Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 81 (2019) 671–676

www.elsevier.com/locate/procedia

52nd CIRP Conference on Manufacturing Systems

Evolutionary algorithms in additive manufacturing systems: Discussion of future prospects

Torbjørn Schjelderup Leirmo[a,]*, Kristian Martinsen[a]

[a]Department of Manufacturing and Civil Engineering, Norwegian University of Science and Technology, Teknologivegen 22, 2815 Gjøvik, Norway

* Corresponding author. Tel.: +47 480 88 390. *E-mail address:* torbjorn.leirmo@ntnu.no

Abstract

Additive Manufacturing (AM) as a manufacturing process is increasingly implemented in manufacturing and is thus subjected to the high demands of industry. With the industrialization of AM technologies follows demands regarding not only dimensions and tolerances, but also mechanical properties, processing time and cost. The multi-objective optimization problems arising from AM is just another venue where Evolutionary Algorithms (EAs) are applied. This paper attempts to provide an overview of the current role of EAs in AM in order to make a discussion on the future prospects of EAs in the industry.

Keywords: Evolutionary algorithm; Additive Manufacturing; Optimization; Metaheuristic; Swarm intelligence; Artificial intelligence

1. Introduction

Over the last thirty years, Additive Manufacturing (AM) has developed from a rapid prototyping technology to a broad concept encompassing a variety of manufacturing technologies ranging from desktop 3D-printers for private use, to large industrial machines for high-end metal processing [1, 2]. AM is currently being implemented in industry both as a stand-alone process, as well as in tandem with traditional manufacturing technologies in hybrid manufacturing systems [3]. AM is, however still an immature process and the many challenges has sparked significant efforts in the research community for the optimization of the build process to improve part quality, repeatability and reliability [4, 5]. Mitigating these challenges further enables integration of AM in modern production systems and is vital for the continued growth of AM in manufacturing industry [6, 7].

This paper aims to review the current role of evolutionary algorithms (EAs) in AM systems to get an understanding of the future prospects of EAs in the AM discourse, and possible future developments of EAs in AM industry.

1.1. Additive Manufacturing

Since the first Stereolithography Apparatus (SLA) was patented in 1986 [8], various methods for fabricating three dimensional objects in a layered fashion has been developed, resulting in a total of seven AM process categories as defined by ISO/ASTM 52900:2015 [9]:

- Binder Jetting
- Directed Energy Deposition
- Material Extrusion
- Material Jetting
- Powder Bed Fusion
- Sheet Lamination
- Vat Photopolymerization

The above categorization covers all current AM technologies regardless of build material, and they all involve sequential addition of material with the accompanying benefits and drawbacks [2]. The layered manner of part fabrication results in anisotropic material properties, which is

10.1016/j.procir.2019.03.174

one of the major hurdles to reliability and quality assurance [5]. Other defects and inaccuracies observed in AM includes material failures, stair stepping, surface roughness and dimensional inaccuracies, all of which can be mitigated with proper machine settings and part build orientation [1, 2, 10].

No matter how significant, part properties is only one of several challenges in AM. The long build time of AM compared to its alternative conventional technologies continues to be a compelling argument against the adoption of AM in mass production. On the other hand, has AM large potential for manufacturing of very complex components. The advanced geometries enabled by AM further complicates the already complex problem of part placement in the build chamber [11]. Optimization of geometry, process planning, and layout optimization remains crucial to increase the efficiency and reduce lead time of AM [12]. Such problems are not trivial, and the possibility of mass customization indicates that optimization problems must be solved on a regular basis.

The generic process of additive manufacturing can be decomposed into eight discrete steps from part design to part application as illustrated in Fig. 1 [1]. Depending on the vendor of the AM machine and software, part orientation and placement may be conducted either prior to machine setup, or in the same processing step. The final step of application may not imply end use but could also be additional treatment such as priming or painting, or it could be part of an assembly e.g. in a hybrid manufacturing system.

The need for optimization in AM is perhaps most apparent in the earlier stages of design and process planning, but later stages of the AM process chain are also important and indeed valid for optimization efforts. The development of real-time closed loop feedback control systems for in-build process optimization is an important research area for improved part quality [13].

