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Modularization of joining elements in high variety manufacturing industries

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Abstract

Product variety is a growing trend of offering highly configurable products, but increases complexity costs throughout the entire product lifecycle. Modularization makes managing variety-induced complexity and ensuring profitable production possible. Unfortunately, the interfaces between modules represent joining domains and lack modularization and commonalization solutions. Meanwhile, joining element design finds increasingly more support from automation resulting in optimized solutions for individual product variants. Besides, continuous product development implies sequentially designed product variants that cause ambiguous and unnecessary design iterations for joining element design. This paper presents a five-step methodology to modularize joining elements in early product development, while balancing variety-induced complexity and production costs. It reduces complexity by commonalizing joining elements over product variants. The methodology unifies joining technologies, clusters joining locations and proposes an approach to increase modularity by balanced addition of joining elements.

Keywords: Automation; Design for Assembly; Joining Elements; Product Variety; Design; Engineering; Commonality; Modularization; Complexity

1. Introduction

Product variety enables offering highly configurable products [1] and market competitiveness of companies. However, product variety induces complexity in the entire product life cycle and is likely to cause higher costs, lower quality, and delays [1]. Complexity costs are a monetary reflection of overhead functions and scale with increased variety, quantity, information content of system elements and the significance of their interrelations and dependencies [2]. Various studies present complexity measurements for products [3, 4], processes [2] and assemblies [5, 6]. Modular product design is the general approach used to manage product variety and reduce complexity costs [7, 8]. Hence, Ulrich et al. [9] define modularity as "the standardization of components and processes in an organization that can be configured into a wide range of end products to meet specific customer demands".

Joining is a key process in manufacturing increasing the manufacturability of products by assembling smaller and simpler components. Joining elements (JE) are individual instances of procedures within joints and represent joining technologies as spot-welds, adhesive bonding lines or rivets. Products may contain thousands of JEs often with various aspects and properties [10]. JEs are the assembly operations that join parts and modules and are located on their interfaces. This makes JE design prone to high variety, as their joined-parts with their properties may be change for each product. The state of the art shows that designers and algorithms create JEs for individual variants. However, optimal designs for individual product variants may conflict with profitability of overall product design [10]. No found methodology in literature describes JE modularization.

Previous works stress the necessity [11], process [12] and implementation [13] of automated JE design. This work proposes a methodology to modularize JEs and introduces a tradeoff to reduce the total cost by increasing the number of JEs for increased modularization capacity.

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2. Literature review

Managing product complexity includes design, control and development of product variety throughout the entire company [1]. The number of processes and products creates roughly the overall system complexity [5]. Various strategies can reduce variety-driven complexity on both product and process level, of which modularization and commonality are most applicable for JE design due to their large dependency on part design [14]. The overall tendency in literature is to reduce complexity [15], but Kuhn et al. [15] state, after reviewing literature, that complexity analyses can create chances and companies might benefit from complexity increases due to increased insight, adaptability and communication.

Quantification of complexity enables benchmarking and decision making between product and process alternatives [5]. Alkan et al. [16] pair complexity assessment methods to types and symptoms and examine methodologies using the taxonomy non-linear behavior, physical situation, operational uncertainties and human perception. Later, Alkan et al. [2] present a method to assess assembly complexity using product entities and their topological links, while considering complexity of handling operations using Design for Assembly principles. Bednar et al. [5] integrate the number of product and process variants to assess complexity at an assembly station. They model interactions between components and using Axiomatic design. Hasan et al. [17] propose an approach to classify products for assembly systems by considering assembly and part complexities of which the latter also considers assembly sequences. Hierarchical clustering enables to express similarity between products for classification.

Many, such as the aforementioned [2, 5, 17], methodologies quantify complexity, but neglect calculating their costs due to its difficulty [18]. Ripperda and Krause [19] performed a co-citation analysis on modularization methodologies and found seven clusters for managing complexity costs. Weiser et al. [20] propose to calculate complexity costs using initial and recurring costs per affected department over a product's lifecycle. It enables decisions on new modules and variants while considering commonality. Eilmus et al. [3] propose a methodology to estimate variety-induced complexity cost effects based on module sizes and variety, primarily through usage of code numbers and lifecycles.

