Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 88 (2020) 76–81

www.elsevier.com/locate/procedia

13th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME ‘19

Joining element design and product variety in manufacturing industries

Derk H. D. Eggink[a,b,*], Marco W. Groll[a,b]

[a]Department of Design Production and Management, University of Twente, Drienerlolaan 5, Enschede, 7522 NB, The Netherlands
[b]Daimler AG, Mercedesstraße 137, Stuttgart, 70327, Germany

* Corresponding author. Tel.: +49-176-3095-9411; ORCID: https://orcid.org/0000-0002-7617-4213. *E-mail address:* d.h.d.eggink@utwente.nl

Abstract

Product variety is a growing trend of offering highly configurable products at the cost of inducing complexity in manufacturing. Joining is a key manufacturing process and historically was a paper-based process with incomplete variety documentation. Nowadays, digital joining element design is a substitution of paper for 3D space. Nonetheless, it remains an ambiguous manual task with limited automation, resulting in time-consuming iterative error-prone development trajectories and costly reworks. This contribution addresses the state of the art in joining element design in both research and industry practice. It reviews product variety and its impact on joining processes. The paper identifies a need for integrating product variety into joining element design and it proposes a solution pathway using artificial intelligence methods.

Keywords: Artificial intelligence; Machine learning; Automation; Design for assembly; Joining elements; Product variety; Design; Engineering; Standardization; Modular design; Process selection; Joining locations; Complexity

1. Introduction

Product variety (PV) is a growing trend of offering highly configurable products [1] enabling market competitiveness of companies. PV occurs in all types of products [1], but the numbers of variants in automotive industry can be immense, e.g. there are up to 10^{24} possible Mercedes-Benz E-Class configurations [2]. PV induces complexity in design and manufacturing and is likely to cause higher costs, lower quality, and delays over the entire product life cycle [1]. Studies indicate that increased PV negatively affects performance of manufacturing processes [3].

Joining is a key process in manufacturing, provides function to a product as a whole and increases the manufacturability hereof [4]. Products can easily contain thousands of joining elements (JE) [5]. JE design became an iterative manual time-consuming multi-disciplinary process partly due to the historical transition from 2D paper-based to 3D Computer-Aided-Design (CAD) approaches. JEs are mainly the result of design experience and trial-and-error approaches [6]. Currently, there is limited automation supporting JE design risking prolonged development trajectories and costly reworks [6].

The state of the art considers partial solutions to aspects of JE design as shown in Fig 1. Joining technology selection approaches apply optimization [7], assessment [8] or knowledge-based [9] methods. Topology optimization [5] and rule-based [10] approaches can determine joining locations. Other approaches aim to find the optimal joining parameters [11–13]. Meanwhile, modular product design (MPD) aims to manage PV by considering various focus points, such as assembly complexity [14], product architectures [15, 16], standardization [17] and assembly stations [18]. JE design processes do not explicitly consider modular design and vice versa. Moreover, JE design requires a holistic approach to find optimal solutions [19–21].

This paper addresses the state of art in JE and modular design in industry and practice. It identifies the need for actively integrating PV considerations in JE design. The study concludes with a proposal to implement artificial intelligence methods as a solution pathway for identified issues.

10.1016/j.procir.2020.05.014

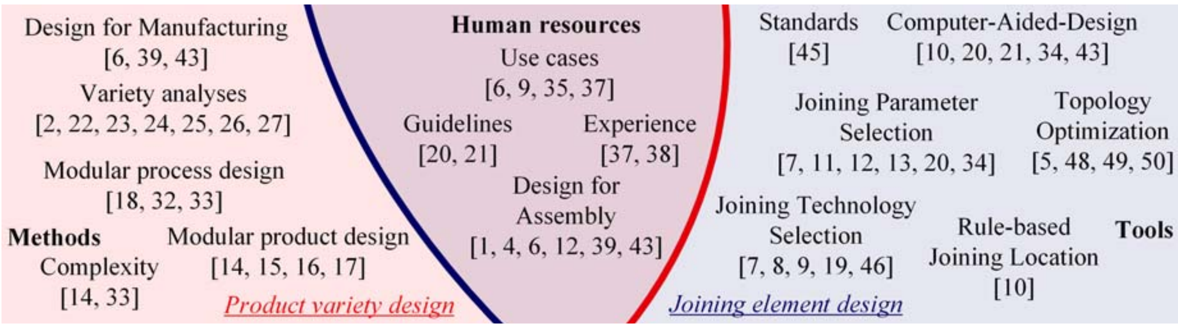

Fig. 1. Overview of influencing factors and references from examples of state of the art approaches on joining element design in manufacturing industries.

