Incorporated design aimed at additive manufacturing through machine learning

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ABSTRACT

For improving manufacturing efficiency and minimizing costs, design for additive manufacturing (AM) has been accordingly proposed. The existing design for AM methods are mainly surrogate model based. Due to the increasingly available data nowadays, machine learning (ML) has been applied to medical diagnosis, image processing, prediction, classification, learning association, etc. A variety of studies have also been carried out to use machine learning for optimizing the process parameters of AM with corresponding objectives. In this paper, a ML integrated design for AM framework is proposed, which takes advantage of ML that can learn the complex relationships between the design and performance spaces. Furthermore, the primary advantage of ML over other surrogate modelling methods is the capability to model input-output relationships in both directions. That is, a deep neural network can model property-structure relationships, given structure-property input-output data. A case study was carried out to demonstrate the effectiveness of using ML to design a customized ankle brace that has a tunable mechanical performance with tailored stiffness.

KEYWORDS: Machine Learning, Additive Manufacturing, Design for AM

1.0 INTRODUCTION

Additive Manufacturing (AM) fabricates products from digital 3D models in a piece-by-piece, line-by-line or layer-by-layer manner, which is different from conventional manufacturing processes. This gives AM more freedom on design as AM can fabricate more complicated parts, theoretically in any shape, without spending more efforts on manufacturing processes. AM bonds, places, and/or transforms volumetric primitives or elements (voxels) of raw material to fabricate the final products. The size and shape of each voxel and the bonding strength between voxels depend on the raw material properties, the AM machine (e.g., nozzle diameter), and the process parameters (e.g., print temperature, print speed, laser power). Therefore, design for additive manufacturing (DfAM) was proposed with the aim of designing and optimizing the product together with its manufacturing systems to increase the product's quality and performance, and to minimize the development time and cost. DfAM actually is a type of Design for Manufacturing and Assembly (DfMA) but is quite different from traditional DfMA. The unique capabilities of AM technologies make designers re-think the traditional DfMA process applied in AM as AM can fabricate complex structures that are impossible in conventional manufacturing techniques. AM also eliminates the assembly process as AM can manufacture the whole product in a single fabrication process [1-11]. This leads to the new term of DfAM. which considers the unique capabilities of AM and the difference between traditional manufacturing and AM techniques. Compared with traditional manufacturing processes, AM mainly has the following four unique capabilities: (1) shape complexity: as AM is a layer-by-layer process, it is possible to fabricate virtually any shape; (2) hierarchical complexity: hierarchical multiscale structures can be designed and manufactured from the microstructure through geometric mesostructure to the part-scale macrostructure; (3) material complexity: material can be processed one point/layer at a time in AM processes; and (4) functional complexity: fully functional assemblies and mechanisms can be fabricated directly in a single AM process. These capabilities also, however, bring new challenges in design search and optimization due to the increased number of design variables and their complicated interactions over multiple domains. Many studies have been carried out for accommodating all these design variables and reflecting their interactions, as discussed, for example, and will not be detailed here. However, all these DfAM approaches are based on traditional surrogate models [12-23]. In fact, machine learning (ML) can now be applied for DfAM due to the increasingly available AM data and the powerful ability of ML to learn complex relationships among data. Table 1 compares the disadvantages and advantages between conventional surrogate model based DfAM and ML based DfAM [24-37].

Table 1 Advantages and disadvantages of conventional surrogate model based and ML based

	Advantages	Disadvantages
Conventional surrogate model based DfAM	-- No need to obtain large amount of data from experiments -- Comparatively low-cost	-- Hard to establish relationship equations and sometimes even impossible, especially for complex optimization problems where there are many design variables and their interactions are complicated and unclear -- Need to explore the design spaces of variables -- Hard/impossible to achieve reversed design
ML based DfAM	-- No need to establish complex relationship equations -- Easy to achieve reversed design -- Not limited by the complexity of the design problem	-- Require large amount of data

The definition of ML is "allowing computers to solve problems without being specifically programmed to do so". The application of ML techniques has increased tremendously over the past years due to the availability of large amounts of data, computer technology development and the increased power of available ML tools. ML has also been used in AM with different aims, including process optimization, dimensional accuracy analysis, manufacturing defect detection and material property prediction. In this paper, a comprehensive ML integrated DfAM framework is proposed to take advantage of ML. The framework is mainly based on using ML to learn process-structure-property (PSP) relationships proposed. ML based DfAM can achieve reversed design without the need of establishing complex relationship equations since an ML-based output-input model can be constructed readily, given input-output data [38-46]. Hence, property-structure relationships can be modelled directly, even though data were generated as structure-property relationships. Furthermore, ML based models have virtually no limitations on the complexity of the design problem if enough data are available. The main contribution of this paper is establishing a ML integrated DfAM framework and detailing the process of design from property to structure through ML. Furthermore, the primary advantage of ML over other surrogate modelling methods is the capability to model input- output relationships in both directions, which can achieve reversed design. The proposed ML integrated design approach can obtain the objective design directly through inputting the property requirements, which traditional surrogate model based design process cannot achieve [47-58].

