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Towards automated joining element design

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Abstract

Product variety and its induced manufacturing complexity remains to increase and therefore greatens challenges for design of joining elements. Historically, joining element design was a paper-based process with incomplete variety documentation and is digitalized only by replacing paper for 3D space. Currently, joining element design remains an ambiguous manual task with limited automation, resulting in long iterative, error prone development trajectories and costly reworks. Thus, processes in practice conflict with required capabilities. Artificial intelligence helps to solve such conflicts by taking over repetitive tasks, preventing human errors, optimizing designs and enabling designers to focus on their core competencies. This paper proposes a novel artificial intelligence method toolbox as a foundation to automate joining element design in manufacturing industries. The methodology aims to incorporate multiple lifecycle requirements including large product variety.

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1. Introduction

Product variety (PV) is a growing trend of offering highly configurable products [1] and enables market competitiveness of companies. PV occurs in all types of products [1], but the numbers of variants in automotive

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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]. Joining is a key process in manufacturing by providing function to a product as a whole and increasing the manufacturability hereof [3]. It enables assembling of smaller cheaper parts into complex components and products [4]. Products easily contain thousands of joining elements (JE) in case of the automotive industry [5]. Due to the transition from a paper-based approach to computer-aided-design (CAD), JE design became an iterative manual time-consuming multi-disciplinary process involving many conflicting requirements. Therefore, JE design is mainly the result of design experience and trial-and-error approaches [6].

An extensive state of the art and research analysis is conducted in still unpublished work of the authors. It stresses the necessity of automated JE design in manufacturing industries considering PV and proposes Artificial Intelligence (AI) methods to be a promising solution path. Literature proposes partial solutions to aspects of JE design, such as joining technology selection [7, 8], topology optimization [9–11] or joining parameter determination [12], but barely considers PV [13]. Modular product design (MPD) is often used to manage PV [2, 14], however such approaches do not consider JE design holistically.

Therefore, this paper presents a novel AI method toolbox for automated JE design in manufacturing industry considering PV requirements. The method toolbox aims to solve issues and requirements from practice based on a target JE design process. To the best of our knowledge, this is the first study that addresses holistic JE design by the use of AI methods.

The paper will address state of the art in section 2, including JE design issues, requirements for automation, state of literature and AI methods in manufacturing industry. Section 3 presents the method toolbox for automated JE design. Section 4 evaluates the toolbox and addresses implementation challenges. Lastly, section 5 contains the conclusion and addresses future work.

2. State of the art

2.1. Practiced process and issues of joining element design

JE design in practice is observed to be a repetitive, ambiguous and complex discipline. The process includes in-depth analyses of variant scenarios and multi-discipline requirement verification. Moreover, authoring results are practical, as the designer is concerned with finding a solution, not the solution. Proper designed JEs require three aspects: 1) technology (e.g. welding or adhesive bonding), 2) locations (e.g. shape or coordinates) and 3) parameters (e.g. diameter, material or object type). Together, these enable downstream processes to continue product development. It is found that designers roughly implement one of three approaches to design an aspect: 1) analysis and application of similar use cases, 2) intuition based design, or 3) minimal design while adhering to standards. Summing it up:

- **Time consumption**. A lot of time on is spend on analysis of joining scenarios due to PV. Moreover, the actual authoring is a rather repetitive task. It leaves little time to spend on challenging tasks that require holistic and creative thinking. Moreover, unaccounted lifecycle requirements, human errors and adaptation to new variants cause unnecessary design iterations.

- **Practical solutions**. As designers have no possibility to find global (business) optima. They design in local space, where it is difficult to consider holistic requirements and design consequences. There are no design tools available nor is there active anticipation of MPD.

2.2. Target process and requirements

The bolded box captions in fig. 1 depict the target process for JE design. The process only requires a starting trigger and result acceptance from a designer. A pre-processing stage determines characteristics of each joining scenario in a joining scene, such as contact regions, constructability and feature classes.

