

Metallurgical and Geometric Properties Controlling of Additively Manufactured Products using Artificial Intelligence

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Abstract: This article has presented a technical concept for producing precisely desired Additive Manufactured (AM) metallic products using Artificial Intelligence (AI). Due to the stochastic nature of the metallic AM process, which causes a greater variance in product properties compared to traditional manufacturing processes, significant inaccuracies in metallurgical properties, as well as geometry, occur. The physics behind these phenomena are related to the melting process, bonding, cooling rate, shrinkage, support condition, part orientation. However, by controlling these phenomena, a wide range of product features can be achieved using the fabricating parameters. A variety of fabricating parameters are involved in the metal AM process, but an appropriate combination of these parameters for a given material is required to obtain an accurate and desired product. Zero defect product can be achieved by controlling these parameters by implementing Knowledge-Based System (KBS). A suitable combination of manufacturing parameters can be determined using mathematical tools with AI, considering the manufacturing time and cost. The knowledge required to integrate AM manufacturing characteristics and constraints into the design and fabricating process is beyond the capabilities of any single engineer. Concurrent Engineering enables the integration of design and manufacturing to enable trades based not only on product performance, but also on other criteria that are not easily evaluated, such as production capability and support. A decision support system or KBS that can guide manufacturing issues during the preliminary design process would be an invaluable tool for system designers. The main objective of this paper is to clearly describe the metal AM manufacturing process problem and show how to develop a KBS for manufacturing process determination.

Keywords: metallurgical properties; geometry; additive manufacturing; artificial intelligence; knowledge-based system.

1. Introduction

Much of the recent research and development in computer science and information technology is leading to the automation of many elements of the Additive Manufacturing (AM) process and system design for metallic products [1,2]. Computer-aided design and manufacturing (CAD-CAM), advanced AM methods, finite element analysis, manufacturing process modeling, and cost estimation/prediction are many areas that benefit from the latest technology [3–5]. New design environments are being postulated and implemented via tool development and enhancement that enable simultaneous design of products and processes [6–8]. The emerging field of multidisciplinary for design, simulation, and manufacturing optimization is providing technologies that are changing the way designers design [9]. In the medical, aerospace, and automotive fields, the design community is showing great interest in manufacturing many components using AM technology [10,11]. This article has addressed the

integration of design and manufacturing problems.

The problem of dimensions is one of the major problems with an AM product [12]. The product dimensions are only slightly different from those of the model CAD. Mingming et al. [13] observed that the film thickness change due to the high power process of selective laser melting. Takayuki et al. [14] have studied the volume fraction of pores that changes due to the change of scanning speeds and scanning space in Selective Laser Sintering process. Their length, diameter and height decrease significantly due to insufficient thermal conduction, material shrinkage and metal pool formation based on laser power, scanning speed, hatch spacing, and power layer thickness. The dimension tends to decrease after heat treatment of the AM product. Sometimes heat treatment of the AM product is required, but a decrease in dimension is not required. Therefore, a Knowledge-Based System (KBS) is required to control the dimension and volume shrinkage.

Neil et al. [15] have studied that the Selective Laser Melting (SLM) process produces large thermal gradients during rapid melting of metallic powdered feedstock. During solidification, thermally induced micro-cracks occur in certain alloys, which can be eliminated by process optimization. Olakanmi et al. [16] observed that in SLM process the bonding problem occurs between two adjacent layers. The bonding problem occurs due to laser power, scanning speed, material properties, layer thickness, etc. between two adjacent layers (both vertical and horizontal) during the formation of AM products [17,18]. The surface texture varies in different dimensions of the AM product [19]. Qiu et al. [20] have investigated that the evolution of the surface texture and porosity of Ti-6Al-4V samples produced by selective laser melting under different laser scanning speeds and powder layer thicknesses, and correlated with the melt flow behaviour by both experimental and modeling approaches. Minimising supports causes less heat conduction and improper weight distribution, both of which lead to bending and disorder of AM products [21–23]. On the other hand, maximising the supports leads to poor surface finish [24], more material loss, problems in removing the product from the support, and also more time consuming. So, it is necessary to design the support in such a way that these problems can be reduced, and an optimal design can be achieved. Gaard et al.