2.0 LITERATURE REVIEW

In conventional surrogate model based design processes, design exploration and exploitation are often adopted which are the two main strategies to provide insight into the design space. Studies proposed a combined model for conceptual design, considering both multi- attribute utility theory and the perspective of set-based design [1-6]. With the aim of designing heterogeneous scaffolds for tissue engineering, projects built multi-stage Bayesian surrogate models to describe the relationship between the design parameters and the therapeutic response. Studies proposed a covariance-based method to establish multistage surrogate models in the conceptual design stages for a thermal design problem. Bayesian network classifier (BNC) based design exploration methods were proposed by projects to design negative stiffness metamaterials with better mechanical stiffness and loss properties. In addition, research proposed a Bayesian network classifiers model to classify the design space into unsatisfactory or satisfactory regions for designing a spring and an unmanned aerial vehicle [7-16]. These BNC methods formulated relationships between design spaces in the analysis direction (e.g., structure to property), then used back-propagation to invert the relationships. Studies combined model-based simulation and set-based design to obtain the design space for designing seismic resisting structural frames. Choi et al. (2008) developed an inductive design exploration method for designing robust multiscale materials. However, since these design approaches are surrogate model based, each requires an iterative approach to inverting an input-output relationship that is central to their design process [57-66]. It is recognized that Bayesian network classifiers are often considered as a ML method. Machine learning has already been used in AM with different aims such as process optimization and manufacturing defect detection. Table 2 lists the available studies that can be seen as using ML for some DfAM considerations with corresponding objectives. They mainly focus on using ML to improve or optimize the process parameters for AM techniques with corresponding property requirements. However, they are not proposed in a systematic way for DfAM. References used ML to predict surface roughness of AM printed parts in different process parameters in material extrusion (MEX) (informally called fused deposition modeling (FDM)), while others used ML to predict the surface roughness of AM fabricated Ti-6Al-4V parts in powder bed fusion. References used ML to predict the surface qualities of AM fabricated parts in 3D Concrete Printing and binder jetting, respectively. The above studies can be used to design AM products with required surface quality [67-73]. ML has been applied to predict geometric accuracy and dimensional variations of AM printed parts using MEX and in polymer powder bed fusion (PBF). Several groups have applied ML to predict deposit sizes in directed energy deposition, including bead width and height in wire-arc DED and printed part height in laser-based DED. Thermal deformation of printed parts has been modeled using ML for PBF parts. These studies can be used to design AM products with geometric requirements. Studies used ML to predict printable bridge length in different process parameters that can be used to design support structures in AM. All the above research works can be seen as process-structure relationship studies from the viewpoint of DfAM. Regarding mechanical and physical properties, some groups have developed process-property relationships using ML [71-77]. One group applied ML to predict the mechanical properties of polymer powder bed fusion manufactured polyamide 2200 parts. Projects used ML to predict wear strength of printed parts in MEX. Studies used ML to optimize the process parameters for obtaining required viscoelastic properties of fabricated parts in MEX. ML has also been applied in projects to optimize the process parameters for obtaining required shrinkage behaviour of printed PA 3200GF specimens in PBF. These studies can be used to design AM products with mechanical requirements. However, the research focused on property prediction, not part design from a holistic DfAM viewpoint. In contrast, this paper will propose a comprehensive ML integrated DfAM framework based on process-structure-property relationships. A case study will be carried out to show the ML enabled design process from property to structure [1-16].

3.0 RESEARCH METHODOLOGY

A design problem formulation was proposed (Rosen 2007) for computer-aided design (CAD) using the process-structure-property (PSP) linkage, as shown in Fig. 1. For example, in the MEX process, PSP relationships for polymers relate process conditions such as print temperature, to microstructure characteristics such as voids, to mechanical properties such as strength. Traditionally, PSP relationships are mainly obtained through surrogate models [7-18]. However, the PSP relationships are generally highly non-linear, high-dimensional and even non-convex, which makes it hard to establish the PSP relationships with high accuracy, particularly for some complicated problems. In this paper, we propose a ML integrated framework to establish the relationships between process, structure and property as shown in Fig. 2(a).