1.2. Evolutionary Algorithms

In this paper, an EA is defined in accordance with the definition of Dan Simon as "[…] an algorithm that evolves a problem solution over many iterations" [14, p. 3]. This generally includes population-based and bio-inspired metaheuristics and, perhaps more controversial, swarm intelligence. This definition further places EAs under the umbrella of artificial intelligence as a subset of soft computing and related to machine learning [14].

Finding the exact solution to an optimization problem is a complicated task that has been relying on computers for half a century [15]. As the complexity of optimization problems increases, the means to solve them inevitably do the same. One measure to overcome the complexity of optimization problems is to take inspiration from how optimization problems are solved in nature. EAs were originally developed by biologists in the late 50s and early 60s to simulate biological evolution [16]. However, the algorithms turned out to be well suited for optimization problems, and so the Genetic Algorithm (GA) was applied to optimization problems. This created the foundation for other algorithms such as Genetic Programming (GP) and Evolutionary Programming, and also more recent concepts such as Simulated Annealing (SA) and swarm intelligence including Particle Swarm Optimization (PSO) and Ant Colony Optimization [14].

The basis of any EA is a general architecture inducing certain properties and basic abilities providing wide applicability in problem solving. Yet, the algorithms are adaptable, and it is advised to include problem specific information to improve performance [14].

One of the great contributions of EAs is their ability to maintain a population of candidate solutions, effectively exploring different areas of the solution space simultaneously. When considering multiple contradicting objectives, the complexity of optimization becomes increasingly difficult as a trade-off must be made. This trade-off can either be conducted in one of two ways. The weighted sum method effectively converts a multi-objective problem into a single-objective problem by normalizing the objectives before they are multiplied with a scaling factor. However, the result will be biased by the weights assigned to the objectives and thus the validity of results are questionable.

Another approach strongly advocated in more recent research, is to allow the optimization algorithm to converge to multiple solutions constituting the Pareto front. The Pareto front is the set of non-dominated solutions, i.e. solutions where an improvement in one objective has a negative effect on at least one other objective. An educated selection can then be made among the presented set of non-dominated solutions resulting in a more fitting solution [17].

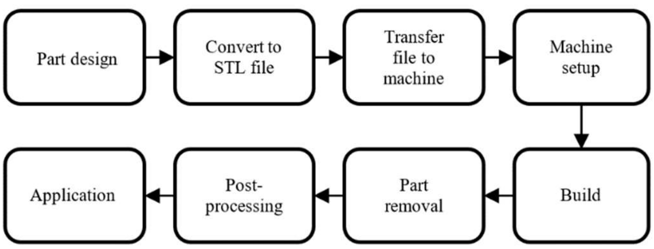

Fig. 1. Typical additive manufacturing processing steps. Adapted from [1].

2. Current situation

EAs have been applied to a number of problems in AM ranging from the design stage through process planning to machine setup [6]. The following section provides a brief overview of current applications of EAs in AM systems.

2.1. Design for Additive Manufacturing

AM relieves designers of traditional manufacturing constraints, and new AM-specific constraints are imposed [2]. This calls for a paradigm shift from traditional design for manufacture and assembly, to design for AM (DfAM) [1, 18].

GAs have been extensively used in engineering design at an early stage outside the AM domain, and a thorough review of early use cases is provided by Renner and Ekárt [19]. The geometric freedom available in AM makes it possible to design cellular structures and topologically optimized (TO) parts unattainable by conventional methods [20]. The complex structures of such designs make EAs a good tool for computer-aided design [21].

Salonitis et al. used a GA to reduce part weight by optimizing the strut diameter in a lattice structure with constraints formulated as maximum displacement [22]. GA can also be found in TO of concrete structures enabled by additive deposition of concrete [21]. Other efforts utilize PSO for design of cellular structures in AM [23, 24], and the performance of PSO is found to exceed that of the Levenberg-Marquardt method which is widely used [24].

EAs can also be used to create the design from scratch with a process known as generative design. Dhokia, Essink, Flynn and Goguelin demonstrates how a termite nest building algorithm inspired by Ant Colony Optimization is used to generate a design given some loading conditions, a build envelope and some general objectives [25, 26]. Yao et al. applied the Non-dominated Sorting Genetic algorithm (NSGA-II) of Deb et al. [27] to aid the designer in selecting proper materials, components, AM technology and dimensional parameters [28]. GAs have also proven useful for assessing design feasibility [29].

