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Build Orientation Optimization for Strength Enhancement of FDM Parts Using Machine Learning based Algorithm

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Abstract. The layered fabrication approach induces directional anisotropy and impacts mechanical strength of FDM components significantly. This paper proposes generalized machine learning based parameter optimization framework to determine optimal build orientation for FDM components. The algorithm determines ideal build orientation by maximizing the minimum Factor of Safety (FoS) for the component under prescribed loading conditions ensuring its even distribution. An Artificial Neural Network (ANN) coupled with Bayesian algorithm has been employed to accelerate the optimization process. The algorithm begins with an initial sample data collected using brute force approach; uses single layered ANN for approximation and optimization is achieved using Bayesian algorithm. A series of computational experiments considering five different test components has been devised to evaluate the performance and efficacy of the proposed algorithm. These experiments demonstrated that the proposed algorithm can determine the optimum building orientation effectively with certain limitations.

Keywords: 3-D Printing, Building Direction, Finite Element Method, Machine Learning, Optimization
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1 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. Initially, 3-D Printing was confined to polymers but it expanded subsequently to support an increasing array of material such as metals, ceramics, composites and biological materials [10]. Additive manufacturing technique is categorized into six groups as per ASTM classification [13]: Material extrusion, Photo polymerization, Material jetting, Sheet lamination, Powder bed fusion and

Directed energy deposition. These processes are unique in terms of manufacturing science, power source and materials used but operate on the identical philosophy i.e. layer based fabrication. The layered fabrication approach has many advantages over conventional processes such as simplified tool-path planning and capability to manufacture complex parts. 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 [10].

The layered nature of the process has major impact on characteristics of the resulting part affecting build time, surface quality, amount of support material required, geometrical accuracy, overall cost and material strength [11].The effects of build orientation and its optimization have been well-researched in the literature. The height of the object for a given build orientation is directly proportional to the build time and hence cost of the component [2]. The stair casing effect is common due to layered fabrication approach and results into poor surface roughness. It has been observed that the stair-casing effect is largely dependent on the component geometry and building orientation [5]. The amount of support structure required for building of the component is decided based on the choice of building orientation and thereby influences the total build volume, build time, post-processing time and overall cost. It has been observed that the thermal distortion is affected by the build direction for metal additive manufacturing [19]. The layered fabrication approach also induces anisotropy in the final part therefore; structural performance of the component is dependent on the choice of build orientation. This intricacy was reported in the past literature but the efforts are not made to explore the best building orientation for the maximum strength. Ahn et al. [1] characterized anisotropic mechanical properties of ABS parts manufactured using FDM and showed that the components are stronger under tensile load if the orientation and loads are aligned with the fibers. Umetani and Schmidt [28] addressed structural anisotropy of FDM components and showed that the vertical bonds between layers are much weaker than the in-layer bond for pure bending cases.

A set of automation techniques were explored by researchers to optimize build orientation that meets user needs. Peng et al. [20] presented an algorithm to optimize build orientation for Direct Metal Laser Sintering (DMLS) that minimizes the thermal distortion. The work is limited to metal additive manufacturing since thermal distortions are not significant in polymer based additive manufacturing process. Thompson and Crawford [26] performed set of experiments to generate quantitative measures for various aspects of part quality affected by build orientation. A set of design guidelines was proposed based on these quantitative results. Byun and Lee [6] presented an automated approach to determine optimal build orientation for improved surface quality and minimal supports volume. Sood et al. [24] conducted comprehensive study to examine the impact of build orientation, layer thickness and layer pattern on compressive strength of the part. This was achieved using experimental data and Artificial Neural Network (ANN) model to generate processing map for parameter optimization and obtain the maximum compressive strength. Zhou et al. [30] adapted the worst-case analysis approach to identify structurally weaker parts from the design. A constrained optimization problem was formulated to obtain the worst loading configuration with orthotropic material assumptions. Thompson and Crawford [26] introduced an algorithm with loading conditions and material properties using Tsai-Wai failure condition to determine the safer design configurations for a given build orientation. Ulu et al. [27] introduced build orientation optimization algorithm based on maximum-minimum FoS approach under fixed loading conditions. A novel methodology was introduced in the work that utilizes Finite Element Method (FEM) coupled with surrogate optimization to find the best build orientation. Tam and Mueller [25] presented novel approach that synthesizes tool paths along the principal stress lines opening up new possibilities for structurally performative fabrication.

