Chapter 91
Additive Manufacturing Simulation: A Review

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Abstract Additive manufacturing is a printing successive layer process with the capability to manufacture complex geometries. Due to that the process consist on forming layers of material following a previously designed 3D shape, it is useful for many kind of materials as metals, ceramics, polymers, composites and biological systems. For many years, additive manufacturing was only used for prototypes, but now days, by its versatility, it is used in many industries, mainly in automotive and aerospace industry to manufacture components as gearboxes, airboxes, dashboards, motorcycle stands and suspension systems. However, this versatility can be also counterproductive because the measurement and control of the involved variables in this process is complicated, due to the different material's properties. For this reason, a previous simulation results important before to carry out additive manufacturing process. This article is a review of research of additive manufacturing simulations with different materials, as well as their results, focusing on additive manufacturing processes with metals.

Keywords Additive manufacturing · Simulation · Metals

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S. Li (ed.), *Computational and Experimental Simulations in Engineering*, Mechanisms and Machine Science 145, https://doi.org/10.1007/978-3-031-42987-3_91

91.1 Introduction

Additive manufacturing (AM) is a revolutionary method that opposes conventional manufacturing processes such as a machining. This process had been used for many years only for the prototype manufacture, although recently, due to its application capacity in different areas, it has managed to revolutionize manufacturing methods. This was a consequence of the first patents for additive manufacturing devices and processes expiring and anyone has access to this type of technology [1].

The automotive and aerospace industries started to use the metal additive manufacturing as an option to manufacture different parts such as gearbox, engine blocks, turbine nozzles, this is because with this method production costs are reduced. However due to metals have different thermal, physical, and chemical properties, it is difficult to measure these variables, which represents a large area of opportunity for mathematical modeling, since carrying out a simulation prior to additive manufacturing is efficient to improve these processes.

This article presents an overview of different additive manufacturing process, as well as a bibliographic review of simulations that have been carried out in metal additive manufacturing processes.

91.2 Additive Manufacturing

91.2.1 Definition and Classification

Additive manufacturing, the technology that was developed in 1986 by the inventor Charles Hull, consists of printing successive layers of materials, its process is known as stereolithography (SLA), followed by developments such as powder fusion, fused deposition modeling (FDM), and contouring.

The complex geometries manufacture is the main advantages that AM presents over traditional manufacturing. Some other benefits of using this manufacturing mechanism are [2]:

- Reduction of manufacturing times
- Less material wastes
- Ability to create lightweight structures
- No molds are needed to manufacture parts.

The American Society for Testing and Materials (ASTM) and International Organization for Standardization (ISO), classify the different additive manufacturing processes, Table 91.1 describes these seven categories [3]:

The two main categories of AM of metals are: Directed Energy Deposition (DED), which includes laser metal deposition (LMD) and powder fusion bed (PFB) including selective laser melting (SLM) [4].

Table 91.1 Additive manufacturing processes classification

Process	Description	Materials
Photopolymerization	A liquid deposit of photopolymeric resin is cured by selective exposure to light (via laser or projector)	UV photocurable resins (various fillers)
Powder bed fusion	A heat source, such as a laser or electron beam is used to selectively melt the powdered materials	Plastics, metals, ceramic powders and sand
Binder jetting	Liquid bonding agents are selectively applied in small layers of powdered material to build parts layer by layer. Binders include organic and inorganic materials	Powdered plastics, metals, ceramic materials, glass and sand
Material jetting	Drops of material are deposited layer by layer to manufacture parts. Common variations include UV curing and photocurable resin blasting	Photopolymers, polymers and waxes
Sheet lamination	The sheet-shaped material is laminate to create an object. This method can be applied in different ways, adhesive or chemical, ultrasonic welding or brazing	Paper, plastics, sheets, metals and ribbons
Material extrusion	Material is extruded through a die to form multi-layered patterns	Thermoplastic Filaments and Pellets (FFF); liquids in siring
Direct energy deposition	Trough laser or electron beam, the powder or wire used are adhered layer by layer until the object is formed	Powder or metal wire and ceramics

LMD plays an important role because this type of process is useful for the manufacture of industrial parts with complex and innovative structures on free-form surfaces, as well as for the reinforcement of light structures, Reconditioning and repair of high-value components and worn dies for metal stamping are just some of its typical applications [5]. It's an additive manufacturing process that falls within the direct energy deposition classification and is the most widely used in metal additive manufacturing.