AM enables new functionally graded materials, allowing two or more materials to be seamlessly combined in a single part [20]. As the multimodal nature of the solution space makes it difficult for numerical methods to obtain optimal results, EAs are often utilized to determine material distributions. Kou et al. demonstrates the ability of PSO to design functionally graded materials [30], and a case study on functionally graded materials in a dental implant found that GA and SA achieve better results than the more traditional response surface method [31]. Hiller and Lipson reports interesting work on automatic design of soft robots building on functionally graded materials for ductility and applies a GA [32].

2.2. Optimization of part build orientation

The problem of orientation in AM can be traced back to 1994 [33], but it took another ten years before Thrimurthulu, Pandey and Reddy proposed a solution using a GA and the weighted sum method [34]. Later the same year they used the NSGA-II to find the Pareto front [35]. Both of these applications was applied to Fused Deposition Modelling (FDM) considering surface roughness and build time [34, 35].

In addition to FDM [36-39], later applications of EAs also includes other AM technologies such as SLA [40-43], Selective Laser Sintering (SLS) [44, 45], Selective Laser Melting (SLM) [46, 47], and combinations of SLA, SLS and FDM [48, 49]. Furthermore, other objectives are considered for the optimization problem such as material use [44, 46], volumetric error [37, 39, 50-52], support structures [36, 43, 46, 47, 52] and mechanical properties [36, 47]. The objective of minimizing post processing time and cost by GA was proposed by Kim and Lee who considered part height, surface roughness and support structures in SLA [42]. Zhang et al. used a GA to simultaneously optimize the orientation of 16 parts for minimizing build cost in multi-part production with a total of five objectives [41]. A recent optimization scheme also using GA was proposed by Brika et al. where eight objectives was considered in SLM including yield strength, tensile strength and elongation, in addition to typical objectives such as build time, surface roughness and support structures [47].

It is clear that GA is the most widely used EA in the field of part build orientation, but examples of other population based algorithms do exist. Padhye, Deb and Kalia compared the performance of NSGA-II with a multi-objective PSO and found that the latter was outperformed, both in terms of execution time and quality of results [38, 45]. A more recent application of PSO is proposed by Barclift et al. who applied the algorithm to minimize cost in SLM [46].

Other implementations include the unconventional DNA-based EA proposed by Tyagi et al. for minimizing stair stepping and build time [39].

2.3. Placement of parts in the build space

The placement of parts in the AM build space, also known as layout planning, nesting or part packing, is important to reduce build time and improve efficiency. EAs was applied to the packing problem at an early stage with GA being applied to SLA already in 1994 for the sequential packing of boxes in two and three dimensions [53]. A GA directed at SLS was introduced in 1997 working on bounding boxes [54] and later improved to utilize multiple CPUs [55]. GAs was later used in two dimensions for packing parts according to their projections onto the build plane [12, 56, 57].

Some years after the first GA, Dickinson and Knopf applied SA to the packing problem [58, 59] and inspired further applications of SA in the field [60]. More recently, a re-seeding mechanism in SA was proposed by Cao et al. [61]. The re-seeding is a measure to prevent pre-mature convergence to a sub-optimal solution manifested as a local optimum in the solution space.

Zhang et al. [12] argues that orientation should be considered in the packing process to ensure part quality. GAs are used to solve this problem both for two [12, 57] and three dimensions [11, 62-64].

2.4. Build parameter optimization

Rong-Ji et al. used a combination of GA and Artificial Neural Network (ANN) to optimize the process parameters of SLS considering part shrinkage [65]. The relations between seven processing parameters and part shrinkage was described by ANN, and later used as input for the GA which optimized the parameter settings. GA has also been applied in Direct Metal Laser Sintering to optimize hatch direction to improve material properties [66]. The melt pool of Laser Direct Metal Deposition is shown to be predictable by ANN [67], and PSO was proposed by Mozaffari et al. in combination with a Self-organizing Pareto based EA for optimizing process parameters [68]. A modified version of the NSGA-II has also been proposed to optimize final part properties [69].