In order to determine build orientation for the maximum part strength, it is important to study the mechanical behavior of 3-D printed materials. The mechanical strength of the printed part is dependent on multiple factors such as machine, material, process parameters, building direction, environmental conditions etc. However, approximations based on the previous studies can reduce number of experiments required for examining material characteristics. Based on the physical experiments, Ahn al. [1] concluded that the compressive strength of FDM specimen is approximately twice of the tensile strength. Barclift and Williams [4] conducted experiments to study and analyze the effect of process parameters on mechanical properties of components fabricated using jetting technology. It was concluded that the behavior of the 3-D printed material can be considered orthotropic and failure theories such as Tsai-Wu criterion [9] can be used to analyze the components. Tsai-Wu criterion is a special case of the generalized Hill Yield criterion [12] and it is commonly used for orthotropic materials. These theories are useful to assess the design safety where FoS can be considered as a performance indicator of the design. The maximum stress theory is considered as a failure criterion and structural robustness of the part has been quantified using FoS.

The evaluation of FoS for each build orientation is practically impossible and robust virtual physics-based simulation module is necessary. FEM based simulations are frequently employed to simulate the part under given loading conditions in design and manufacturing domain. As FEM simulations are computationally expensive, approaches resulting into the minimum number of simulation trials are necessary. Surrogate modeling is suggested in the literature for engineering design optimization but it involves costly function evaluation [8], [18], [21]. Zhang et al. [29] proposed machine learning based algorithm for powder spreading speed optimization for powder bed fusion process. The study employed ANN to interpolate highly nonlinear results obtained from discrete FEM simulations.

The purpose of this paper is to introduce machine learning based optimization framework for parameter optimization of 3-D Printing process. The paper proposes computational framework for the build orientation optimization that aims at maximizing resistance to failure under prescribed loading conditions. An objective function has been formulated to determine the optimal build orientation taking into account maximizing the minimum FoS considering the maximum stress failure theory. An orthotropic material model is used in the computational framework to establish the compliance matrix. As the objective function is dependent on component geometry and loading conditions, its analytical value and gradient cannot be determined. Such problems cannot be solved using conventional optimization methods and requires different approaches. This optimization problem can be considered as black box and it can be solved analytically or by using surrogate approximation. The present work employs hybrid approach i.e. analytical algorithm and surrogate approximation algorithm to address this challenge. A single hidden layer ANN is employed to simplify computationally expensive black box optimization problem and Bayesian optimization algorithm is implemented to determine the minimum of black-box objective function. The framework proposed in this work utilizes small number of FEM simulations to accelerate the optimization process. The major deliverables from the present work are summarized below;

1. The conceptual framework based on machine learning based algorithm is presented for parameter optimization in 3-D Printing process.
2. A build orientation optimum algorithm is presented for FDM process that maximizes the minimum factor of safety under defined boundary and geometrical constraints.
3. A hybrid optimization approach using machine learning coupled with stochastic optimization algorithm is proposed and implemented.

Further, the paper is structured as follows; a generalized machine learning based framework is proposed for parameter optimization initially. Based on proposed framework, a build orientation optimization is developed for maximum resistance to mechanical forces. A set of computational and physical experiment consisting of five test cases are devised for validating the algorithm and results are presented subsequently.

2 METHODOLOGY

This section summarizes generalized machine learning based parameter optimization framework proposed in this paper. The framework is inspired from the three-step approach presented by Zhang et al. [29] to determine optimal powder spreading pattern in AM. The proposed algorithm aims at determining the optimal building direction for FDM components maximizing the minimum FoS under defined boundary and geometrical constraints. Figure 1 shows the framework proposed in this paper consisting of four stages: Physical Experimentation, Virtual Simulation, Machine learning and Optimization.