2. State of the art

2.1. Product variety in manufacturing industry

PV requires high manufacturing flexibility as components vary in technical and functional aspects, such as shape, size and configuration [22]. This increases complexity and costs, as equipment and processes need to facilitate PV [23]. Here, equipment refers to design, engineering and manufacturing systems in both physical and digital form. PV often forces variety in production and therefore requires a concurrent development strategy [24], again increasing manufacturing complexity [23]. Process variety induces planning, controlling and logistic difficulties in production [25], as every manufacturing system must be aware that any product variant can come at any time [26].

Product development processes must consider PV from early on [2]. Industries want to offer an as many external product variants as possible, while minimizing the induced internal variety [2]. Product architectures and technologies determine the ratio of internal and external PV [27]. Various strategies can reduce variety driven complexity on both product and process level [25]: modularization, commonality, product configurations and delayed differentiation.

2.1.1. Modular design

Modular product design (MPD) intends to manage PV. It enables to offer affordable products for customers [2] and to manufacture with mass production efficiency [28]. Hence, modularity is key to achieve mass customization. MPD divides products and processes into smaller chunks and connects these through architectures and schemas [29]. In addition, it positively affects modularity in production [24]. Modular products tend to have fewer components, enable pre-assembly processes and use common interfaces. Hence, modularization can decrease assembly costs [30].

Nowadays, research focusses on Design Structure Matrices (DSM) to model, study and optimize modular products [14, 15, 17]. DSMs can represent relationships between components mutually [14], but also between components and requirements [17]. AlGeddawy et al. [14] present a methodology to optimize product modularity using hierarchical classifications. It considers assembly complexity by balancing assembly time and module interchangeability. Kashkoush and ElMaraghy [15] developed a methodology to determine the optimal overall modularity of product architectures. The methodology uses a genetic algorithm to determine module granularity by considering the amount of intra- and interrelationships between module's components. Daie and Li [16] propose a hierarchical cluster analysis to develop a product architecture considering PV. The methodology bases on bus components that have relationships to most other modules. In addition, it prefers clustering components that have relationships with common components. Stocker et al. [17] propose a two-step methodology to determine modules for chassis-mounted components. Multiple Domain Matrices enable incorporating strategic and technical requirements to evaluate module alternatives, after which a packaging heuristic considers topological standardization and 3D space.

However, these methodologies modularize by clustering physical components and fail to recognize the modularization potential of JEs. JEs on module interfaces encounter the largest variety and induced complexity due to module interchangeability. Changes to module interfaces affect other modules and their interfaces [31]. Hence, solely component-based clustering is expected to result in frequently changing JE module definitions.

Meanwhile, other studies focus on process modularity to manage PV. Salonitis and Konstantinos [32] developed a framework for concurrent design of modular products and automated manufacturing systems using DSM and Modular Function Deployment. A hierarchical analysis of assembly steps evaluates alternative manufacturing system designs considering product commonality, modularization capability and automation prospect. Ren et al. [18] developed a clustering methodology for assembly system modularization. A similarity matrix represents relationships between assembly technology, equipment and components. Fuzzy clustering methods create modules by aiming to group subassembly processes. Keckl et al. [33] propose a methodology focusing on production time variety considering workstation complexity. It links MPD potential to assembly line requirements enabling to stabilize workflow processes and to increase workload utilization.

Even though from a manufacturing perspective, these approaches still cluster on component level and thus have similar issues as found in MPD. They either aim to define strategic modules that can be shared by many products or technical modules with highly interconnected components [17]. Hence, they largely neglect strategic JE clustering.

2.2. Joining element design

2.2.1. Industry practice

Designers author JEs in early product development, often relying on past designs, experience and knowledge [5, 34, 35]. Searching and analyzing past information can take up to 20% of a designer's time [36]. Design engineering is prone to error and failure [37], yet experience is only to be gained through trial-and-error practices [35]. Design processes have not adapted adequately to growing PV reducing transparency on variety implications [38].