[25] have observed that Direct Metal Laser Sintered Invar36-TiC composites led to the formation of microstructures with homogeneous distributions of TiC particles in the metal matrix. Changes in the chemical composition of the liquid Invar36 alloy led to the formation of spherical particles, changes in the phase composition during solidification and loss of the low CTE properties.

A few types of research have been conducted on the design and control of the mechanical properties of products manufactured by the Selective Laser Melting process employing Artificial Intelligence (AI). Rabemanantsoa et al. [26] presented an innovative AI approach to generating assembly sequences on a consortium of database emulating expert systems. Their methods involve only shape and feature recognition using a model-based computer-aided design (CAD) analyser, data structure and data modeling, knowledge-based representation, and inference processing through a set of heuristics and rules. The main tool here was an object-oriented concept as a means of managing geometric data, topological data, and abstraction. Subashini et al [27] explored a non-invasive methodology for astrocytoma grading using image processing and artificial intelligence techniques.

However, the desired properties of SLM products also depend on tensile and compressive strength, fatigue strength, porosity, microcracks, bonding, defects, ductility, weight, surface morphology, chemical properties, and so on. These properties majorly depend on scanning speed [11], laser power/beam power [28], hatch spacing [29], scanning strategy [30], beam offset, layer thickness [31], properties of raw material [32], etc. To achieve those product characteristics, it is necessary to find out the suitable combination of the above dependent manufacturing factors with the help of KBS.

2. Product quality control

Certain assumptions have been proposed regarding product modeling and structural analysis, as well as model optimization and manufacturing optimization, which are controlled by KBS. Here, KBS will integrate powder meteorology, mechanical properties of the metal produced by AM processes, process parameter hardware, simulation software Finite Element Method (FEM), CAD -CAM and other AIs. First, the materials from which the

product is to be made are pre-selected from a database of possible candidates before modeling and optimization. Second, dimensions will vary significantly for different materials depending on the model, performance requirements, and support conditions. Third, some of the process selection knowledge is abstracted to the functional level. In AM system, manufacturing processes are selected after modeling the part in CAD systems. The process selection is made using the finite element analysis of the model and the corresponding selection heuristics. This is the only way to make the CAB a viable tool for a designer who wants to reduce the error rate and design cycle time in the conceptual and preliminary design phase, when there is still some flexibility in the design parameters.

The desired measure could be obtained by applying error correction through mathematical formulas in the model CAD. The applications of the mathematical formulas could be different for different types of dimensions and volumes. These applications could also depend on the orientation of the model in the AM chamber. The second option is to control the laser/beam power, scanning speed, scanning type, and layer thickness using KBS so that we can obtain the desired products [33]. It could also be possible to control the metal bath and thermal shrinkage by increasing or decreasing the thermal conductivity [12], which can be controlled by increasing or decreasing the support conditions to obtain the desired dimensions [24].

It could be possible that we use KBS to control the metallurgical, mechanical and chemical properties of AM products by varying the laser power, scanning speed, powder layer thickness in the given powder raw materials [34][35]. It might also be possible in obtaining the desired mechanical and chemical properties by combining the control of rapid fabrication and post-processing of the product. The material properties of AM products need to be verified by metallurgical tools and finite element analysis. To reduce the microcracks, we should vary the support conditions (to control the thermal stress and support strength), the laser parameters, the powder layer thickness, and the production chamber environment using KBS. It is needed to determine the perfect support conditions (support density, hatch type, outline support, etc.) to minimize the supports due to the orientation of the product model. To reduce

the internal support in the model, it is required to place the model in perfect orientation. The support conditions for all other conditions, such as: thermal conduction, dimension, micro-crack, bending, overhanging position, expansion, timing, support removal, surface conditions, etc. To achieve the desired bonding state between two adjacent layers (both vertical and horizontal) during the formation of AM products, the laser parameters, powder layer thickness and production chamber environment should be varied. To obtain the desired surface finish, it is needed to vary the laser parameters for surface preparation, the thickness of the powder layer, and the orientation of the model. The surface finish at the interface of supports can be modified by changing the support conditions [19].