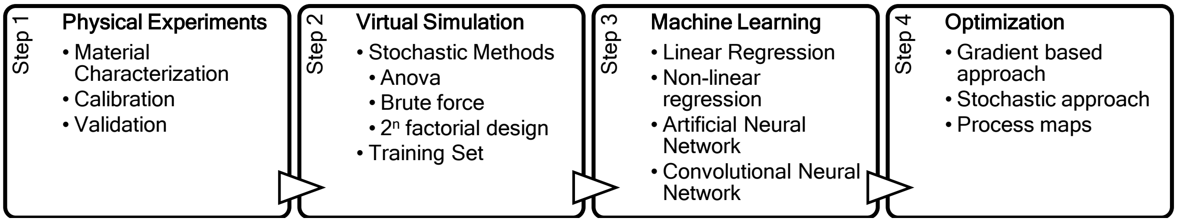


Figure 1: Machine learning based optimization framework.

The first step involves characterization of the FDM printed material with the change of parameter of interest (building direction in the present work) and other process parameters maintained at constant level. The data obtained from characterization is necessary to calibrate the physics based virtual simulation model. This involves validating the virtual simulation results by comparing computational results and physical experiments. The recalibration may be necessary if results are not comparable. Once calibration is achieved, virtual physics-based model is simulated over the entire design space generated using various methods e.g. ANOVA, 2-factorial design, brute force, FEM etc. The present study uses a hybrid approach combining brute force and FEM for this purpose. The data generated by a series of virtual simulations can be used further to approximate physics-based model using linear or non-linear regression techniques, machine learning etc. The present work approximates the physics-based model using ANN based machine learning algorithm. The final step is to optimize the approximated model-using gradient based or stochastic based optimization methods depending on the complexity of approximated model. The Bayesian optimization algorithm has been used in the study to determine optimal process parameter (building direction in the present work). The proposed framework is generic and it can be executed to perform parameter optimization for any AM process and associated parameters. The algorithm has been implemented to determine optimal build orientation for maximizing the strength of FDM printed components in the present work. Figure 2 summarizes the overall computational framework developed in the present work.

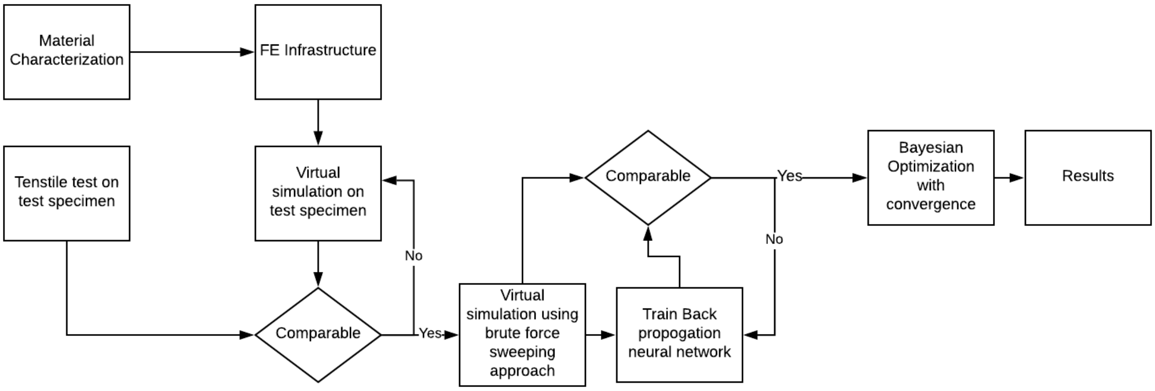


Figure 2: Flowchart of build orientation optimization algorithm.

2.1 Physical Experiments: Material Characterization

The first step of the framework requires determination of the material behavior in physical environment. The given problem statement requires determination of the mechanical properties of components printed using FDM. It is well established that the mechanical properties of 3-D printed components are dependent on large number of variables such as machine parameters, process parameters, material used for printing, and post-process operations. A set of experiments are conducted to determine mechanical properties of components in different build orientations maintaining other parameters at constant level. As per ASTM D638, nine different build orientations are possible however, three principle directions have major impact on the part strength considering an in-layer isotropy. Figure 3 shows these three principle directions used for building of the components for physical experiments. The orthotropic material model enables properties to be determined with a minimal number of tests using well-established techniques such as tensile, compressive and shear strength tests. An orthotropic material model requires determination of nine parameters experimentally viz. Young's Modulus, Shear modulus and Poisson's ratio for the three principle directions. Additionally, tensile and compressive yield strengths along with shear strength for each principal direction are necessary to compute the FoS.

