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Optimization of fused deposition modeling process using teaching-learning-based optimization algorithm

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A B S T R A C T

The performance of rapid prototyping (RP) processes is often measured in terms of build time, product quality, dimensional accuracy, cost of production, mechanical and tribological properties of the models and energy consumed in the process. The success of any RP process in terms of these performance measures entails selection of the optimum combination of the influential process parameters. Thus, in this work the single-objective and multi-objective optimization problems of a widely used RP process, namely, fused deposition modeling (FDM), are formulated, and the same are solved using the teaching-learning-based optimization (TLBO) algorithm and non-dominated Sorting TLBO (NSTLBO) algorithm, respectively. The results of the TLBO algorithm are compared with those obtained using genetic algorithm (GA), and quantum behaved particle swarm optimization (QPSO) algorithm. The TLBO algorithm showed better performance as compared to GA and QPSO algorithms. The NSTLBO algorithm proposed to solve the multi-objective optimization problems of the FDM process in this work is a posteriori version of the TLBO algorithm. The NSTLBO algorithm is incorporated with non-dominated sorting concept and crowding distance assignment mechanism to obtain a dense set of Pareto optimal solutions in a single simulation run. The results of the NSTLBO algorithm are compared with those obtained using non-dominated sorting genetic algorithm (NSGA-II) and the desirability function approach. The Pareto-optimal set of solutions for each problem is obtained and reported. These Pareto-optimal set of solutions will help the decision maker in volatile scenarios and are useful for the FDM process.

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1. Introduction

In recent years, due to globalization, the market scenario for the manufacturing industries has become extremely competitive and volatile. To survive in such a dynamic market scenario, it is inevitable for the manufacturing industries not only to manufacture products with highest quality at a lowest possible cost, but also fulfill the fast-changing customer desires, consider significance of aesthetics and conform to environmental norms. In order to achieve these goals, manufacturing industries are constrained to adopt flexibility in the production system and minimize time-to-market of their products. In the pursuit of these objectives, manufacturing industries have opted to implement advanced and automated machine tools. In addition to this, the manufacturing industries are also adopting a new paradigm of technology known as the Rapid Prototyping (RP).

RP is a process in which physical objects are directly produced from computer-aided design (CAD) data. RP uses a process in which a physical model is created by selectively adding material in the form of thin cross-sectional layers. Hence, RP is also referred to as additive manufacturing.

RP allows engineers to produce tangible prototypes quickly rather than mere two-dimensional pictures, these prototypes can be used for various important purposes from communicating ideas to co-workers and customers to testing of different aspects of a prototype. Besides this, RP offers a plethora of other advantages such as unambiguous data handling and storage, ability to create complex shapes and interlocking structures, free from tool/workpiece debris, absence of molds, dies, fixtures and patterns, mass customization and democratized manufacturing.

Owing to these advantages, nowadays, RP processes are being widely used in the manufacturing industries not only for production of prototypes but also for large-scale production of biomedical, aeronautical and mechanical models.

The dominant RP processes currently available in the market are fused deposition modeling (FDM), stereolithography (SL), selective laser sintering (SLS), laminated object manufacturing (LOM),

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3D printing and solid ground curing (SGC). However, the performance of any RP process is measured in terms of build time, quality characteristics such as surface roughness and dimensional accuracy, mechanical and tribological properties, cost of production and energy consumption. These performance measures of RP processes are significantly influenced by their process parameters. Due to this reason, many studies have been directed toward determining the optimum combination of process parameters for RP processes using traditional and advanced optimization techniques.

Pandey et al. [1] applied multi-criteria genetic algorithm (GA) to determine the optimum part deposition orientation in order to minimize the build time and improve the average surface quality of the FDM models. Lee et al. [2] applied Taguchi's method to optimize the process parameters of FDM to achieve the optimum elastic performance of the compliant acrylonitrile butadiene styrene prototype. Byun and Lee [3] applied GA to determine the optimum part deposition orientation in layered manufacturing (LM) in order to minimize the average weighted surface roughness, build time and support structure.

Thrimurthulu et al. [4] applied GA to determine the optimum part deposition orientation in FDM in order to minimize the average weighted surface roughness and build time of the models. Singhal et al. [5] determined the optimum part deposition orientation in SL process using the trust region method in order to achieve the best overall surface quality of the models. Chockalingam et al. [6] used design of experiments in order to optimize the SL process parameters to achieve maximum part strength. Raghunath and Pandey [7] applied Taguchi's method to optimize the SLS process in order to improve the accuracy through shrinkage modeling.

