1278, 2016, doi: 10.1108/IMDS-07-2015-0297.

[19] T. Dewett and G. R. Jones, “The role of information technology in the organization: a review, model, and assessment,” Journal of Management, vol. 27, no. 3, pp. 313–346, 2001, doi: 10.1016/S0149-2063(01)00094-0.

[20] J. Siegert, T. Schlegel, E. Groß, and T. Bauernhansl, “Standardized Coordinate System for Factory and Production Planning,” Procedia Manufacturing, vol. 9, pp. 127–134, 2017, doi: 10.1016/j.promfg.2017.04.032.

[21] M. Schreiber, P. Bausch, J. Best, and J. Metternich, “Datenanalyse in Produktionsprozessen,” ZWF, vol. 115, no. 5, pp. 309–313, 2020, doi: 10.3139/104.112285.

[22] K. Rönick, B. Röhm, P. Bausch, R. Anderl, and J. Metternich, “Digitale Informationsbereitstellung in der Produktion,” ZWF, vol. 115, no. 6, pp. 438–441, 2020, doi: 10.3139/104.112372.

[23] A.-S. Chaxel, C. Wiggins, and J. Xie, “The impact of a limited time perspective on information distortion,” Organizational Behavior and Human Decision Processes, vol. 149, pp. 35–46, 2018, doi: 10.1016/j.obhdp.2018.09.001.

[24] E. Polman, “Information distortion in self-other decision making,” Journal of Experimental Social Psychology, vol. 46, no. 2, pp. 432–435, 2010, doi: 10.1016/j.jesp.2009.11.003.

[25] J. Russo, V. H. Medvec, and M. G. Meloy, “The Distortion of Information during Decisions,” Organizational Behavior and Human Decision Processes, vol. 66, no. 1, pp. 102–110, 1996, doi: 10.1006/obhd.1996.0041.

[26] S. D. Bond, K. A. Carlson, M. G. Meloy, J. E. Russo, and R. J. Tanner, “Information distortion in the evaluation of a single option,” Organizational Behavior and Human Decision Processes, vol. 102, no. 2, pp. 240–254, 2007, doi: 10.1016/j.obhdp.2006.04.009.

[27] K. M. Carley and Z. Lin, “A Theoratical Study of Organizational Performance Under Information Distortion,” MANAGEMENT SCIENCE, vol. 1997, Vol. 43, No.7, pp. 976–997, 1997.

[28] E. Polman, “Effects of self-other decision making on regulatory focus and choice overload,” Journal of personality and social psychology, vol. 102, no. 5, pp. 980–993, 2012, doi: 10.1037/a0026966.

[29] M. R. Endsley, “Toward a Theory of Situation Awareness in Dynamic Systems,” Hum Factors, vol. 37, no. 1, pp. 32–64, 1995, doi: 10.1518/001872095779049543.

[30] F. A. Csaszar and J. P. Eggers, “Organizational Decision Making: An Information Aggregation View,” MANAGEMENT SCIENCE, vol. 59, no. 10, pp. 2257–2277, 2013, doi: 10.1287/mnsc.1120.1698.

[31] L. Bouargane and A. Cherkaoui, “Towards an explicative model of human cognitive process in a hidden hazardous situation and a cognitive ergonomics intervention in railway environment,” in 2015 International Conference on Industrial Engineering and Systems Management (IESM), Seville, Spain, Oct. 2015 - Oct. 2015, pp. 968–976.

[32] M. R. Endsley, “Situation awareness in aviation systems,” in Human factors in transportation, Handbook of aviation human factors, Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers, 1999, pp. 257–276.

[33] M. Endsley, “Situation awareness analysis and measurement, chapter theoretical underpinnings of situation awareness,” A Critical Review, pp. 3–33, 2000.

[34] Vidulich, M., Dominguez, C., Vogel, E., McMillan, G., Situation Awareness: Papers and Annotated Bibliography., 1994.

[35] M. Hoedemaeker, Summary Description of Workload Indicators: WP1 Workload Measures. Human Machine Interface and the Safety of Traffic in Europe Growth Project: HASTE. Leeds UK: GRD1-2000-25361, 2002.

[36] J. Hiba, H. Hadi, A. Hameed Shnain, S. Hadishaheed, and A. Haji, “BIG DATA AND FIVE V’S CHARACTERISTICS,” pp. 2393–2835, 2015.