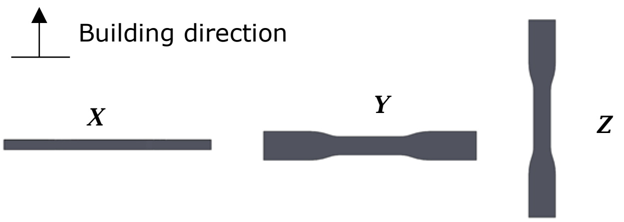


Figure 3: Build orientations for physical experiments.

A set of standard tensile test specimens (ASTM D638) are built along three principle building directions using ABS (ABS*plus* P430) as specimen material and material extrusion process based FDM printer uPrint (Stratasys Inc.). Three specimens are printed at a 100% infill for each building direction to ensure repeatability of the test results. The tensile test is conducted on Floyd UTM instrument at an extension rate of 0.5mm/min and constant load of 50N. Table 1 summarizes physical properties of 3-D printed components extracted from the stress-strain curve obtained from the tensile test. The Young's modulus and tensile yield strength were 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 [23].

Principal Axes	Average Yield Strength (MPa)	Average Young's Modulus (GPa)	Shear Strength (MPa)	Shear Modulus (GPa)	Poisson's Ratio
X	31.722	1.360	4.50	0.51	0.11
Y	26.392	0.975	4.37	0.28	0.39
Z	19.530	0.930	4.31	0.30	0.31

Table 1: Mechanical properties obtained from stress-strain curve

2.2 Virtual Simulation: FE Infrastructure

The second step of the proposed framework is to establish physics-based model for virtual simulation of the 3-D printed components. FEM is commonly employed for simulating the effect of static and dynamic loading on engineering components. The present work employs ANSYS Parametric Design Language (APDL) [3] to establish a FEM infrastructure for virtual simulations. APDL is preferred for parametric simulations as it can be controlled using a script generated by an external program e.g.

MATLAB or Python. The FEM based virtual model is simulated over entire design space generated using brute force sweeping approach. A total of 320 evaluations are performed using brute force approach. The number represents uniform grid of 45° increments for each design variable i.e. build orientation. Figure 4 represent the complete process of obtaining data from FEM model in the form of a process flow chart. In general, FEM simulation is required to perform three steps; pre-processing, solver and post-processing. The pre-processing step is required to define geometry, material properties, loading conditions and boundary conditions. Once pre-processing is accomplished, the user needs to specify the solution steps. Finally, the post-processing step is required to visualize and record results for further discovery. FEA script performing each of these steps is developed using APDL for given geometry, boundary and loading conditions. The model is also validated by comparing values of maximum stress and highest stress concentration point in FEM along with breaking point in a tensile test.

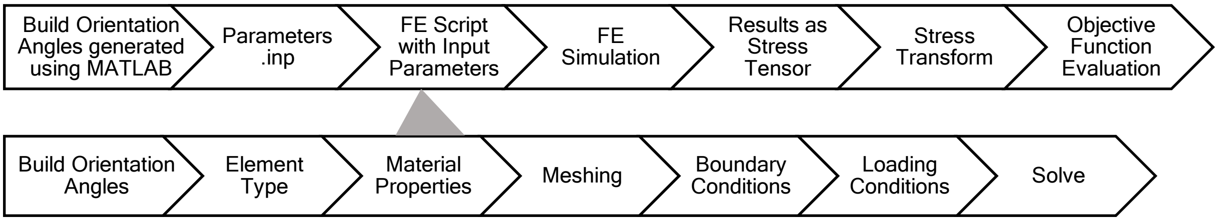


Figure 4: Flowchart of the virtual simulation module.

To simulate the effect of build orientation change using FEM, geometric coordinate frame is adjusted operating on fixed geometry, mesh and boundary conditions. Since geometric coordinate frame is different from material coordinate frame, each FEM simulation will be unique and result in a different stress value. A new local (a⊥b⊥c) and global (x⊥y⊥z) coordinate system is defined for each build orientation angle for a given geometry and boundary conditions. A new local coordinate system is defined using LOCAL command, which contains three variables. The local coordinate system is assigned as geometric coordinate system using CSYS command and global coordinate system is assigned as material coordinate system using ESYS command. APDL accepts variables from another external script instead of changing the main FEM script every time. An input file *"parameters.inp"* containing build orientation angles is generated using MATLAB.