A joining scenario is the input state containing geometries, product manufacturing information (PMI), product architecture and assembly information. Joining classes are clusters and defined by feature identification stage. Predicted JEs automatically contain confidence values enabling evaluation and verification. A variety prediction stage aims to optimize JE design by clustering, modularization and considering reuse of joining modules. The determined requirements for automation of JE design are as follows:

- **JE aspects**. Automation outputs completion of product design phase, thus joining technology, joining locations and joining parameters.
- **Input data**. Automation bases upon generic industry data structures and formats: tessellated geometry, product manufacturing information (PMI), utilization and assembly information. Thereby, the target process is independent of both company and industry.
- **Product life cycle**. Predictions must return a confidence factor enabling selection and verification. Holistic requirements are considered for JEs.
- **Generic knowledge**. Ability to distill PV into joining scenarios for analysis and prediction. Thereto, predictions are compliant to company and industry standards. The methods adapt to trends and changes in design requirements.
- **Containment of complexity**. Ability to modularize JEs for downstream processes to adhere to MPD and reduce complexity. The methods evaluate reusability of JEs. In addition, predictions are transparent to enable evaluation by designers.

2.3. State of literature

Current research tackles partial problems of JE design. Firstly, Design for Assembly (DFA) is a general approach to aid designers with guidelines, standards and assessments. However, DFA processes are often not concrete [15] and require formalization and quality data to enable optimization [16].

Hereby, research focuses on joining technology selection, that aims to find an optimal assembly process considering design, production and other product lifecycle requirements [7, 8, 17]. However, none of these actively consider PV. Moreover, the approaches depend on input and preferences of engineers. By definition these will not output an optimum solution and possibly errors [18].

Studies proposing finite-element (FE) based methods aim to find optimal joining locations considering performance metrics such as crashworthiness, noise-vibration-harshness, stiffness [9, 10], or structural layout [11]. However, mathematical optimization functions require high data quality. In addition, meshes for FE require models of a completely defined product. Thereto, these approaches are computationally expensive, require explicit engineering knowledge in development and leave room for interpretation.

CAD systems contain various tools that enable JE design [19] and can assess these, e.g. the welding capability [15]. CAD systems are limited to a small scope of PV and designs tend not to be optimal for the product as a whole. Moreover, CAD systems are computationally heavy programs and aim to assist designers not to automate design.

MPD is intended to manage PV internally in companies, while creating affordable products for customers [2]. Nowadays, research focusses on finding optimal modularity for e.g. product architectures [20] or product family design [21] by implementing Design Structure Matrices. Also, MPD considers production requirements as assembly systems [14] and complexity [22]. However, these approaches modularize by clustering components, thereby not recognizing modularization potential of JE design alone. Thereto, MPD must be sustainable as uncontrolled module generation still increases complexity [23]. Often, a complexity cost calculation [22, 23] assesses potential of module reuse.

2.4. AI in manufacturing industry

Roughly, AI methods implemented in manufacturing industry can be divided into four areas: Rule based reasoning (RBR), Case based reasoning (CBR), Search and Optimization (S&O) and Machine learning (ML). In the state of the art, human equivalence in JE design tasks are observed for all these fields and the equivalence is addressed further in the method toolbox.