There are several important topics that have related to the development of knowledge and rule bases. Powder meteorology, mechanical properties of the metal produced by AM processes, hardware of the process parameters, CAD-CAM and FEM simulation knowledge are integrated here. Much of the data needed to build the knowledge bases will be brought together. In order to collect the necessary data, an extensive knowledge acquisition process is required.

Khokhar et al. [36] have surveyed a comprehensive review of the application of signal processing and artificial intelligence techniques in power quality disturbance classification. The directions of AI research and the main features of KBS market phases through a survey of KBS tools and applications in the technical domain. The KBS can be developed using this research method and will be used within an integrated design environment along with existing tools, which can demonstrate its functionality as a design tool. The system will enable engineers to design the desired features at the lowest cost that satisfies all mechanical properties. The illuminated concept in this paper provides an overview of the development of the knowledge and rule base required to build the KBS. The interfaces and relationships to CAD packages, external synthesis and analysis codes, and links to cost estimation software and methods are developed. The system can be integrated with existing tools and desired artificial intelligence, as Fig. 1 shows. Several existing tools and codes are used within the system to perform the desired product and process modeling and design trades. The other tools in Fig. 1

that are currently used for product design analyses can be used.

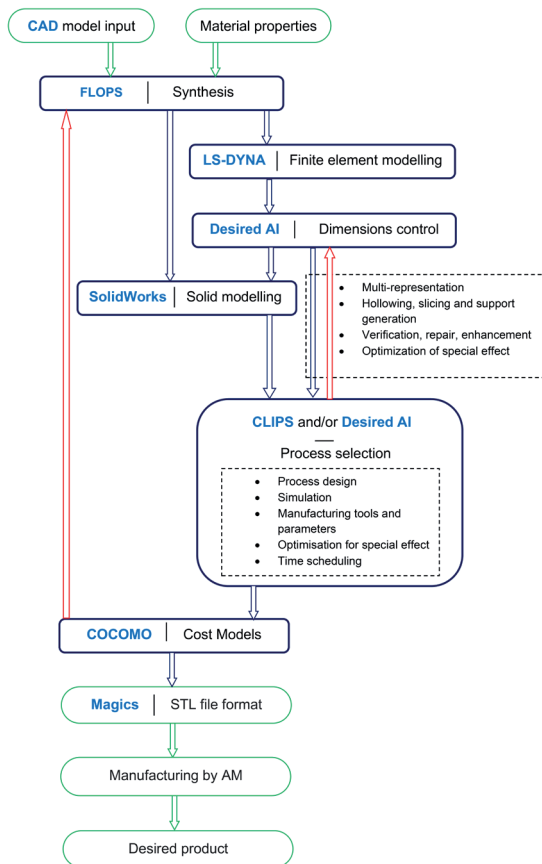


Figure 1: Integrated Design Environment

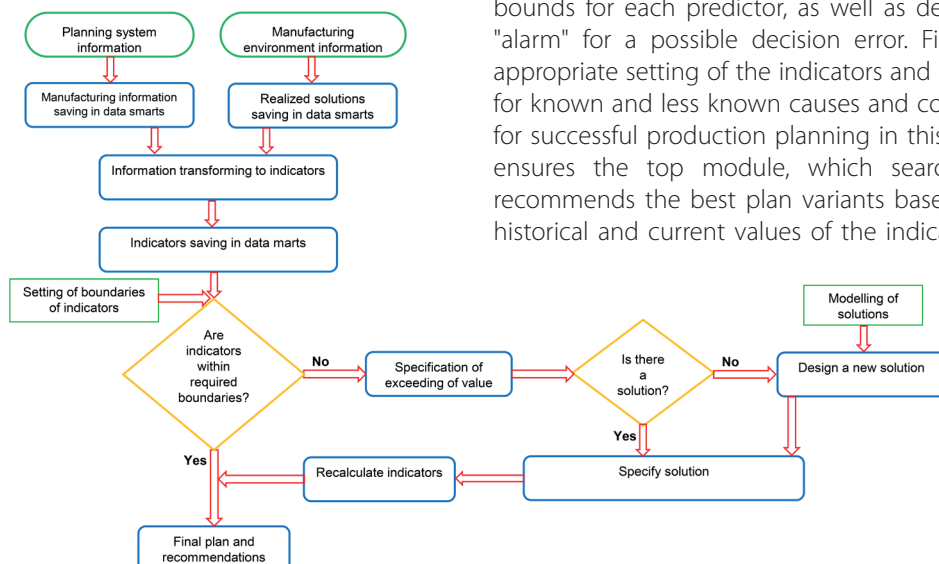


Figure 2: A Knowledge-Based system planning for AM process.