After completing solver step in APDL, the stress values of each element are being stored in a file. This file is subsequently read by MATLAB and stress tensor is evaluated for each element. Since computed stress tensor is in geometry coordinate frame, stress transformation is necessary to evaluate stresses in the material coordinate system and determining mechanical properties. The Stress tensor for each element is transformed using Cauchy's relation for 3-D stress transformation [22]. Cauchy's relation can be expressed in the primed coordinate frame as $[\sigma'] = \mathrm{a}\,[\sigma]\mathrm{a}^{\mathrm{T}}$. Here a is another transformation matrix that serves to transform the vector components in the original coordinate system to those in the primed system. The final axes are visualized as being achieved in three steps: Firstly, rotation of original x-y-z axes by Ψ about the z-axis to obtain new frame termed as x'-y'-z. Secondly, rotation of the new frame by θ about the x' axis to obtain another frame termed as x'-y''-z'. Finally, rotation of this frame by ϕ about y'' axis to obtain the final frame x''-y'''-z'. These three transformations correspond to the transformation matrix given using a as Equation (2.1) which is used for the transformation from geometry to material coordinate frame.

$$a = \begin{bmatrix} \cos(\Psi) & \sin(\Psi) & 0 \\ -\sin(\Psi) & \cos(\Psi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta) & \sin(\theta) \\ 0 & -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} \cos(\phi) & 1 & \sin(\phi) \\ 0 & 1 & 0 \\ -\sin(\phi) & 0 & \cos(\phi) \end{bmatrix} \tag{2.1}$$

The structural robustness of component is quantified using FoS criterion as per the maximum stress theory. The primary objective of the proposed algorithm is to select a build orientation that maximizes FoS for the component. This is achieved by evaluating stress tensor for each element which consists of 6 components σ_x,σ_y, σ_z, σ_{xy},σ_{yz},σ_{xz}. An approach to determine FoS for a given element requires computation of 6 independent values based on maximum stress theory and assigning minimum value as an output. The normalized objective function is defined as a function of build orientation angles (α, β, γ) using Equation (2.2).

$$\min f(x) = \sum_{i=1}^{n}[\sum_{k=1}^{6}\frac{1}{(F(x_{ki}))^r}] \quad \text{where, } x = [\alpha, \beta, \gamma] \quad \text{subject to } \alpha, \gamma = [-\pi, \pi] \ and\ \beta = [0, \pi] \tag{2.2}$$

2.3 Machine Learning

The objective function described using Equation 2.2 is computed using FEM results and stress tensor for each orientation considering fixed geometry and boundary conditions. The determination of optimum building orientation using conventional methods such as brute force approach is computationally expensive due to large number of FEM simulations. Also, the computational effort will increase with geometric complexity of the components as large number of element level calculations is necessary. Therefore, it is important to minimize the number of function evaluations. Such problem is well suited for implementation of machine learning techniques to regress between the data obtained using brute force sweeping approach in the previous step. The approximated function can be used to determine the minimum of objective function and optimum angles using a suitable optimization method. Levenberg Backpropagation algorithm [15] with Bayesian regularization ANN is implemented for an unbiased fit over the dataset. The Backpropagation algorithm is commonly employed for regression problems in ANN due to its efficiency. The Backpropagation with Bayesian regularization ensures optimum weight distribution and does not over fit the network [14].

ANNs are derived from biological systems and can be expressed as mathematical models of biological neurons in simpler terms. ANN has three categories of layers in the network: input layer, hidden layers and output layer. The input layer is a vector of input variables, which are build orientation angles (α, β, γ) in the present work. Similarly, output layer is a vector of output variable i.e. objective function. The hidden layers connect the input with output layer and it is responsible for regression of the dataset. There can be one or few hidden layers with multiple nodes in the network depending on complexity of the problem. A non-linear activation function is used to capture complex relationships involved for the problem under consideration. The network is trained by minimizing a loss function described using Equation (2.3). Here, N is the total number of training datasets; Y_i is the actual output vector for i^{th} training data; O_i is the target output vector for i^{th} training data, λ is the regularization control parameter and W is the weight.