The JE design process includes multi-discipline in-depth analyses and verifications of variant scenarios. Authoring results are highly practical [39], as designers are not able to find global optimums [5]. Overall Equipment Manufacturers compartmentalize work packages and tend to increase outsourcing of processes and disciplines such as design [2] and manufacturing [40] to reduce investment and complexity costs and to increase quality. This at the cost of losing knowledge, control over activities [2] and possibly increasing PV [38]. Moreover, it cannot be expected of designers to have complete and high level knowledge of the entire product lifecycle [6]. Hence, disciplines such as simulation, planning and suppliers must verify JE designs with respect to manufacturability, quality control, costs and lead-time.

At the end of product design, three aspects define JEs: 1) technology (e.g. spot welding or adhesive bonding), 2) locations (e.g. shapes or coordinates) and 3) parameters (e.g. diameter, material or object type). Designers tend to use various approaches to design a new JE aspect: 1) similar use cases consultancy [36], 2) intuition based design [35], or 3) minimal design while adhering to standards and guidelines. The latter approach directly considers cost and time requirements by aiming to reduce number and costs of JEs. Although, such JE designs require additional attention to robustness, quality and performance.

Fig 2 shows a generic JE design process as observed in industry. Based upon design requests, designers filter and select joining scenes from a product data management (PDM) system. PDM systems contain repositories for design files, to enable systemic, modular and effective design of products and to archive data [6]. It enables to implement methods such as concurrent design, Design for Manufacturing and Design for Assembly (DFM/A) [6]. Designers store JEs in modules ideally to improve management and downstream processes. Although, they create modules arbitrarily preferring larger modules as these tend to be more transparent and manageable. Naturally, this risks design iterations as new product variants may inflict a violation of standards and requirements resulting in a need to split modules [31]. Continuous product development and delayed differentiation require sustainable modular design as uncontrolled module generation and editing increase complexity [31]. Component reuse and commonality over products enable to reduce such unnecessary risks [41].

Further into product development, designs become fixed increasing costs of rework and iterations. In addition, higher

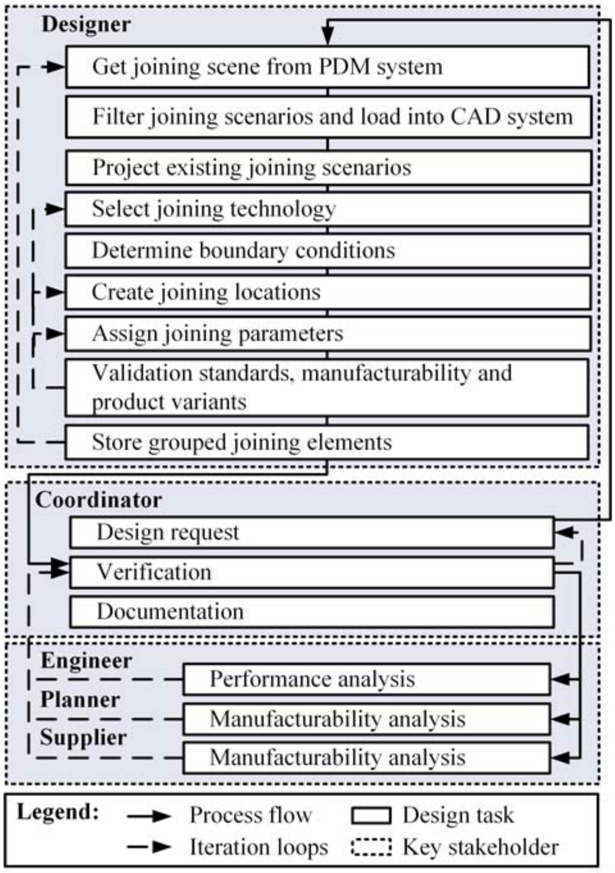

Fig. 2. Design process of JE design in manufacturing industry. Starting point for joining element design is the design request of the coordinator.

product maturity limits design freedom and optimization potential and it imposes increasingly complex requirements. In a worst case scenario, the documentation complexity doubles for every new option or component [42]. New product variants often contain similar joining scenarios enabling reutilization of JEs in multiple variants [38]. Hence, JE design becomes highly iterative due to the sequential design of new product variants [25] and concurrent design methods [39]. Summing up the identified issues of JE design in manufacturing industry:

- **Time consumption**. Much time is spend on analyzing and verifying joining scenarios, increasingly when considering high variety. The actual authoring is a rather repetitive task. Unaccounted lifecycle requirements, human errors and adaptation due to new variants cause unnecessary design iterations. This leaves little time to spend on challenging tasks that require holistic and creative thinking.

