OBJECTIVE: To better distribute, monitor, and control the processing energy in a laser metal powder bed fusion additive manufacturing (AM) system by incorporating artificial intelligence (AI) technologies (machine learning (ML), deep neural networks, neuromorphic processing or others) for purposes of real-time process monitoring and control towards producing high-quality, defect-free AM parts with build periods comparable to or shorter than present ones.

DESCRIPTION: Despite the continued progress in AM technologies, AM parts still require several trial and error runs with post-processing treatments and machining to optimize the build, reduce defects and residual stresses, and meet tolerances. AM still lacks a stable process that can produce consistent, defect-free parts on a first time basis due to our inability to reliably predict the optimal trajectory in the multidimensional process parameter space due to the inherent spatiotemporal variability in the process parameter and the chaotic nature of the AM process.

Factors that make AM, and in particular laser powder bed fusion AM, such a challenging manufacturing process are:

1. The smallness of the laser processing volume and rapid melt time when compared to the final part size and build time respectively and the associated process variabilities that result from them.
2. The intrinsic variability of all the powder bed physical (mass, heat capacity, thermal conductivity, emissivity, reflectivity) and chemical (composition, oxidation state, wetting angle) properties that compound to the above-mentioned process variabilities.
3. The large power densities required to process the powder bed and the associated large heating rates and thermal gradients, which when combined with the above-mentioned variability makes it difficult to control the microstructure of the processed volume.
4. The chaotic nature of the AM process that results from combining the small spatial and temporal scales described above with the high energy densities required for melting the powder, which makes it difficult to reliably predict the process trajectory in the multi-parameter process space before the build process starts and virtually impossible to control it in real time.
5. The large number of process parameters (in some cases over 100) that can affect the outcome of the AM process and make it almost impossible to model with physics-based models.
6. The non-symmetric deposition of the processing energy that results from rastering a single laser beam over the powder bed which leads to non-uniform heating/cooling rates, thermal gradients, residual stresses and part defects and distortion.

Most of these challenges can be alleviated by better controlling and distributing the laser energy at and around the melt pool area and/or the processing part surface area combined with real-time monitoring of the same area or beyond and by intelligently linking the laser energy control parameters with the process monitoring sensors to learn and adapt to the continuously evolving environment. Distributing the process energy intelligently at and around the melt pool would help reduce the process variability, the powder bed physical property variability, the heating/cooling rates and the thermal gradients. For example, it might be desirable to pre-heat the powder ahead of the melt-pool without melting it, to reduce the heating rates and thermal gradients later during melting. Doing so might allow processing the powder faster and reducing the build time while at the same time reducing evaporative recoils, ejecta and denudation effects (which induce defects in the final part). Monitoring the temperature profile around the melt-pool area could be used to adjust the distributed laser energy control parameters (power levels and distribution) in real time in a system where the temperature profile is directly linked to the heating source control parameters via an AI processor. Similar improvements could be achieved by intelligently distributing the laser processing energy over the entire part surface while monitoring the temperature evolution over the same area.

AI is starting to be used in several aspects of the AM process. For example, similar to combinatorial chemistry, ML is being used to develop and test new AM alloy systems to quickly identify those alloys with optimal properties for specific application. ML is also being used to correlate AM layer features with computed tomography inspection images to learn how to predict problem areas. In another application, various forms of microstructure data are correlated to process parameters to predict the optimum strategy to build AM parts. All these approaches and others are important contributions to make quality AM parts.
In contrast with the above-mentioned approaches, this STTR topic seeks innovative solutions that link the actuators controlling the laser energy distribution over the powder bed with the sensors that monitor the temperature distribution and/or other relevant process parameters over the powder bed using a real-time AI controller (ML, deep neural network, neuromorphic processor) for purposes of making better AM parts.

Since only a limited number of sensors will be installed in the intelligent AM system, human assistance will be indispensable during the training period by providing the necessary digital maps of the part microstructure, defect and residual stress distributions as well as performance parameters such as surface roughness, strength, stiffness, fatigue life or any other relevant training data set.

PHASE I: Define, design and develop a concept for an intelligent AM (IAM) system for laser metal powder bed fusion or modify a conventional one to make it intelligent. The IAM system design will include subsystems to: (1) distribute the laser energy over the powder bed and provide a list of the control parameters; (2) monitor the response of the powder bed and provide a list of the sensed parameters (temperature being the main preferred monitored parameter); (3) generate auxiliary digital training data and a list of the different physical measurands; and (4) link the control parameters to the monitoring sensors values and auxiliary digital data via an artificial intelligent processor for training and operation purposes. Finally, the performer will start acquiring parts of the IAM system, developing the software and graphical user interface (GUI) and will provide a validation plan with a list of planned coupons and tests. Due to the limited funds available in a Phase I STTR contract, the performer will limit the validation tests to just those subsystems, coupons, and tests consistent with the resources available. For the Phase I Option, the performer will continue progress towards IAM system parts and refining the design of the system based on validation test results. Develop a Phase II plan.

PHASE II: Complete the purchase of all the components necessary for the development of the IAM system or for modification of a commercial one. Start assembling the unit and developing the controls software and GUI. Perform validation tests after completing all the training exercises required for the IAM system to learn how to make quality coupons. To further validate the performance of the system, identify a challenge part between the performer and the Navy team and demonstrate that the IAM system can fabricate two of them, one for destructive microstructural analysis and another for mechanical testing. The success criteria consists in making coupons or parts with less defects or distortions and/or better control of the microstructure than the same coupon or part made by a state of the art AM platform but without AI.

PHASE III DUAL-USE APPLICATIONS: Support the Navy in transitioning the IAM system for Navy use. Working with the Navy, integrate the IAM system into a Navy platform for evaluation to determine its effectiveness. Define the IAM system integration strategy and test plan for qualification.

Commercial applications of IAM include almost all commerce sectors such as: aerospace, shipping, transportation, rail, automobile and medical. Applications include almost all technology areas such as: engine parts, structural parts, mechanical or electrical parts, medical prosthetics, and tooth implants. Finally, material applications focus is on metals.

REFERENCES:


KEYWORDS: Artificial Intelligence; AI; Machine Learning; ML; Neural Networks; Additive Manufacturing; Laser Based Powder Bed Fusion; Process Monitoring Sensors