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Parametric design evolution for production setups; a case study for welding fixtures

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Abstract

Automated design evolution and optimization are concepts of utmost interest to the industry for reducing design time and cost. This paper addresses the development of an automated design solution based on an evolutionary algorithm for a parametric design problem. The design problem addresses welding fixture designs as an integrated geometric design and configuration problem. The suggested automation approach is based on the parameterization of the fixture geometry and the welding process to minimize collisions across moving and static bodies during the welding operation. The aim is to produce a welding fixture design simulation that can be adjusted for specific requirements based on expert knowledge without re-iterating the entire composition of the problem. The modularity is demonstrated by modifications of the design problem formulation aimed at altering the exploration spectrum and design proposals of the welding fixture. An early system integration shows a reduction of designer efforts to 30% compared to a manual process, with an increase in overall process time due to software computational times.

Keywords: Automated Design; Multi-Objective Optimization; Multi-stage Design; Meta-heuristic Algorithms; Parametric Design

1. Introduction

Automated design evolution is a process by which a design can progressively mature using (semi)-automated software. Evolution occurs through an algorithm that can produce design proposals by exploration of a predefined design space. Automated solutions are becoming more attractive for industries as they can provide a broader range of design proposals with reduced efforts [1]. The generation of these design proposals allows design experts to save time in repeatable and simple tasks by initiating design concepts [2]. Exposure to algorithmically generated designs can also enhance the designer's imagination, nudging them towards feasible design solutions [3]. The current research aims to improve the design of welding fixtures by means of parametric design automation.

The challenge lies in formulating a design problem for an automation system. The development of an automated system requires continuous iterations [4] to account for variations/changes in a design problem and its formulation. In addition, an automation system has to produce designs that satisfy conflicting design criteria such as cost, material, and design time while generating a design proposal that is considered feasible based on the design objectives and experts' opinions. A distinction is made in the paper between a design solution and a design proposal, the latter being a generated design that does not meet all requirements but is a local minimization to the design optimization that could lead to a design solution with minor designer efforts.

The primary industrial application discussed in the paper is the automation of conceptual design proposals for welding fixture designs. However, the paper makes some generalizations to broaden the solution's applicability to other industrial design problems and manufacturing systems that can be formulated in a similar approach [5, 6]. Welding fixtures are assemblies used to enable a welding process by securing the components that compile the final welded product [7, 8]. In addition to securing the components, a welding fixture has a series of design requirements (see Section 2) that should be fulfilled for a robust and high-quality welding process [9, 10]. Due to geometrical and physical restrictions in the design of the welding fixture [11], the fixture may impact the course and quality of the welding process. Hence, fixture geometry is a dynamic variable during product development [12]. Furthermore, it can be deduced that reducing the lead time of a fixture design can positively impact a product's design and lead time.

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The paper proposes welding fixture design's parameterization [13] and optimization through meta-heuristic evolutionary algorithms. The aim is to design an automated design system to produce design proposals that meet the design requirements. Considering the iterative design process to design both an automated system and a welding fixture, the proposed methodology accounts for future improvements and iterations in the design problem formulation. The paper's focus is to provide the following evidence: i) design parameterization and meta-heuristic algorithms are a viable approach to solve the geometrical design problem of a welding fixture, and as such, ii) the design objective can be revised to fit varying expectations of the automated design system.

The suggested approach is to express the welding fixture geometry through standalone fixture blocks, each designated to contribute to the product's fixation through clamping, positioning, and supporting [14, 15]. Each fixture block is evaluated individually, while a global design objective is derived for the fixture design (Section 3). This approach can be perceived as a cooperative/competitive environment [16, 17] or a swarm-intelligence [18] between the blocks under a common objective. This paper defines each block by the following properties: i) geometry design parameters, ii) welding process stages, and iii) local design evaluation. Subsequently, a global design objective is constructed by the weighted sum of the blocks' evaluation (Section 4). The weights are tuneable coefficients that define the prioritization of objectives according to the designer's needs.