$$L = \frac{1}{N}\sum_{i=1}^{N}\|Y_i - O_i\|^2 + \lambda \|W\| \tag{2.3}$$

The over-fitting of the data is one of the major challenges during training of ANN. This happens when the data is quite complex and higher magnitudes of weights are assigned. The regularization term in Equation (2.3) helps in preventing over-fitting of the data by ensuring lower magnitude of weights. The weights are initially generated randomly and corresponding output values are evaluated. The value of loss function is calculated subsequently and it is used to update weights using Equation (2.4). Here, α is the learning rate that controls the step size of gradient descent for the iteration.

$$W^{n+1} = W^n + \alpha \frac{\delta L}{\delta W} \tag{2.4}$$

The present work uses machine learning toolbox of MATLAB software to develop ANN model [17]. The input data is split into two dataset for training (70%) and testing (30%) purposes. A network of one hidden layer with variable number of nodes is developed. The number of nodes in a hidden layer is selected based on the performance of neural network. As a general thumb rule, more number of hidden nodes is required for the complex systems to improve the performance of ANN. Table 2 summarizes network parameters used in the development of ANN model.

ANN Parameters	Associated Value
Number of input data set	320
Number of hidden layers	1
Number of nodes in input layer	3
Number of nodes in hidden layer	150
Number of nodes in output layer	1
Activation Function of hidden layer	Tansigmoid
Training function	Bayesian regularization
Learning rate	0.0001
Regularization control parameter	0.1

Table 2: ANN Parameters.

2.4 Optimization Algorithm

The development of an analytical expression between input and output of ANN is not possible due to non-linear activation function and complex relationship between nodes. Additionally, ANN is dependent on FEM results and development of an expression will not be an efficient approach. ANN treats the process as black box and similar optimization algorithm is necessary to get the optimum output value [7]. As ANN can reduce computational time to few milliseconds, optimization process can be accelerated. Bayesian optimization [14] is an efficient way to deal with this problem and it is popular for solving global optimization problems with non-convex or black-box functions without using the gradient. As the objective function is not known, Bayesian strategy treats it as a random function and place prior over it which captures the behavior. The prior will update automatically after each iteration and forms posterior distribution over the objective function. The posterior distribution can be used to construct an acquisition function that determines the next query point. The maximum of the acquisition function is found by resorting to discretization or by auxiliary optimization. Bayesian optimization with exponent convergence is implemented in the present work for solving the optimization problem [16]. As Bayesian optimization method is used to find the maximum of black box function, objective function is modified by adding a negative sign, i.e.$f(x) = -g(x)$. Figure 5 shows number of ANN evaluations along with process map and Bayesian algorithm. It can be seen from Figure 5(b) that the number of function evaluations are reduced significantly using the proposed approach. A visual representation can also be generated in order to evaluate the effect of the build orientations on FoS distribution using Figure 5(a). The process map approach allows selection of build orientation as per the user needs and desired FoS. However, it is not precise and requires human interpretation of the visual representation.

3 COMPUTATIONAL EXPERIMENTS

The proposed algorithms are implemented in the form of an integrated computational tool developed using MATLAB, APDL, ANN toolbox and Bayesian optimization routine. To examine the efficacy of proposed framework, five different cases were conceptualized with varying level of complexity of geometry, loading and boundary conditions. Figure 6 shows schematic CAD representation of these test cases. The first test case represent ASTM D638 sample subjected to tensile load of 50N with fixed supports at bottom edges (Figure 6(a)). The motivation for this test case is the ease of fabrication, physical validation and intuitive optimal build orientation. This helps in quick benchmarking of the proposed algorithm with relative ease.

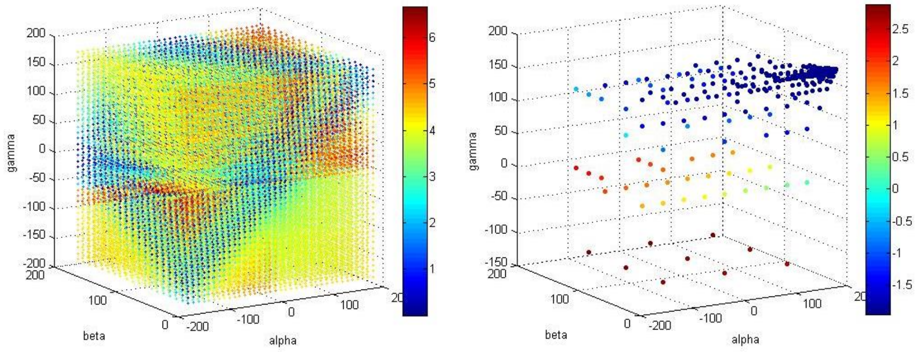


Figure 5: ANN evaluations: (a) Process Map (b) Bayesian Optimization.

