Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 103 (2021) 164–169

www.elsevier.com/locate/procedia

9th CIRP Global Web Conference – Sustainable, resilient, and agile manufacturing and service operations: Lessons from COVID-19

Manufacturing resilience and agility through processes digital twin: design and testing applied in the LPBF case

Alexios Papacharalampopoulos[a], Christos K. Michail[a], Panagiotis Stavropoulos[a,*]

[a]*Laboratory for Manufacturing Systems and Automation (LMS), Department of Mechanical Engineering and Aeronautics, University of Patras, Rio Patras 26504, Greece*

* Corresponding author. Tel.: +30-2610- 910160; fax: +30-2610-997314. *E-mail address:* pstavr@lms.mech.upatras.gr

Abstract

Digital twins can be very promising towards offering agility and resilience in manufacturing. Especially at process level, the adaptability and the real-time optimization they can bring along is highly desired. However, digital twins, being the outcome of severe systems integration are difficult to be designed and be implemented integrating all the desired functions, such as process control and quality assessment. This work investigates the opportunity to integrate different models under the concept of a digital twin of a manufacturing process (namely LPBF) and be able to meet diverse requirements, such as adaptivity, real-time optimization and uncertainty management. The suggested framework takes into account all the phases of the digital twin, such as sensorization, modelling, diagnostic and prognostic functions and puts together an architecture including all available models and thus paving the way towards achieving to meet all the requirements. A case study is also presented showing the capabilities of the partial models utilized as well as the performance of the digital twin in closed-loop control. The digital twin is proved to be highly feasible and appears to have good performance indicators.

Keywords: Digital Twin; Manufacturing Resilience; Surrogate Models; LPBF

1. Introduction

The concepts of resilience, agility and resiliency (A&R) [1–3] are well discussed in literature and are linked to the way the changes can be predicted, avoided and absorbed. Thus they are systemic terms, closely related to control and stability [4], as these are prerequisites towards achieving A&R. So, there are repercussions for both Design and Operation of a manufacturing system and of a manufacturing process in particular, because specific objectives have to be able to be met; namely the First-time-right [5] is a valuable objective, then the concept of flexibility [6] as well as the concept of quality [7].

A digital twin (DT), on the other hand, being an emerging concept potentially integrating numerous key enabling technologies ranging from monitoring, control, IoT, ICTs and surrogate models [8], could boost the design and the operation of manufacturing process. The DT aims (as per the adopted definition [9]) at the real-time manipulation of Key Performance Indicators (KPIs) through utilizing virtual (digital) entities; high-fidelity simulations and high-knowledge databases for instant decision-making.

Recently, there has been an interest on the Digital Twin performance of thermal manufacturing processes such as laser-welding and laser-based additive manufacturing (AM). The performance of AM process has been investigated through

2212-8271 © 2021 The Authors. Published by Elsevier B.V.

10.1016/j.procir.2021.10.026

robust control design [10], while the laser-welding case has been regarded [11] for studying the process control efficiency under the cryptographic delays.

As aforementioned, DT relies on the real-time execution of simulations. The key enabler in that case, is the surrogate models (SMs). The SMs in reality constitute an approximation to the actual results of the simulations. A comprehensive investigation of the potential roles of SMs in the DT concept is conducted by Bárkányi et al. [12]. The simulations are mainly formulated with the help of finite element method [10], finite difference [13], level set method, volume of fluid method, and lattice Boltzmann method [14]. SMs can be divided into reduced order model (ROMs) [15], data-driven methods (DDMs) [16], hybrid modelling (HMs) [17], meshfree methods [18] and more recent method of physics-informed neural network (PINNs) [19]. Stathatos and Vosniakos [20] have developed artificial neural networks with arbitrary paths in a thin powder layer and fixed process parameters (power and scan speed). The same authors continue the implementation of a feedforward control scheme in line with the SM [21].

However, with the DT inevitably being a result of severe integration [22], due to its multifold character, a specific framework has to be set up towards a DT being implementable. This work describes the framework and tests its functionality in the context of laser based processes and LPBF in particular, under the scope of achieving A&R.