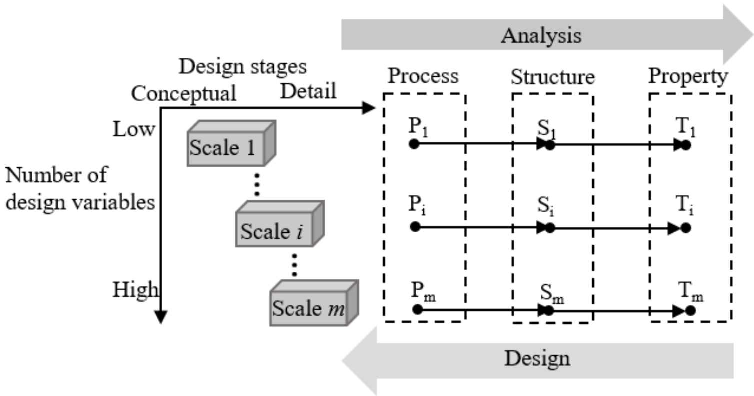

Fig. 1 Process-structure-property-based design problem formulation for DfAM proposed

Alternatively, an ML-trained model can utilize the structure parameters (e.g., surface roughness, dimensional accuracy) as the inputs while the AM process parameters (e.g., print speed, print temperature, layer thickness and others) can be the outputs for obtaining the relationship from structure to process [19-27]. Thus the trained ML model can be used for future designs from structure to process. Similarly, other relationships among process-structure-property can also be established in whichever direction through ML as shown in Fig. 2(b).

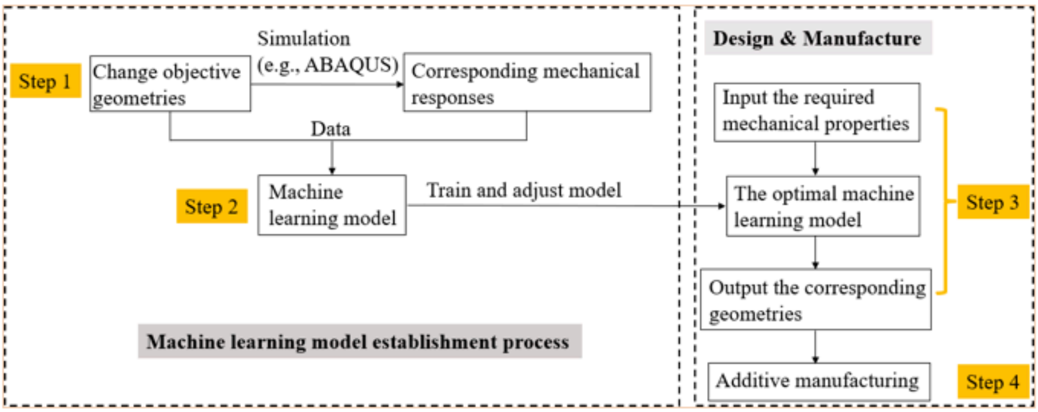

Fig. 3 Framework of the proposed design method

In fact, the studies listed in Table 2 can be categorised into establishing the relationships of process-structure or structure-property. However, none of these studies proposed a complete framework for ML integrated DfAM based on PSP model. Fig. 2 depicts how the complex relationships between process-structure-property can be learned using ML. With the help of ML, the analysis process from process to structure then to property and the design process from property to structure then to process (as shown in Fig. 1) can now be combined with the help of ML (Fig. 2). Next, we will provide and detail a ML integrated DfAM method based on property-structure relationships. For instance, the process parameters from AM processes (e.g., print speed, print temperature, layer thickness and others) can be the inputs for ML model, while corresponding obtained structure parameters (e.g., surface roughness, dimensional accuracy, voids) can be the outputs for training the ML model [28-36]. Then the trained ML model records the process-structure relationship that can be used in future design processes. In this section, we propose a specific ML integrated DfAM method based on property-structure relationships. This design method can be used to design products where distributions of mechanical properties are desired. The achievement of these mechanical property distributions will be achieved by tailoring part geometry, not by using multiple materials. Fig. 3 shows the framework of how this design method works [37-46]. The proposed design method includes four steps. Determine the desired design space. This includes determining the properties/responses that are of interest (e.g., stress-strain responses of an ankle brace) and the design variables that are of interest (e.g., the geometric variables of horseshoe structure for ankle brace). Design a sampling strategy for the design space, then for each sampled point obtain the corresponding mechanical properties through simulation (e.g., ABAQUS). This will record the mechanical properties of parts in different geometries. The aim of this step is to get enough data for machineleaning model establishment [48-57].