The second test case shown in Figure 6(b) is modified version of the first case but the component complexity is relatively higher. The component is subjected to tensile load of 50 N and fixed at the bottom edges. This can also be fabricated easily and physically tested on UTM for validation. In the third case, the component geometry is ideal as second case but it is subjected to bending loading condition in place of tensile pull of the previous case. This test case is conceived to evaluate the effect of the loading conditions on the optimum build orientation. Figure 6(c) shows the fourth test case i.e. door handle subjected to bending loading condition as commonly employed in the practice. The last test case is a wheel hub shown in Figure 6(d) and it is subjected to both radial and bending load as in practice.

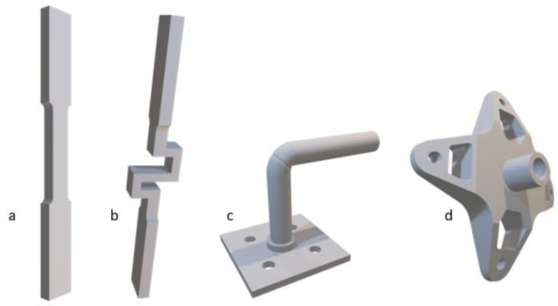


Figure 6: CAD models for test cases :(a) ASTM D638 (b) Modified ASTM D638 (c) Door handle (d) Wheel hub.

3.1 Algorithm Implementation

To demonstrate the effectiveness of proposed framework is determining optimal building direction, second test case shown in Figure 6(b) is discussed in this section. The optimal build orientations for other components are determined computationally using the proposed framework and results are discussed in the subsequent subsection. The second test case is chosen in the present study as it is easy to fabricate using FDM 3-D printer and subsequently testing on UTM for validation. The first step of the algorithm is to determine mechanical properties of the 3-D printed material which are identical as derived in Section 2.1 and are summarized in Table 1. The second step is to develop FEM architecture for the component. The study uses tetrahedron elements for discretizing the component followed by input related to material properties. The boundary and loading conditions are defined by fixing the bottom surface and application of 50 N tensile pull at the top. Figure 7 shows FEM model of the component along with application of boundary conditions and pull load. Total 320 FEM simulations were executed for training of the ANN model based on parameters outlined in Table 2. Based on these simulations, the optimum orientation is determined using Bayesian optimization considering ANN based objective function. The optimum build orientation was found to be [-179, 2, 178]. Two identical components corresponding to the second test case are fabricated using material extrusion based 3-D printer uPrint, Stratasys Inc. The first variant was fabricated as per default build orientation meanwhile the second variant was fabricated as per optimal building direction determined using proposed framework. Both these components were tested using Floyd UTM instrument at an extension rate of 0.5mm/min and constant load of 50 N. The test set up and experimental results in the form of stress-strain curves are shown in Figure 8(a) and 8(b). The tensile strength showed improvement of 126% with optimal building direction in comparison to the initial design configuration. The results are summarized in Table 3.