2. A theoretical framework for designing the Digital Twin

As indicated in Figure 1, the aspects of digital twin in literature form a rather complicated mapping with respect to its architecture. As a matter of fact, it has been stated explicitly that the digital twin is an outcome of severe systems integration [22].

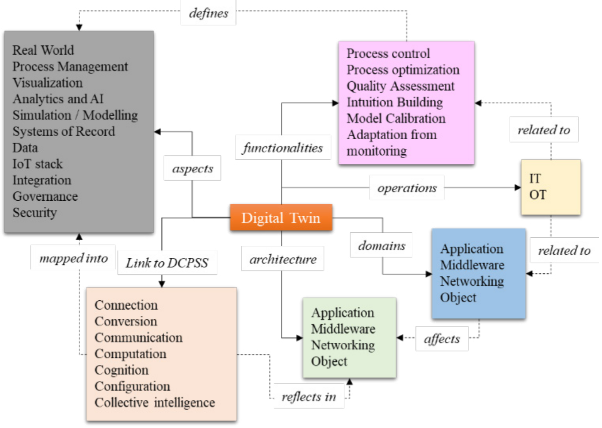

Figure 1. Digital twin and related concepts based on literature [22–27]

Mathematically, it is a design problem that can be modelled in a rather complicated way (provided that it can be formulated and it is a well posed problem), however, its solution seems to be even more difficult. The main difficulty in the implementation is addressing the real-time character that it ought to have, especially regarding manufacturing processes optimization. Simultaneously, it has to be interoperable enough with respect to data transmission. Specifically, the state of the physical (real) system (RS) and the structure of the digital twin structure (DTS) can be abstractly defined by the sets:

RS=(Process Parameters, Performance Indicators, Intermediate Variables, Actuators)

DTS=(Model M, sensors S, Controller C, Architecture A)

It is noted that this is not an strict mathematical definition, as the involved sets are not necessarily quantifiable. Then, after some detailed definitions are given and the search space for each one of the aforementioned entities is set, a target T could be defined for the problem of designing the digital twin, such as the one provided in Eq. 1, provided that $\tilde{x}(\mathrm{t})$ is the response of the real system and $\tilde{y}(\mathrm{t})$ is the response of the digital twin. Both of them are functions of time. Also, all the situations, such as the ones characterized by the ensemble of process parameters, are annotated with the letter W.

$$T = min_{(S)} max_{t,W} (\tilde{x}(t) - \tilde{y}(t))^T (\tilde{x}(t) - \tilde{y}(t)) \quad (1)$$

This is a complex problem which also includes coupled parameters. Also, with many of the involved entities being described by categorical variables, such as the set of sensors (S), one needs to assign values and perform some kind of optimization. Thus it is a mixed problem, meaning that there are parameters that are discrete (i.e. alternative configurations of sensors) and other parameters that are continuous (i.e. time, or process parameters). Consequently, it would be highly interesting to study whether decoupling of the parameters and simplification would lead to a feasible methodology.

So, to simplify the problem, the model, the sensors, the controller and the architecture will be selected independently of each other; the assumptions are shown below:

- Data communication is taken for granted, while links to higher-level and machine-level functionalities (maintenance) are ignored
- The digital twin is considered to be also a digital representation of the physical system (Figure 2)
- Functionalities are considered to be mainly Process Control (Figure 3a) and no analytics or uncertainty management mechanisms are considered
- The available models are Data Driven Models (empirical) and accelerated physics models offering flexibility, resilience and agility
- The workflow is operated by a software called orchestrator

Thus, only the connectivity is pending to be defined, which is also application-dependent.

