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COMPUTER-AIDED PROCESS PLANNING FOR WIRE ARC DIRECTED ENERGY DEPOSITION

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Abstract

Wire arc directed energy deposition provides a rapid and cost-effective method for fabricating low-to-medium complexity and medium-to-large size metal parts. However, the complex nonequilibrium phase transformations, inherent to this process, make it a challenging task to produce consistent and high-quality parts, especially for parts with materials or geometries that have not been manufactured before. This study outlines a holistic and data-centric computer-aided process planning framework utilizing a knowledge base to assist engineers in selecting optimal process parameters that reduce dimensional deviations, and therefore to obtain near-net-shape parts using directed energy deposition only. The knowledge base has a data-knowledge-service architecture and is proposed to synthesize information from various sources, e.g., characterization tests. Based on these collected data, several knowledge representations, including database, metamodels, and planning rules, are constructed to support decision-making in the process planning. The proposed framework is demonstrated in the fabrication of components from industrial applications.

Keywords: Process Planning, Directed Energy Deposition, Knowledge-Based Engineering, Design for Additive Manufacturing

1. INTRODUCTION

Directed energy deposition (DED) refers to a category of additive manufacturing (AM) processes that utilizes a high energy source to melt the feedstock material, which comes in either wire or powder form, and patterns this energy source with motions provided by a computer numeric control (CNC) machine or robot to infill enclosed regions for creating a single layer of a three-dimensional (3D) part. The DED process is suitable for fabricating low-to-medium complexity and medium-to-large size metal parts, in which other metal AM processes such as powder bed fusion (PBF) cannot be used [1,2]. Due to its high deposition rate and low setup cost, DED offers an efficient and effective method for applications that require large near-net-shape parts at a short lead time. Hence, it has been utilized in the maritime, aerospace, and automotive industries with applications including marine propellers [3], winglets [4], excavator arms [5]. In addition to creating new parts, DED can also be used for on-site remanufacturing applications due to its portability and large work volume when robots are used as motion devices.

Although wire arc DED has many favorable characteristics, several challenges should be solved to make this manufacturing method easier to operate and more reliable for industrial production. The most difficult challenge is that the physical and chemical processes within manufacturing, e.g., nonequilibrium phase transformations are complex and not well understood. The lack of understanding of these underlying processes has greatly hindered the development of optimal process planning strategies for fabricating consistent and high-quality parts. To address this issue, many studies have been conducted to establish process-structure-property relationships and to utilize these relationships for exploring optimal process planning strategies.

However, these studies are often ad hoc that are either focus on specific materials or specific geometry features such as thinned-walls. Additionally, these data, models, and knowledge acquired are not correlated and formalized for reuse. More importantly, current computer-aided process planning tools are mainly based on frameworks that were developed for either less complicated AM processes such as fusion deposition modeling or subtractive manufacturing such as milling. Hence, these CAPP tools often do not allow adaptive process planning for complex features. Above limitations in existing methods and tools necessitate a computer-aided process planning framework for wire-arc DED that considers different materials and geometry features, allows capitalization of existing knowledge, and evolves with times.

To support this view, this study outlines a knowledge-based computer-aided process planning framework to assist operations engineers in selecting optimal process settings for obtaining high-quality near-net-shape parts through the wire arc DED process. More specifically, the knowledge base about the wire arc DED process is constructed with a data-knowledge-service architecture to capture, represent, and reuse domain knowledge. The rest of the paper is organized as follows. Section 2 reviews related works in this field. The data-knowledge-service based computer-aided process planning framework is illustrated in Section 3. Section 4 presents the software tool implementation of the proposed process planning framework. Finally, conclusions are drawn in Section 5.

2. RELATED WORK

This section reviews relevant work on two research topics: process planning for wire arc DED and AM knowledge management. This will serve as the basis for the research presented in this paper.

2.1. Research in process planning for wire arc DED

Process planning is a significant step in the AM workflow that links design and manufacture. It converts geometric models together with their functional requirements into process plans that are to be executed by AM machines. According to [6], the conversion is supported by two types of activities: decision-making processes and algorithmic operations. The decision-making process searches for compromise process settings that satisfy multiple goals. Then, these settings are converted into process plans through algorithmic operations. This general categorization is also valid for the wire arc DED process, and we review literature in these two categories.