Modular product design (MPD) makes it possible to offer affordable products for customers [7] and to manufacture with mass production efficiency [21]. It positively affects modularity in production [22] and can decrease assembly costs [6]. MPD must be sustainable as uncontrolled module generation still increases complexity [20]. Gauss et al. [23] performed a systematic literature review on module-based product family design and synthesized these into a meta-process. They describe four classes of modular design problems: planning, market-driven design, modeling and configuration selection. Meanwhile, Han et al. [24] performed a systematic literature review on product platform design and argue that traditional product platforms lack the ability to adapt to dynamic market changes, which causes risks, costs and propagations of module changes. Specific methodologies considering assembly and joining are for example presented by AlGeddawy et al. [6]. They modularize product architectures using hierarchical classification, a design structure matrix and an assembly complexity metric that balances assembly time and module interchangeability. Stocker et al. [25] studied efficient modularization of chassis-mounted components. Module variant evaluation regards strategic and technical development requirements, but focusses on standardization. Final module selection considers geometrical feasibilities in products. Ma et al. [26] propose an heuristic approach to select the most costly components as individual modules and adds other components with respect to assembly cost.

The mentioned complexity metrics consider intra-module relationships as measurements for complexity. These metrics are often interchangeable with modularity indices i.e. as seen in Jung and Simpson [4] who consider connection strengths, densities and bus components in product architectures [4]. MPD methodologies that modularize by clustering of components fail to acknowledge the modularization necessity of JEs on interfaces between modules. For example, Design Structure Matrices (in e.g. [4, 6, 25]) enable to visualize relationships between parts, but are incapable to represent assembly specifics due to geometrical dependencies [25].

3. Method

The methodology's objective is to reduce the product complexity experienced in joint and assembly design by implementing modularization. Typical part design should already consider JE design [14]. JEs are individually configured objects in products and this methodology regards JEs on the same hierarchical level as parts, as product data management studies propose (e.g. [27]). This perspective enables to take control in the handling of JE modules in various product variants. A five-step process (see Fig. 1) modularizes any set of designed JEs: 1) Preprocessing, 2) technology unification, 3) spatial aggregation, 4) element densification and 5) module creation. Firstly, the preprocessing step determines the geometrical boundary conditions for modularization through the overlapping contact regions, which are created by virtual stacking of product variants. Then, technology unification reduces the number of different processes applied on the overlapping contact regions (CR) to join the involved parts. Spatial aggregation considers joining locations from overlapping CRs of multiple variants and clusters these into unique and reusable locations. Element densification aims to commonalize entire joints by applying JEs of one variant onto others within their geometrical boundaries. Lastly, module grouping collects the shared joining elements between product variants and stores these in JE modules.

The modularization method is indifferent of the JE design method, i.e. rule-based CAD design, topology optimization methods [10], or machine learning [13]. Every step has variety-based parameters to influence modularization results.

3.1. Preprocessing

JEs spread throughout the entire product and require a method to identify modularizable ones. A joining scenario (JS) is the input state containing geometries, product manufacturing

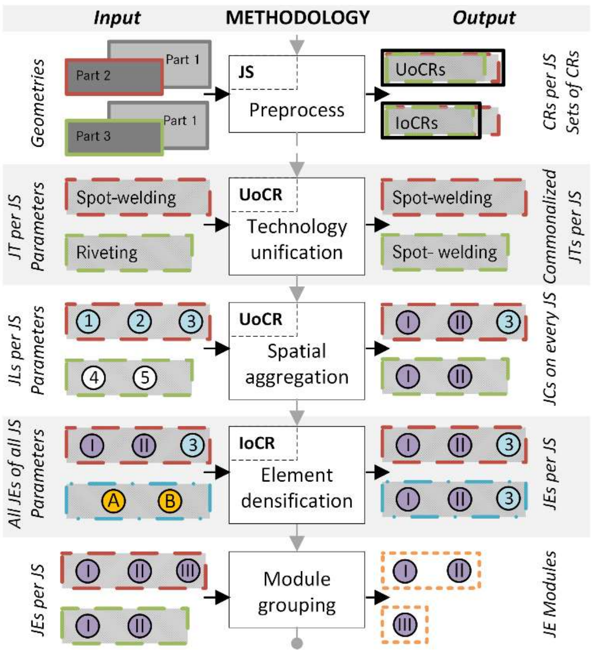

Fig. 1. Visualization of methodology with input and output dependencies. (JS) Joining scenario, (CR) Contact region, (UoCR) Union of contact regions, (IoCR) Intersection of contact regions, (JT) Joining technology, (JL) Joining location, (JC) Joining cluster, (JE) Joining element.