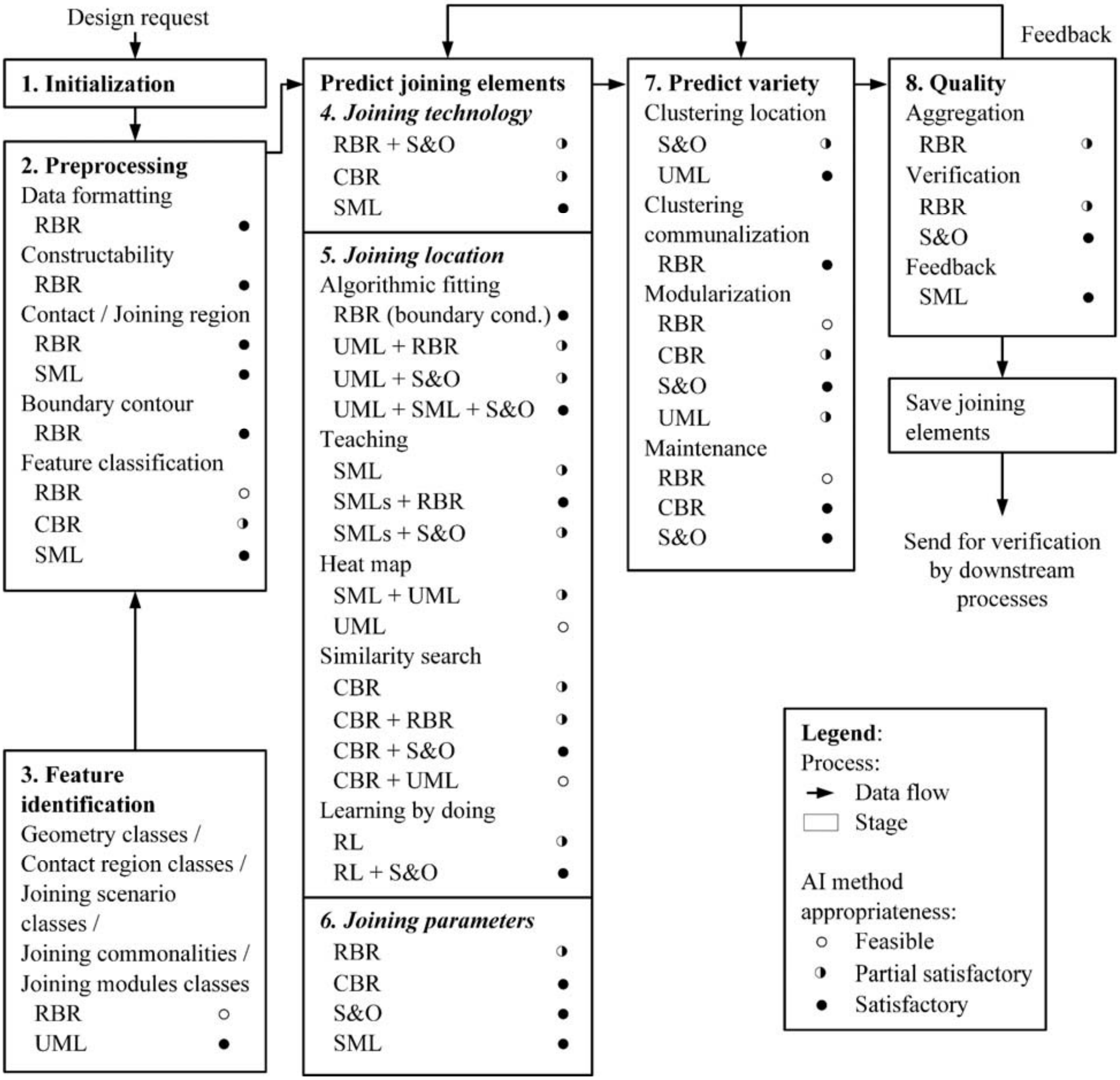

Fig. 1. The target process of the toolbox with AI methods for automation of joining element design.

RBR is a method to create designs following a systemic path of human-engineered constraints and conditions. It outputs feasible solutions, yet these tend to be sub-optimal due to high dependence on input use cases. RBR is used in JE design to predict joining locations [19] and screen for feasible joining technologies [17]. CBR is a field that analyzes and retrieves past problems and applies their solutions to problems of unseen use cases. It requires a large database and memory to search through cases. The output remains often sub-optimal as it retrieves the solution of the most similar problem. Hence, CBR is analogue to a JE design approach of analyzing past solutions. Similarly, knowledge based frameworks can aid in joining technology selection [13]. S&O methods aim to find optimal solutions, however require such as handcrafted boundary conditions and constraints to ensure convergence when solution spaces become large. The methods include finding mathematical extremes in optimization functions [9, 17] and evaluating structured permutations of solutions [7]. S&O can predict joining aspects as technologies [7, 17], locations [9–11] and parameters