- **Practical solutions**. Designers have no possibility to find global (business) optima. They design in local space increasingly on outsourced basis, where it is difficult to consider holistic requirements and design consequences. Design aiding tools solve only partial aspects of JE design, thereby not supporting proper modularization.

2.2.2. Design for Manufacturing and/or Assembly

Traditionally, both methods (DFM/A) were applied to products with complex geometries and large quantities of components [43] aiming to reduce costs and lead time [6]. Design for Manufacturing guidelines and practices are a necessary basis in designing JEs, but often ignore varying product geometry [43]. Design for Assembly (DFA) aims to minimize variety and assembly complexity [6], but tends to ignore assembly performance [43] and PV [1]. Assembly generally focusses on temporary fasteners in montage, whereas joining handles permanent non-losable connections between components. DFM/A imposes by definition design iterations, as product specific production knowledge is necessary to design [6, 39]. They can manage complexity [6, 43], although their methodologies tend not to get concrete enough to make appropriate decisions during product design [43]. Design problems are often not explicit and require formalization to enable optimization [39]. In addition, industry struggles with having quality and consistent data to enable this [44]. Guidelines and best practices, such as [21], are difficult to automate due to high fluidity in a designer's creative problem solving process. Standards impose design, production and quality requirements, such as ISO 14373 [45] for resistance spot welding (RSW) of steel metals. Guidelines consider general construction methods and processes [20, 21]. Together, they ensure manufacturability of joints, regardless of performance requirements or production capabilities. Companies can enhance standards and guidelines conforming to their needs.

However, successful JE design also relies on load carrying capacity, life expectancy and use environment [6]. Certain sub-assemblies may not compromise on quality and require extensive verification activities, such as structural components in automotive industry.

2.2.3. Joining technology

One aspect of DFA and JE design is joining technology selection, where methodologies aim to find the optimal technology given a set of requirements [39]. Traditionally, joining technology selection was performed based on experience, vague supplementary information [12] and company practices. The selection procedure is prone to non-efficient solutions, misjudging parameters [46], and a large time investment. In addition, products are expected to consist out of more varied joining technologies [47]. Literature states that component geometry, materials, and joining technologies depend on each other and should be designed iteratively [4].

Choudry et al. [8] developed a six module methodology for optimal joining technology in automotive Body-in-White (BIW) structures. An assessment considers economic, technological and ecological criteria by taking requirements from a stakeholder-analysis. Das & Swain [9] propose a knowledge-based framework using a liaison. This enables querying of joining technologies based on ontologies of variant requirements. Chien et al. [19] created a multi-objective decision-making methodology to evaluate sheet metal joining technologies. It incorporates both a lifecycle analysis and a lifecycle cost analysis by considering energy consumption and material flows. It selects a technology using a Pareto analysis.

None of these methodologies actively considers PV. They treat joining scenarios individually without considering successful manufactured products. In addition, they depend on engineer's inputs such as weights [8, 19, 46], are not expected to reach an optimum and are prone to errors [3, 37].

2.2.4. Joining locations

Joining technologies invoke a JE's geometrical type, e.g. points for RSW and curves for adhesive bonding. Nowadays, JEs are positioned largely based on design experience [5]. CAD systems contain various tools implementing rule-based methods [10]. They derive guidelines from the shapes of component contact regions along which to distribute a number of JEs equally. Designers can edit the positioned JEs individually and assign further Product Manufacturing Information, such as joining parameters and component variants. However, CAD systems require large computational resources and can manage only small PV portions, which makes it difficult to find optimal solutions.