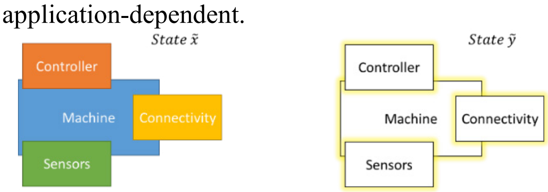

Figure 2. Physical (left) and digital (right) systems with corresponding states

In the next section, an example of an architecture is given, where the orchestrator has been reduced down to regulating a closed-loop scenario for temperature-tracking (process control) of LPBF

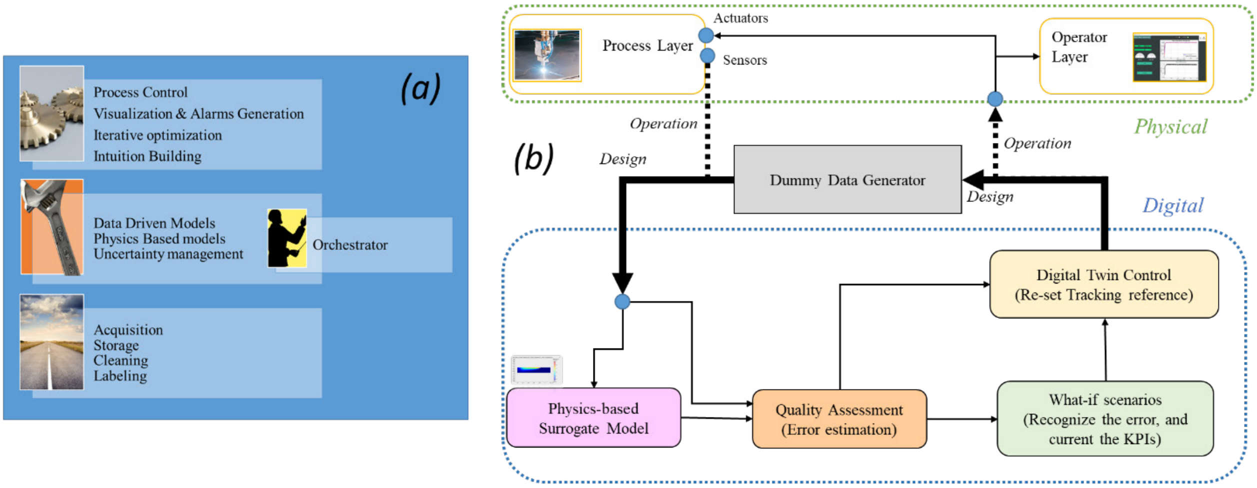

Figure 3. Simplified list of aspects of a digital twin (a) and the proposed digital twin architecture (b)

3. Implementation

The Digital Twin architecture proposed in here attempts to address all the aforementioned challenges (Figure 3b). Thus, there are included: (a) a physics surrogate model that will allow the smooth installation in a new line (first-time-right), (b) a dummy data generator which will allow testing without compromising the production, (c) a Quality assessment monitoring, able to aggregated characteristics from machine learning and control output, (d) running a set of what-if-scenarios boosting productivity and (e) the control generation which will generate the signals that will drive the machine actuators. It is noted that the control is able to integrate various criteria, such as KPIs tracking (as showcased here), robustness [10], energy efficiency [28] and others.

Overall, the Digital Twin in AM design and process-level operation is mandatory to achieve high quality and defect-free production. Hence, an effective procedure has to be designed to keep in track the desired key performance indicators (KPIs). Besides, a DT targets on the:

- Offline prediction of both KPIs and process parameters (PPs)
- Online prediction of KPIs

Thus, both forward and inverse models are required for proper functionality; the first ones guarantee the prediction of KPIs given the values of PPs, and the second ones are assigned with the exact opposite task. This research work adopts machine learning (ML) regression techniques and especially the recurrent neural networks (RNNs). The prediction models are developed through special forms of RNNs and namely the long short-term memory (LSTM), bidirectional LSTM (BiLSTM) and the gated recurrent units (GRUs) [29–31].

However, large datasets are required for the proper training of such algorithms. To this end, and under the spirit of making things first the first time, simulation results are utilized to pre-train this. Uncertainties could be integrated [10] also extending the usability of the models. Furthermore, to guarantee a verisimilar character in the dummy data generator, integrating any variances in behavior or uncertainties to the response the digital twin retrieves during testing phase, AR-X models are used [32] that are able to integrate artificial uncertainty in their response. Finally, the Quality assessment module is augmentable through some if-then rules integrating the error of control and potential use of additional sensors [33]. Also, the uncertainty management mechanism, albeit neglected herein, can easily be integrated thanks to the closed loop control criteria. Regarding the orchestrator, it seems that its role has been limited to handling the data. It can even be a human-in-the-loop workflow.