[12]. ML aims to find patterns in datasets to predict solutions for unseen cases. The quality of ML methods directly correlates with the dataset size and dimensionality, which makes the training of models computationally costly. However, ML can find generic solutions with much less expert engineering of models. Roughly, ML contains three branches: supervised learning (SML), unsupervised learning (UML) and reinforcement learning (RL). SML methods learn by comparing input and output states to extract a mapping between those [24]. UML methods identify implicit patterns in data [25]; they can cluster data and find anomalies herein. RL is an artificial trial-and-error approach, where the model takes actions in an environment and analyzes the consequences hereof using a reward function [26]. ML has not seen implementation in JE design specifically, yet found SML use in predicting manufacturing processes [24].

3. Method toolbox

3.1. Initialization

The AI method toolbox considers several stages of automated JE design. Fig. 1 shows the applicability of AI methods in various stages of the target process. A joining scene initializes based on a design request. Here, data and requirements are collected, formatted and structured for further processing. A joining scene contains arbitrary product architectures and product variety at various hierarchical levels. Generally, CAD files contain very complete definitions of parts and thus unnecessary information for predicting JEs. Therefore, this stage extracts tessellated geometries and PMIs from CAD files. Discretizing geometries enable AI to learn features of components and their relations.

3.2. Preprocessing

A preprocessing state decomposes the joining scene into joining scenarios. A joining scenario results from the distillation of PV into component combinations. Thereby, it tests joining scenarios for constructability with RBR that evaluates Boolean algebra code rules [27]. The contact regions are areas of components' surfaces where components can be joined together. Both SML [28] and UML [25] can predict contact surfaces using a shape segmentation approach. Here, SML can specifically to find joining regions, which are contact regions with defined JEs. RBR can determine contact surfaces by a set of criteria [19], however requires a CAD system. A contour is the boundary edge enclosing each contact region and is relatively simple to determine with RBR. Together, contact regions and contours enable to screen for joining technologies and determine boundary limits for joining locations. Thereto, they contain characteristics specific to joining scenarios. UML can segment geometry to identify potential joining regions (e.g. surfaces, holes, flanges, etc.) to reduce solution spaces. Furthermore, SML and CBR can classify properties of joining scenarios determined in the feature identification stage.

3.3. Feature identification

Features extracted from joining scenarios in a product data management (PDM) system enable scenario classification and dimensionality reduction in successor stages. Manufacturing industries with large PV often have reoccurring joining scenarios varying only little in properties. For example, joining classes contain a set of component versions and variants that have similar characteristics. Geometrical clustering of components, joining regions, and joining shapes, as well as defeaturing, enable dimensionality reduction for approaches in stages where no specific geometry is required. Moreover, feature identification enables to predict joining properties even in early product development by predicting joining classes on still vague scenarios. Thereto, features enable to map high-level requirements to individual joining scenarios. In addition, cluster methods identify outliers that divert from standard design practices to prevent these affecting other predictions. Moreover, they help to identify JE modules and enable reuse for sustainability of MPD. Typically, UML can solve all aforementioned applications [25]. However, feature clusters are identified once, thus the results can influence classification and functionality of other approaches significantly. RBR also is able to create clusters, however requires significant development effort due to the high dimensional and heterogenic data.

3.4. Joining technology

Classification is a typical task for SML [24], where a model predicts the most suited joining technology for a given joining scenario. Also, S&O approaches solve this problem rather well [7, 17], but depend largely on data consistency, development effort, designer inputs and do not consider PV. RBR can screen for feasible technologies before S&O algorithms perform optimization tasks [17]. Implementation of CBR [13] enables reducing production variety as similar joining scenarios and technologies tend to be clustered. A joining scenario becomes more detailed as a product matures. Hence, predictions receive higher confidence values. The most confident joining technologies continue to location prediction.

3.5. Joining locations

Based on practiced JE design, various approaches are conceptualized to predict joining locations. Thereby, some approaches combine multiple AI methods. Joining technology implicitly contains information about geometry, such as points, curves and areas. In addition, the technology directly imposes location requirements through standards [29].