The tool path in Laminated Object Manufacturing is similar to that in conventional machining operations and can also be optimized by GA [70].

The surface quality of FDM has been optimized by applying ANN in combination with bacterial foraging optimization algorithm [71], and an improved ANN based on PSO and the Imperialist Competitive Algorithm [72].

Rao and Rai used their Teaching-Learning Based Optimization EA for optimizing the compressive strength in FDM and achieved better performance compared with GA and a PSO algorithm [73]. A non-dominated sorting version of PSO was also applied to a multi-objective problem and performed similarly to NSGA-II.

Vijayaraghavan et al. proposed using GP in FDM to enable offline prediction of final part properties and achieved results comparable to ANN and support vector regression [74]. A similar effort is found in [75] where GP is proposed for modelling characteristics of SLS, and in [76] where GP is used to model the bead size in Wire and Arc AM.

2.5. Other applications in additive manufacturing systems

Ewald et al. used a mixed integer GA to find the most cost effective solution for hybrid manufacturing using wrought material as a basis for Laser Metal Deposition [77]. The single objective GA varied the size, orientation and position of the work piece to obtain the most economical work distribution between conventional milling and additive manufacturing.

Xu et al. applied a GA to the problem of adaptive part slicing for improved surface roughness in SLA. Their algorithm considered horizontal sections of the STL model sequentially and determined the slice thickness for each section independently of neighboring sections. The benefit of an EA became apparent with increasing geometric complexity as the number of local optima increased drastically [78].

3. Trends and future prospects

New and better applications of EAs are still published regularly even 25 years after its initial introduction to the field of AM. Based on the literature presented in the previous section, it is apparent that few variations of EAs are documented in the literature as most efforts focus on GAs. Furthermore, a rather limited range of technologies and materials have been subjected to EAs in the literature except for FDM which is generally quite well covered. Future developments should contribute to closing this gap by testing of new algorithms on different technologies and materials.

3.1. Variations of evolutionary algorithms

The long history of GAs may explain why this is such a popular method even though closely related metaheuristics such as Evolutionary Programming and Evolution Strategies are not to be found anywhere in AM discourse, and GP is only found to be used by a single group of researchers [74-76]. The meta-perspective of these methods facilitates flexibility and might enable a single solution for multiple technologies. This contradicts the recommendation of tailoring EAs to specific problems to improve performance [14].

Other variations of EAs may be introduced in the field of AM as they mature over the years to come. New EAs are proposed with different inspirations, most of which are bio-inspired and draw parallels to natural optimization processes e.g. Ant Colony Optimization and Bacterial Foraging Optimization. An argument could be made that separating the algorithm from its original biological inspiration may be the path to more effective solutions as they relieve the developer from constraints imposed by the biological origins of the algorithm.

History show that increasing computational power enables more complex algorithms with more constraints, objectives and parameters. Part packing is a good example where the problem has been simplified due to computational limitations. With more power, comes more possibilities as it not only facilitates details in optimization, but also enables the consideration of more parameters and constraints. Future applications of EAs in AM are likely to benefit from advancements in computational power and generally produce results of higher quality [6].

3.2. Processes and materials

The literature on EAs in AM is dominated by the plastic processing technologies SLA, FDM and SLS. The large players in industry are however often primarily interested in high value metal applications where mechanical and geometrical tolerances are paramount [7]. The reasons why there are so few use cases in metal AM is surely many, but one major factor is the need for establishing process knowledge and discovery of causal relationships between process parameters and final part properties. With better understanding of the process, better predictions can be made on part properties which enables EAs to be applied to optimize process parameters.

The application of machine learning could play a major role in the optimization of individual AM machines settings. The customization of process parameters for a single machine or even a specific part is made possible through e.g. Artificial Neural Networks. Further advances could be achieved if knowledge gained from one process could be transferred to another. The extraction of process knowledge from one machine to another without human involvement is an interesting area of future research which requires computational intelligence.

3.3. Other prospects

Integration of AM in industrial environments is likely to bring about more hybrid manufacturing solutions where AM is used together with conventional manufacturing technologies. EAs have already been used to aid in process planning for hybrid systems [77]. However, designing for hybrid manufacturing could bring about previously unknown issues where EAs are good problem solvers due to the complex and multimodal nature of real-world problems.

