Title:
Build Orientation Optimization for Strength Enhancement of 3-D Printed Parts Using Machine Learning based Algorithm

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Introduction:
3-D Printing, also referred as Rapid Prototyping (RP) or Additive manufacturing (AM) is a fundamentally different process from conventional manufacturing techniques. 3-D Printing integrates Computer Aided Design (CAD), Materials Science and Computer Numerical Control (CNC) to fabricate physical prototypes from virtual models directly by depositing material in the form of layers. The process fabricates 3-D parts by deposition of layers in 2-D using three linear motions in the Cartesian axes. The layer-based fabrication approach has many advantages such as simplified tool-path planning and capability to manufacture complex parts which cannot be built by conventional processes. Nevertheless, it suffers from drawbacks such as stair-casing (aliasing) effect, varying structural properties along different build directions, support structure requirements and inability of building around inserts which limits its potential as an alternate to conventional manufacturing processes [3].

In the context of varying structural properties and design of 3-D printed components, automated technique such as deformation control [2], physical appearances [4] and innovative design such as balancing shapes [7] have been reported in the literature. It has been observed that build orientation has major impact on strength properties of 3-D printed components due to induced anisotropy in the material. This intricacy has been observed and experimentally demonstrated [1] but very few attempts are reported that aims at enhancing structural robustness of 3-D printed components. Thompson and Crawford [9] introduced direction selection algorithm with loading conditions and material properties using Tsai-Wai failure condition to determine safer designs for a given build orientation. Umetani and Schmidt [11] addressed structural anisotropy in Fused Deposition Modeling (FDM) with the assumption that the vertical bonds between the layers are weaker than the in-layer bond for pure bending cases. Ulu et al. [10] introduced build orientation optimization algorithm based on the maximum Factor of Safety (FOS) approach under single loading conditions using surrogate based method. However, it requires a large number of simulations for accurate results which is computationally expensive, especially for multiple loading conditions. Thus, there is need of a better algorithm for such cases which can be implemented in determining optimal building orientation.

This work proposes generalized framework for build orientation selection which aims at maximizing resistance to the failure under prescribed loading conditions. The problem has been formulated as a build orientation optimization problem to achieve the maximum FOS considering the maximum stress failure theory. The algorithm uses orthotropic material model characterized by performing physical experiments that establishes the compliance matrix. The objective function in this case is solely dependent on build orientation angles with other parameters at constant levels. As optimum build orientation changes with the loading conditions and orientation angles impact mechanical properties significantly, it is difficult to establish analytical relationship between build orientation and corresponding objective function. Such problems cannot be solved using conventional optimization methods and can be considered a black box. It can be solved using brute force approach or using approximate techniques such as surrogate approximation [10]. The brute force approach utilizes large number of FE (Finite Element) simulations to cover the design space which is computationally expensive. This work presents a hybrid approach combining two-layer Artificial Neural Network (ANN) model to simplify computationally expensive brute force approach and Bayesian Optimization algorithm to determine optimal orientation.

Methodology:

This work presents generalized machine learning based parameter optimization methodology for strength enhancement of 3-D printed components. The proposed methodology is a modified version of three step approach presented by Ulu et al. [10]. Fig. 1 shows the methodology proposed in this work which can be divided into four steps: Physical Experiments, Virtual simulation, Machine learning and Optimization. The subsequent subsection discusses individual elements of proposed optimization framework.

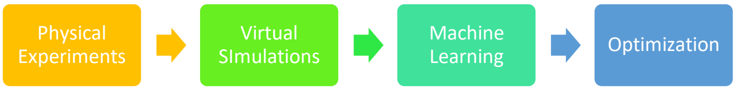

Fig. 1: Machine learning based optimization framework.

Material Characterization (Physical Experiments):

A set of experiments are conducted to characterize and determine mechanical properties of the 3-D printed component in different orientations. The standard tensile test specimen (ASME D638) is prepared using FDM based 3-D printer uPrint, Stratasys Inc. along three principle building orientations. Fig. 2 shows these three principle building directions for the component designated as *X*, *Y* and *Z*. Three specimens were printed for each principal direction to assess precision of the results. These components are tested on Universal Testing Machine to extract material properties from the stress-strain curve by conducting the tensile test. The Young's Modulus and Tensile Yield Strength are obtained using 0.2% strain-offset method. The corresponding compressive strength is assumed to be double of the tensile yield strength [1] and shear strength is assumed to be half of the lowest yield strength according to the maximum shear theory [8].