Evolutionary algorithms are based on the trade-off between convergence (risk of sub-optimal solutions) and exploration (risk of unproductive search). The choice between the two often boils down to the choice between optimizing for the best design or optimizing for the best method to get to a feasible design. This paper uses two meta-heuristic algorithms: Genetic Algorithm [19] and Simulated Annealing [20]. The two algorithms, presented in Section 5, are implemented for the same welding fixture design to demonstrate the feasibility of convergence and minimization of the design objective. The methodology and models are validated in Section 6.

2. Welding Fixture Design Requirements

Computer-aided welding fixture design is one of the categories of fixture designs [7, 11] used to position and fixate a set of components during welding. This paper addresses conceptual, explorative welding fixture design problems. Resulting fixture proposals produced through automation aim to satisfy the design requirements for a feasible design proposal, as specified in the problem formulation of a use case. The requirements imposed during early design conceptualization are summarised as follows:

Physical requirements: Fixtures must be able to fit the components and support their weight. Fixture geometry must allow access to the components for external actors (e.g., operator, welding robot, etc.)

Tolerance: Fixture accuracy shall be enough to satisfy reference points and product tolerances.

Constraining: Positioning and fixation of the components in all DOFs, force, and moment equilibrium.

Collision prevention: Fixture geometry shall allow a clear path for welding (or other tools). The fixture shall not collide with the product components except for the expected contact points. Fixture internal collisions shall be prevented.

Placement Sequence: Fixtures shall accommodate proper component placement sequences.

Welding & Process: Fixtures shall allow for adequate positioning of welding tools to minimize spatters, stubbing, arc flare, etc.

The use case addresses the above design requirements through design objectives and constraints. The reference points between the fixture and the components are predetermined to adhere to the welded components' tolerances [9] and welding quality [10]. Those are applied as constraints to the welding fixture design. The reference points abide by the fixation requirements of the components towards forces and moments in the welded components. Similarly, stresses allowed on the fixture are also implemented through constraints on the fixture geometry. The placement sequence feasibility of the welded components, the reachability for the operator and weld gun, the internal fixture collisions, and the collisions between the fixture and components are the design requirements to be optimized through parameterization of the welding fixture design. The parameterization of the fixture and its exact composition is elaborated in later sections.

3. Design Parameterization

In essence, any conceptual welding fixture design challenge is a configuration problem in which various standardized blocks can be selected and positioned so that the welding components are adequately positioned and fixated. Hence, the variety and unique combination of welded components, one example seen in Figure 1 (middle), presents a large design space. To navigate this design space in a manageable manner, the design problem is parameterized. The parameters are associated with the geometric properties of the fixture blocks, as seen in Figure 1. Each fixture block has a set of variable parameters related to its design. Each fixture block fulfills one or more fixture functions (i.e., locator, clamp, support), where blocks within the same functionality can be interchanged. Figure 1 (left) shows an example of one locator, one support, and two clamp variations. The expert defines the selection of a block within a function group; however, additional steps can be performed to include the choice as a variable parameter to the design automation.

A welding fixture design comprises its block constituents and multiple stages of the welding process. The overall approach considers the welding process stages as a series of steps that alter the fixture configuration. With each stage, the welding process evolves, thus changing the fixture configuration accordingly. For the welding fixture use case, the welding process starts with the stages of the operator placing and secur-