Studies proposing FE based methods aim to find optimal joining locations based on performance metrics such as crashworthiness, noise-vibration-harshness (NVH) and stiffness [5]. Such methods can reduce the amount of joining elements [5, 48] and can consider structural layout simultaneously [49, 50]. Research focusses largely on topology optimization of RSW structures, such as BIW in automotive industry [5, 48]. Long et al. [48] propose a methodology to determine the optimal number and distribution of RSWs in BIW structures. The methodology represents RSWs by relating artificial material densities to stiffness of connecting material, e.g. weldments. A rig test and FE analyses verify the methodology. Yang et al. [5] present a more efficient approach by balancing structural performance and manufacturing costs. It alternates between local and global optimization problems. Locally, it aims to maximize the stiffness of a sub-domain, globally it minimizes amount of RSWs. Woischwill and Kim [49] created a methodology that optimizes simultaneously a structure's multi-material topological layout with the quantity and type of joints. Here, joining regions and quantities derive from the interim structural optimization results, thus are not defined a priori. Florea et al. [50] also propose a multi-material and joint layout topology optimization methodology. Nevertheless, they balance structural performance loss and usage of joints by constraining the structure's resulting weight.

FE-based methods define an optimal performance for a single completely defined product variant [48], thereby neglecting commonality between variants [51]. Optimization functions require high data quality from often manually prepared meshes, models and boundary conditions [50]. These approaches are computationally expensive, require explicit engineering knowledge [5] and their results leave room for interpretation. In addition, results often require large safety factors to account for uncertainties of real world products such as buckling effects and crash behavior.

2.2.5. Joining parameters

Parameters are specific to selected joining technologies. They include additive filler materials required for technologies as MIG welding or adhesive bonding, but also object types for methods as riveting and stud welding. The parameters tend to be considered at the manufacturing stage, thus after finishing a product's detailed design [6]. Hence, joining parameters should not invoke changes to component designs. This is in contrast to joining technology selection, which frequently impacts component design [4].

Industry standardizes joining parameters to reduce product complexity [27] and relate MPD to modular process design [40]. CAD systems often incorporate catalogues to retrieve company standardized components as rivets, adhesive materials and screws [20]. Kwon et al. [34] propose a weld design methodology implementing an infeasibility screening in CAD systems for early design phases. It aims to incorporate concurrent engineering knowledge and outputs a feasible set of welding parameters. Friedrich et al. [11] present a methodology to optimize design parameters of screw joints. A multi-objective optimization process balances parameters, such as diameter, assembly method and preload loss. Ghazilla et al. [12] propose a multi-criteria decision making model to support fastener selection considering product recovery. This work builds upon a heavily studied approach for joining technology selection consisting out of four steps [7]: requirement gathering, technology screening, ranking and selection. The methodology can trade-off quantitative, but also qualitative measurements such as aesthetics, functionality and ease of assembly. Geda & Kwong [13] implement a genetic algorithm to find optimal fastener types considering assembly and disassembly costs. The methodology handles both joining technology and parameters simultaneously.

The aforementioned methodologies that determine joining parameters are similar to those of joining technology selection. However, they act on a smaller scope and are highly subject to standardization, company practices and available capabilities for a given technology. One can argue that, with small adjustments, the methodologies are interchangeable for both applications, such as [7, 12]. Therefore, the issues of joining technology selection apply here as well.

3. Discussion

3.1. Research gap

Various partial solutions of JE design aspects are presented, such as joining technology selection [8, 9, 13], rule-based design [10], topology optimization [5] and joining parameter determination [11]. However, they barely consider PV and successful marketed products. Meanwhile, MPD is often used to manage PV [2, 18], nevertheless such approaches do not support JE design. Therefore, a gap exists between JE and modular design. This prevents designers to find global optima. It constraints JE design to remain highly experience based [5] resulting in error prone processes and costly reworks [6]. Meanwhile, design processes are time-consuming due to work compartmentalization and many stakeholders.

3.2. The case for artificial intelligence

Artificial Intelligence (AI) is a field that enables automation and can enhance process efficiency [52]. It refers to the ability of performing tasks by mimicking human cognitive functions and understanding [52]. AI has various successful applications in manufacturing industry [53]. Nowadays, highly human engineered AI methods, such as rule-based reasoning [10], search and optimization [5, 11], and case-based reasoning [9], support designing JE aspects. However, such solutions are stand-alone and do not consider holistic requirements of JE design. Studies largely neglect machine learning as a viable option, although it enables to automate expert-driven processes and reduce costs [53].

Manufacturing industries with large PV have much data of successful and verified products. As PV is expected to grow [1] and new products will be developed, the amount of data will continue to grow. Successful marketed products can be regarded as ground truths and therefore represent a balanced form of global (business) optimality. AI methods, such as unsupervised machine learning [53], can extract implicit knowledge of cross company requirements, generalize it and use it to support automation. However, this requires to solve challenges with data dimensionality, quality, heterogeneity and structures [44, 53]. Successful JE designs contain considerations of properly implemented standards, guidelines, performance, modularity, complexity and design experience.