Based on the above problematic characteristics, we need to evaluate a proactive approach in knowledge-based manufacturing planning systems that can assume that the manufacturing planning system will play an active role in meeting the objectives based on the requirements defined by the manufacturing system management. For example, (see in Fig. 2), the manufacturing engineer will try to keep the processes that fall within his competence within the predefined values for a selected indicator. Here, the knowledge-based system must take into account the current and expected evolution of CAD modeling [37] and manufacturing mechanisms and processes [38]. The result of this analysis and the subsequent transformation of the indicators would then decide the ability of the manufacturing processes to deliver the product at the required quality, cost and time based on the proactively created plan. Based on the status of the evolution of the monitored indicators, the AM machine then evaluates its ability to manufacture and deliver the product within the required time frame.

Fig. 3 shows a Knowledge-Based System Planning Process for AM that describes the transformation of data into indicators that represent the state of the manufacturing system. The evaluation of the implementation of the plan based on the manufactured product is the result of each phase, and it clearly defines the suitability or unsuitability of the decision taken. When modeling techniques are used, the term allows defining upper and lower bounds for each predictor, as well as defining an "alarm" for a possible decision error. Finding an appropriate setting of the indicators and searching for known and less known causes and correlations for successful production planning in this concept ensures the top module, which searches and recommends the best plan variants based on the historical and current values of the indicators. The