information (PMI), product architecture and assembly information [12]. Parts in JSs create contact regions (CRs), partial part surfaces or edges touching each another geometrically thereby defining joining areas. Geometries of CRs differ with regard to applicable joining technologies. Discrete technologies such as spot-welding require a minimum surface area [28], while continuous technologies, such as laser welding, join edges of parts. The union of contact regions (UoCR, see Fig. 1) enables finding JSs from which to modularize JEs. The UoCR is the merger of multiple CRs of JSs by considering all product variants at once. Hence, CRs in the UoCR are positioned approximately on the same surface.

Transforming certain JSs, of which their CRs do not yet belong to the same UoCRs, into arbitrarily defined origins can increase the number of CRs in UoCRs. This leads to increased modularization potential and the definition of three scopes: global, domain and local. A global scope would create the lowest number of modules, but also affect the most variants by transforming most JSs into fewest origins. Local modularization considers the UoCRs in product space. Here, JE parameters remain specific to those locations, but at the cost of additional modules. Domain-based modularization takes a subset of JEs defined by an arbitrary criterion such as function, space, or assembly station. For example, discriminating between structural and aesthetic purposes causing JE modules to have individual properties and complexity.

3.2. Technology unification

Process variety is one of the main complexity and production cost factors [5]. Fig. 1 presents technology unification using the UoCR on parts 1&2 with parts 1&3. Here, a joining technology describe the specific implementation of a production process, such as type of adhesive or specific stud weld. Predict, optimized or selected joining technology algorithms often output sets of potential technologies. This enables implementing majoritarian voting systems to determine the variety-based optimal joining technology. A consistent second best solution might be overall the optimal technology considering variety. Technology unification utilizes an overall ranking for each technology over summing weighted JSs (see Eq. 1):

$$t_u = \underset{t}{argmax}\left\{\sum_{s}^{JS\in UoCR} t_s\, w_s^u\right\} \tag{1}$$

Where t_u represents unified technology that is the result for technology t with the largest sum. JS includes all joining scenarios in the union of contact regions. t_s is the joining technology of scenario s. w_s^u weights every joining scenario s based on its properties for technology unification u (see Eq. 2). The unified technology requires validation against standards and guidelines to ensure manufacturability with respect to different properties as geometry, material and function.

Modularization purposefully treats technologies unequally to reduce randomness in outcome and control biases of the algorithm. Weights w_s^u consider various product variety-relevant parameters to tune unification. These parameters regard aspects as confidence, sales prospect, contact region size, and implementation factor. Algorithms that predict or select joining technology (e.g. [14]) output values to select a solution. This *confidence* or fitness factor c_s^u expresses certainty in prediction and reduces importance of improbable outcomes. Secondly, higher *sales prospects* R_s require higher cost optimality and thus changes induced up by modularization. JEs built in almost every product variant require more optimal technologies and should settle difficultly for joining aspects of exotic variants. The number of predicted configurations highly determines its necessity to be cost-optimal. Next, a top-down view enables to derive smaller scenarios from default variants indicated by JS's *relative contact region sizes* A_s compared to the UoCR. A bottom-up approach would aggregate smaller scenarios to construct large scenarios and require taking the inverse of A_s. Fourthly, product development may create continuously new variants and thus JEs. This leads to implemented and manufactured JEs that need to modularize with newly designed JEs. JEs in production have high rework costs due to design changes and require a high attribution in tuning weights. The *implementation factor* I_s can either scale with the number of implemented variants or product maturity. Normalized *engineer's preferences* E_t enables strategic tuning to consider holistic requirements or company strategies. Also, parameters used in state of the art technology selection methodologies (e.g. listed in [11]) enable further tuning. Eq. 2 shows a simple proposal of a generic linear function w_s^u to weigh technologies with a normalized vector x^u to balance, scale and tune every dimensionless parameter.