Algorithmic fitting; JEs populate contact regions considering boundary limits due to standards and guidelines, such as minimum mutual JE and edge distances. Defining the boundary limits is a typical problem for RBR [19]. Besides defining boundary limits, algorithmic fitting can pick and place joining modules onto contact regions. These joining modules can consist of engineered and clustered features. Utilization of modules is analogue to stacking LEGO-blocks onto a structure. The definition of joining modules requires a balance between flexibility and complexity [30]. As in PV management, Boolean algebra adds and subtracts JE modules to contact regions. Picking and placing modules is possible using RBR, however location results will be suboptimal [19]. An S&O algorithm evaluates various module combinations and translations, however requires further constraints due to the immense solution space. Supplementary features predicted by a SML aid to define constraints, such as joining scenario class and the number of required JEs.

Teaching; Each input (joining scenario) has one ground-truth output (joining scenario with JEs). High dimensionality of 3D geometry makes implementing SML difficult (elaborated in section 4.1). SML segments geometry by classifying whether a discretized unit is empty, material or a JE. This is analog to SML segmentation approaches in computer vision [28]. Another approach is a stack of SML expert systems to predict the amount, shape and distance of JEs. Prediction of the amount of JEs implicitly considers function, loads and structural performance [9]. The shape represents a guideline along which JEs are placed. Lastly, the distance between JEs considers the available contact region. Here, RBR or S&O finalizes joining locations according to the SML predictions. Other approaches can utilize the predictions of the expert systems as additional input features.

Heat map; Designers and workers instinctively determine where to join upon seeing a contact region. They induce joining regions based on their experience. Similarly, an UML model builds heat maps on contact regions that enables convergence of joining locations by increasing local probabilities. For example, mixture models can represent the subpopulations (JEs) in a population (heat map) and assign subpopulation attributes to joining scenarios. Thereby, the model creates a probability map by concentrating spread out probabilities into peaks. Identified features, such as classifying the amount of JEs, aid the heat map approach by indicating the required number of peaks. However, it can be expected that the heat map approach can output fuzzy results in case of too little training data [31]. Thereby, JE locations become difficult to point down.

Similarity search; CBR can mimic designers searching similar use cases in a PDM system. However, CBR requires coherent knowledge representations of joining scenarios. Thereby, searching for complete component geometries can give noisy results due to potentially large impacts of small features. Hence, feature recognition is favored instead but requires additional development effort. However, a simple similarity search is not sufficient to predict joining locations as similar problems still can contain JEs that do not fit the joining scenario at hand. Therefore, CBR requires interpretation and application of search results by complementary methods such as RBR or S&O. Moreover, other location prediction approaches, such as algorithmic fitting and heat maps, can complement similarity searching as well. In addition, CBR can enrich other location prediction approaches by retrieving features such as quantity, shape or mutual JE distance.

Learning by doing; Students understand that contact regions can contain JEs. Using trial-and-error techniques, a mentor gives to feedback to the student's JEs creations enabling the student to adapt and learn. Equivalently, a RL model learns to predict JEs by doing. Then, an adversary approves or disapproves predictions. However, if the adversary is a designer, it requires much effort to evaluate every single joining scenario in the training phase. FE analyses simulate various performance metrics of a product from which RL models can learn [26]. This enables quick evaluation of many predictions at once and thus faster training. Nevertheless, FE analyses have high computational cost and require large development effort in meshing, modeling and simulating. Thereto, these analyses require a complete product variant, into which the joining scenarios must be configured. Moreover, the specific product variant influences the joining locations. Therefore, the scenarios are modeled and evaluated in multiple variants for multiple performance metrics. Lastly, FE analyses are evaluated and the results are aggregated into a reward for the RL to learn from. Better joining locations result in higher values for performance metrics and therefore a greater reward for the RL model. SML [32] and UML [33] can predict structural topologies. Theoretically, they can learn workings of FE methods [9–11] to predict optimal joining locations. Although, their effectiveness is not verified for large and complex structures or JE design.