4. Concluding remarks

EAs are popular tools for optimization of complex multi-objective problems in the AM domain related to design, process planning and machine setup. Many applications of GA and PSO are present in the literature, but rather few variations of EAs are found in use cases. It is expected that future applications derive advantage from increasing computational power which enables new algorithms to be more sophisticated and precise.

EAs are already present in design applications but is likely to become even more important as hybrid manufacturing becomes more common in industry. The complexity induced by combining additive and subtractive technologies inspires for increased exploration of EAs in the AM domain.

Finally, closed loop process control and optimization by machine learning could be of major importance in the effort towards industrialization of AM. Part quality and repeatability is vital to inspire wide spread implementation of AM in the manufacturing industry. EAs are crucial tools in the optimization processes necessary to achieve this goal, and collaboration between academia and industry will be the final step in bridging the gap from research to implementation.

Acknowledgements

This research is funded by the Norwegian Ministry of Research and Education, and is associated with SFI Manufacturing.

References

[1] Gibson I, Rosen DW, Stucker B. Additive manufacturing technologies. 2nd ed. New York: Springer; 2015.

[2] Gao W, Zhang Y, Ramanujan D, Ramani K, Chen Y, Williams CB, et al. The status, challenges, and future of additive manufacturing in engineering. Comput Aided Des. 2015;69:65–89.

[3] Dilberoglu UM, Gharehpapagh B, Yaman U, Dolen M. The Role of Additive Manufacturing in the Era of Industry 4.0. Procedia Manuf. 2017;11:545–54.

[4] Delgado J, Ciurana J, Rodríguez CA. Influence of process parameters on part quality and mechanical properties for DMLS and SLM with iron-based materials. Int J Adv Manuf Technol. 2012;60(5):601–10.

[5] Horn TJ, Harrysson OLA. Overview of current additive manufacturing technologies and selected applications. Sci Prog. 2012;95(3):255–82.

[6] Majewski C. Applications of Evolutionary Computing to Additive Manufacturing. In: Tiwari M, Harding JA, editors. Evolutionary Computing in Advanced Manufacturing. Massachusetts: Scrivener Publishing LCC; 2011. p. 197–234.

[7] Pradel P, Zhu Z, Bibb R, Moultrie J. Investigation of design for additive manufacturing in professional design practice. J Eng Des. 2018;29(4–5):165–200.

[8] Hull CW. Apparatus for production of three-dimensional objects by stereolithography. US patent US4575330 A. 1986.

[9] ISO/ASTM 52900:2015. Standard Terminology for Additive Manufacturing – General Principles – Terminology. ISO/ASTM; 2015.

[10] Baturynska I. Statistical analysis of dimensional accuracy in additive manufacturing considering STL model properties. Int J Adv Manuf Technol. 2018;97:2835–49.

[11] Gogate AS, Pande SS. Intelligent layout planning for rapid prototyping. Int J Prod Res. 2008;46(20):5607–31.

[12] Zhang Y, Gupta RK, Bernard A. Two-dimensional placement optimization for multi-parts production in additive manufacturing. Robot Comput-Integr Manuf. 2016;38:102–17.

[13] Chua ZY, Ahn IH, Moon SK. Process monitoring and inspection systems in metal additive manufacturing: Status and applications. Int J Precis Eng Manuf-Green Technol. 2017;4(2):235–45.

[14] Simon D. Evolutionary optimization algorithms. New Jersey: John Wiley & Sons; 2013.

[15] Dantzig GB. Reminiscences about the origins of linear programming. Operations Research Letters. 1982;1(2):43–8.

[16] Goldberg DE. Genetic Algorithms in Search, Optimization and Machine Learning: Addison-Wesley Longman Publishing Co., Inc.; 1989.

[17] Deb K. Multi-Objective Optimization Using Evolutionary Algorithms. Chichester: John Wiley & Sons; 2008.

[18] Thompson MK, Moroni G, Vaneker T, Fadel G, Campbell RI, Gibson I, et al. Design for Additive Manufacturing: Trends, opportunities, considerations, and constraints. CIRP Annals. 2016;65(2):737–60.

[19] Renner G, Ekárt A. Genetic algorithms in computer aided design. Comput Aided Des. 2003;35(8):709–26.