Decision-making for wire arc DED is a challenging task because the underlying mechanisms are complex and not well understood. Hence, research efforts have been made to establish relationships between process variables and properties of fabricated parts such as geometries[7], surface roughness [8], and mechanical properties [9]. Both experimental and theoretical tools have been used to reveal the physical mechanism. For instance, thermal imaging techniques were utilized in [10] for obtained the surface temperature field of deposited parts to study the effect of interlayer cooling time on the surface quality and part geometries. In addition, the internal flow behavior of melt pools was studied [11] through a high-energy synchrotron radiation experiment. Meanwhile, analytical and numerical models have been developed to predict bead geometries [12] and residual stresses [13], respectively. Finally, these process-property relationships were represented in various forms such as response surface methodology [14] and neural networks [15] to support engineers to define process windows and settings for the arc DED process.

Meanwhile, various process planning algorithms have been developed for the wire arc DED process. For instance, reference [16] developed a medial axis transformation (MAT) based toolpath generation algorithm to increase the production speed and to improve the geometry accuracy. This algorithm was further developed in [17] [18] with more robust solutions such as the level-set method to generate toolpaths with variable bead width. In addition, sequential path planning methodology based on a water-pouring rule has been investigated in [19] to enable real-time hatching with a feedback loop. Some recent research efforts [20,21] focused on feature/modular-based algorithms in which specific toolpaths are generated for various manufacturing features such as free end walls, t-crossings, and direct-crossings, which are segmented from a design part.

2.2. Research in AM knowledge management

Previous research has addressed the need for knowledge management in AM that allows information storing and information reuse to support decision-making. AM knowledge was defined to include design knowledge, manufacturing knowledge, and other knowledge within the AM value chain. Methods from knowledge-based engineering (KBE) have been used as primary tools. Ontologies for AM have been proposed for knowledge formation and reasoning. For instance, a computational ontology has been proposed in [22] for representing and reasoning over AM knowledge and data. A design for AM ontology has been developed in [23] primarily for knowledge documentation using the formal web ontology language (OWL)/ resource description framework (RDF). This ontology was used for manufacturability analysis. Also, the innovative capabilities of additive manufacturing (ICAM) ontology was proposed in [24] for innovative design ideation.

Other research focused on the development of hierarchical models for knowledge management. Reference [25] presented a hierarchical object-oriented model with a seven-layer data organization that covers steps from the manufacturing planning until post-production. In addition, a four-tier framework based on a closed-loop data-information-knowledge-application framework was proposed in [26] for self-improving additive manufacturing knowledge manufacturing.

Research gaps are evident with the above studies on AM knowledge management.1) The existing AM knowledge bases were targeted at general AM processes whereby unique characteristics and requirements of AM knowledge base for a specific AM process, i.e., wire arc DED were not explored and identified. 2) The method to utilize AM knowledge base for CAPP was not studied. 3) Additional research is needed on the user interface characteristics of knowledge base systems, such as ease of use, support to designers as services, and classification of users. In this paper, a data-knowledge-service architecture is proposed for capitalization and reuse of manufacturing knowledge about the wire-arc DED process.

3. KNOWLEDGE BASED COMPUTER AIDED PROCESS PLANNING

This section first provides an overview of the proposed data-knowledge-service architecture for wire-arc DED. Each level of the knowledge base is explained in detail at each subsection.

3.1. Data-knowledge-service architecture

The proposed knowledge-based computer-aided process planning framework consists of three layers: data, knowledge, and service. As shown in Figure 1, these three layers are organized in a hierarchical structure that reflects the abstraction process from data to service. The basic layer includes data obtained from three sources: process characterization, in-process monitoring, and post-process measurement. Based on the data layer, knowledge is stored in various formats, such as metamodels, database, and planning rules. The above knowledge is then used as a basis for two types of services: 1) supporting operations engineers in selecting process settings; and 2) communicating with product designers regarding the potential design freedom in the domain of process control. The first type of service can be viewed as an extension of existing process planning to consider complex AM processes. The second type of service is a unique service in the context of design for additive manufacturing which emphasizes the possibility to explore new design freedom.