4.0 RESULT

When a person's ankle joint is injured (e.g., acute sprains), ankle braces generally can be used as orthoses for assisting rehabilitation. Ankle braces help to prevent further injury to the ankle joint while allowing restricted movements. The range of motions and allowable loading conditions for joints along the course of recovery can be adaptively adjusted by using the optimally designed ankle braces, ensuring tissue healing while avoiding extreme load conditions. In this case study, the design of the geometric structure of the ankle brace is carried out by using ML and compared to results using a different design method and surrogate models based on Gaussian process regression. Before using ML to design the required geometric values (W, R, L, α and β) for meeting corresponding stress-strain responses, the ML model and the data for training the model should be obtained [58-66]. The ranges of the design variables are listed in Table 5. Thousands of data points within the range of each variable were generated randomly and different variable values were also combined randomly to obtain different groups of values of the variables. Then, geometric models of horseshoe lattice structures representing the data point were fed into ABAQUS/STANDARD (Dassault Systèmes®, 2017) to characterize their corresponding stress-strain responses in both orientations. This study considers the in-plane deformation only, and the structure was therefore modelled as 2D beams using B32H elements. To avoid edge effects, a square matrix with a sufficiently large number of horseshoe unit cells (5×5) was used in the simulation. Nodes on the bottom edge of the horseshoe matrix were fixed with an encastre boundary condition; meanwhile, a tensile load was applied through a displacement control of nodes on the top edge of the horseshoe matrix [67-77]. A Deep Neural Network (DNN) was used to establish the ML model for this case study as the relationship between inputs and outputs can be cast as a regression problem that can be well resolved by DNN. In this case study, a deep neural network model with ten layers (as shown in Fig. 4(b)) was used to establish the relationship between the W, R, L, α and β variables and stress-strain responses. The corresponding numbers of neurons and activation functions used in each layer are listed at the bottom of each layer in Fig. 4(b). The number of neurons should be increased and then decreased as the layer number increases. The neuron number in the middle layer should be the largest. This is the general case and, in these settings, the machine learning model generally can work with better accuracy. The corresponding ankle brace design with the requirements as listed in Table 4 can be obtained now using the established ML model. For the horseshoe geometry of Zone 1, the corresponding stresses of 0.47 and 0.24 were fed into the ML model to obtain the geometric values *W, R, L*, α and β. Similarly, Zones 2 and 3 were designed using their ML models. To illustrate the advantage of the ML based method, computation times will be considered for determining design variable values. Our ML method only takes 2ms or so to compute the design once the ML model has been established. For the conventional surrogate model in (Y. Xiong et al. 2019), it takes about 19s to get the design, about 5 orders of magnitude difference. The effectiveness of our method is based on the ability of ML to establish the process-structure- property relationship in whichever direction as shown in Fig. 2. This paper only shows the example of "from property to structure" due to the current limited data from AM. However, as additional AM data and relationships are determined, more complete and powerful PSP models can be established in the future directly through ML to support a wide range of design problems.

5.0 CONCLUSIONS

In this paper, a ML integrated DfAM framework is proposed to establish process-structure- property relationships, which can be helpful to design for additive manufacturing. With the help of ML, the analysis and design processes based on PSP no longer need to establish complex surrogate models which are also unable to establish the relationships of PSP in a reversed direction. The relationships between process, structure, and property can be established simply through ML in whichever direction is desired using the available AM data. DNNs for point data and CNNs for distributions and image data were proposed as the specific ML techniques for the proposed DfAM framework. An ankle brace design problem was used to illustrate the application of the proposed framework. DNNs modelled property-structure relationships used for ankle brace design. Based on the results, it was demonstrated that the property-structure DNN models were significantly more computationally efficient than conventional surrogate models in computing design variable values, given desired property values. The conventional surrogate models (Gaussian process regression models) needed to be inverted using an optimization method to enable design variable calculation. The property-structure DNN models were trained with the same number of data points as the GPR models and proved to be as accurate. This example helps validate the proposed DfAM framework. The DfAM framework proposed the use of process-structure-property relationships; however, only structure-property and property-structure relationships were investigated in this paper. Thus, more research is needed to extend the models and method for the larger PSP scope. The property-structure relationships modelled using DNNs in this work related stress-strain values to five design variables (2 inputs, 5 outputs). It is an open issue to determine how well more general, larger, and more complex relationships can be modelled using DNNs and CNNs.

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