4. Case study and Results

Regarding the applicability of the current framework, a case study has been set up, with the help of a finite element method assumed for the single-track laser-powder bed fusion (LPBF) AM process as a reference model, while the vital process parameters have been considered to be the power and scan speed of the laser in that case. The dataset consists of 121 different process parameters. A widely used material of Ti64, a Gaussian distribution as the heat source with a laser beam diameter at 100μm and a layer thickness at 30μm are assumed in the simulation for reasons of simplicity. The design space of process parameters is shown in Figure 4. The ranges take into account the process window of Ti64 for high-density parts.

The following subsections are utilized to study the performance of the partial models. More specifically, subsection 4.1 deals with the performance of the forward models predicting the (static) values of KPIs given the PPs, subsection 4.2 deals with the performance of the inverse models and subsection 4.3 presents the performance of the surrogate models predicting the evolution of temperature, given the profile of the PPs in time. Subsection 4.4 is about testing the performance of the overall DT.

4.1 Digital Twin Forward Design (DT FR)

The AM workflow for the selection of process parameters (PPs) is usually driven by the AM engineer, who takes into account the melting material, the pre-heating temperature, the process window of selected material and approximately other 50 in total parameters. Herein, the two key process parameters that have been selected for the DT-FR are the laser power and the scan speed and the targeting KPIs are considered to be the peak temperature and the melt-pool lateral dimension (length), estimated by two separate artificial NNs (ANNs).

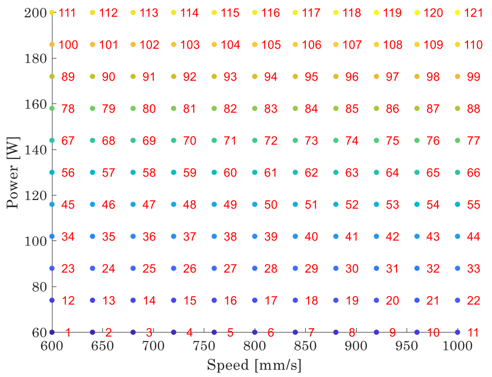

Figure 4. Process parameters space

The ANN characteristics for both aforementioned cases are: two layers, eight hidden neurons per layer, a ratio of 80-10-10 for the training, validation and testing phase, and resilient backpropagation algorithm (Rprop). The extracted KPIs are extracted as values from the simulations (121 sets of Fig. 4 times the configurations of the final temperature). The process parameters of the design space are imported as inputs to the DT-FR then KPIs (temperature or melt-pool length) are predicted, as shown in Fig. 5.

4.2 Digital Twin Inverse Design

A second ANN is trained using as inputs the predicted KPIs and as outputs the PPs, aka inverse design (DT-INV) where the operator can select the desired KPI and the algorithm can return the appropriate machine parameters for the initialization and also in-process level. For the validation of inverse design methodology, ten values of the desired KPI (i.e. melt-pool length) are selected ranging from 0.2 to 0.7 mm where the DT-INV returns the process parameters and imports them to the initial simulation model with the same settings. Fig. 6 depicts the difference between the desired and the actual KPI with the maximum absolute error reaching at 14.7% at the 9th design point (DP). It can be illustrated that the differences appeared in DPs 8-10 are the only ones that are relatively high, in comparison with the case of DPs1-7, due to the training ranges. This issue can be resolved with more time-consuming simulations resulting to a considerable dataset.

