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Fast adaptive modeling method for build time estimation in Additive Manufacturing

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ABSTRACT

Build time estimation for parts is very important for the design, process planning & optimization and price quotation in Additive Manufacturing (AM). However, the related factors are numerous and have complicated interrelations with each other. This makes it difficult for current methods to obtain an accurate estimation model without inputting a relatively large quantity of data on part specifications, machine setup, processing details or production requirements. To construct build time estimation models more rapidly and simply to meet the needs of price quotation, design, process planning and optimization in AM, with acceptable accuracy by inputting less data, this paper introduces an integrated adaptive modeling method derived from Grey Theory. A numerical example used for comparing it with current modeling methods and a case study of building an estimation model for an FDM machine have evidenced the availability and advantages of this proposed modeling method. The average estimation accuracy is within 10%, which is acceptable for many application contexts and better than several current parametric and analogical models.

Introduction

Additive Manufacturing (AM), evolved from rapid prototyping (RP), is a layered manufacturing method which uses a different construction principle to the traditional manufacturing methods. Due to the rapid development of AM and its unique layer by layer processing approach, it can not only produce prototypes with complicated geometric characteristics in a very short time, but can also manufacture functional parts or near shape parts for industrial application with different types of materials, for example, metals, plastics, alloys and composite or other special gradient materials. Therefore, the AM industry is constantly expanding and has been accepted by a large number of application fields [1–4]. Usually, current or potential AM users have to compare AM with other traditional process technics before decision making when setting AM processes as alternatives to produce a part. Production time, part cost and quality are the three main factors within the comparison. Rapid prototyping (RP) service bureaus or providers are always facing urgent price quotation requirements for RP parts from customers in today's competitive market [30]. The build-time estimation is especially critical for the RP&M service industry to quote each job correctly [30] since a part's build time directly determines the full production time and part cost. Accurate build-time prediction not only benefits the service industry with necessary information for correct pricing and effective job scheduling, it also provides researchers with valuable information for various build parameter studies [11]. For example, the build time of a part is one of the most important objective functions used for optimization problems such as determining the optimum part orientation in rapid prototyping (RP) systems [10]. Therefore, build time estimation is within the needs of real practices, such as comparing AM processes with traditional technologies, competitive bidding and process planning. To meet these needs, build time estimation models should have high accuracy, rapid prediction and simple forms for easy use. However, it is hard to meet all of the requirements at the same time. On the one hand, the behind factors affecting build time are numerous and different from one AM process to another and have complicated interrelations with each other. On the other hand, it is difficult for current methods to obtain an accurate estimation model with a simple form without inputting relatively large quantities of data on part specifications, machine setup, processing details or production requirements.

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Hence, in real application contexts, compromise is usually necessary. For the design verification, process planning and optimization, price quotation, etc., users are prone to use a fast and simple model while sacrificing a little accuracy. This is because information on detailed process parameters and process planning is usually unavailable or difficult to obtain in those stages; while for benchmarking and calculating of the real cost of parts, users prefer to use more accurate models, for example, the analytical models, but have to compromise on time and model complexity.

In this paper, a fast adaptive modeling method is proposed to deal with the build time estimation problem for the design verification, process optimization and planning, scheduling, etc. in AM. This modeling method is based on Grey Theory which is widely-used to solve forecasting problems of complex uncertainty systems with insufficient information. To improve the prediction accuracy, the proposed method uses a Bayesian form to integrate two Grey modeling methods, linear modeling and non-linear modeling, to simulate the unclear relationship between the build time and the related factors. Build time estimation model can be quickly-constructed by using limited production data sets as inputs. Prediction is fast, simple and has certain accuracy (tested average accuracy is within 10%), which meets the general requirements of design, optimization, planning, etc. in AM. In addition, by modifying the input data sets, estimation models can be easily-modified or reconstructed. This enables the modeling method to own an adaptive characteristic to adapt the changes of machine set-up and working conditions.

The following sections are organized as follows: the second section will review current representative methods or models for AM build time estimation with some comments; the third section will present the overview of the proposed adaptive modeling method; the fourth section will introduce the modeling procedure in detail; the fifth section will carry out a numerical simulation for the verification and comparison with several current models; the sixth section will conduct a case study for an FDM machine and the remainder of this paper will present discussions and come to a conclusion.

Related works

Due to the importance of build time estimation for AM, many works have been done by former researchers. Generally, the former models can be classified into three main types: parametric, analytical and analogical. The representative methods are presented in Table 1 with their pros and cons and applicability.

For parametric methods, one of the earliest researches was reported by Clemson University (1994) [29]. A time estimator, named STLtime, was programmed to estimate build time based on part volume, height and surface area. The model is simple, but it ignored some key parameters of the machine setup and processing details. It could not be used for some AM processes where support structures are needed. Later, Kamash and Flynn [5] proposed a model based on laser speed obtained from statistical data and scan length for SL (StereoLithography) machines. This model did not take laser jumps and hatching vectors into consideration, which would have resulted in an underestimation. In addition, the effect of build orientation or build height on the part's build time was also not considered. Choi and Samevedam [6] developed a parametric model for SLS (selective laser sintering) machines. The model only considers the laser speed and part height. The accuracy is relatively low due to the lack of enough detailed information on the building styles, such as orientation, support, layer thickness, etc. Kechagias et al. [7] proposed a parametric model for estimating the build-time required by laminated object manufacturing (LOM). The proposed algorithm uses STL file information and takes part volume, surface area and flat areas into account. The accuracy of reported predictions varies considerably, probably due to the entirely different geometric characteristics of the parts, since some parts were hollow requiring many supports, while other ones required no supports at all [8] Wilson [9] proposed a parametric model for the SLS process in his master's degree thesis. The model is relatively simple. However, the processing details, such as laser jump, hatching vectors etc. were ignored by setting a couple of assumptions, which results in low prediction accuracy. Nezhad et al. [10] proposed a model for the orientation optimization study of parts. The model effectively reduced the computation for build time prediction. It is an effective tool for solving part orientation optimization problems. However, the accuracy is relatively low due to many assumptions and lack of information on processing details.

To improve the prediction accuracy, many other researchers proposed a couple of analytical methods and models. Chen and Sullivan [11] presented an improved analytical laser velocity-based model concerning more processing factors for the SL process. Instead of the conventional methods of predicting build time based on the part's volume and surface, the model used the detailed scan and recoat information from the actual build files by incorporating the algorithms derived from a detailed study of the laser scan mechanism of the Stereo-lithography machine. The accuracy was improved by adding an appropriate correction for the laser beam velocity. However, the complexity of the model greatly increased.

Table 1
Representative build time estimation methods for AM.

Model	Contributors	Pros and cons	Applicability
Parametric	Kamash and Flynn [5] Choi and Samevedam [6] Kechagias et al. [7] Wilson [9] etc.	Pros: Simple, with less input parameters; Cons: Low accuracy, needing assumptions and approximations, without adaptive ability.	Feasibility study; Concept design; Preliminary design.
Analytical	Chen and Sullvan (1996); Alexander et al. [12] Giannatsis et al. [8] etc.	Pros: High accuracy; Cons: Complicated, with many parameters, hard to construct or use, without adaptive ability.	Detail design; Process/production planning; Manufacturing; Product use; Recycling.
Analogical	Ruffo et al. [14] Campbell et al. [15] Munguía et al. [16] Luca and Paolo [17] etc.	Pros: Relatively simple, with less input parameters; Cons: Accuracy varies, hard to construct or use, without adaptive ability.	Feasibility study; Concept design; Preliminary design; Detail design; Process/production planning; Manufacturing.