Tyagi et al. [8] used an advanced stickers-based algorithm inspired by the characteristics of deoxyribonucleic acid (DNA) as a tool to achieve the optimal orientation during fabrication of models in LM process. Singhal et al. [9] determined the optimum part deposition orientation for SL and SLS considering multiple objectives simultaneously, such as overall surface quality, build time and support structure of the models. The optimization problem was solved using an algorithm based on the trust region method. Rong-Ji et al. [10] used artificial neural networks (ANN) to formulate the process model for SLS. GA was applied optimize the process parameters of SLS in order to achieve higher level of accuracy.

Canellidis et al. [11] applied GA to solve the multi-objective optimization problem in SL to improve the fabrication accuracy, minimize the cost and build time. Sood et al. [12] investigated the effect of process parameters on the dimensional accuracy of the FDM models. The optimum combination of process parameters to minimize the dimensional inaccuracy of the models was determined using gray relational analysis (GRA). Sood et al. [13] investigated the effect of process parameters on the mechanical properties of the FDM models. Empirical equations for tensile strength, flexural strength and impact strength of the FDM models were developed using response surface methodology (RSM) and desirability function approach was used to predict the optimum combination of process parameters. Paul and Anand [14] investigated the relationship between the cylindricity tolerance and part build orientation in RP process. Mathematical models were developed and optimum build orientation was determined using a graphical technique.

Paul and Anand [15] presented mathematical analysis of laser energy required for manufacturing parts using SLS process. An optimization model was presented to determine the minimum energy required for manufacturing parts using the SLS process. Sood et al. [16] developed an empirical model for compressive strength of the FDM model, and optimum process parameter setting was predicted using the quantum behaved particle swarm optimization (QPSO) algorithm. Sood et al. [17] investigated the effect of process parameters on the sliding wear of the FDM models, and empirical equation for sliding wear was developed and solved using QPSO algorithm to predict the optimum combination of process parameters for minimizing the sliding wear of the models.

Phatak and Pande [18] applied GA to determine the optimum part orientation in order to minimize the build time and material used and improve the part quality in the RP process. Singh et al. [19] used RSM and desirability function approach to improve the mechanical properties of polyamide parts in SLS process. Li and Zhang [20] applied multi-criteria GA for Pareto based optimization of RP process. Theoretical volume deviation and part height were optimized simultaneously. Boschetto et al. [21] used feed forward neural networks to predict the surface roughness in FDM, and the evaluation function developed was used to find the best solution.

Noriega et al. [22] used ANN to improve the dimensional accuracy of the FDM prismatic parts. Peng et al. [23] applied RSM in combination with fuzzy inference system to develop process models for the FDM process. GA was applied to optimize the responses such as the dimensional error, warp deformation and build time by formulating a single comprehensive response. Gurrala and Regalla [24] applied non-dominated sorting genetic algorithm (NSGA) for optimization of part strength and volumetric shrinkage in the FDM parts.

Rayegani and Onwubolu [25] applied differential evolution (DE) to determine the optimum combination of process parameters in order to improve the tensile strength of the FDM parts. Vijayaraghavan et al. [26] used an improved evolutionary computational approach for the process characterization of 3D printed components. Paul and Anand [27] analyzed the effect of part orientation on cylindricity and flatness error in parts manufactured using the LM process. An algorithm to provide the optimal part orientation to minimize the cylindricity and flatness error was proposed and tested.

Most of the RP process optimization problems involve complex functions and large number of process parameters. In such problems, traditional optimization techniques may get caught into local optima. In addition, traditional optimization techniques require an excellent initial guess of the optimal solution, and the results and the rate of convergence are very sensitive to this guess. In order to overcome these problems and to search a near optimum solution for complex problems, many population-based heuristic algorithms based on evolutionary and swarm intelligence have been developed by researchers in the past two decades. These optimization algorithms require common control parameters like population size, number of generations, elite size, etc. Besides the common control parameters, different algorithms require their algorithm-specific parameters. For example, GA uses mutation rate and crossover rate; particle swarm optimization (PSO) algorithm uses inertia weight, social cognitive parameters, maximum velocity; artificial bee colony (ABC) algorithm uses number of bees (scout, onlooker and employed) and limit; biogeography based optimization (BBO) algorithm requires habitat modification probability, mutation probability, maximum species count, maximum immigration rate, maximum emigration rate, maximum mutation rate, generation count limit and number of genes in each population member; heat transfer search (HTS) algorithm requires conduction factor, convection factor and radiation factor.

Proper tuning of these algorithm-specific parameters is a very crucial factor that affects the performance of the abovementioned algorithms. The improper tuning of algorithm-specific parameters either increases the computational effort or yields to local optimal solution. In addition to the tuning of algorithm-specific parameters, the common control parameters also need to be tuned which further enhances the effort.

Considering this fact, Rao et al. [28] have introduced the teaching-learning-based optimization (TLBO) algorithm that does not require any algorithm-specific parameters. It requires only common control parameters like population size and number of generations for its

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