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INTELLIGENT CONTROL AND TRANSFER LEARNING FOR ENHANCED QUALITY IN METAL ADDITIVE MANUFACTURING: A DATA-DRIVEN APPROACH TO PREDICTIVE OPTIMIZATION

Oleksandr Vasilevskyi, Doctor of Science. Researcher,
Walker Department of Mechanical Engineering,
The University of Texas at Austin, USA
Michael Cullinan, Associate Professor, WalkerDep. of Mechanical Engineering,
The University of Texas at Austin, USA
Jared Allison, ResearchAssociate, WalkerDep. of Mechanical Engineering,
The University of Texas at Austin, USA

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The widespread adoption of additive metal manufacturing for end-use part function depends on our ability to consistently produce high quality parts without iterative test cycles.

A transfer learning approach is proposed to improve part quality for various machine modifications used in additive manufacturing.

This approach is based on an intelligent control methodology using machine learning and on-site optical metrology.

The main focus is on creating transfer learning models to predict and control the geometry of the distribution shape.

The general transfer learning model includes 3 component blocks based on the respective models.

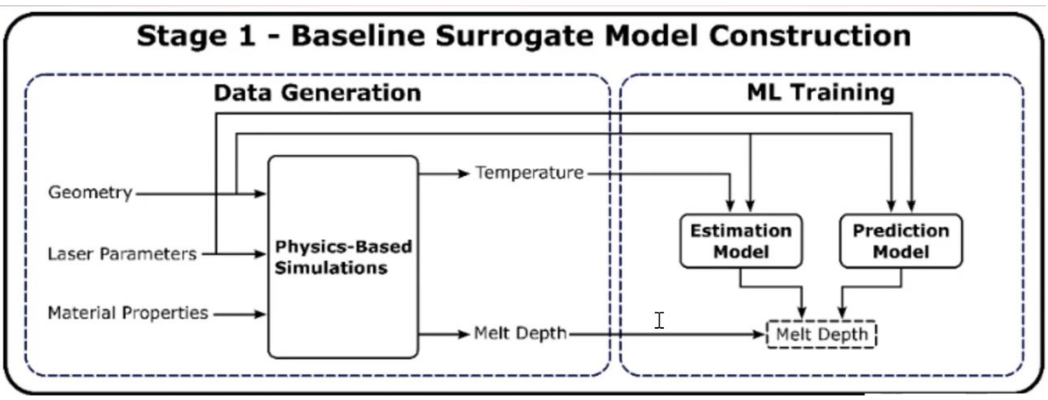

Figure 1 – Surrogate model for data management

The first block is a surrogate model for data management. This model is based on detailed physical modeling that controls the geometric details, material properties, and laser processing parameters with the resulting melt pool depth and surface temperature.

The components are a data generation sub-block, where physical modeling is used to generate data that relates the input and process variables to the corresponding outputs, and a surrogate model sub-block that learns from the simulation data to create the following surrogate models that predict and verify the performance of the additive manufacturing system.

This model predicts the melt bath geometry as a function of process parameters, such as laser power, which can be adjusted in real time, as well as spatial changes in part geometry, such as the presence of thin protrusions.

The second block is the surrogate model corrector, which improves the accuracy of the data-driven surrogate model using experimental data obtained from a fully equipped metalworking machine sample.