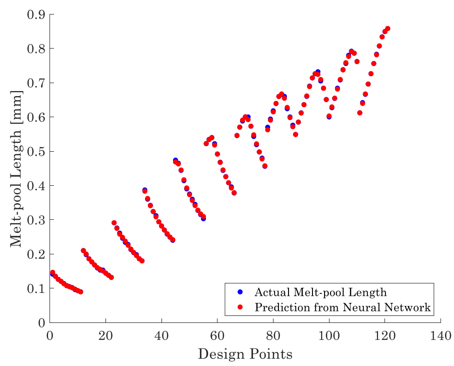

Figure 5. KPIs prediction

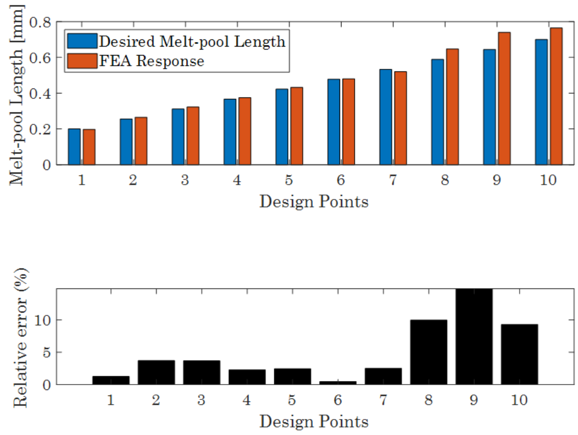

Figure 6. Inverse prediction of process parameters for the desired KPI: melt-pool length

4.3 Real-time Prediction

The DT-AM module is developed herein for the in-layer process level, resulting to the correlation of Virtual Twin (VT) (aka surrogate model) and the Physical Twin. This is the case where the whole response of the physical system is predicted, in terms of a time-series. Hence, the VT considers the temperature prediction at selected nodal coordinates) with an investigation of highly efficient DL algorithms (LSTM, BiLSTM, GRU)

The training procedure of the models that are used as a VT takes into account the ensemble of process parameters. After some trials with respect to the number of layers, the hidden nodes, the number of epochs and the learning rate, the resulted training parameters are shown in Table 1. There are upper limits for the total number of free parameters, as the overfitting is unwanted here. So, in order to decide on the meta-parameters of the model, a brief cross-validation procedure was used, taking into account also the fast convergence of the procedure as an extra criterion of accepting or rejecting alternatives. Extra alternative configurations for really small networks were also pre-excluded, as an ansatz, since the position of the sensor (in the case of nodal temperature prediction), the steady-state temperature value, as well as some artificial uncertainty in the responses were also diversifying factors. For the case of peak temperature evolution prediction, since it refers to a changing node since it is a monitoring problem, the case is slightly different and more neurons are required. As a matter of fact, the investigation of RNNs shows that LSTM achieved the highest accuracy. Hence, the next DT module for the peak temperature prediction, only a LSTM predictive model is developed. The number of hidden neurons is assumed 200, with a learning rate at 7e-3. The response of the predicted time-series is shown in Fig. 11. The accuracy is relative acceptable for a modest dataset, and can predict efficient the actual peak KPI.

Table 1 Training parameters

	Nodal Temperature Prediction			Peak Temperature
Parameters/Model	LSTM	BiLSTM	GRU	LSTM
Optimizer	Adam	Adam	Adam	Adam

Layers	1	1	1	1
Hidden Nodes	128	128	128	200
State Activation Function	tanh	tanh	tanh	tanh
Gate Activation Function	sigmoid	sigmoid	sigmoid	sigmoid
Epochs	50,000	50,000	50,000	20,000
Learning Rate	1e-3	1e-3	1e-3	7e-3

The testing of nine nodal temperature prediction is shown in Fig. 7 for all the developed algorithms. A close-up of the prediction in the case of the first node is depicted in Fig. 8. All three RNNs can successfully predict the response, however quantified methods have to be established. Therefore, the metric R-squared (R^2 – Accuracy (%)) is adopted from regression analysis to compare the testing performance. The R^2(%) values for each nodal position and for each RNN are presented in Figure 9, while the peak temperature prediction is depicted in Fig. 10.