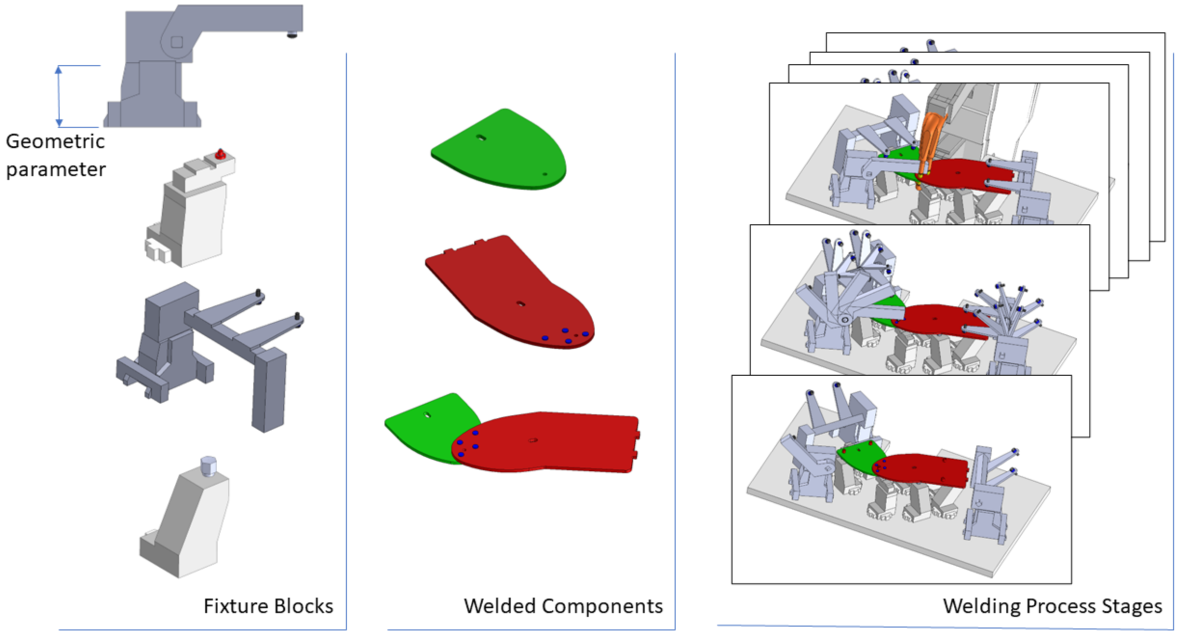

Fig. 1. Representation of the fixture design problem into fixture blocks (left), welded components (middle), and welding process stages (right). An example welding fixture design proposal can be seen in the welding process stages.

ing the welded components based on the defined placement sequence. This is followed by welding the components using a robot manipulator. The final stages include retracting the fixture and removing the welded components. Figure 1 (right) shows a snapshot of fixture configurations in various stages. Distinctly shown are the stages of the welding process representing placing the components, securing the component, and welding. The proposed fixture design evolution assumes that each stage can be assessed independently from the other stages.

Geometric parameters and stages can be used to define a mathematical model per fixture block as shown in equation 1. A fixture block can be defined as the function $f_{b,k}(p_b)$ where subscript b is the specific block and k the welding process stages. The fixture block parameters are defined as p describing the geometry of that block. The function represents the fixture block collisions and interferences with other fixture blocks, the welded components, the welding robot, and the operator. These are all part of the welding process and are associated with a different stage k. A general representation of a fixture block can be defined as

$$F_b(p_b) = \sum_k I_k f_{b,k}(p_b) \quad (1)$$

where I_k is the indicator function of the stages. This means that F is a $k \times 1$ matrix representing the evaluation of the block across all welding process stages.

4. Design Objective

An essential element of design automation is to define a target design objective. This objective describes the goal of the design automation system in deriving feasible design proposals. A multi-objective problem can be formulated as a weighted sum in a single objective cost function. The choice of how the design objective is formulated dictates the algorithm selection, or at least the family of algorithms that can be used and are compatible with the design problem. This section addresses how the mathematical model of the fixture design is derived through individual evaluation of the fixture blocks.

A local representation of a fixture block evaluation is already defined in equation 1 as $F_b(p_b)$ for a block b and all stages k. The weighted sum of all blocks can be expressed as

$$J = \sum_b W_b^T F_b(p_b) \quad (2)$$

where W_b is a vector of dimensions $k \times 1$ corresponding to block functionality and stage weights. For the purpose of this paper, the weights are assumed to be derived from expert knowledge and through a trial-and-error process. From equation 2, the sum of objectives J can be expressed as the minimization objective of the design problem, subject to constraints $g(\cdot)$ applied to the geometric parameters.

$$\min_p(J) \quad \text{s.t.} \sum_b g(p_b) \leq c \quad (3)$$

5. Algorithm Model

The next step in developing the design system is the identification and setup of the algorithm. The algorithm needs to apply an exploration strategy to avoid path-dependent convergence and local optima. For explorative methodologies, the paper discusses two evolutionary algorithms, chosen based on their simplicity and frequent use in literature across many meta-heuristic algorithms: genetic algorithm and simulated annealing. The implementation approach is discussed in this section, whereas further elaboration on the methodologies can be found in the suggested literature.