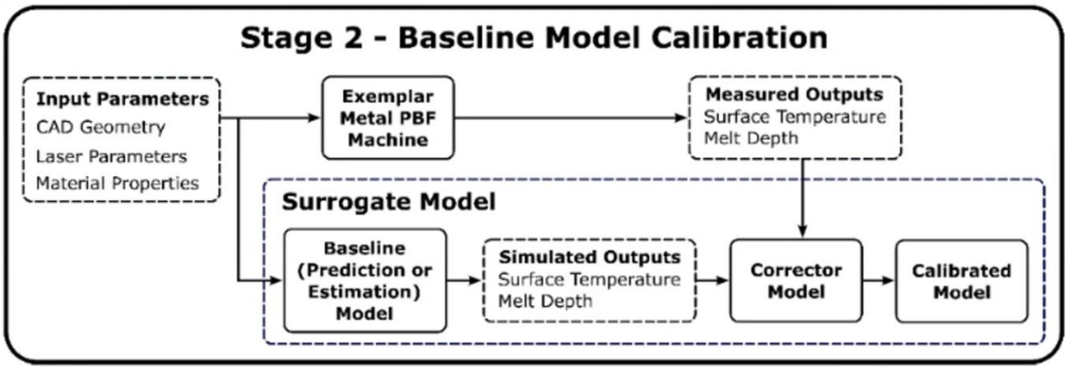

Figure 2 – Base model of calibration and evaluation

The second stage of the proposed system uses the basic forecasting and estimation models created in the first stage. They are calibrated against the actual results of the additive manufacturing system, as shown in Fig. 2.

The test cases are used in an exemplary metal powder bed melting system. The measured results are compared with the results estimated by the basic models.

The conversion factors are used to minimize the errors between the measured and modeled results, resulting in the creation of calibrated surrogate models. The result is a calibrated surrogate model, in Fig. 3, which can organize the bath depth, melt, and surface temperature with a high level of accuracy for a specific machine sample over a range of geometries, material details, and laser powers.

The third block includes a transfer learning model based on empirical data from a specific machine design that can quickly update the surrogate model's predictions to improve accuracy when moving from design to design, or from machine to machine.

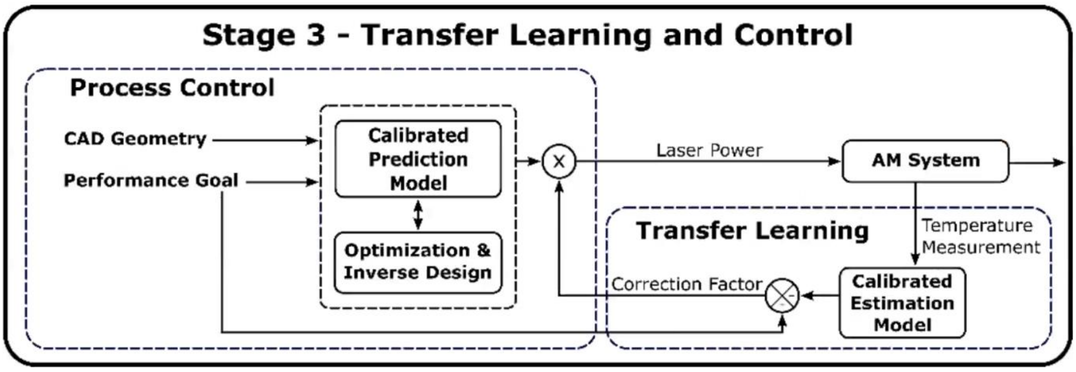

Figure 3 – Model of Transfer Learning

In the third stage of the proposed system, the additive manufacturing process controller and transfer learning scheme are created.

As shown in Fig. 3, the on-site process controller uses the calibrated surrogate model from the previous step to predict how the additive manufacturing system responds to a set of processing parameters and optimizes these parameters to achieve the performance goal, i.e., to maximize geometric accuracy and minimize thermal effects.

The surrogate model is used to optimize the laser path to achieve the desired geometry. In this step, transfer learning is performed using the evaluation model to estimate the actual valid results of the system based on real-time metrology.

The predicted result is compared to the performance target to create correction factors that complement the future predictions of the surrogate models to more accurately control the current additive manufacturing system.

A test scan can be performed at the beginning of each assembly in parallel with the fabrication of the support structure to select the correction factors for each machine. The correction factors can be updated after each layer for additive predictive control.

A sample machine used in additive manufacturing of metal products is shown in Fig. 4.