3.6. Joining parameters

This includes the dimensioning and selection of JEs by predicting parameters as length, height and width, type of object and additive material. The parameters are highly standardized by consideration of DFA, hence they are typically documented in catalogues. Then, joining parameter prediction is a classification task aligning with a typical SML approach. However, the definition of separate SML expert models for each joining technology is an exhaustive and ambiguous task. Reducing the amount of SML models enables robustness to new joining technologies and parameters. Joining parameters and their locations are intertwined. Larger dimensioned JEs can increase performance and enable reduction of the amount thereof. High standardization enables RBR and CBR as viable approaches due to discrete solution spaces. Naturally, S&O aims to find optimal parameters [12], yet requires an optimization objective and thus is data quality dependent.

3.7. Predict variety

Modular product development in the context of this paper is mainly regarded as a grouping of JE predictions and not as a grouping incorporating components per se (e.g. to build sub-assemblies). A less mature product has a larger modularization potential due to fewer predefined joining modules and fewer fixed design requirements. The aim of variety prediction is to reduce the amount of individual predicted JEs over product variants. It identifies JEs that differ only in the components they join, but are otherwise identical. Hence, these JEs can be shared and utilized in multiple joining scenarios. JE clustering contains two steps: location clustering and communalization.

Location clustering assumes that variants of components have the property that their contact regions tend to be defined on the same geometrical surface. For a joining scenario, the specific shape of the contact region can differ depending on variants, yet apart from that the surface remains the same. Therefore, an UML can cluster JE locations on the contact surfaces to identify those that can be shared over product variants. Thereby, each cluster contains one location per joining scenario. The cluster centroid defines the joining location for JE sharing. The algorithm considers boundary limits and the amount of JEs for each scenario. However, clustering is not definitive as JEs can represent different technologies. It sets the basis for the communalization step. Besides UML, S&O and RBR can combine points in close proximity and aggregate results. Nevertheless, such methods require high development effort to consider all use cases.

Communalization aims to define sharable JEs on clustered locations with multiple joining technologies and parameters. Smaller joining property variation induces savings with respect to verification, planning, assembly, capabilities and equipment. Communalization evaluates a JE's technology and parameters to whether they are equal to other JEs on the same location. Thereby, aiming to define one JE to utilize in the affected joining scenarios. RBR enables checking commonalities of JEs and groups.

Modularization enables further complexity reduction [22]. The aim is to utilize the same JE module in various product variants. Increasing the amount of JEs per module reduces development costs and complexity. However, this also reduces flexibility and thus utilization potential in new product variants. A performance metric couples the module to lifecycle costs and incorporates parameters as change probability, complexity and utilization rate. The change probability describes the chance of redesigning a module such as splitting. The utilization rate aims to increase the amount of JEs in a module if they are expected to occur in sold product variants frequently. The approach creates candidate modules by combining and multiplying predicted aspects of JEs. The metric enables S&O to find the optimal modularity by calculating the costs of every candidate module. This enables a global communalization and reduction in production variety. A clustering approach with UML can identify modules as well. The model considers learned patterns of the feature identification stage. However, implementing variables as change probability and utilization rate into UML is difficult. Additionally, the output of UML is not transparent, such that the designer cannot trace the reasoning for the output, which is something that a cost metric can provide. A RBR method is feasible, however inappropriate due to its high development and maintenance effort as every solution variant for every use case must be programmed.

Reutilization considers reuse of successfully designed JE modules to maintain complexity and prevent unnecessary development effort [23]. This step prevents redundant and ambiguous JE development by considering their implementations in other products, versions or variants. Naturally, CBR retrieves similar designed joining modules and evaluates these for reuse. Thereby, the quality of joining module clustering or engineering is key by calculating the return on investment of predicted JE modules. In addition, reutilization evaluates the optimality of the reuse module. Equivalent to the modularization stage, S&O and a cost metric enable decision-making between reusing and developing new joining modules. Evaluation of the reuse module requires considering all affected joining scenarios. Hence, an evaluation for which joining scenario the reuse module is to be utilized. Then, a decision for module reutilization requires the placement of the reused module on the affected joining scenarios, which can be done with the aforementioned algorithmic fitting approach.