5.1. Simulated Annealing

Simulated annealing is a meta-heuristic optimization algorithm originating from metallurgy heating and controlled cooling processes [20]. This process is executed in sequential iterations. For implementation, the algorithm is used to progressively update the parameters through random sampling over distributions of a Δp property. This creates a relative update to the design proposal to the previous iteration. An improved design is accepted for each iteration if it outperforms the results of the previous iteration. On the other hand, a worse design has a lower probability of being accepted based on the exploration policy. This approach allows the algorithm to explore and converge accordingly, as seen in Figure 2. The algorithm parameters that determine the rate of exploration are empirically determined and are described as hyper-parameters. The algorithm can benefit from good initialization of the welding fixture block parameters. Through initialization, the design expert can influence the design proposals of the evolutionary system to possible solutions that seem viable for the expert.

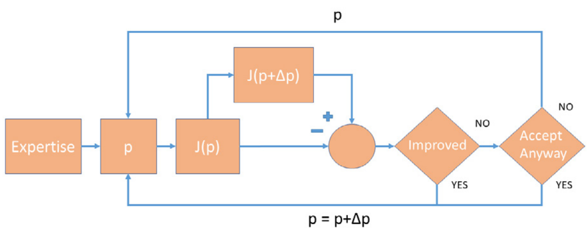

Fig. 2. Simplified diagram of the simulated annealing algorithm

5.2. Genetic Algorithm

The genetic algorithm is another metaheuristic optimization algorithm based on genetic evolution and natural selection [19, 21]. The algorithm selects design parameters by extracting them from previous design evolutions. A set of designs is generated on each algorithmic iteration, referred to as parent designs. Those designs subsequently form the basis for creating new designs with mixed elements of selected parents. The algorithm implementation uses three genetic operators: elite parent, cross-over, and mutation (seen in Figure 3). Elite parent refers to designs with the best evaluation and whose parameters are carried over to the next iteration. Cross-over is performed by combining the parameters from parent designs. Mutation denotes the chance that a parameter is not carried over by an existing parent, in which case the parameter is sampled from a known distribution. This algorithm also benefits from a good initialization of the fixture block parameters, where parameters defined by the experts can be carried through to new design proposal generations.

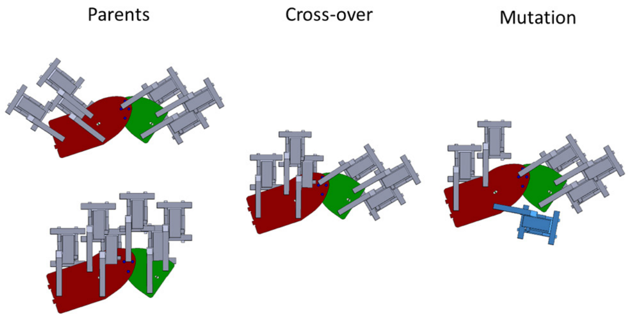

Fig. 3. Graphical representation of evolution in a genetic algorithm

6. Implementation and Validation

The proposed approach is incorporated in the design evolution of the welding fixture use case. To validate the approach, the earlier automation system requirements are revisited. To recap, those are the generation of feasible design proposals and modularity of the system towards the interpretation and formulation of the design problem. Figure 1 shows an example of an evolved design proposal by the simulated annealing algorithm. The welding fixture design proposal can be seen in some welding process stages, where major collisions are prevented. The design expert can handle minor collisions that are present through modifications and improvements of the welding fixture design that exceed the capabilities of the automation system and the current parameterization.