The use of the data-knowledge-service architecture brings several advantages to move wire arc DED from the R&D arena towards the production line. First, the bottom layer that is data-driven stores information in a central repository and fills the increase needs of part quality assurance and qualification. Second, the middle layer that is knowledge-based offers an integrated method to capture and represent knowledge which moves process planning from an information intensive basis towards a knowledge intensive foundation. Finally, the top layer that is service-oriented provides manufacturing bureaus a way to formalize their know-how for guaranteeing their competences.

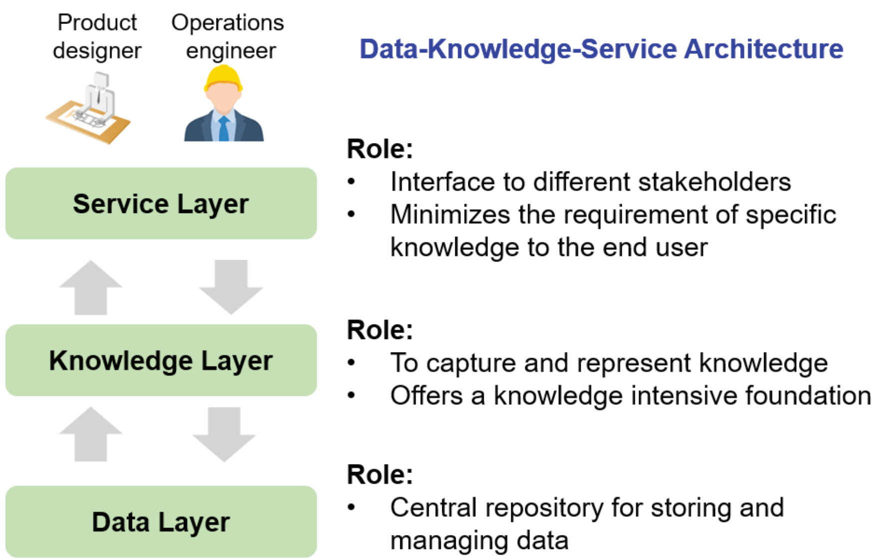


Figure 1 A knowledge base with a data-knowledge-service architecture for computer aided process planning

3.2. Data layer

Wire arc DED utilizes a complete digital workflow in design and manufacture. Various data are generated at different steps of the workflow. The primary function of the data layer is to store these data in a structured manner for retrieving. Based on their sources, collected data are categorized into three groups: process characterization, in-process monitoring, and post-process measurement. Heterogeneous data are stored in each category that includes various formats, e.g., CAD models, point clouds, and images.

For wire arc DED, process characterizations are often conducted for new materials and new geometric features, as these variations significantly affect the process. Hence, process settings must be adjusted accordingly based on the newly established relationship between process settings and performance of fabricated parts. Typical process characterization tests include: single-bead single-layer build; multi-bead-multi-layer-build; singe-bead multi-layer-build; and builds for specific geometry features such as overhangs. As summarized in Figure 2, each test is designed to gain an understanding of the process from a certain aspect. For instance, the single-bead single-layer build is conducted to define a process window from where feasible process settings are selected. However, for bulk parts and thin-walled structure, their distinct conditions for the phase transformations require specific investigations. In this context, multi-bead multi-layer and single-bead multi-layer builds are fabricated and the part geometries such as the layer height and wall thickness are measured. For specific geometry features, the process settings should be adjusted according to feature characteristics such as hole sizes and overhang angles to obtain satisfactory performance of fabricated parts.

	Test	Measurement	Outcome
1	Single-bead single-layer build	Bead geometries	Process parameter (PP) window/ Step-over ratio
2	Multi-bead multi-layer build	Layer heights/ Part geometries	Optimized PP for bulk structures
3	Single-bead multi-layer build	Layer heights/ Effective wall thickness	Optimized PP for thin structures
4	Overhang structure	Layer heights/ Part geometries	Dataset / metamodel

1. Single-bead single-layer build 2.Single-bead multi-layer build 3.Multi-bead multi-layer build 4.Overhang structure

Figure 2 Process characterization data

Nowadays, more and more sensors are installed in wire arc DED systems for in-process monitoring. On the one hand, condition monitoring sensors, e.g., temperature sensors, high-speed cameras, and photodiodes offer data about the melt-pool, thermal distribution, and thermal history for facilitating understanding of underlying mechanisms that are hard to model and predict. On the other hand, online non-destructive testing (NDT) methods, e.g., infrared thermography and laser thermography provide data that include layer defects information for the increasing demands of part qualification. In-process monitoring data are acquired at a high sampling rate and often stored as images. This requires specific data infrastructure and data processing methods, such as data compression and feature extraction.