$$w_s^u = x_1^u c_s^u + x_2^u A_s + x_3^u I_s + x_4^u R_s + x_5^u E_t \tag{2}$$

3.3. Spatial aggregation

Due to numerical, optimization and prediction approaches, JEs do not necessarily align with one another considering product variety. Fig. 1 visualizes spatial aggregation creating clusters I and II from joining locations 1 with 4 and 2 with 5. Spatial aggregation applies a clustering algorithm to find common centroids for groups of joining locations. It reduces locational variability and enables reuse of joining locations.

The algorithm has K-Means clustering [29] at its core (Table 1). K-Means has a number of properties that fit this particular purpose. Firstly, it creates 'circular' clusters that solve the accuracy variability of joining locations. Secondly, results are density-invariant and respect outliers as individual clusters. Lastly, a K-Means algorithm can consider constraints (e.g. [29]) to prevent clustering joining locations of the same JS. The maximum cluster size r_{max} ensures minimum mutual and edge distances described in standards (e.g. [28]) and controls aggregation effectiveness. Every joining location requires a unique cluster ensuring transparency and simplicity and JSs must have equal number of JEs after spatial aggregation. Hence, the number of final clusters is unknown requiring an incremental iterative search. The starting number is the maximum number of joining locations a JS has in UoCR, smaller clustering results are not permissible. The algorithm can stop once finding the first solution complying with requirements. Additional optimization iterations might create better outcomes, but require an evaluation approach for the optimal number of clusters, such as the elbow, average silhouette or gap statistic method [29]. Spatial aggregation also works for joining technologies having curved geometry, i.e. adhesive bonding or laser welding. Discretizing curves into equidistant points enables spatial aggregation as is with only small changes to parameters as r_{max}. Modeling straight line-based curves with point-line intersections, i.e. where one curved-JE ends and another continues. Spatial aggregation then clusters the start and end-points of curves.

Various parameters enable to better control clustering results and expand weight w_s^u from technology unification. A weighted average scales coordinates of joining locations to new cluster centroids (JC). Firstly, *distance-to-center* $d_{p,c}$ focuses on small dense groups and can fortify the cluster centroids by reducing impact of outliers. $d_{p\to c}$ is the Euclidean distance between the joining location p and nearest cluster centroid c. Dividing this by the minimum joining distance d_{min}^u creates a dimensionless parameter. The negation enables the parameter weight to go to zero in case once a joining location moves towards d_{min}^u . *Confidence* c_p^a considers probabilities of prediction or fitting methods for individual locations. Less confident locations should have less influence in moving cluster centroids. Proposing a linear spatial aggregation weight w_p^l for joining location p (Eq. 3) with normalized vector x^l to balance, scale and tune every parameter:

$$w_p^l = w_s^u \left(x_1^l c_p^a + x_2^l \left(1 - \frac{d_{p\to c}}{d_{min}^u} \right) \right) \quad (3)$$

Table 1. Spatial aggregation clustering algorithm for one set of joining scenarios based on content of one union of contact regions.

Input	Superset with joining scenarios $j \in JS$ Sets of joining locations for each set $p \in j$ Minimum number of clusters k_{min}
Output	Set of joining clusters C containing aggregated joining locations p
1:	For $k \in \{k_{min}, \ldots, \lvert JS \rvert\}$
2:	Let C have k clusters with first k_{min} clusters from p of $\max_j \lvert j \rvert \in JS$ and random selected p for all other clusters c
3:	Calculate Euclidian distances $d_{p,c}$ for all $p \in JS$ to all $c \in C$
4:	For each location $p \in JS$
5:	Sort C in ascending order on distances d_p from p to c
6:	For every cluster $c \in C$
7:	If point p within maximum cluster size, $d_{p,c} \le r_{max}$
8:	If no locations of same JS, $c \cap \{p \supset j\} = \emptyset$
9:	Assign p to cluster c
10:	If all locations assigned, $C \supseteq JS$
11:	For each cluster $c \in C$
12:	Update centroid $c \coloneqq \sum\{w_p^l p \in c\} / \sum\{w_p^l \in c\}$
13:	Iterate between line 3 and line 12 until convergence
14:	If all locations of joining scenario $p \in j$ for $j \in JS$ are okay with standards
15:	Return clusters C

