Understanding of the Modeling Method in Additive Manufacturing

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Abstract. With the development of additive manufacturing, how to improve the efficiency and accuracy of manufacturing and prediction has attracted more and more attention. This paper focuses on three basic modeling methods, which are summarized according to the issue: empirical method, analytical method and numerical method. These methods are used differently based on practical circumstances. Besides, due to the improvement of computer computing power, machine learning and digital twin have also been applied to the study of additive manufacturing. Machine learning has a good performance in the prediction and optimization of process parameters, but the characteristic of machine learning that requires a lot of data leads to the increase of experimental cost. Digital twin does a good job in monitoring the condition of equipment. In addition, it can replace expensive and time-consuming physical experiments with inexpensive and efficient digital experiments, which can provide data for analysis. However, because of insufficient research, its application is still limited.

1. Introduction

As a new manufacturing technology, additive manufacturing has developed rapidly in the past few years. How to improve the accuracy and manufacturing efficiency along with how to accurately predict the manufacturing process has become focused concerns. In this paper, the method of survey is used to introduce the modeling method in the process of additive manufacturing.

Additive Manufacturing is a new manufacturing technology, which is defined as “the process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing and formative”. Unlike traditional manufacturing technologies, such as subtractive manufacturing and equivalent manufacturing, additive manufacturing adds materials to create the final shape [1]. It can utilize raw materials effectively, produce the least waste and achieve satisfactory geometric accuracy. Additive manufacturing has revolutionized the way prototyping and small batch manufacturing is done [2]. Nowadays, additive manufacturing is not only used in aerospace, medical and automotive industries, but also in fashion, food industry, jewelry production and construction [3]. It has many advantages: (1) customized healthcare products to improve population health and quality of life; (2) reduced environmental impact for manufacturing sustainability; (3) simplified supply chain to increase efficiency and responsiveness in demand fulfillment [4].

This paper will introduce three kinds of modeling methods to solve the problems of additive manufacturing. The first one is the empirical method, which mainly analyses a series of experimental results, then establishes models, draws conclusions and verifies them through further experiments. The second one is the analytical method, which builds models based on physical laws and uses mathematical methods to analyze them. The third one is the numerical method, which is solved by numerical methods.
on the basis of physical laws in order to simplify and obtain useful results. Finally, some examples are given to illustrate the application of artificial neural network in additive manufacturing in recent years to promote and broaden the development of model methods.

2. Empirical Method

2.1. Introduction

Empirical method is a method which conducts an investigation relying on experiments and not theories. Empirical method focuses on the observations and measurements rather than understanding of the principles themselves. Empirical method consists of a series of experiments, and the results are summarized according to the experiment data. Then, further experiments are also required for verifying and improving previous findings.

The main advantage of empirical method, compared with other modeling methods, is that it requires the least effort to explore the physical laws in the process of additive manufacturing. Empirical method is a good method for some processes that are difficult to explore their specific physical laws, or those whose physical laws are too complex. However, its disadvantages are also obvious: In most cases, the results only apply to the specific case of a particular process. Besides, a large number of experiments are expensive and time consuming.

2.2. Examples

Empirical methods are usually used to find out the relationship between two or several parameters in order to optimize the process.

In vat photo polymerization, Wang et al. [5] use the least-squares method to find out the relationship between the post-cure shrinkage and process parameters. Lan et al. [6] do experimental research on dimensional accuracy of parts and the associated parameters. Karalekas et al. [7] study the shrinkage characteristics of stereolithography built square laminate plates using an acrylic-based photopolymer.

In powder bed fusion, Raghunath et al. [8] investigate the relationship between shrinkage and the various process parameters namely laser power, beam speed, hatch spacing, part bed temperature and scan length.

In material extrusion, Anitha et al. [9] explore the effect of process parameter like layer thickness on design quality. Sood et al. [10] focus on the effect of some important parameters such as layer thickness, part build orientation, raster angle, raster width and air gap on the compressive stress of test specimen.

In sheet lamination, Kechagias and John [11] use typical test part and carry out matrix experiments based on Taguchi design to find out the influence of different process parameters (layer thickness, heater temperature, platform retract, heater speed, laser speed, feeder speed and platform speed) on the roughness of vertical surfaces along Z-axis on ZX-plane of parts.

In previous studies, we can find that most of the researches focus on exploring the relationship between two or several different parameters in order to seek the optimization of process or part quality.

3. Analytical Method

3.1. Introduction

Analytical method is a method which gets exact function relation or forms a theorem from existed theories to establish mathematical model. Its principle is clear and every process has theoretical support. The analytical model is the output of a mathematical analysis of the process that considers the laws of physics and related physical processes.

The main advantage of analytical method is that the result obtained can be easily transferred to other related processes. Besides, it does not need to spend too much time and money on experiments. However, sometimes the physical laws of some processes are too complex or unclear, which will make it difficult to establish analytical models.
3.2. Examples
Analytical methods usually use formulas and models derived from theoretical calculations to control and predict manufacturing process.

Ramanath et al. [12] focus on the study of the melt flow behavior of Poly-ε-caprolactone (PCL) as a representative biomaterial. Mathematical model is established, and the melt flow behavior is studied by changing the inlet filament velocity and the outlet nozzle diameter and angle. Muller [13] introduces a process modeling and a system control to manufacture Functionally Graded Materials parts with a direct laser deposition system. This work enables to choose an adapted manufacturing strategy and control process parameters to obtain the required material distribution and the required geometry. Strano et al. [14] propose a mathematical model to accurately predict surface roughness, which takes into account the staircase effect and the existence of surface particles. This model is conducive to improving the surface quality of parts.