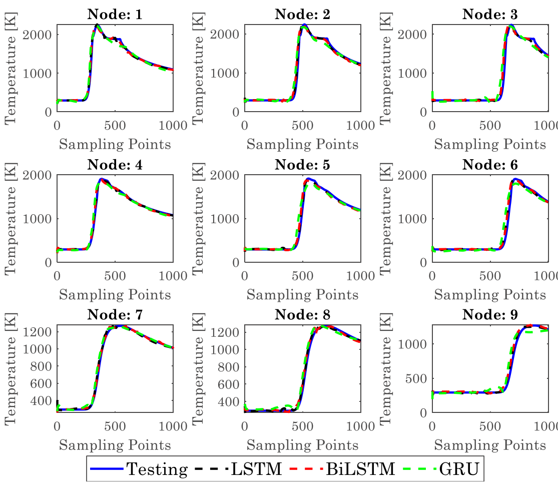

Figure 7. Prediction of nodal temperature

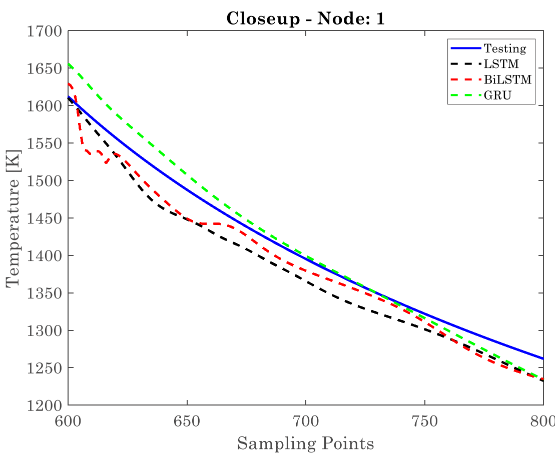

Figure 8. Close-up of prediction on 1st node

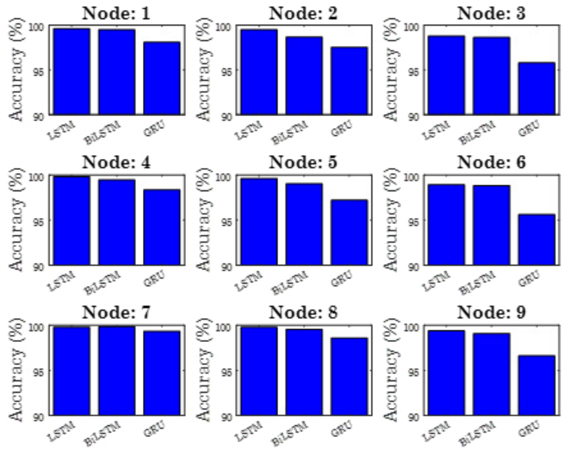

Figure 9. Accuracy of all the RNN models. R-Squared metric multiplied by 100%

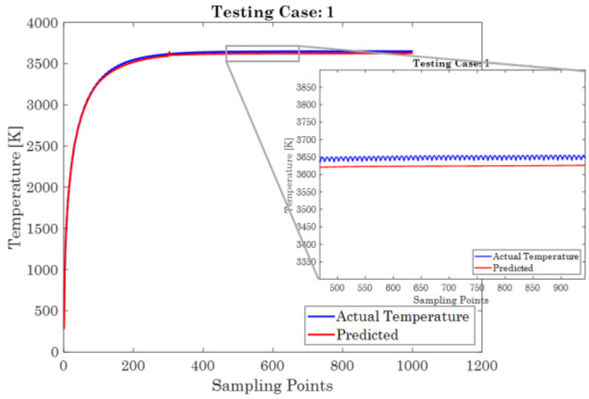

Figure 10 Peak temperature prediction

4.4 Closing the loop

Finally, in Fig. 11, the implemented platform that acts as a digital twin is shown and the scenario of estimating the error between the digital twin and controlling the dummy data generation through a PID controller is shown.

This workflow demonstrates the use of forward and inverse models (gauges on the left of the figure), the Digital Twin where the appropriate PPs are applied (Red line on the right), as well as the AR-X model, where a PID has been applied (blue line on the right).