In this type of AM, the heat source is a laser beam, is used to melt a material that is supplied in wire or powder form. Once the molten material cools and solidifies the next layer is deposited on top of the solidified layer. Thus a three-dimensional product with designed geometry can be fabricated layer by layer [6]. A wide variety of materials are usually used, the main ones being titanium alloys and stainless steel [7]. Figure 91.1 shows the experimental schematic diagram for an LMD process where the material is used in powder form.

The main advantages that LMD has over other processes are, for example, that its heat source is less intense, therefore the zone affected by the heat is smaller, so the deformation is significantly reduced, in addition the cooling speed is faster, which directs the material to a finer microstructure, this being a positive aspect for it [9].

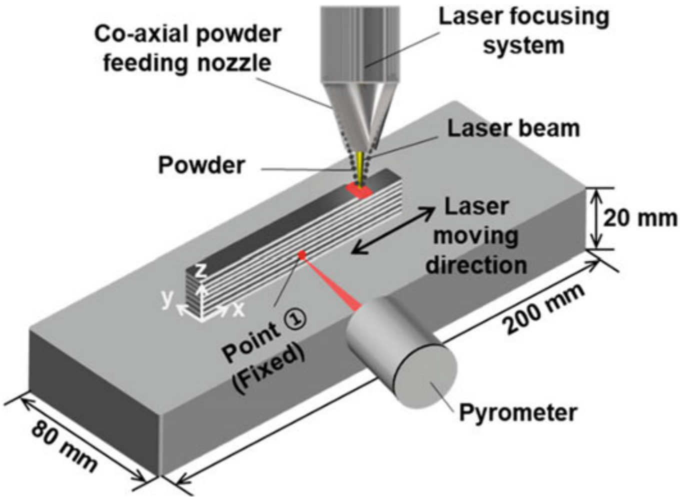

Fig. 91.1 Experimental scheme for the laser metal deposition process [8]

91.2.2 *Simulation*

The numerical simulation of engineering processes allows to obtain data and predict the behavior of the variables involved before carrying out experimentation, which is useful for every industry to apply it, since it is possible to optimize costs, times and materials, times and materials, as well as explore different alternatives [10].

The measurement of the variables involved in a metal AM process is difficult, due to the small scales that are used. Hence the importance of having preliminary data. Numerical simulations allow the experimental effort to be reduced, since the parameters involved in the AM process can be iterated, according to the type of product and the characteristics with which it is desired to manufacture [11].

In AM processes carried out by LMD the pre-existing material is periodically reheated, creating complex effects such as thermal stresses, local melting, phase transformations and annealing. When building large parts, such as turbine casings or excavator arms, the build is set up experimentally and iterated multiple times for parameter lookup; which implies hours of machine and personal time before achieving the expected results.

Despite the growth in the production of various components using LMD, this process is still not fully efficient and replicable when it comes to aluminum alloys, due to the fact that the temperature distribution is not homogeneous, which is derived from aluminum properties and generates unwanted residual stress, porous microstructures and inconsistent layer geometries.

Due to above Bock [12], used the finite element method to simulate the heat distribution during an LMD process, in which they used an AA5757 aluminum alloy. The results obtained in the simulation were validated experimentally, using the same alloy as wire and temperature measurements were made with thermocouple and thermography. They observed agreement in both results.

On the other hand, Gu and Li [13], through computational fluid mechanics reported the possible effects of gravity and pressure on DML with wire, for possible space applications. To do this, they used a moving heat source and took into account the various factors involved in the process such as phase change, surface tension, melting, solidification and the properties of the material that depend on temperature.