4. Numerical method

4.1. Introduction
The numerical method is a method based on physical laws, which uses numerical step-by-step method to obtain useful results. It processes data and solves problems by means of computer or computational model. The purpose of numerical analysis is to design and analyze some computational methods to obtain approximate but accurate results for the problem. It is often used in situations where the process is complex and difficult to get exact solutions.

The main advantage of numerical method is that it has a wide range of applications. There are many kinds of analytical software based on numerical methods, which can be used to solve problems faster and more accurately.

4.2. Examples
Numerical method is usually a method for solving problems after modeling. Tiebing Chen and Yuwen Zhang [15] use numerical simulation to study the effect of process parameters on the process of stratified sintering in selective laser sintering. Sachs et al. [16] use numerical simulation to develop a mathematical model for binder flight trajectory. Podshivalov et al. [17] apply numerical methods to the generation of microscale scaffolds.

One of the widely used numerical method is finite element method. Finite element analysis uses a mathematical approximation to simulate real physical systems (geometry and load cases). With simple and interacting elements, a finite number of unknowns can be used to approximate an infinitely unknown real system. Since most practical engineering problems are difficult to obtain accurate solutions, the finite element analysis which has high computational accuracy and adapts to various complex shapes makes it an effective engineering analysis tool.

Finite element analysis can be used to solve one-dimensional, two-dimensional and three-dimensional engineering problems. Nelson et al. [18] use one-dimensional finite element model to describe heat transfer of powder bed fusion process. Singh et al. [19] use two-dimensional finite element model to measure the evolution temperature distribution and density of bisphenol-A polycarbonate in selective laser sintering process with time, and determine the important technological parameters affecting the final density of laser sintered parts and their relationship. Bugeda et al. [20] establish a three-dimensional finite element model of single-track sintering in selective laser sintering process, which considers both the thermal phenomena and the sintering phenomena involved in the process. Dong et al. [21] establish a transient three-dimensional finite element model to study the phase transition in selective laser sintering process, which also considers the thermal phenomena and sintering phenomena during sintering. António and Vilar [22] propose a model coupling finite element heat transfer calculations, phase transformation kinetics and microstructure-property relations in Ti-6Al-4V, and use the model to obtain the processing maps of deposition parameters related to the microstructure and properties of the parts.
It can be seen from the above studies that the applications of finite element analysis are mainly focused on the thermodynamic study in the powder bed fusion process.

5. Machine learning and digital twin in additive manufacturing

In addition to the traditional methods mentioned above, due to the improvement of computer computing power, the modeling method of additive manufacturing based on machine learning and digital twin provides a direction for future research.

5.1. Machine Learning

Because machine learning can optimize and predict the parameters only through the relationship between input and output without knowing the internal rules of the system, it is suitable for predicting and optimizing the process parameters of additive manufacturing in the case of difficult to explore the internal physical laws of the process. In addition, compared with traditional methods, the application of machine learning in additive manufacturing is conducive to improving efficiency and accuracy. Therefore, in recent years, machine learning has been widely used in the optimization and prediction of the process parameters in additive manufacturing. Lee et al. [23] build a neural network model to find out the influence of process input parameters on the dimensional accuracy of parts and predict the dimensional accuracy of parts. Rong-Ji et al. [24] use genetic algorithm and back propagation neural network algorithm to determine the optimal process parameters of parts to produce parts with higher accuracy. Munguia et al. [25] propose an estimator based on artificial neural network to estimate the build-time and related costs (labor, machine costs and daily expenses) of selective laser sintering process. Padhye and Deb [26] consider the minimization of surface roughness and construction time in the process of selective laser sintering for multi-objective optimization, which use non-dominated sorting genetic algorithm (NSGA-II) and multi-objective particle swarm optimizer (MOPSO). Garg and Lam [27] apply genetic programming, support vector regression and artificial neural network in formulating the laser power-based-open porosity models. Garg and Lam [28] also use the computational intelligence (CI) approach of multi-gene genetic programming (MGGP) to formulate the model for predicting open porosity in selective laser sintering process. Stoyanov and Bailey [29] put forward State-Space Model Identification-minimization of the prediction error in the space of the model structure to predict and monitor trends and quality online. Machine learning can also be combined with model methods. Salonitis et al. [30] propose a method for the design optimization of lattice components towards weight minimization, which combines finite element analysis and evolutionary computation.

However, machine learning still has limitations. It is expensive to carry out a large number of experiments in additive manufacturing, while machine learning needs a lot of data for training. Therefore, the sample size in most machine learning experiments is insufficient. This problem needs to be solved in the future to further improve accuracy.

5.2. Digital Twin

Digital twin is a simulation process that makes full use of physical model, sensor update, operation history and other data. The purpose of digital twin is to evaluate and predict the condition of equipment.

In additive manufacturing, digital twin can be used to assess the health of the system and to evaluate and predict process parameters. After full experimental verification, this efficient and cheap digital experiment, which has high accuracy and stability, can replace expensive and time-consuming physical experiment. Some attempts have been made in this field. Knappe et al. [31] design a digital twin model to predict cooling rates, temperature gradients, solidification rates, SDAS and micro-hardness values. Debroy et al. [32] study the current status and needs of the first generation digital twin of additive manufacturing. In the above research, we can find that although the digital twin has a good performance in prediction and evaluation, its application is still limited because the current research on it is insufficient.
6. Conclusion
In this paper, three basic modeling methods for additive manufacturing are introduced: empirical method, analytical method, and numerical method. We introduce the main idea and significant applications of these three methods respectively. These methods are used in different situations. Besides, due to the improvement of computer computing power, recently machine learning and digital twin have also been applied to the study of additive manufacturing. With the development of modeling methods for additive manufacturing, the technology of additive manufacturing will surely make rapid progress.

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