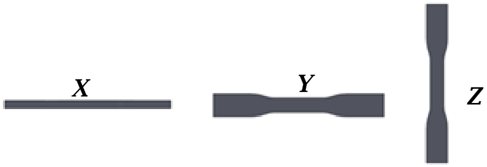

Fig. 2: Build Orientations for Physical Experiments.

Virtual Simulation: FE Infrastructure:

The second step of the proposed methodology is to establish a physics-based model for the virtual simulation of 3-D printed components. FE simulations are used frequently for simulating the effect of static and dynamic mechanical loading on components. This work employs ANSYS Parametric Design Language (APDL) to establish FE infrastructure for virtual simulation. APDL is preferred for parametric simulations as it can be controlled using a script generated by another external program e.g. MATLAB or Python. FE model is simulated over a design space, generated using brute force sweeping approach. A total of 256 objective function evaluations are performed using brute force approach. This number represents a uniform grid of 45-degree increments for each of the design variables i.e. building direction.

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Fig. 3 shows the complete process of obtaining data from FE model represented in the form of a process flowchart.

Fig. 3: Process Flow of Virtual Simulation Module.

As per the maximum stress theory, structural robustness of an object is quantified using FOS criterion. The primary objective is to choose the build orientation that maximizes the minimum FOS. This requires evaluation of a stress tensor for each element consisting of 6 components: - σ_x, σ_y, σ_z, σ_{xy}, σ_{yz}, and σ_{xz}. An approach assigning FOS value to the element necessitates computation of six independent FOS for each component and obtaining the minimum value for a given element. The normalized objective function is defined as a function of build orientation angles α, β, and γ along principle building directions *X*-, *Y*- and *Z* respectively using Eqn. (5.1).

$$\text{Min}\, f(x) = \sum_{i=1}^{n}[\sum_{k=1}^{6}\frac{1}{(F(x_{ki}))^{r}}] \tag{5.1}$$

$$where\ x = [\alpha,\beta,\gamma]$$

$$subjected\ to\ \alpha,\gamma = [-\pi,\pi]\ and\ \beta = [0,\pi]$$

Machine Learning:
The objective function described using Eqn. (5.1) is based on Stress Tensor obtained from FE analysis applied for each orientation on the fixed geometry and boundary conditions. As determination of optimum building angles using conventional methods such as brute force approach is computationally expensive, it is necessary to reduce the number of function evaluations. This can be effectively attempted using machine learning based techniques that regress between data obtained using brute force sweeping approach. ANN has been used to find the minimum of objective function and thereby optimum build angles. This work proposes use of Levenberg Backpropagation algorithm with Bayesian regularization Neural Network for unbiased fit over the dataset. The Backpropagation algorithm is widely employed for regression problems in ANN and it is substantially efficient than other algorithms [6]. The input dataset to the ANN is the build orientation angles in three directions and the output is the objective function defined using Eqn. (5.1).

Optimization:
It is not possible to obtain an analytical expression between input and output data using ANN model. This paper considers ANN as a black box therefore classical optimization algorithms cannot be applied to obtain the optimum value. A map between output and input can be generated or a derivative free optimization method can be implemented for the same. The derivative free methods such as trade-off exploration and exploitation methods utilize minimum number of function evaluations and are simpler to implement in contrast to the map. This study implements Bayesian optimization with exponent convergence, without auxiliary optimization and δ-cover sampling for obtaining optimal solution [5]. This results into significant reduction of computational time in determining optimal build direction and simpler implementation in the practice. Fig. 4 shows overall process map of the proposed methodology which uses values as per the need of the step.

Results and Discussion:
The proposed algorithm is implemented using computational programs developed using MATLAB, APDL, ANN toolbox and Bayesian optimization routine. To examine the efficacy of the proposed algorithm, four

different cases were conceptualized with varying level of complexity in the geometry and boundary conditions. Fig. 5 summarizes results of build orientation optimization for these cases. It can be seen that significant improvement in FOS can be observed when proposed approach is implemented in determining build orientation. It can also be observed that the strength of component is changed from unsafe (FOS<1) to safer conditions (FOS>1) under given loading and boundary conditions by changing build orientation and without modifying geometrical attributes. A physical component corresponding to Case 2 is fabricated as per optimal building direction determined from the proposed algorithm. The experimental results of tensile strength showed improvement of 126% with optimal building direction in comparison to the initial design configuration (Figure 5(c)).