Other data comes from the quality check for fabricated parts. These data contain information about the achieved performance of fabricated parts such as mechanical properties, microstructure, and part geometries. These data provide feedback to compare against the desired performance and guide further corrections. For instance, since the part fabricated by wire arc DED is near net-shaped, its geometry is required for further post-processing such as machining. The fabricated parts are often scanned through a 3D scanner and the outcomes are point clouds, which are further processed and converted into geometric part models for downstream machining.

3.3. Knowledge layer

The knowledge layer allows capturing and representing information stored in the data layer and supports the service layer for decision making by utilizing knowledge. Because of the heterogeneity of data, knowledge is represented in various formats, such as metamodels, database, and planning rules.

Metamodels are often used for describing knowledge that has an implicit form. Examples of these models are response surface models, radial basis functions, and Kriging models. These models are often constructed based on datasets obtained from either experiments or simulations. For instance, two response surface models for describing relationships between bead geometries and process variables are constructed as shown in Figure 3. The inputs of these models are often continuous variables that allow selections within a value range. For discrete variables that have finite values, a database can be used to store the relationship between inputs and output. For example, wire arc DED utilizes different sheltering gases for fabricating different metals and alloys. For fabricating stainless steels, 95% Argon and 5% CO2 is used as the sheltering gas, whereby for fabricating nickel aluminum bronze, pure Argon is used. Additionally, planning rules are used to store heuristic knowledge including know-how accumulated during fabrications and other knowledge that has an explicit form. For instance, for the tapper part shown in Figure 3, an outside-in scanning sequence will lead to a failed print, while an inside-out sequence will likely lead to success. It is assumed this is caused by the heat accumulation that is trapped within the part center. However, a complex heat transfer and thermal mechanical model is required to give a complete understanding of the physical phenomena. These types of generally applicable heuristic knowledge are therefore stored as planning rules for reusing.

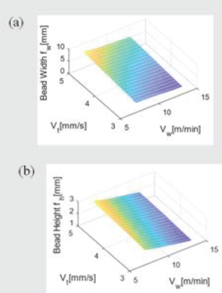
Knowledge Type	Metamodel	Database	Planning Rule
Example:	Kriging Model: Process-Bead Geometry Relationship 	Switch: Material Case= Stainless Steel • Sheltering Gas= Ar(95%) and CO2(5%) Case= nickel aluminium bronze (NAB) • Sheltering Gas= Ar End	If Part=Solid Then, Inside-Out Sequence Outside-In  Inside-Out 

Figure 3 Different knowledge types: metamodels, database, and planning rules

3.4. Service layer

The concept of the service layer is introduced to the knowledge base for supporting end-users while addressing issues identified in Section 2.2. On the one hand, it is evident that the end-user will still play a pivotal role in process planning before the arrival of fully automated process planning tools. Therefore, it is important to consider how to support the end-user in decision-making through services. In an ideal scenario, the designer does not need to fully understand the complex underlying relationships at lower levels for solving the decision problem. On the other hand, providing service is an important mechanism for manufacturing bureaus to capitalize on their know-how and to stay competitive. Given the fact that AM hardware is becoming more standardized and has fewer differences, the advantage of providing services to fabricate high-quality optimal products is more apparent. Services should be provided to end-users including product designers and operations engineers for analyzing the process capabilities and constraints, for visualizing the consequence of different decisions, and for understanding the trade-off among different objectives.