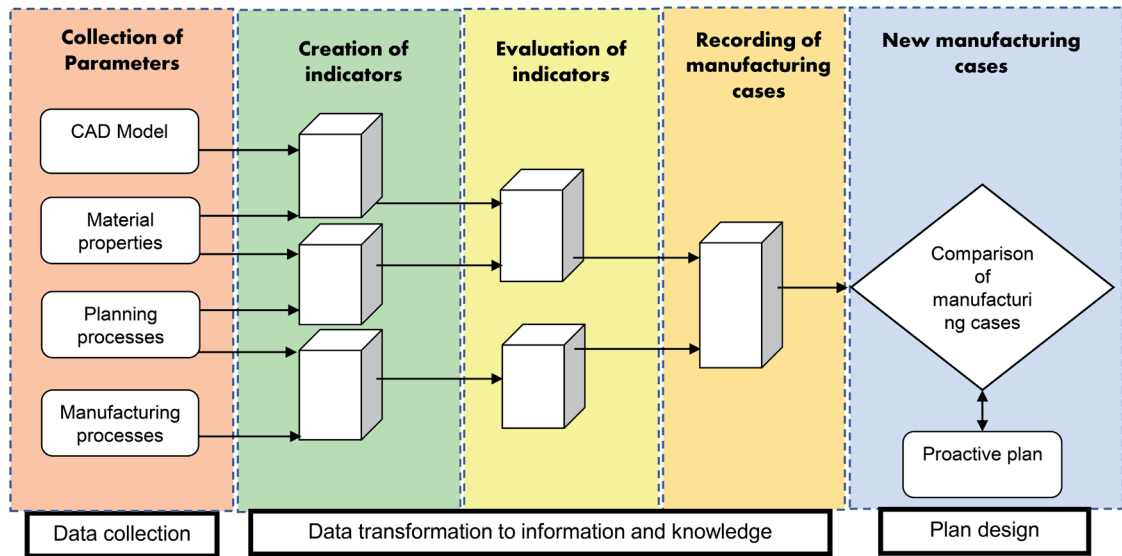


Figure 3: System of transformation of indicators.

best variant is characterized by the required values of selected parameters, which are adjusted by the production planner.

The manufacturer will establish a set of indicators to monitor the performance of each process. The existing system of indicators and their influencing parameters must be brought into a suitable structure for the purpose of further use. The present concept provides for a group of selected indicators, which will be constantly updated by the data warehouse. The exact number of selected indicators depends on the manufacturer. Stochastic algorithms are to be used in the creation of the process optimization. Occurring situations are therefore analysed using data mining methods such as Spearman's correlation method and decision tree learning. The resulting knowledge about the behaviour of indicators in a given situation is input into a knowledge-based system for further use. Data mining techniques can reveal seemingly hidden correlations that can have a great impact on the final decision. At the same time, they can recommend which exact values should be set as warning limits, i.e., when the values of the monitored indicators are already insufficient to fulfil the set task.

The training data is recursively partitioned with a splitting attribute until all records in the partition belong to the same class [39]. In this case, a working model of the device behaviour is constructed based on historical indicator values. This model would then

be used to identify the current state based on the attributes used. If the current state is unfavourable or the thresholds of the target indicator have been reached, the task of the system is to perform a shift of the independent variables so that the current value falls through a more favourable leaf of the decision tree, proactively preventing further deterioration of the target indicator. This technique is illustrated in Fig. 4. It is necessary to reprocess the decision tree model over time as different circumstances occur to maintain its accuracy. The event that triggers the reprocessing of the mining model can either be triggered by the calculation of the actual value when the set thresholds are exceeded, or it can be triggered at regular intervals.

In addition, the article has discussed the process of AM that allows for the creation and control of novel geometry, material, computation, and manufacturing methods, enabling designs that are currently not feasible with current technology. Fig. 6 depicts the problems and solution directions in four research areas that should be pursued: Design of (1) geometry, (2) material, fabrication of (3) computational tools, and (4) fabrication methods proposed for the AM method. This discussion not only assist to the engineers and researcher for further improving the AM product but also help to obtain knowledge about the application in the other technologies such as binder jetting and deformation during sintering.