Therefore, AI enables to automate repetitive ambiguous tasks in JE design while reducing failures and lead-time. In addition, AI methods can learn particularities to predict JEs closer to global optima and increase effectiveness of design processes. This enables designers to concentrate on their core competencies and to work on creative holistic problems.

4. Conclusion

This study describes the state of the art of joining element design and product variety in both research and industry. It reveals that joining element design lacks modularity considerations to manage product variety properly resulting in design iterations and costly reworks. In addition, design processes are time-consuming and designers have no possibility to find global optima. The state of the art proposes only partial solutions for joining element and modular product design separately. Artificial intelligence is a solution pathway enabling to consider successful verified products already in early design phases. It can mimic design processes to predict transparent and verifiable joining elements. Moreover, it can increase design time efficiency and enable to find quicker and better global optima.

Future work will focus on analyzing the applicability of artificial intelligence methods for various aspects of joining element design considering product variety. In later work, artificial intelligence methodologies will be prototyped for all aspects of joining element design and evaluated to their appropriateness.

References

[1] ElMaraghy H, Schuh G, ElMaraghy W, Piller F et al. Product variety management 2013;62:629.
[2] Parry G, Graves A, Editors. Build To Order: The Road to the 5-Day Car. Springer-Verlag; 2008.
[3] Hu SJ, Zhu X, Wang H, Koren Y. Product variety and manufacturing complexity in assembly systems and supply chains 2008;57:45.
[4] Martinsen K, Hu SJ, Carlson BE. Joining of dissimilar materials 2015;64:679.
[5] Yang S, Yan L, Qi C. An adaptive multi-step varying-domain topology optimization method for spot weld design of automotive structures 2018;5:129.
[6] Tasalloti H, Eskelinen H, Kah P, Martikainen J. An integrated DFMA–PDM model for the design and analysis of challenging similar and dissimilar welds 2016;89:421.
[7] Esawi AMK, Ashby MF. Computer-based selection of joining processes 2004;25:555.
[8] Choudry SA, Müller S, Alber U, Riedel F et al. A Multidimensional Assessment and Selection Methodology: Optimized Decision-making of Joining Technologies in Automobile Body Development 2018;21:281.
[9] Das SK, Swain AK. Knowledge-Based Application of Liaison for Variant Design 2016.
[10] Thompson TR, Salerno AJ. Automatic generation of joint locations(WO2009158562A1).
[11] Friedrich C, Hubbertz H, Roser H, Walker P. Towards Automated Design of Fastening Systems for Accelerated Product Development 2014:V02BT02A009.
[12] Ghazilla RAR, Taha Z, Yusoff S, Rashid SHA et al. Development of decision support system for fastener selection in product recovery oriented design 2014;70:1403.
[13] Geda MW, Kwong CK. Simultaneous consideration of assemblability and disassemblability for fastening method selection 2018.
[14] AlGeddawy T, Samy SN, ElMaraghy H. Best design granularity to balance assembly complexity and product modularity 2017;28:457.
[15] Kashkoush M, ElMaraghy H. Designing modular product architecture for optimal overall product modularity 2017;28:293.
[16] Daie P, Li S. Matrix-based hierarchical clustering for developing product architecture 2016;24:139.
[17] Stocker J, Chavushoglu M, Felgenhauer M, Lienkamp M. Efficient Module Design for Chassis-Mounted Components of Commercial Vehicles 2018.
[18] Ren W, Wen J, Guan Y, Hu Y. Research on assembly module partition for flexible production in mass customization 2018;72:744.
[19] Chien JM, McKinstry KC, Baek C, Horvath A et al. Multi-objective Analysis on Joining Technologies 2012:287.
[20] Rieg F, Steinhilper R. Handbuch Konstruktion. 2nd ed. München. Carl Hanser Verlag; 2018.
[21] Haberhauer H. Maschinenelemente. Berlin, Heidelberg. Springer Berlin Heidelberg; 2018.