Dao and Lou [14], performed a mathematical model with smoothed particle hydrodynamics (SPH), a mesh-free Lagrangian method where the coordinates move with the fluid. In that investigation they simulated the heat transfer of dust particles used in an LMD process. Figure 91.2 shows the results obtained from these simulations, which were validated experimentally, demonstrating that the model is stable and efficient to model additive manufacturing processes specifically LMD.

Davlyatshin et al. [15], using the smoothed particle hydrodynamics (SPH) simulation method, they modeled the effect of vibration on the hydrodynamic behavior of molten metal droplets in additive manufacturing processes. The numerical tests were carried out with a 12x18H10T steel, which were compared with experimental results using the same steel. This study determined that the value of the coefficient of surface tension depends on the amplitude of the velocity of the vibrations. Figure 91.3 shows the simulation of the behavior of a drop of molten metal when vibration is applied and when vibration is not applied.

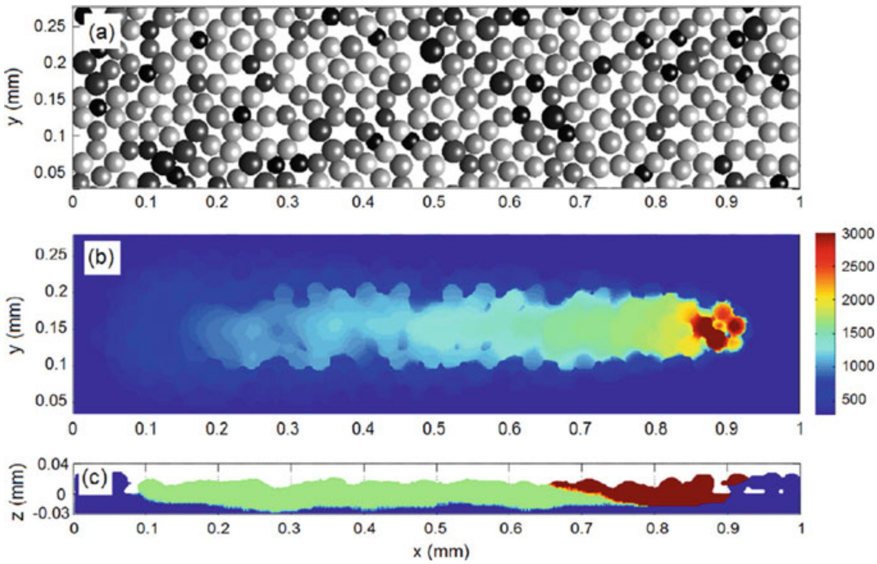

Fig. 91.2 Simulation result of a laser track on a d50 = 27 μm powder bed. The laser power is 200 W, d4sigma is 54 μm and scan speed is 2 m/s. **a** Powder distribution; **b** top view of temperature field (K) of the full track with current laser beam at x = 0.9 mm; **c** side view of the track with material state: blue—original solid (un-melted), green—solidified solid, red—liquid [14]