The two evolutionary algorithms presented in Sections 5.1 and 5.2 have been implemented in an industrial use case to demonstrate the approach's validity and gain experience with the initialization of parameters and the derivation of weight coefficients. The algorithm convergence speed and consistency depend on the initialization of the parameters, the complexity of the fixture design (i.e., the number of parameters), and the fine-tuning of weight coefficients dependent on the specific welding fixture design problem. The algorithm could provide viable design proposals within a few iterations for fixture design problems with a small number of parameters and welding process stages. An example of this type of design problem is presented in this paper (Figure 1), whose implementation is discussed later in this section. The convergence time exponentially increases for larger welding fixture designs (i.e., more parameters and more stages). The current implementation is performed on existing CAD software (SolidWorks), where communication with the software consumes 80% of the evaluation time. Viable design proposals were evaluated for welding fixture designs with fewer parameters within the first few hours. Alternatively, the algorithm would require running overnight for welding fixture designs with more parameters. In both scenarios, the effort to initialize and execute the algorithms was approximately

30% of the time required to design the welding fixture manually, showing a substantial reduction in designer efforts. In contrast, the processing period to execute the algorithm was two to five times longer than the manual design process, depending on the complexity of the welding fixture design. Multiple mitigation strategies are available to improve the computational performance; however, this is not yet addressed in the current work [22].

Both algorithms are implemented on the same fixture problem with the same design objective cost function as defined in equation 3. For the genetic algorithm, exploration is achieved by creating a population of six fixture designs. A design expert sets the parameters of the first design, while the other fixtures' parameters are initialized randomly. For simulated annealing, the parameters are updated based on a delta-value update. The parameters are initialized identically by a design expert. Geometric parameter updates are sampled through probability distributions for rotations and linear distances. Used distributions are Von-Mises, beta, and uniform distribution applied accordingly in both algorithms. The coefficients of the distributions were set up empirically. Figure 4 shows the performance of both algorithms in deriving a similar quality design proposal after a given number of steps. The objective cost refers to the numerical approximation of collisions and interferences associated with the fixture during all welding process stages. Due to the computational demand of performing a single evaluation, the algorithms are compared on the number of evaluations, not algorithm iterations. This is a one-to-one association for simulated annealing, whereas, for the genetic algorithm, the association is six evaluations for one algorithm iteration. The algorithms have equivalent performance, and any indicative advantages between the algorithms depend on the empirical setup of the algorithm's hyper-parameters [20]. The evolved design proposals from both algorithms were validated by design experts and approved as viable design concepts.

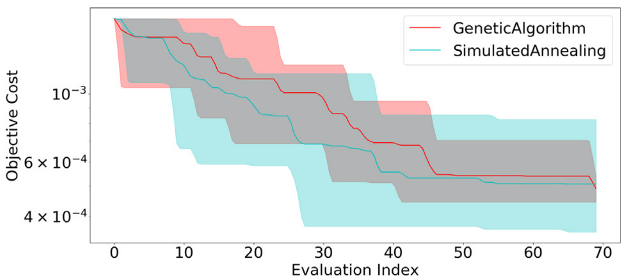

Fig. 4. Convergence of two algorithms, (red) genetic algorithm and (blue) simulated annealing, on the same fixture design using the same design objective cost function.

Modifying the interpretation of the design objective cost function can tailor the design solution closer to the expectations of such a solution. This modification is possible by defining the weight coefficients of the objective cost function. Assuming that a limited computational period is provided to derive a design proposal, the algorithm could run the risk of proposing a sub-optimal design solution. In that scenario, experts state that providing favoritism across requirements could derive design proposals with more manageable and easily corrected issues [6]. The impact of the design objective modification can be observed by the control given to the designer to alter the direction of design solutions by selecting the weights of the design requirements accordingly. To demonstrate this, a welding fixture block is observed when comparing two executions of a simulated annealing algorithm with variations in the design objective cost function. The algorithm versions differ only in the weighting of collisions during the welding stage. The first version prioritizes collision prevention with the welding tool, and the second prioritizes collision prevention with the welded components. Figure 5 shows the same crop section of two resulting design proposals for the same fixture design problem. The design proposal in the figure (left) prevents collisions with the product, but a collision with the weld gun is still present. The opposite is true for the design proposal shown in the figure (right). The choice between the two depends on the experts' perspective on which collision can be resolved with minimum effort by the expert. This varies between welding fixture design problems.