[22] Chinnathai MK, Alkan B, Harrison R. Convertibility Evaluation of Automated Assembly System Designs for High Variety Production 2017;60:74.
[23] Alkan B, Vera DA, Ahmad M, Ahmad B et al. Complexity in manufacturing systems and its measures: A literature review 2018;12:116.
[24] Landahl J, Johannesson H. Product variety and variety in production 2018;2:817.
[25] Bednar S, Modrak V. Mass customization and its impact on assembly process' complexity 2014;8:417.
[26] Fettermann DC, Soares Echveste ME. New product development for mass customization: a systematic review 2014;1:266.
[27] Kampker A, Burggräf P, Deutskens C, Maue A et al. Integrated Product and Process Development: Modular Production Architectures based on Process Requirements 2014;20:109.
[28] Daaboul J, Da Cunha C, Bernard A, Laroche F. Design for mass customization: Product variety vs. process variety 2011;60:169.
[29] Hankammer S, Steiner F. Leveraging the Sustainability Potential of Mass Customization through Product Service Systems in the Consumer Electronics Industry;30:504.
[30] Fukushima T, Horike S, Kobayashi H, Tsujimoto M et al. Modular design of domain assembly in porous coordination polymer crystals via reactivity-directed crystallization process. J Am Chem Soc 2012;134:13341.
[31] Weiser A-K, Baasner B, Hosch M, Schlueter M et al. Complexity Assessment of Modular Product Families 2016;50:595.
[32] Salonitis K. Modular design for increasing assembly automation 2014;63:189.
[33] Keckl S, Abou-Haydar A, Westkämper E. Method for Evaluating Modularization Potential in Product Design Based on Production Time Variety 2016;41:213.
[34] Kwon Y, Wu T, Saldivar JO. SMWA: A CAD-based Decision Support System for the Efficient Design of Welding 2016;12:295.
[35] Yongsheng C, Haijiang L. Feature model and case retrieval for body-in-white part 2011;54:231.
[36] Lowe A, McMahon C, Culley S. Information access, storage and use by engineering designers: part 1 2004;30:30.
[37] Pärttö M, Saariluoma P. Explaining failures in innovative thought processes in engineering design 2012;41:442.
[38] Felgenhauer M, Stocker J, Lienkamp M. New Approach for Architecture Design of High Variable Vehicle Portfolios 2017:V011T15A019.
[39] Groche P, Bruder E, Gramlich S. Manufacturing Integrated Design 2017.
[40] Kubota FI, Hsuan J, Cauchick-Miguel PA. Theoretical analysis of the relationships between modularity in design and modularity in production 2017;89:1943.
[41] Wang W, Wang Y, Mo D, Tseng M. Component Reuse in Remanufacturing Across Multiple Product Generations 2017;63:704.
[42] Mittal S, Frayman F. Towards a generic model of configuration tasks 1989:1395.
[43] Madrid J, Forslund A, Söderberg R, Wärmefjord K et al. A Welding Capability Assessment Method (WCAM) to support multidisciplinary design of aircraft structures 2018;12:833.
[44] Hagemann S, Stark R. Automated Body-in-White Production System Design: Data-based Generation of Production System Configurations 2018:192.
[45] International Organization for Standardization. Resistance welding – Procedure for spot welding of uncoated and coated low carbon steels (ISO 14373:2015). 2nd ed;25.160.10 2015(14373).
[46] L'Eglise T, Lit P de, Fouda P. A multicriteria decision-aid system for joining process selection 2001:324.
[47] Zhu J-H, Zhang W-H, Xia L. Topology Optimization in Aircraft and Aerospace Structures Design 2016;23:595.
[48] Long H, Hu Y, Jin X, Yu H et al. An optimization procedure for spot-welded structures based on SIMP method 2016;117:602.
[49] Woischwill C, Kim IY. Multimaterial multijoint topology optimization 2018;115:1552.
[50] Vlad Florea, Vishrut Shah, Stephen Roper, Garrett Vierhout, Il Yong Kim. Coupled Multi-Material and Joint Topology Optimization: A Proof of Concept 2018.
[51] Eichstetter M, Müller S, Zimmermann M. Product Family Design With Solution Spaces 2015;137:121401.
[52] Salehi H, Burgueño R. Emerging artificial intelligence methods in structural engineering 2018;171:170.
[53] Dekhtiar J, Durupt A, Bricogne M, Eynard B et al. Deep learning for big data applications in CAD and PLM – Research review, opportunities and case study 2018;100:227.