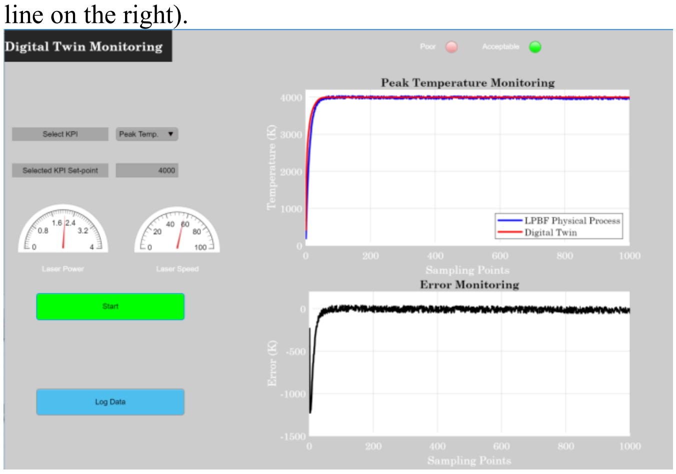

Figure 11. Applying process control through the Digital Twin

It is noted that the AR-X module, as a dummy data generator, as well as the controller have been modelled as individual and autonomous software modules and can be used even under the framework of cloud-control.

5. Conclusions

This research provides a roadmap for designing and implementing Digital Twins with respect to adding agility and resilience in manufacturing. Also, a particular architecture has been applied in AM-LPBF process, as a result of various models integration, integrating three different approaches, i) the forward predictive model where the process parameters, such as power and scan speed, are used to estimate the actual values of the pre-defined KPIs at the steady-state ii) the inverse predicted model where the operator selects the desired KPI value, such as melt-pool length in the current paper, and the algorithm provides the appropriate process parameters, iii) the real-time DT module where the process parameters can instantly predict both the nodal temperature response and the peak temperature.

All the developed DT modules can be integrated into AM machines for near- or real-time prediction with the feedback from monitoring devices for the correlation of responses and the digital twin as a whole has been proved to be quite promising in terms of closed-loop control functionality.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 869986 (EU Project AVANGARD). The dissemination of results herein reflects only the authors' view and the Commission is not responsible for any use that may be made of the information it contains.