3.4. Element densification

After the spatial aggregation step, joining scenarios might have different numbers of JEs on the same IoCR. This implies that the same piece of geometry with similar boundary conditions has different JEs on it depending on the product variant. Increasing JEs in some joining scenarios from the same IoCR enables to create and utilize JE modules in multiple variants. However, this may lead to increased manufacturing costs, as modularization will induce unnecessary joining processes. Element densification balances JE modules with a complexity and production cost perspective. The algorithm considers joining performances by preventing removal of JEs. Fig. 1 visualizes element densification and illustrates that the blue JS adopts all three JEs of the red JS. All JEs must lay on the intersection of contact regions (IoCR) and must have the same technology. Element densification considers standards and guidelines e.g. edge and mutual JE distances (see [28]). A tradeoff balances product variety-induced complexity costs against production costs of additionally manufactured JEs. The size and variety in product documentation mainly contribute to complexity costs c_c [3, 20] and are a function of the total number of modules n_m and JEs n_{je}. Production costs c_p are a function of the number of JEs n_{je} and the (prospected) number of produced products n_s . Assuming a linear relationship between complexity and production costs to find the total costs c_t [20] results in Eq. 4.

Imagine a situation to densify two joining scenarios JS^A and JS^B. To apply element densification and for JS^B to obtain the joining elements of JS^A, the total costs c_t^A of JS^B with joining elements of A must be less than the costs c_t^B of JS^B with joining elements of B itself.

$$c_t = c_c(n_m, n_{je}) + c_p(n_{je}, n_s) \tag{4}$$

$$c_c(n_m^{all} + 1, n_{je}^{all} + n_{je}^B) - c_c(n_m^{all}, n_{je}^{all}) > c_p(n_{je}^A - n_{je}^B, n_s^A) \tag{5}$$

Table 2. Joining element densification algorithm for one set of joining scenarios based on unions of contact regions.

Input	Set of joining scenarios JS Sets of joining clusters $JC \in JS$ Sets of joining locations $JL \in JC$
Output	Set of joining clusters for each joining scenario $JC \in JS$
	Sort JC on number of JL in descending order Sort JS by containing JC with most JL; then most JC on JS For each intersection of contact regions $iocr \in IoCRs$ For all equal joining technologies t_u grouped in $iocr$ For each joining scenario $s \in iocr$ Get JCs laying on $iocr$ of joining scenario s Number of JCs n_{jc} in $s \in iocr$ is highest $\max_s n_{jc}^s$ For JCs on s (jc) are manufacturable on other JS u If densifying tradeoff (Eq. 5) is profitable Append jc to joining scenario u

Defining sales prospects as n_s^A and n_s^B for JS^A and JS^B respectively, the tradeoff balances differences between an added module and the total produced number of JEs. n_m^{all} and n_{je}^{all} represent all modules and joining elements of the entire product family.

If Eq. 5 holds then it is beneficial to densify JEs of JS^A to JS^B. The additional complexity costs of using original JEs from JS^B as an individual module are higher than the production costs created by the additional manufactured JEs considering the sales prospect n_s^A of the modularized JS^A. Especially few sold exotic modules, when n_s^A is low, are profitable to modularize as additional production costs are relatively small. Vice versa, densifying JEs that occur in virtually all products are expensive due to rapidly scaling production costs.

The joining element densification algorithm (Table 2) starts with sorting joining clusters (JC) in descending order by the number of spatially aggregated joining locations. Then, it sorts JSs on the number of joining locations in their JCs in descending order and on the number of JEs in the JS itself.