[20] Rosen DW. A review of synthesis methods for additive manufacturing. Virtual Phys Prototyp. 2016;11(4):305–17.

[21] Duballet R, Gosselin C, Roux P. Additive Manufacturing and Multi-Objective Optimization of Graded Polystyrene Aggregate Concrete Structures. In: Thomsen MR, Tamke M, Gengnagel C, Faircloth B, Scheurer F, editors. Modelling Behaviour: Design Modelling Symposium 2015. Cham: Springer International Publishing; 2015. p. 225–35.

[22] Salonitis K, Chantzis D, Kappatos V. A hybrid finite element analysis and evolutionary computation method for the design of lightweight lattice components with optimized strut diameter. Int J Adv Manuf Technol. 2017;90(9):2689–701.

[23] Chu C, Graf G, Rosen DW. Design for Additive Manufacturing of Cellular Structures. Comput Aided Des Appl. 2008;5(5):686–96.

[24] Chu J, Engelbrecht S, Graf G, Rosen DW. A comparison of synthesis methods for cellular structures with application to additive manufacturing. Rapid Prototyp J. 2010;16(4):275–83.

[25] Essink WP, Flynn JM, Goguelin S, Dhokia V. Hybrid Ants: A New Approach for Geometry Creation for Additive and Hybrid Manufacturing. Procedia CIRP. 2017;60:199–204.

[26] Dhokia V, Essink WP, Flynn JM. A generative multi-agent design methodology for additively manufactured parts inspired by termite nest building. CIRP Annals. 2017;66(1):153–6.

[27] Deb K, Agrawal S, Pratap A, Meyarivan T. A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II. In: Schoenauer M. et al., editors. Parallel Problem Solving from Nature PPSN VI; Paris, France: Springer; 2000.

[28] Yao X, Moon SK, Bi G. Multidisciplinary design optimization to identify additive manufacturing resources in customized product development. J Comput Des Eng. 2017;4(2):131–42.

[29] Hsiao S-W, Chiu F-Y, Lu S-H. Product-form design model based on genetic algorithms. Int J Ind Ergon. 2010;40(3):237–46.

[30] Kou XY, Parks GT, Tan ST. Optimal design of functionally graded materials using a procedural model and particle swarm optimization. Comput Aided Des. 2012;44(4):300–10.

[31] Sadollah A, Bahreininejad A. Optimum gradient material for a functionally graded dental implant using metaheuristic algorithms. J Mech Behav Biomed Mater. 2011;4(7):1384–95.

[32] Hiller J, Lipson H. Automatic Design and Manufacture of Soft Robots. IEEE Trans Robot. 2012;28(2):457–66.

[33] Allen S, Dutta D. On the computation of part orientation using support structures in layered manufacturing. Proceedings of Solid Freeform Fabrication Symposium, University of Texas at Austin; 1994.

[34] Thrimurthulu K, Pandey PM, Reddy NV. Optimum part deposition orientation in fused deposition modeling. Int J Mach Tool Manuf. 2004;44(6):585–94.

[35] Pandey PM, Thrimurthulu K, Reddy NV. Optimal part deposition orientation in FDM by using a multicriteria genetic algorithm. Int J Prod Res. 2004;42(19):4069–89.

[36] Luo Z, Yang F, Dong G, Tang Y, Zhao YF. Orientation Optimization in Layer-Based Additive Manufacturing Process. Computers and Information in Engineering Conference; Charlotte, North Carolina, USA: ASME; 2016.

[37] Ghorpade A, Karunakaran KP, Tiwari MK. Selection of optimal part orientation in fused deposition modelling using swarm intelligence. Proc Inst Mech Eng B J Eng Manuf. 2007;221(7):1209–19.

[38] Padhye N, Kalia S. Rapid prototyping using evolutionary approaches: part 1. In: Raidl G, editor. Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers; Montreal, Canada: ACM; 2009.

[39] Tyagi SK, Ghorpade A, Karunakaran KP, Tiwari MK. Optimal part orientation in layered manufacturing using evolutionary stickers-based DNA algorithm. Virtual Phys Prototyp. 2007;2(1):3–19.