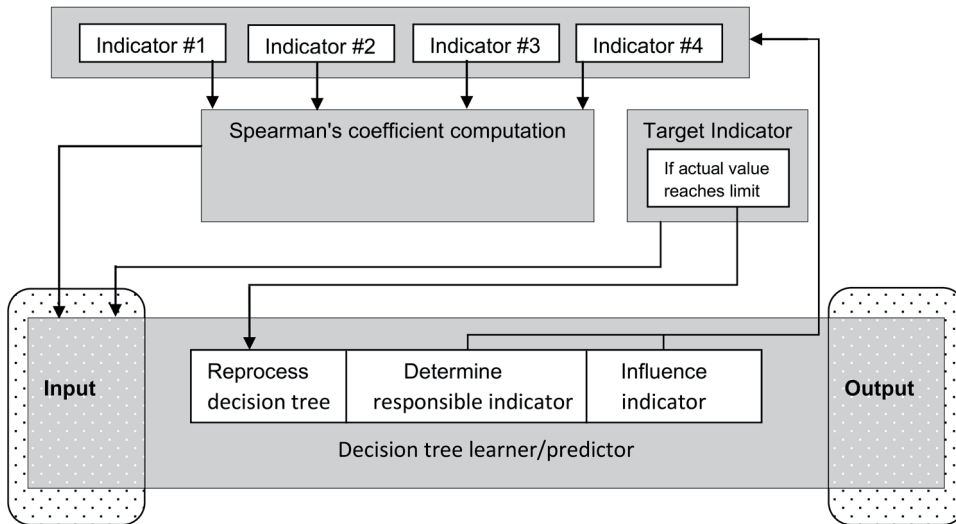


Figure 4: Data mining techniques applied to indicators.

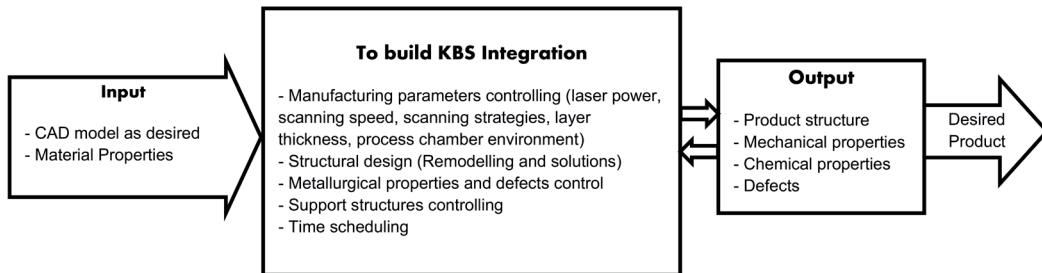


Figure 5: Knowledge-Based system building process.

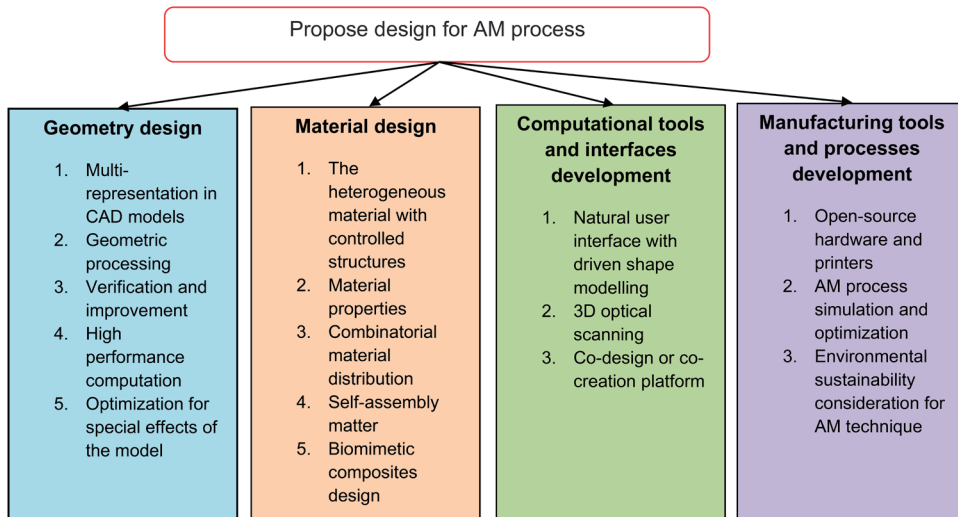


Figure 6: The problems and the fields of solution directions.

3. Conclusions

The dependence of AM techniques on related technologies such as materials modeling, design software, computers, and process design presents

challenges for both applied and basic research; here we describe a possible solution to the current problems.

Artificial Intelligence technology is to be developed for use in computer-aided design and manufacturing. A Knowledge-Based system

to be developed for use in selecting laser melt manufacturing processes for desired complex designs for medical, aerospace, and automotive applications.

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