To illustrate the concept of service, we provide an example on selecting wire feed rate and scan speed for obtaining desired bead geometries. As shown in Figure 4, a design space exploration tool is constructed to link its performance space and design space. Once the designer adjusts the target bead geometries in the performance space, corresponding feasible design space is displayed accordingly. Since there are two design targets, i.e., target height and width, design space that satisfy each target is shown in Figure 4 (b) and (c). The feasible design space that satisfies both goals is obtained by overlapping feasible design spaces for each goal. The above service is supported by surrogate models, i.e., Gaussian Process Regression models and Bayesian Network Classifiers, and single-layer single-bead characterization data. More details can be found in our earlier work [27].

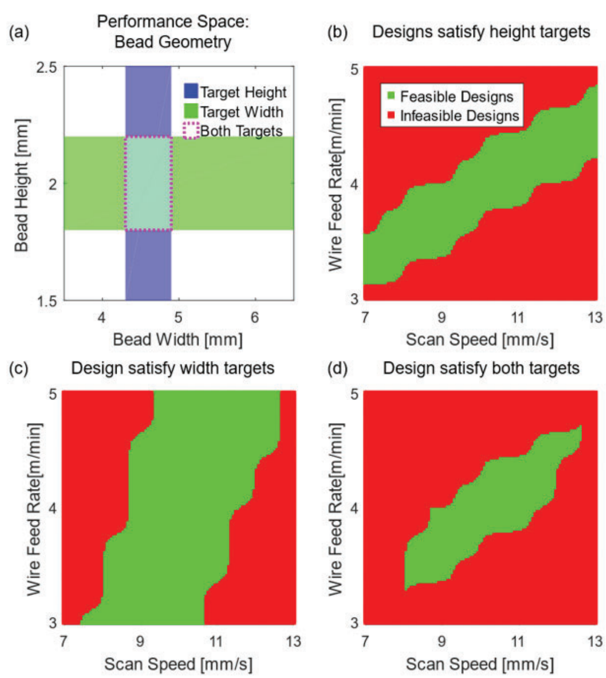


Figure 4 Design space exploration between process variables and bead geometries

4. EXAMPLE: SOFTWARE TOOL IMPLEMENTATION FOR OVERHANG FABRICATION

A software tool that embodies the proposed data-knowledge-service framework was implemented. The current version is developed for fabricating parts with overhang features, which is a common but challenging feature for the wire arc DED process. As shown in Figure 5, the user interface includes various buttons for users to interact with. Each section of the user interface is explained briefly as follows.

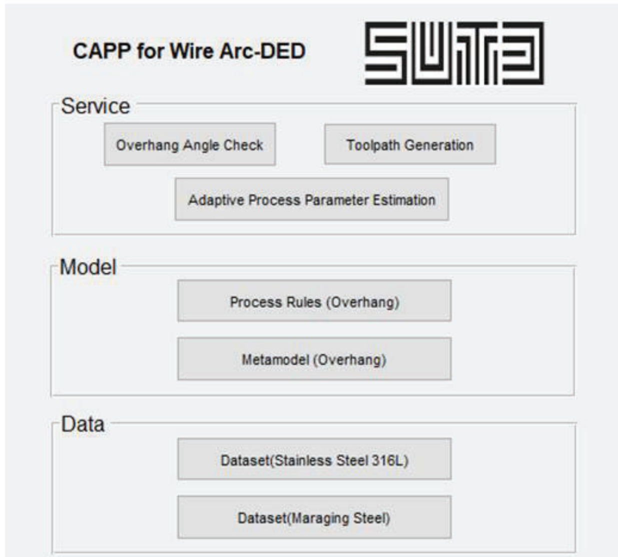


Figure 5 The CAPP tool with a data-knowledge-service framework

- Data
  For overhang features, characterization tests were carried out on a benchmark part that has various overhang angles (from 0 to 50 degree). Different process settings were used to fabricate these parts with stainless steel 316 L and the geometries of fabricated parts were measured using a laser scanner. In addition, the melt pool image and base plate temperature can also be measured. These data were stored within a dataset and can be updated for other materials such as maraging steels.

- Knowledge
  Both process rules and meta models were constructed in the knowledge layer. In the characterization tests, the maximum overhang angle using a flat deposition strategy was found to be 40 degrees. This is formalized as a design rule: if the overhang angle is larger than 40 degree, then the feature is not printable. In addition, a response surface was built based on a meta model to represent the relationship among the process setting, overhang angle, and resulting feature geometry.