[37] J.-C. Pomerol, “Artificial intelligence and human decision making,” European Journal of Operational Research, vol. 99, no. 1, pp. 3–25, 1997, doi: 10.1016/S0377-2217(96)00378-5.

[38] F. Emmert-Streib, O. Yli-Harja, and M. Dehmer, “Artificial Intelligence: A Clarification of Misconceptions, Myths and Desired Status,” Frontiers in artificial intelligence, vol. 3, p. 524339, 2020, doi: 10.3389/frai.2020.524339.

[39] A. Falck, Roland Örtengren, and M. Rosenqvist, “Relationship between complexity in manual assembly work, ergonomics and assembly quality,” in 2012.

[40] Y. Wang and G. Ruhe, “The Cognitive Process of Decision Making,” International Journal of Cognitive Informatics and Natural Intelligence, vol. 1, no. 2, pp. 73–85, 2007, doi: 10.4018/jcini.2007040105.

[41] D. M. Haftor, M. Kajtazi, and A. Mirijamdotter, “A Review of Information Logistics Research Publications,” in Business Information Systems Workshops, 2011, pp. 244–255.

[42] Barbara Dinter, “Success factors for information logistics strategy — An empirical investigation,” Decision Support Systems, vol. 54, no. 3, pp. 1207–1218, 2013, doi: 10.1016/j.dss.2012.09.001.

[43] K. A. Brookhuis and D. Waard, “Monitoring drivers' mental workload in driving simulators using physiological measures,” Accident; analysis and prevention, vol. 42, no. 3, pp. 898–903, 2010, doi: 10.1016/j.aap.2009.06.001.

[44] De Waard, “On the measurement of driver mental workload,” p. 161, 1997.

[45] M. G. Lenné, T. J. Triggs, and J. R. Redman, “Time of day variations in driving performance,” Accident Analysis & Prevention, vol. 29, no. 4, pp. 431–437, 1997, doi: 10.1016/S0001-4575(97)00022-5.

[46] S. Leung and G. Starmer, “Gap acceptance and risk-taking by young and mature drivers, both sober and alcohol-intoxicated, in a simulated driving task,” Accident Analysis & Prevention, vol. 37, no. 6, pp. 1056–1065, 2005, doi: 10.1016/j.aap.2005.06.004.

[47] L. N. Boyle, J. Tippin, A. Paul, and M. Rizzo, “Driver Performance in the Moments Surrounding a Microsleep,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 11, no. 2, pp. 126–136, 2008, doi: 10.1016/j.trf.2007.08.001.

[48] T. Nilsson, T. M. Nelson, and D. Carlson, “Development of fatigue symptoms during simulated driving,” Accident Analysis & Prevention, vol. 29, no. 4, pp. 479–488, 1997, doi: 10.1016/S0001-4575(97)00027-4.

[49] M. E. Rakauskas, N. J. Ward, E. R. Boer, E. M. Bernat, M. Cadwallader, and C. J. Patrick, “Combined effects of alcohol and distraction on driving performance,” Accident; analysis and prevention, vol. 40, no. 5, pp. 1742–1749, 2008, doi: 10.1016/j.aap.2008.06.009.

[50] P. Thiffault and J. Bergeron, “Monotony of road environment and driver fatigue: a simulator study,” Accident Analysis & Prevention, vol. 35, no. 3, pp. 381–391, 2003, doi: 10.1016/S0001-4575(02)00014-3.

[51] W. B. Verwey and D. M. Zaidel, “Preventing drowsiness accidents by an alertness maintenance device,” Accident Analysis & Prevention, vol. 31, no. 3, pp. 199–211, 1999, doi: 10.1016/S0001-4575(98)00062-1.

[52] S. Loft, P. Sanderson, A. Neal, and M. Mooij, “Modeling and predicting mental workload in en route air traffic control: critical review and broader implications,” Hum Factors, vol. 49, no. 3, pp. 376–399, 2007, doi: 10.1518/001872007X197017.

[53] F. P. Da Silva, “Mental Workload, Task Demand and Driving Performance: What Relation?,” Procedia - Social and Behavioral Sciences, vol. 162, pp. 310–319, 2014, doi: 10.1016/j.sbspro.2014.12.212.