[40] Canellidis V, Giannatsis J, Dedoussis V. Genetic-algorithm-based multi-objective optimization of the build orientation in stereolithography. Int J Adv Manuf Technol. 2009;45(7):714–30.

[41] Zhang Y, Bernard A, Harik R, Karunakaran KP. Build orientation optimization for multi-part production in additive manufacturing. J Intell Manuf. 2017;28(6):1393–407.

[42] Kim H-C, Lee S-H. Reduction of post-processing for stereolithography systems by fabrication-direction optimization. Comput Aided Des. 2005;37(7):711–25.

[43] Nezhad AS, Barazandeh F, Rahimi AR, Vatani M. Pareto-Based Optimization of Part Orientation in Stereolithography. Proc Inst Mech Eng B J Eng Manuf. 2010;224(10):1591–8.

[44] Phatak AM, Pande SS. Optimum part orientation in Rapid Prototyping using genetic algorithm. J Manuf Syst. 2012;31(4):395–402.

[45] Padhye N, Deb K. Multi‐objective optimisation and multi‐criteria decision making in SLS using evolutionary approaches. Rapid Prototyp J. 2011;17(6):458–78.

[46] Barclift M, Armstrong A, Simpson TW, Joshi SB. CAD-Integrated Cost Estimation and Build Orientation Optimization to Support Design for Metal Additive Manufacturing. 43rd Design Automation Conference; Cleveland, Ohio, USA: ASME; 2017.

[47] Brika SE, Zhao YF, Brochu M, Mezzetta J. Multi-Objective Build Orientation Optimization for Powder Bed Fusion by Laser. Journal of Manufacturing Science and Engineering. 2017;139(9):111011-1–9.

[48] Byun HS, Lee KH. Determination of the optimal part orientation in layered manufacturing using a genetic algorithm. Int J Prod Res. 2005;43(13):2709–24.

[49] Ahn D, Kim H, Lee S. Fabrication direction optimization to minimize post-machining in layered manufacturing. Int J Mach Tool Manuf. 2007;47(3):593–606.

[50] Li Y, Zhang J. Multi-criteria GA-based Pareto optimization of building direction for rapid prototyping. Int J Adv Manuf Technol. 2013;69(5):1819–31.

[51] Zhang J, Li Y. A unit sphere discretization and search approach to optimize building direction with minimized volumetric error for rapid prototyping. Int J Adv Manuf Technol. 2013;67(1):733–43.

[52] Jibin Z. Determination of optimal build orientation based on satisfactory degree theory for RPT. In: Martin, DC, editor. Ninth International Conference on Computer Aided Design and Computer Graphics; Hong Kong, China: IEEE; 2005.

[53] Wodziak JR, Fadel GM, Kirschman C. A genetic algorithm for optimizing multiple part placement to reduce build time. Proceedings of the Fifth International Conference on Rapid Prototyping, Ohio: University of Dayton; 1994.

[54] Ikonen I, Biles WE, Kumar A, Wissel JC, Ragade RK. A Genetic Algorithm for Packing Three-Dimensional Non-Convex Objects Having Cavities and Holes. Seventh International Conference on Genetic Algorithms; Michigan State University; 1997.

[55] Lewis JE, Ragade RK, Kumar A, Biles WE. A distributed chromosome genetic algorithm for bin-packing. Robot Comput Integr Manuf. 2005;21(4):486–95.

[56] Canellidis V, Giannatsis J, Dedoussis V. Efficient parts nesting schemes for improving stereolithography utilization. Comput Aided Des. 2013;45(5):875–86.

[57] Canellidis V, Dedoussis V, Mantzouratos N, Sofianopoulou S. Pre-processing methodology for optimizing stereolithography apparatus build performance. Comput Ind. 2006;57(5):424–36.

[58] Dickinson JK, Knopf GK. Serial packing of arbitrary 3D objects for optimizing layered manufacturing. In: Casasent DP, editor. Intelligent Robots and Computer Vision XVII: Algorithms, Techniques, and Active Vision. Boston: SPIE; 1998.

[59] Dickinson JK, Knopf GK. Packing Subsets of 3D Parts for Layered Manufacturing. Int J Smart Eng System Design. 2002;4(3):147–61.