3.8. Prediction quality

A designer can accept predictions or aspects of it, such as only the technology. Thereby, designers can conduct various assessments [8, 15, 23] or send predictions to downstream processes for verification, such as simulation, production planning and suppliers. Here, SML enables the toolbox' methods to continue learning while adapting to new design cases, requirements and trends. The final prediction is a list with highest cumulative confidence predictions ensuring transparency for the designer. Each final prediction is a set of modules with joining technologies, locations, parameters for a given joining scenario. The designer can select the most appropriate or decline all predictions giving feedback to the system.

4. Discussion

The proposed method toolbox incorporates addressed issues in JE design by mimicking various human design practices with AI methods. It aims to improve efficiency by automating analysis of joining scenarios, authoring of JEs and potential reduction of design iterations. Thereto, ML models learn design experience and are expected to predict better business optimal JEs and modules to contain PV-driven complexity.

However, this is a novel research area and more study is required to utilize automated JE design. Applicability of AI methods can differ between companies and industries. In addition, expected trends in industry, such as lightweight design, require new joining technologies and component designs. These scenarios are hard to model, fall outside AI model boundaries and therefore require human designers. However, the method toolbox tackles repetitive time-consuming tasks and enables designers to concentrate on their core competencies. The methodology requires the existence of successful product variants as it requires training data. However, studies are required to validate the methods in various companies and industries to determine its genericity.

4.1. Challenges

Generally, ML approaches require discretized data and often require fixed number of inputs and outputs. However, a joining scenario can consist of a varying amount of components, for example, in case of two or three sheet welding. Moreover, geometries vary in size and complexity inducing mapping issues and high dimensional data. Various studies are conducted to determine the best methods for discretized geometry representations [34] such as point clouds, voxels or screenshots, or analyze implementing feature based geometries [35]. The reduction of dimensionality tends to lead to information loss for large and complex components and unnecessary dimensionality increase for small and simple components. Moreover after dimensionality reduction, predicted joining locations must be mapped back to a global coordinate system.

However, an implementation of 2D instead of 3D geometry reduces dimensionality significantly. Yet, joining regions can be curved in 3D space and components can be joined by multiple contact regions. In the latter case, it introduces another mapping problem as component data has to be divided over various contact regions. These inputs have to be brought together to predict for a joining scenario. Thereto, neural networks require that input data samples are independent of one another. In addition, not all contact regions need to be filled with JEs. Some might be too small for any joining technology, some do not require any JEs and some require multiple joining technologies. The joining region's form highly influences selection of joining technology. This includes characteristics as size, shape and type, which is deduced from the orientation of the components to one another, such as T- and butt-joints. For example, MIG welding used in a long stretched corner of T-joint, where resistance spot welding requires overlapping surfaces. The toolbox has to recognize such various technical infeasibilities throughout the JE design stages.

The method toolbox chains various predictions. Hence, the resulting cumulative confidence values have to be analyzed such as the prediction robustness to both sabotage and data quality sensitivity. Thereto, designers require transparency of predictions in the verification stage to make informed decisions, as they themselves remain to judge with their experience.

5. Conclusion and future work

This study discusses the applicability of AI methods for the design of JEs in manufacturing industries considering large PV. PV and its induced complexity is expected to grow [1], yet no approach has considered holistic JE design in their solution. An analysis reveals issues of JE design in practice and concludes that the state of the art only contains partial solutions. A target process for JE design is proposed together with requirements for implementation. A novel method toolbox is proposed for automating holistic JE design whereby the applicability of AI methods are identified and discussed. The toolbox can predict joining technology, joining locations, joining parameters and can modularize these aiming to contain complexity and costs.

Future research focusses on the implementation of the AI methods for various stages of the toolbox. Approaches will be evaluated against the state of the art. Thereto, studies will be conducted that evaluate AI methods within each stage. The performance of the toolbox as a whole will be studied. Lastly, studies will be conducted to resolve the discussed challenges for implementation of AI methods.

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