References

[1] Stavropoulos P, Papacharalampopoulos A, Tzimanis K, Lianos A. Manufacturing Resilience during the Coronavirus Pandemic: On the investigation Manufacturing Processes Agility. 1 2020;1(3):28–57.
[2] McCann J, Selsky JW. Mastering Turbulence: The Essential Capabilities of Agile and Resilient Individuals, Teams and Organizations: John Wiley & Sons. 2012.
[3] Gu X, Jin X, Ni J, Koren Y. Manufacturing System Design for Resilience. Procedia CIRP 2015;36:135–40.
[4] Girod B, Stenger A, Rabenstein R. Signals and systems: J. Wiley & Sons. 2001.
[5] Wang KS. Towards zero-defect manufacturing (ZDM)—a data mining approach. Adv. Manuf. 2013;1(1):62–74.
[6] Mourtzis D, Angelopoulos J, Dimitrakopoulos G. Design and development of a flexible manufacturing cell in the concept of learning factory paradigm for the education of generation 4.0 engineers. Procedia Manufacturing 2020;45:361–66.
[7] Stavridis J, Papacharalampopoulos A, Stavropoulos P. A cognitive approach for quality assessment in laser welding. Procedia CIRP 2018;72:1542–47.
[8] Assad Neto A, Ribeiro da Silva E, Deschamps F, Pinheiro de Lima E. Digital twins in manufacturing: An assessment of key features. Procedia CIRP 2021;97:178–83.
[9] Bao J, Guo D, Li J, Zhang J. The modelling and operations for the digital twin in the context of manufacturing. Enterprise Information Systems 2019;13(4):534–56.
[10] Stavropoulos P, Papacharalampopoulos A, Michail CK, Chryssolouris G. Robust Additive Manufacturing Performance through a Control Oriented Digital Twin. Metals 2021;11(5):708.
[11] Papacharalampopoulos A, Michail C, Stavropoulos P. Manufacturing Process Control Through a Digital Twin: Encoding Issues. 9th International Conference on Through-life Engineering Service 2020.
[12] Bárkányi Á, Chován T, Németh S, Abonyi J. Modelling for Digital Twins—Potential Role of Surrogate Models. Processes 2021;9(3):476.
[13] Foteinopoulos P, Papacharalampopoulos A, Stavropoulos P. On thermal modeling of Additive Manufacturing processes. CIRP Journal of Manufacturing Science and Technology 2018;20:66–83.
[14] DebRoy T, Zhang W, Turner J, Babu SS. Building digital twins of 3D printing machines. Scripta Materialia 2017;135:119–24.
[15] Favoretto B, Hillerin CA de, Bettinotti O, Oancea V, Barbarulo A. Reduced order modeling via PGD for highly transient thermal evolutions in additive manufacturing. Computer Methods in Applied Mechanics and Engineering 2019;349:405–30.
[16] Zhang Z, Liu Z, Wu D. Prediction of melt pool temperature in directed energy deposition using machine learning. Additive Manufacturing 2020:101692.
[17] Moges T, Yang Z, Jones K, Feng S, Witherell P, Lu Y. Hybrid Modeling Approach for Melt-Pool Prediction in Laser Powder Bed Fusion Additive Manufacturing. Journal of Computing and Information Science in Engineering 2021;21(5).
[18] Yavari R, Williams R, Riensche A, Hooper PA, Cole KD, Jacquemetton L, et al. Thermal modeling in metal additive manufacturing using graph theory – Application to laser powder bed fusion of a large volume impeller. Additive Manufacturing 2021;41(2):101956.
[19] Liu R, Liu S, Zhang X. A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing. Int J Adv Manuf Technol 2021;113(7-8):1943–58.
[20] Stathatos E, Vosniakos G-C. Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach. Int J Adv Manuf Technol 2019;104(5-8):1967–84.
[21] Stathatos E, Vosniakos G-C. Efficient temperature regulation through power optimization for arbitrary paths in Laser Based Additive Manufacturing. CIRP Journal of Manufacturing Science and Technology 2021;33(8):133–42.
[22] IBM Developer. What are digital twins? 2019 . Accessed on 01-06-21. Available from: https://developer.ibm.com/technologies/iot/articles/what-are-digital-twins/.
[23] Stavropoulos P, Papacharalampopoulos A, Athanasopoulou L. A molecular dynamics based digital twin for ultrafast laser material removal processes. Int J Adv Manuf Technol 2020;108(1-2):413–26.
[24] Fuller A, Fan Z, Day C, Barlow C. Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access 2020;8:108952–71.
[25] Coolfire. What is the Difference Between IT and OT? | Coolfire Solutions Blog . Accessed on 01-06-21. Available from: https://www.coolfiresolutions.com/blog/difference-between-it-ot/.
[26] Andre P, Azzi F, Cardin O. Heterogeneous Communication Middleware for Digital Twin Based Cyber Manufacturing Systems. International Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing 2019:146–57.
[27] Yin D, Ming X, Zhang X. Understanding Data-Driven Cyber-Physical-Social System (D-CPSS) Using a 7C Framework in Social Manufacturing Context. Sensors (Basel, Switzerland) 2020;20(18).
[28] Apostolos F, Alexios P, Georgios P, Panagiotis S, George C. Energy Efficiency of Manufacturing Processes: A Critical Review. Procedia CIRP 2013;7:628–33.
[29] Ghavamian F, Simone A. Accelerating multiscale finite element simulations of history-dependent materials using a recurrent neural network. Computer Methods in Applied Mechanics and Engineering 2019;357:112594.
[30] Shrestha A, Mahmood A. Review of Deep Learning Algorithms and Architectures. IEEE Access 2019;7:53040–65.
[31] Mohan AT, Gaitonde DV. A Deep Learning based Approach to Reduced Order Modeling for Turbulent Flow Control using LSTM Neural Networks. arXiv:1804.09269v1. 24-Apr-18.
[32] Ljung L. System Identification: Wiley encyclopedia of electrical and electronics engineering. 2017.
[33] Stavropoulos P, Papacharalampopoulos A, Stavridis J, Sampatakakis K. A three-stage quality diagnosis platform for laser-based manufacturing processes. Int J Adv Manuf Technol 2020;110(11):2991–3003.