- Service
  Three services are provided for designers in fabricating parts with overhang features. First, in the early design stage, the designer checks the manufacturability of their part designs based on the knowledge acquired about the capability of the wire-arc DED. Based on the feedback from the service, the designer makes necessary changes to the part design and iterates this process until the part fully meets the manufacturability requirement. Second, the toolpath generation service automatically hatches the layer slice based on the configured settings. Then, the knowledge regarding the design feature, process settings, and part performance is used to estimate the optimal process settings to guarantee a constant layer height over different overhang angles.

The software tool developed is used in the process planning stage within the AM workflow to manufacture part designs with variable overhang angles as shown in Figure 6. As explained earlier, the CAPP tool provides service, i.e., overhang manufacturability check to communicate with product designers about design constraints and freedom. If the part design contains features that are not manufacturable, it will be returned to the previous stage of the AM workflow, i.e., the product design stage. Once the manufacturability has been checked, operations engineers can use two services, i.e., toolpath generation and adaptive process parameter estimation to obtain an adaptive process plan for fabricating the part. In addition, both in-process monitoring data and post-process measurement data are fed back to the knowledge base to update and improve the service provided. This allows the knowledge base to evolve with new data.

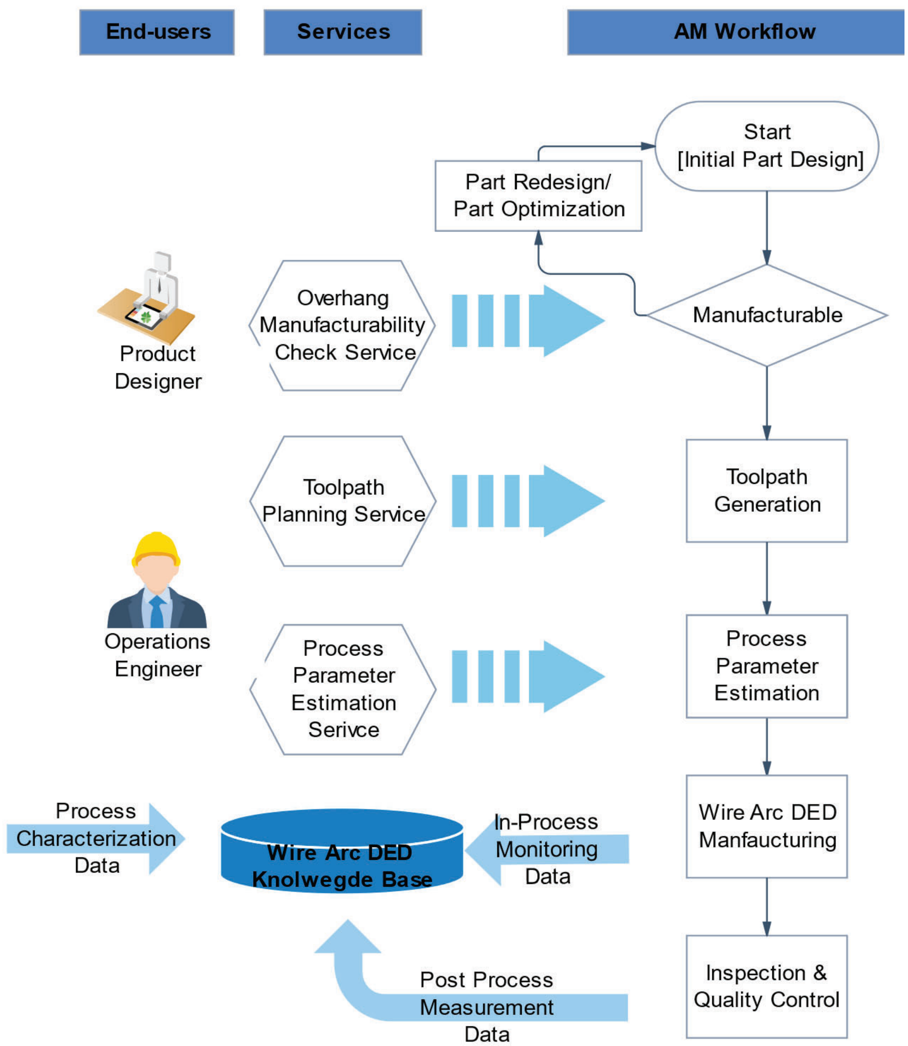


Figure 6 The proposed CAPP tool to support end-users in the manufacture of a part with overhang features.