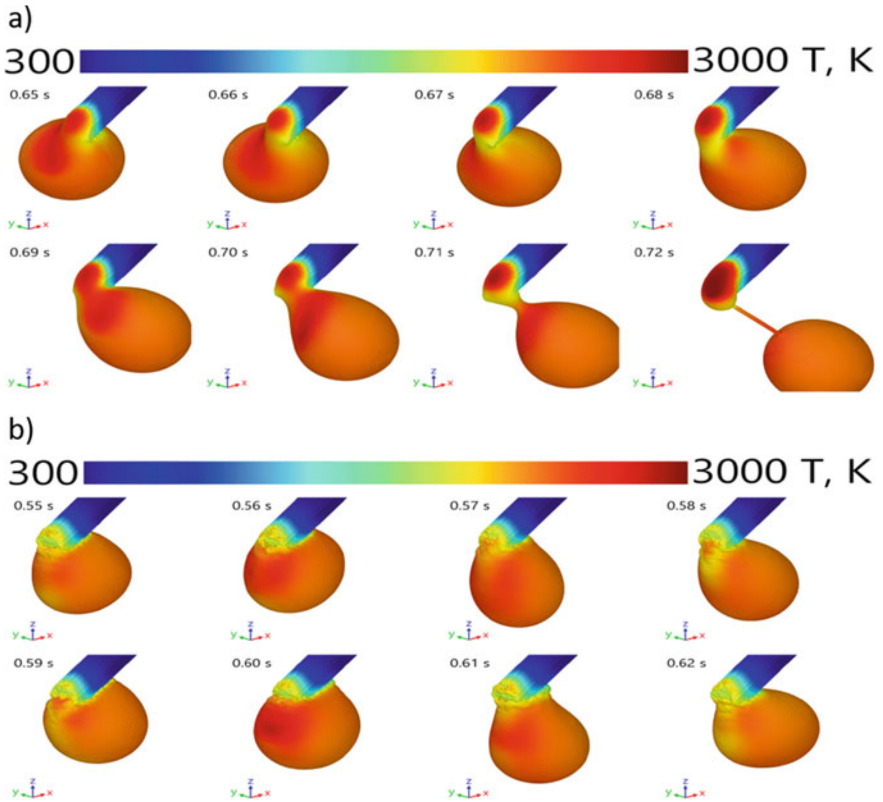

Fig. 91.3 Simulation result. **a** Metal wire melting process without the introduction of vibrating influences; **b** metal wire melting process with the introduction of vibrating influences [15]

In addition, it was concluded that the proposed SPH mathematical model is effective and can be useful to study in greater depth the influence of vibrations in additive manufacturing processes.

Zhu et al. [16] report the first attempt to use artificial intelligence to predict the temperature of the molten pool in additive manufacturing processes, through the physics-informed neural network in which only a small amount of information is used amount of data that is merged with the first physical principles, including the laws of conservation of momentum, mass and energy to carry out the modeling. Figure 91.4 represents a physically informed neural network model applied to a solidification problem.

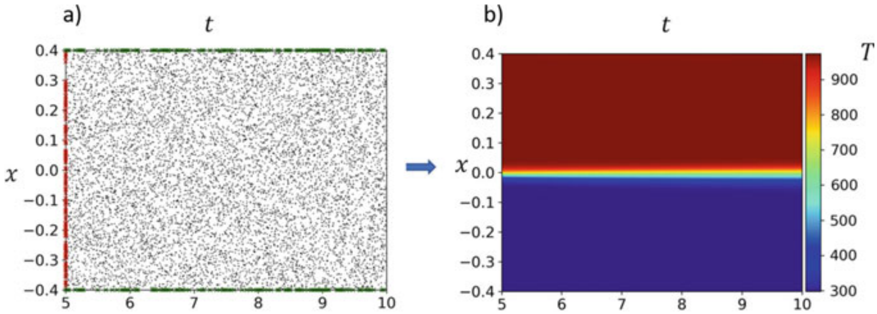

Fig. 91.4 Physics-informed neural network model for solidification problem. **a** Physics-informed neural network setup; **b** temperature prediction [16]

91.3 Conclusions

The positive impact that AM has had recent years in various industries, is mainly because it has been present as an alternative production effective, rapid and lower cost. However, the fact that the different AM methods that currently exist allow the manufacture of pieces or objects from any type of material, regardless of their shape, it is a fundamental part of the growth of this form of manufacturing.

The aerospace and automotive industry have benefited when apply until you want the piece. Thanks to this type of manufacturing, they have significantly reduced the weight of some pieces, which represents a competitive advantage for the aforementioned industries.

According to the researchers who have reported their work, it is concluded that it is possible to carry out the simulation of different phenomena involved in additive manufacturing processes, which, when validated experimentally, have turned out to be efficient.

The numerical modeling is a very useful research tool to study many processes occurring in the weld pool, with a great potential to study the vibration effects on metal flows, and the micro and macro structures formation.

Artificial intelligence is even being used to simulate and predict the behavior of various phenomena involved in additive manufacturing.

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