Figure 4 – EOSINT M280 machine

It is for these types of machines that the above additive intelligent control with machine learning is offered. First of all, it is an intelligent control of laser power, which makes it possible to improve the quality of manufactured products.

Based on the proposed models, a controller was created and tested on an unsupported ledge in order to achieve an acceptable melt depth profile despite changes in the thermal conductivity of the base material.

A drawing of the geometry and the desired space profile is shown in Fig. 5a.

Gray represents the solid material, turquoise represents the powder material, and red represents the desired melt profile.

The laser profile predicted by machine learning is shown in Fig. 5b and the resulting melt profile shown in Fig. 5c. The standard deviation of the melt for the optimized laser power profile ranged from 9 micrometers to 14 micrometers.

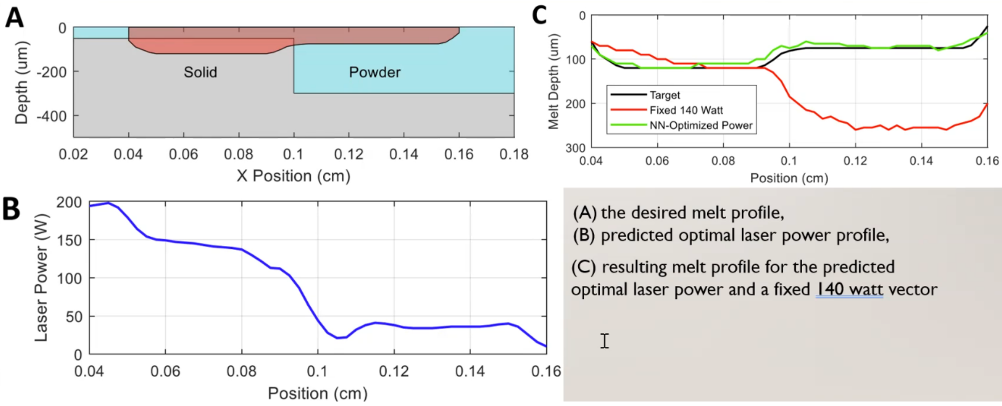

Figure 5 – Melt depth control of an unsupported overhang

To implement the proposed intelligent control of additive manufacturing using transfer learning, a measuring system for infrared visualization of optical emission spectroscopy is required, as shown in Fig. 6.

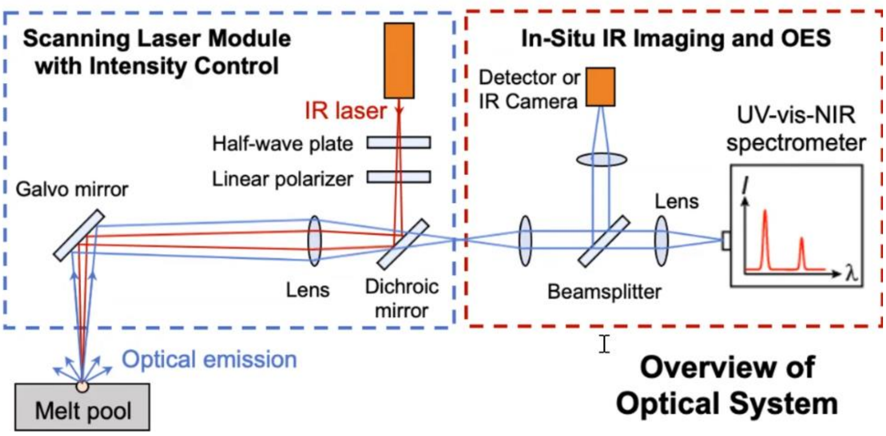

Figure 6 – Proposed optical layout for in-situ metrology and real-time sensor control

It consists of 2 blocks: module 1 of the on-site infrared imaging system, emission spectroscopy, and module 2, which includes real-time laser intensity control.

Based on the presented models, adaptive intelligent control, melting of metal powder during the additive manufacturing of metal products is realized.