Achieving "Just Press Print" for Metal Additive Manufacturing

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Metal additive manufacturing (AM) has found broad application in the manufacturing sector, from medical devices to jet engine fuel nozzles. Key sectors of the metal AM market include aerospace and medical device manufacturing, where the emphasis on part quality is paramount. However, despite the huge benefits that AM offers manufacturers (e.g. speed, versatility, and adaptability), with today's approach, a qualified process can be costly and time consuming, particularly for complex parts [1]. To overcome current barriers to adoption, it is necessary to develop a science-based, automated approach that can be easily implemented on the factory floor. Achieving the needed control to build a part using a metal powder-bed additive process requires voxel-by-voxel control of input parameters, such as the laser power, speed, and beam shape. Moreover, careful tuning of the laser spatiotemporal profile can enable voxel-specific microstructures and topological optimization of mechanical properties. The vision of achieving *a precise, optimized 3D map of input parameters* is referred to as intelligent feed forward (IFF) control. By removing barriers to adopting metal AM for complex metal parts through IFF, a broad impact can be expected across multiple industries, and new applications can be explored.

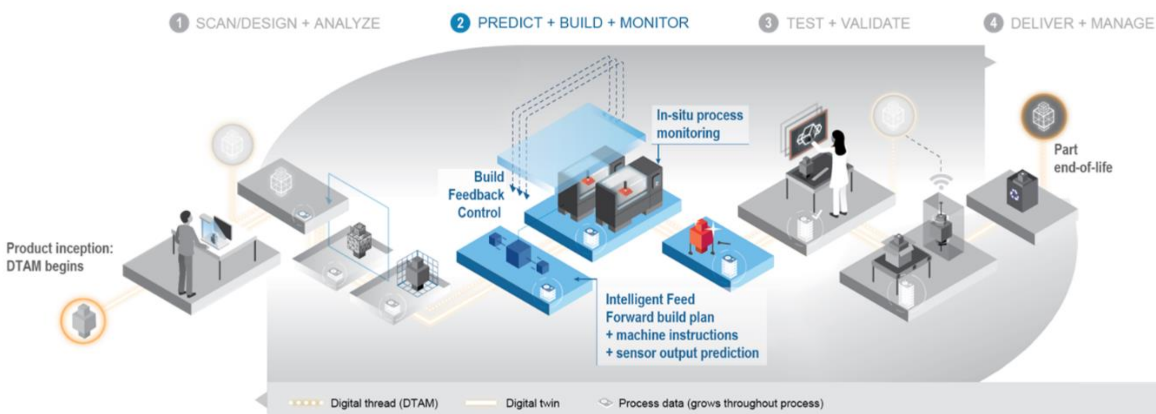

Figure. Diagram of a *smart* metal additive manufacturing process, highlighting the role of feed forward control (see step 2). IFF holds the potential to ensure that high-quality, complex metal parts are produced more rapidly, while reducing safety risks for critical parts and decreasing manufacturing costs. (Reproduced and modified with permission of Deloitte.)

Qualification of critical components typically has three major components: engineering qualification, production qualification, and materials qualification. Because with additive manufacturing we are creating the material at the same time as we create the part, materials qualification becomes a complex issue. Indeed, several recent works detailing the physics of the process through both experiment and simulation have shown that the interaction of the moving laser with the rapidly heated and quenched melt pool is complicated and dynamic[2, 3]. The nonequilibrium conditions driving the solidification process leads to microstructures that are very different from those produced in standard processes (e.g. casting), thus predicting the final mechanical properties of the build becomes difficult. Moreover, the local material properties are generally dependent on not only processing conditions but also on part geometry due to changing thermal boundary conditions. In current powder bed fusion systems, geometry-specific parameters can be entered only for simple geometries such as overhangs or contours and usually in a binary manner which imposes discontinuities that can affect local part quality. This intertwined relationship between designed geometry, production parameters, local material properties and final engineering performance create a significant challenge to the traditional approach to qualification which requires new thinking to overcome.

Optimization of the metal AM process is not trivial. Today, we use extensive, iterative experimentation to optimize input parameters for the process such as the laser power, scan speed, hatch spacing, and beam size. However, as many as 130 process parameters are known to affect the final build quality and there is still debate in the industry whether all the necessary parameters are being properly monitored and controlled. In situ sensors and feedback schemes can aid with process control. However, feedback is most efficient when the input parameters are close to optimal for the given geometry. Achieving the needed control throughout a part build requires local, geometry-based control of the input parameters, ideally driven by comprehensive analytics and not user-based experience.

Modeling and simulation, combined with high-performance computing optimization, have the potential to move us to the next stage in controlling the process [4, 5]. In this methodology, the simulation will be used to *teach* the additive manufacturing machine how to build the part on a voxel-by-voxel basis and at the same time predict the output of the process sensors. Because we cannot expect the simulations to be perfect, feedback control will be used to correct the simulation-based build. After the build is complete, the sensor data will be compared with the simulation-based prediction. If the prediction and the experiment agree within some specified uncertainty, we believe that it will be possible to establish confidence with product engineers that the material is of the required quality to fulfill mission requirements. Not only could this provide more uniform material properties throughout a part, intelligent feed forward will also provide means to produce controlled gradient properties within a component.

Conventional qualification requires many nondestructive and destructive evaluations. This procedure has been demonstrated to work well when producing thousands of copies of the same part per year. The situation is significantly different for short-run manufacturing which is common in Department of Energy labs which have a somewhat unique mission/application space. More generally however, the risk to the overall AM industry if feed forward concepts are not put into action is the potential of not being able to gain sufficient confidence in the quality of small lot production of parts for them to be qualified. The *intelligent feed-forward* approach, when successfully implemented, will ensure "right every time" production or early automated rejection, thus buying down risk.

As we learn more about the detailed physics of laser-powder interactions, melt-pool dynamics, microstructure development, and thermal stresses during cooling, the capabilities of the detailed simulation models will improve. However, in addition to being based on the knowledge gained from detailed high-performance computer simulations, a true *intelligent feed forward* predictive model will need to be based on fast-running, reduced-order simulations and machine learning algorithms that can be run for every new part or configuration to be manufactured. Development of sufficiently accurate, rapid, reduced-order predictive models will be the key to wide application of the *intelligent feed forward* concept. That is a new challenge that will have to be met. In this presentation, I will describe the physics of the process, methods for process monitoring and control, and the enabling models and hardware of the IFF process that have the potential to transform metal AM into a truly 'smart' manufacturing technology over the next decade.
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