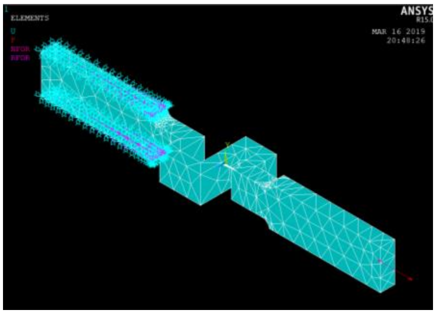


Figure 7: FEM infrastructure for test case 2

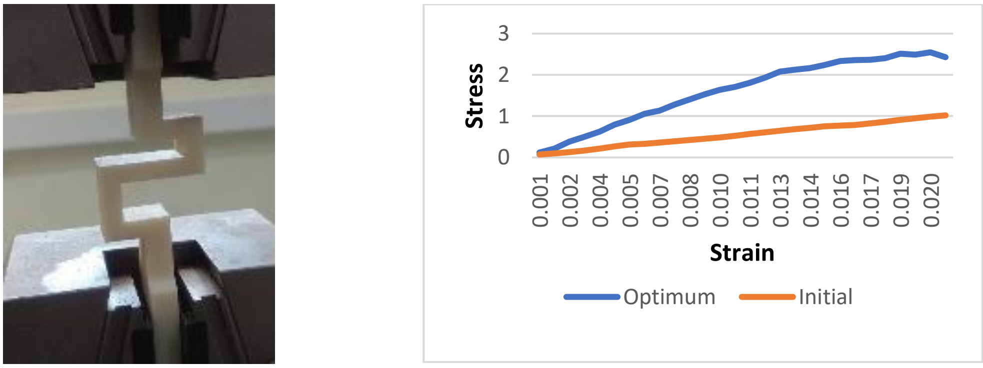
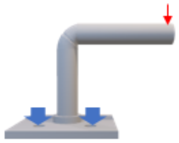
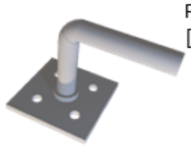
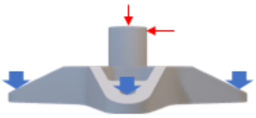


Figure 8: Algorithm implementation on test case 2: (a) UTM set up (b) Stress-strain curve.

3.2 Test Cases

The proposed framework has been extended to other test cases shown in Figure 6 to determine optimal build orientation for given loading and boundary conditions. Table 3 summarizes optimal building orientation of components determined using proposed framework for given boundary and loading conditions. The optimal building direction is shown schematically as well as numerically along with FoS in the original and optimum conditions. It can be seen that the build orientation has significant effect on mechanical properties of 3-D printed components. The results show significant improvement in the FoS when component is built along optimal build direction in each case. The results corresponding to the first test case corroborate with intuitive findings i.e. the best properties when loading is along build direction. The other test cases i.e. door handle and Wheel hub also show improvement in the FoS with the optimum build orientation. It can also be observed that the strength of component is changed from unsafe (FoS<1) to safer (FoS>1) conditions under given loading and boundary conditions by changing build orientation and without any modification of any geometrical attributes. This is one of the major advantages of 3-D printing process, which can be explored, with the support of such computational tools.

Test Cases	Loading conditions and Initial Minimum factor of safety	Optimum Build Orientation
ASTM D638	FOS = 0.89 	FOS = 1.35 [-180,0,180]
ASTM D638 modified (Tension)	FOS = 1.02 	FOS = 1.42 [-179,2,178] 
ASTM D638 modified (Bending)	FOS = .97 	FOS = 1.32 [-180,90,179] 
Door Handle	FOS = 1.47 	FOS = 2.17 [49,20,35] 
Wheel Hub	FOS =2.03 	FOS = 2.45 [22,185,51] 

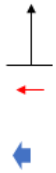


Table 3: Summary of computational experiment results.

The results corresponding to test case 2 considering modified ASTM sample with tensile loading conditions result in horizontal build orientation. Meanwhile, the same sample with bending loading condition results into completely different build orientation. Based on these results, it can be inferred that the loading conditions influence the optimum build orientation significantly and proposed framework captures this phenomenon very well. An important point to note here is that the other factors associated with 3-D printing process such as surface roughness, support material requirement etc. are not considered in the proposed framework. Although the proposed algorithm successfully finds ideal build orientation for a given component and loading conditions, there are few limitations associated with the proposed method. The mechanical strength is not the sole criterion in most cases and it is necessary to consider other factors such as surface roughness or support structure requirements. This necessitates formulation of multi-objective optimization problem instead of focusing on mechanical strength of components only. FEM consumes considerable amount of time in the optimization process limiting its applicability to simpler components. The computational time can be improved by developing a simple design guidelines based computational tool. A single layer ANN is able to approximate such expensive function but it still requires a large training data to achieve prediction accuracy. A deep neural network can be implemented to produce accurate ANN model with lesser training data.

4 CONCLUSIONS

The present work proposed 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 the experiments are used subsequently in FEM 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 for 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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