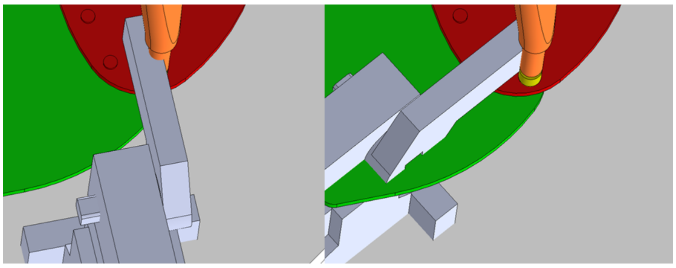

Fig. 5. Collision prevention of fixture with (left) prioritization on the welded product (right) prioritization on welding tool.

A revision to an existing design problem, such as the fixture design, can be of many forms, such as removing, adding, or updating elements of the fixture, such as fixture blocks, stages, or numerical approximation methods of the design objectives. To demonstrate the ease of substituting, a scenario is used where a numerical approximation method is revised due to computational cost. The scenario assesses the ability to remove the welded component from the fixture after completing welding. This objective is addressed through feasible pathfinding to extract the components while avoiding interference with the welding fixture. The objective cost was computed based on total collision areas over the identified path. Due to the computational cost of this evaluation, the evaluation was revised into collision detection following a predefined extraction path defined by the design expert. This substantially reduced the computational cost of executing an evaluation without significantly increasing design expert efforts or causing a drop in the design proposals' quality.

7. Conclusion

The paper proposed an approach to automating welding fixture design problems as a parametric optimization problem derived from multiple fixture blocks. The proposed methodology uses individual assessments for each fixture block to describe the overall performance of the fixture design. The fixture design process is also divided into welding process stages, each assessing the viability of the fixture geometry towards minimization of collisions and interference. The presented problem is evaluated by means of two evolutionary algorithms that show equivalent performance in proposing viable designs.

The multi-objective design problem is formulated in terms of a single objective cost function whose weights can be modified based on the experts' intentions and the framework in which the automation is implemented. Automation and expert cooperation can lead to tailored improvements and specific, localized optimizations. Similarly, the fixture block options could be expanded and added to the automation solution without changing the design objective.

Implementing the algorithms in an industrial use case showed a reduction of manual designer efforts to 30% for generating early concepts of welding fixture design proposals. This is countered by increased process time, where automated design proposals take longer than a manual design. The current system is coupled with CAD software resulting in extended communication and updating time per algorithm iteration. Future work could look into methods to improve the design evaluation approach with the intention of real-time optimization.

Additional work is required for welding fixture designs with many parameters, where complexity and computation time increase. Different algorithm families, such as swarm intelligence, game theory, or multi-objective optimization, could address the problem dimensionality more efficiently. The current implementation is a stepping stone in generating geometry constraint welding fixture proposals toward the overall product development of challenging welded components, where the limitations of the welding fixture geometry can influence welding quality and product tolerances.

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References

[1] C. Johansson, T. Larsson, S. Tatipala, Product-service systems for functional offering of automotive fixtures: Using design automation as enabler, Procedia CIRP 64 (2017) 411–416. doi:10.1016/j.procir.2017.03.006, 9th CIRP IPSS Conference: Circular Perspectives on PSS.

[2] E. Lutters, F. J. V. Houten, A. Bernard, E. Mermoz, C. S. Schutte, Tools and techniques for product design, CIRP Annals - Manufacturing Technology 63 (2014) 607–630. doi:10.1016/J.CIRP.2014.05.010.

[3] C. Obieke, J. Milisavljevic-Syed, J. Han, Supporting design problem-exploring with emergent technologies, Procedia CIRP 91 (2020) 373–381. doi:10.1016/J.PROCIR.2020.02.189.

[4] T. Tomiyama, P. Gu, Y. Jin, D. Lutters, C. Kind, F. Kimura, Design Methodologies: Industrial and Educational Applications, CIRP annals : manufacturing technology 58 (2009) 543–565. doi:10.1016/J.CIRP.2009.09.003.

[5] A. Osman, Y. Kutay, I. Mozgova, R. Lachmayer, Procedure to create an automated design environment for functional assemblies, Proceedings of the Design Society 2 (2022) 553–562. doi:10.1017/PDS.2022.57.

[6] D. Mourtzis, M. Doukas, D. Bernidaki, Simulation in manufacturing: Review and challenges, Procedia CIRP 25 (2014) 213–229. doi:10.1016/J.PROCIR.2014.10.032.