[60] Zhang X, Zhou B, Zeng Y, Gu P. Model layout optimization for solid ground curing rapid prototyping processes. Robot Comput Integr Manuf. 2002;18(1):41–51.

[61] Cao P, Fan Z, Gao RX, Tang J. Harnessing multi-objective simulated annealing toward configuration optimization within compact space for additive manufacturing. Robot Comput Integr Manuf. 2019;57:29–45.

[62] Hur S-M, Choi K-H, Lee S-H, Chang P-K. Determination of fabricating orientation and packing in SLS process. J Mater Process Technol. 2001;112(2–3):236–43.

[63] Wu S, Kay M, King R, Vila-Parrish A, Warsing D. Multi-objective optimization of 3D packing problem in additive manufacturing. In: Guan Y, Liao H, editors. Industrial and Systems Engineering Research Conference; Montréal, Canada: Institute of Industrial and Systems Engineers (IISE); 2014.

[64] Arndt A, Hackbusch H, Anderl R. An algorithm-based method for process-specific three-dimensional nesting for additive manufacturing processes. International Solid Freeform Fabrication Symposium; University of Texas at Austin; 2015.

[65] Rong-Ji W, Xin-hua L, Qing-ding W, Lingling W. Optimizing process parameters for selective laser sintering based on neural network and genetic algorithm. Int J Adv Manuf Technol. 2009;42(11):1035–42.

[66] Ning Y, Wong YS, Fuh JYH. Effect and control of hatch length on material properties in the direct metal laser sintering process. Proc Inst Mech Eng B J Eng Manuf. 2005;219(1):15–25.

[67] Caiazzo F, Caggiano A. Laser Direct Metal Deposition of 2024 Al Alloy: Trace Geometry Prediction via Machine Learning. Materials (Basel). 2018;11(3):444.

[68] Mozaffari A, Fathi A, Khajepour A, Toyserkani E. Optimal design of laser solid freeform fabrication system and real-time prediction of melt pool geometry using intelligent evolutionary algorithms. Appl Soft Comput. 2013;13(3):1505–19.

[69] Möller M, Baramsky N, Ewald A, Emmelmann C, Schlattmann J. Evolutionary-based Design and Control of Geometry Aims for AMD-manufacturing of Ti-6Al-4V Parts. Phys Procedia. 2016;83:733–42.

[70] Wah PK, Murty KG, Joneja A, Chiu LC. Tool path optimization in layered manufacturing. IIE Trans. 2002;34(4):335–47.

[71] Mahapatra SS, Sood AK. Bayesian regularization-based Levenberg–Marquardt neural model combined with BFOA for improving surface finish of FDM processed part. Int J Adv Manuf Technol. 2012;60(9):1223–35.

[72] Ebrahim V, Sadegh R. Improvement of FDM parts' surface quality using optimized neural networks – medical case studies. Rapid Prototyp J. 2017;23(4):825–42.

[73] Rao RV, Rai DP. Optimization of fused deposition modeling process using teaching-learning-based optimization algorithm. Eng Sci Technol Int J. 2016;19(1):587–603.

[74] Vijayaraghavan V, Garg A, Lam JSL, Panda B, Mahapatra SS. Process characterisation of 3D-printed FDM components using improved evolutionary computational approach. Int J Adv Manuf Technol. 2015;78(5):781–93.

[75] Vijayaraghavan V, Garg A, Wong C, Tai K, Regalla SP, Tsai M. Density characteristics of laser-sintered three-dimensional printing parts investigated by using an integrated finite element analysis–based evolutionary algorithm approach. Proc Inst Mech Eng B J Eng Manuf. 2016;230(1):100–10.

[76] Panda B, Shankhwar K, Garg A, Savalani MM. Evaluation of genetic programming-based models for simulating bead dimensions in wire and arc additive manufacturing. J Intell Manuf. 2019;30(2):809–20.

[77] Ewald A, Sassenberg T, Schlattmann J. Evolutionary-based optimization strategy in a hybrid manufactured process using LMD. Procedia CIRP. 2018;74:163–7.

[78] Xu F, Wong YS, Loh HT, Fuh JYH, Miyazawa T. Optimal orientation with variable slicing in stereolithography. Rapid Prototyp J. 1997;3(3):76–88.