As shown in Figure 7 (a)-(b), a thin-walled part design with overhang features was fabricated with the CAPP tool developed. The 3D scanned model of fabricated model is shown in Figure 7 (c). It indicates that the fabricated part (in green color) is larger than the than the part design (in red color) with marginal volumes that allow post-processing, e.g., milling. To demonstrate the improvement achieved with the proposed CAPP tool, a reference part fabricated using a constant process setting is shown in Figure 7 (d). The fabricated part significantly deviates from the design part geometry.

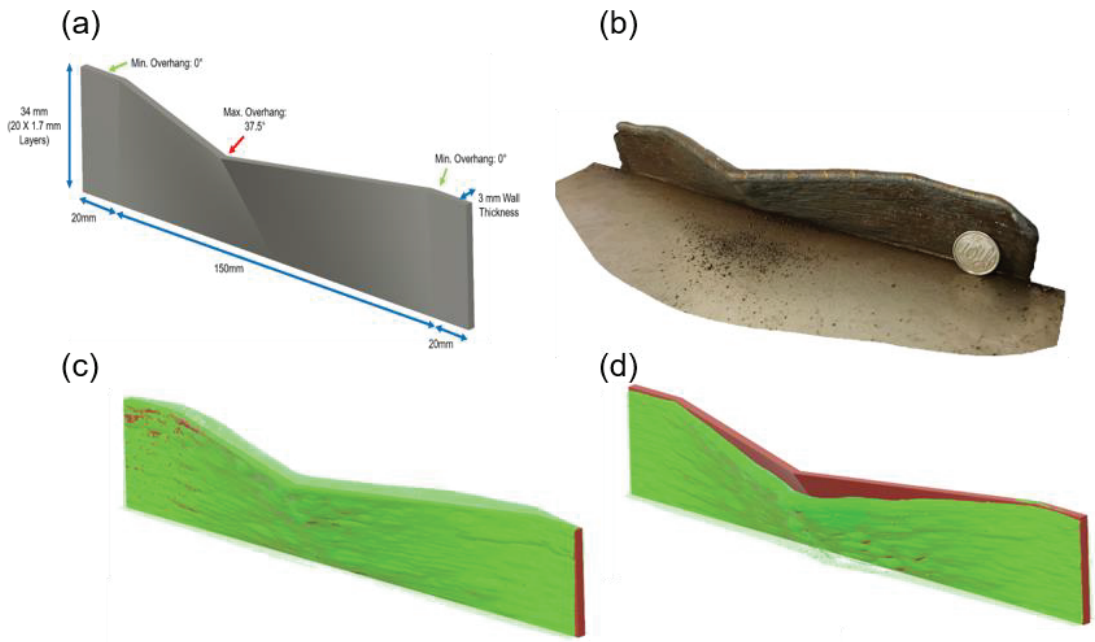


Figure 7 (a) CAD model; (b) part fabricated with the CAPP tool; (c)3D scans of part manufactured with the CAPP tool; (d) 3D scans of part manufactured without the CAPP tool. Both scans are marked in green and the original design is in red

5. CONCLUSIONS

This study outlined a holistic and data-centric computer-aided process planning framework utilizing a knowledge base for the wire arc DED process. The knowledge base was constructed based on a data-knowledge-service architecture which can evolve with new data. In the context of design for AM, this CAPP framework communicates with both up and down streams of the AM workflow: 1) inform designers about freedom and constraints on product design; and 2) assists operations engineers to search optimal process settings for manufacture.

This method brings several advantages. First, the use of the knowledge base offers manufacturing bureaus a way to formalize their know-how for guaranteeing their competences. In addition, the modularized layer structure eases the decision-making for operations engineers in process planning as there is no need to understand complex physical phenomena within the manufacturing process.

Future work will focus on examining data mining and machine learning methods that can transfer existing knowledge that was gained from fabricated parts onto process planning for parts with materials or geometries that have not been manufactured before.

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