[7] I. Boyle, Y. Rong, D. C. Brown, A review and analysis of current computer-aided fixture design approaches, Robotics and Computer-Integrated Manufacturing 27 (2011) 1–12. doi:10.1016/j.rcim.2010.05.008.

[8] R. Förstmann, J. Wagner, K. Kreisköther, A. Kampker, D. Busch, Design for automation: The rapid fixture approach, Procedia Manufacturing 11 (2017) 633–640. doi:10.1016/J.PROMFG.2017.07.161.

[9] R. Söderberg, K. Wärmefjord, J. Madrid, S. Lorin, A. Forslund, L. Lindkvist, An information and simulation framework for increased quality in welded components, CIRP Annals 67 (2018) 165–168. doi:10.1016/J.CIRP.2018.04.118.

[10] P. Sathiya, K. Panneerselvam, M. Y. A. Jaleel, Optimization of laser welding process parameters for super austenitic stainless steel using artificial neural networks and genetic algorithm, Materials and Design 36 (2012) 490–498. doi:10.1016/J.MATDES.2011.11.028.

[11] H. Wang, Y. Rong, H. Li, P. Shaun, Computer aided fixture design: Recent research and trends, Computer-Aided Design 42 (2010) 1085–1094. doi:10.1016/J.CAD.2010.07.003.

[12] E. A. Nasr, A. Al-Ahmari, A. A. Khan, S. H. Mian, O. Abdulhameed, A. Kamrani, Integrated system for automation of process, fixture and inspection planning, Journal of the Brazilian Society of Mechanical Sciences and Engineering 42 (2020) 52. doi:10.1007/s40430-019-2129-5.

[13] I. Caetano, L. Santos, A. Leitão, Computational design in architecture: Defining parametric, generative, and algorithmic design, Frontiers of Architectural Research 9 (2020) 287–300. doi:10.1016/J.FOAR.2019.12.008.

[14] A. Kampker, G. Bergweiler, A. Hollah, K. Lichtenthäler, S. Leimbrink, Design and testing of the different interfaces in a 3d printed welding jig, Procedia CIRP 81 (2019) 45–50. doi:10.1016/J.PROCIR.2019.03.009.

[15] A. Gameros, S. Lowth, D. Axinte, A. Nagy-Sochacki, O. Craig, H. R. Siller, State-of-the-art in fixture systems for the manufacture and assembly of rigid components: A review, International Journal of Machine Tools and Manufacture 123 (2017) 1–21. doi:10.1016/J.IJMACHTOOLS.2017.07.004.

[16] O. J. Lopez Orozco, J. L. M. Lastra, Agent-based control model for reconfigurable manufacturing systems, in: 2007 IEEE Conference on Emerging Technologies and Factory Automation (EFTA 2007), 2007, pp. 1233–1238. doi:10.1109/EFTA.2007.4416922.

[17] N. R. Jennings, An agent-based approach for building complex software systems, Communications of the ACM 44 (2001) 35–41. doi:10.1145/367211.367250.

[18] L. Xiong, R. Molfino, M. Zoppi, Fixture layout optimization for flexible aerospace parts based on self-reconfigurable swarm intelligent fixture system, International Journal of Advanced Manufacturing Technology 66 (2013) 1305–1313. doi:10.1007/S00170-012-4408-5.

[19] D. E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, 1st ed., Addison-Wesley Longman Publishing Co., Inc., USA, 1989.

[20] P. J. M. van Laarhoven, E. H. L. Aarts, Simulated annealing, Springer Netherlands, Dordrecht, 1987, pp. 7–15. doi:10.1007/978-94-015-7744-1_2.

[21] K. F. Man, K. S. Tang, S. Kwong, Genetic algorithms: Concepts and applications, IEEE Transactions on Industrial Electronics 43 (1996) 519–534. doi:10.1109/41.538609.

[22] D. Fuchs, R. Bartz, S. Kuschmitz, T. Vietor, Necessary advances in computer-aided design to leverage on additive manufacturing design freedom, International Journal on Interactive Design and Manufacturing (IJIDeM) 16 (2008) 1633–1651. doi:10.1007/s12008-022-00888-z.