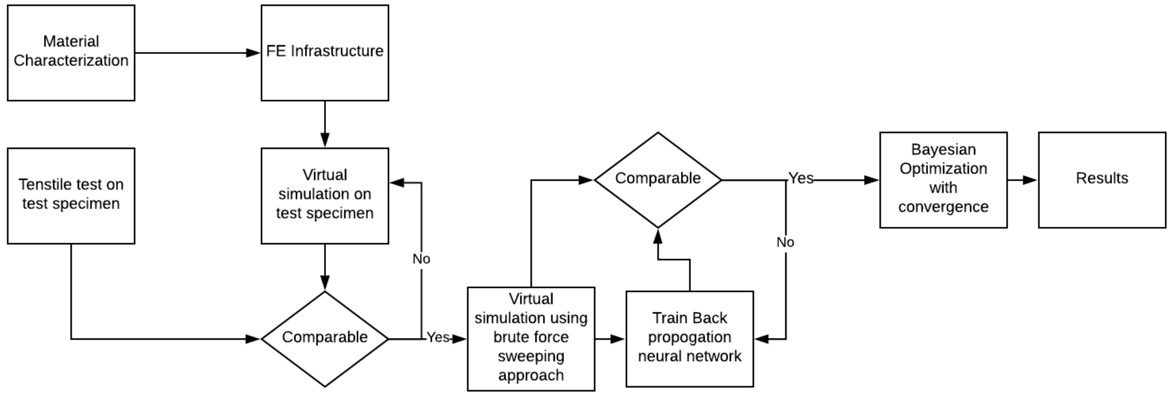
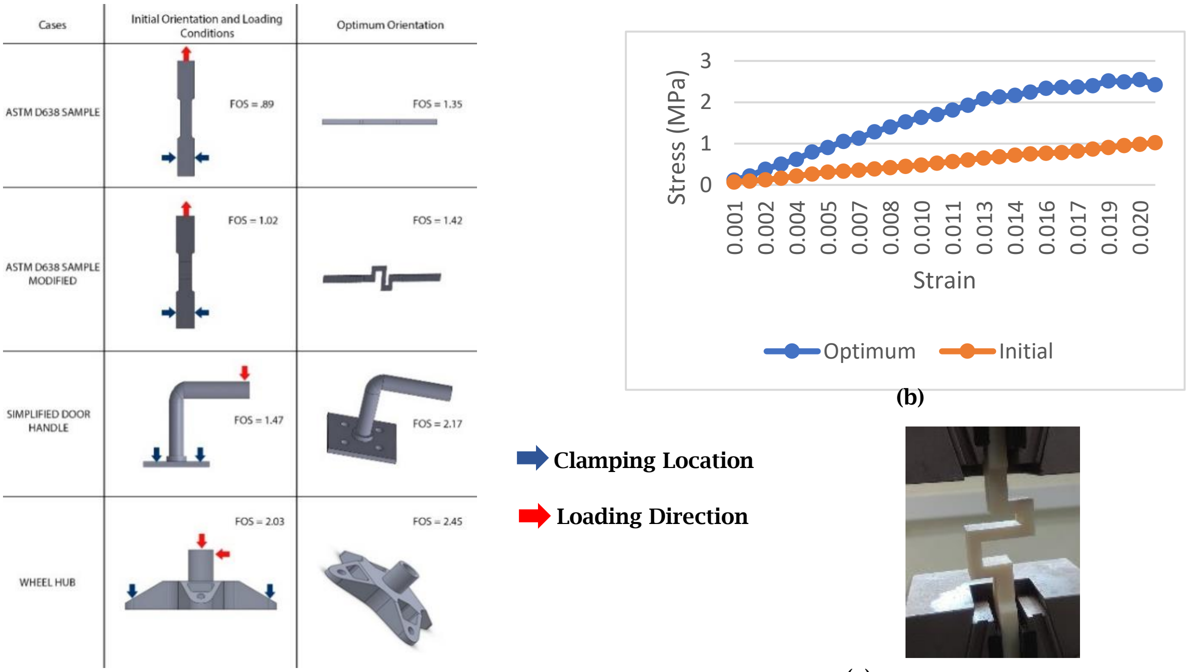


Fig. 4: Flowchart of build orientation selection algorithm.



(a) (c)

Fig. 5: (a) Computational Experiments (b) Experimental Results (c) Custom design object on UTM.

Conclusions:

This work presents an integrated approach to determine optimal building direction that enhances mechanical strength of 3-D printed components. The first step of the algorithm is to determine anisotropic properties of a 3-D printed component by performing strength testing experiments on UTM. The material properties derived from experiments are used subsequently in FE simulations and machine learning based optimization algorithm to determine optimal building direction. The proposed methodology has been implemented in the form of an integrated computational model that determines optimal building direction under known loading and boundary conditions. A set of computational and experimental studies are conducted for sample components to determine optimal building direction using proposed algorithm. It has been observed that the optimal building direction has significant impact on load withstanding abilities of 3-D printed components.

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