[54] M. Kandler, J. J. Kurtz, N. Stricker, and G. Lanza, “Digitales, agiles Management auf dem Shopfloor,” ZWF, vol. 115, 1-2, pp. 23–26, 2020, doi: 10.3139/104.112241.

[55] M. Paul, D. Leiber, J. Pleli, and G. Reinhart, Simulation of Reconfigurable Assembly Cells with Unity3D, IFIP Advances in Information and Communication Technology: Springer International Publishing, vol. 566.

[56] J. Siegert, L. Zarco, T. Rossmeissl, and T. Schlegel, “Software Control for a Cyber-Physical System in a Manufacturing Environment based on a Game Engine,” in 2019 Global IoT Summit (GIoTS), Aarhus, Denmark, Jun. 2019 - Jun. 2019, pp. 1–7.

[57] J. Siegert, L. Zarco, T. Schlegel, and T. Bauernhansl, “Software Control System Requirements for Ultra-Flexible Learning Factories,” Procedia Manufacturing, vol. 45, pp. 442–447, 2020, doi: 10.1016/j.promfg.2020.04.050.

[58] J. Siegert, L. Zarco, and T. Schlegel, “Universal Accessibility Concept for Controlling Production Means in Manufacturing Systems,” in 2020 IEEE International Conference on Industrial Technology (ICIT), Buenos Aires, Argentina, Feb. 2020 - Feb. 2020, pp. 349–354.

[59] P. Nyhuis, T. Heinen, G. Reinhart, C. Rimpau, E. Abele, and A. Wörn, “Wandlungsfähige Produktionssysteme. Theoretischer Hintergrund zur Wandlungsfähigkeit von Produktionssystemen,” Werkstattstechnik online, 98 (1-2), pp. 85–91, 2008.

[60] J. F. Arinez, Q. Chang, R. X. Gao, C. Xu, and J. Zhang, “Artificial Intelligence in Advanced Manufacturing: Current Status and Future Outlook,” Journal of Manufacturing Science and Engineering, vol. 142, no. 11, 2020, doi: 10.1115/1.4047855.

[61] C.-F. Chien, S. Dauzère-Pérès, W. T. Huh, Y. J. Jang, and J. R. Morrison, “Artificial intelligence in manufacturing and logistics systems: algorithms, applications, and case studies,” International Journal of Production Research, vol. 58, no. 9, pp. 2730–2731, 2020, doi: 10.1080/00207543.2020.1752488.

[62] A. Kusiak, “Convolutional and generative adversarial neural networks in manufacturing,” International Journal of Production Research, vol. 58, no. 5, pp. 1594–1604, 2020, doi: 10.1080/00207543.2019.1662133.

[63] Deutscher Ethikrat, Wie wird die Zukunft mit intelligenten Maschinen? Berlin, 2017. Accessed: Dec. 12 2020. [Online]. Available: https://www.ethikrat.org/mitteilungen/2017/wie-wird-die-zukunft-mit-intelligenten-maschinen/

Biography

Jörg Siegert (*1978) has been the Senior Engineer and Deputy Head of the Institute of Industrial Manufacturing and Management IFF since 2012: He has also been acting deputy head of the newly founded Institute of Energy Efficiency in Production EEP since 2012.

Thilo Schlegel (*1985) graduated in industrial engineering at the University of Stuttgart and is working as a research assistant for Fraunhofer Institute for Manufacturing Engineering and Automation IPA and the Institute of Industrial Manufacturing and Management IFF where he heads the Matrix Fusion Factory since 2019.

Liliana Zarco (*1989) graduated in bionic engineering at the National Polytechnic Institute of Mexico and master of industrial business and management at the University of Applied Sciences Esslingen. Since 2018, she is doctoral candidate and research assistant for the Institute of Industrial Manufacturing and Management IFF on the topics of ontology, gamification and information models of the adaptive factory.

Thomas Bauernhansl (*1969) has been the director of the Institute of Industrial Manufacturing and Management IFF at the University of Stuttgart and the Fraunhofer Institute for Manufacturing Engineering and Automation IPA since 2011. He is a member of the WGP, the Scientific Society for Production Technology as well as Deputy Chairman of the Steering Committee of Allianz Industrie 4.0 BW.