Next, the algorithm iterates through all IoCRs and iterates through all similar joining technologies per IoCR. The next nested iteration creates retrieval of JCs. Densification is possible for JCs of both JSs that lay on the same IoCR. The algorithm does not consider individual JEs to densify, as these might require unavailable space and reintroduce additional variety. Testing for standards and guidelines ensures that JCs that create new joining locations on other JSs are manufacturable considering edge distances, sheet thicknesses or materials. Lastly, the algorithm applies the complexity versus production cost tradeoff.

3.5. Module creation

Joining clusters created by spatial aggregation and redistributed by densification provide the basis to create JE modules. Module creation collects those JEs occurring in the same variants, because their underlying clusters assign joining locations to JSs. Then, each module becomes the largest subset of all JEs reoccurring for the same set of variants. Hence, JSs have sets of JE modules. Algorithmically, module creation consists of two group-by operations. Fig. 1 shows the visualization of module grouping illustrating creation of two JE modules: one using JEs I and II, and one with JE III. Starting with a dictionary of JSs and the JEs they contain, the first group-by function creates a dictionary of JSs for each JE. Then, a group-by function determines unique sets of JSs collecting those JEs that occur in the same variants. The methodology automatically regards local, global and domain-scopes as they derive from joining clusters that origin from transforming of CRs of joining scenarios into UoCRs.

4. Discussion

The proposed methodology reduces variety in JE design by modularizing and commonalizing joining aspects. It aims to reduce complexity costs induced by product variety and makes it possible to automate the entire JE design [12]. This work is premiering JE modularization and contrary to the state of the art, it considers Design for Assembly principles in early product development phases. Balancing complexity and production costs lead to moderate modularization and prevent over-commonalization. The methodology does not alter already created modules and specifically focusses on the joining interfaces between modules. The method considers production information solely on part design level by reducing the variety in JEs, between them and between component modules. This work considers JE design to be subordinate to part design, hence suboptimal designs or variety considerations may result in a low degree of (JE) modularization. However, results of individual steps enable further analysis and insight into the complexity induced by JE designs [15]. Weights can consider already modularized and produced JEs and their modules aiding modular sustainability.

CR-bounded modules risk future changes as new product variants might induce module splitting due to changing IoCRs. The methodology does not actively consider modules where JEs occurring in the same product but in different JSs such as subassemblies. Here, the scope (local, global, or domain) enables to control module creation and sustainability.

Technology unification functions independently in the methodology. This optimizes results of joining technology selection methodologies with respect to product variety reasons. Automated JE design processes can use unified technologies to predict joining locations. Besides, location clustering and technology unification are interchangeable enabling to modularize with multiple joining technologies on each CR. This reduces the overall modularization granularity and requires more complex process documentation, i.e. [27]. Technology unification might create less optimal solutions for individual JSs and potentially violate performance-containing requirements. Standards and guidelines only validate manufacturability of JSs, but not their performance. Besides, the approach might leave multiple technologies open due to manufacturability limitations and requires multiple technologies to further modularize in parallel or implementation of optimization algorithm.

As described in [12], modularization enables to create a set of 'Lego'-based JE modules to pick and place onto contact regions. For example, defining three modules that each have four spot-welds only with different mutual distances. Authoring such JE modules into JSs standardizes product documentation. However, this requires further research.

The proposed process does not actively incorporate performance validation (e.g. using Finite-Element-Methods). Proper distribution of JEs is crucial in high performance structures such as the crash-worthiness of automotive Body-in-White [10]. Therefore, uncontrolled or arbitrary removal and addition of JEs might induce reduction in performance [10].

5. Conclusion

Nowadays, modularization is one of the main approaches to manage product variety while containing complexity costs. However, current methodologies do not consider joining elements that experience a permutation of variety. This leads to increased complexity and thus to increased rework and costs.

This work presents a methodology to modularize joining elements in high variety manufacturing industries. It describes a five-step process that reduces process variety through technology unification, geometrical variety through spatial aggregation, joining features through element densification and determines the final JE modules. Modularization must warrant the joining performance increasing the number of joining elements resulting in higher production costs. Hence, the study presents a cost tradeoff that enables balancing of complexity and production costs.

Future research includes experimental evaluation of the methodology. It determines the benefits of combining JE prediction methodologies (e.g. see [13]) with modularization. Besides, further work will be done into evaluating the weighting functions and quantifying their parameters.

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