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APPLICATIONS OF MACHINE LEARNING IN INDUSTRY 4.0 FOR ADDITIVE MANUFACTURING

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Abstract: The shift from traditional industrial automation to smart manufacturing systems, commonly known as Industry 4.0, has revolutionized the production landscape. This transformation is characterized by high levels of automation and the integration of information technology into manufacturing processes. Smart manufacturing systems utilize machines and robots with the ability to process information, improve production yields, provide real-time performance visualization, enable intelligent predictive maintenance, and facilitate the alignment of service providers with customer demands. While various control systems have been proposed for smart factories, challenges remain in coordinating the actions of individual machines with the broader objectives of the system. Most control systems incorporate a combination of centralized and decentralized architectures, which may not fully meet the requirements of Industry 4.0. Furthermore, there is a scarcity of information on how to manage, ensure interoperability, and control data within a smart factory. Prior research has predominantly focused on the control system and communication aspects, often overlooking the technical aspects of machine enablement in a smart factory. This paper explores the dynamic landscape of smart manufacturing, discussing the challenges and opportunities in implementing effective control systems and enabling seamless data management within Industry.

Keywords: Smart manufacturing, Industry 4.0, control systems, data management, automation.

1. Introduction

The industrial automation was previously enabled by Programmable Logical Controller (PLC) that provided synergy between information technology and electronics. In this system, the workforce has a specific and repetitive task generally without high-level skills. In smart manufacturing system (also known as Industry 4.0) (Hermann, Pentek, & Otto, 2016), machines and robots provide a high automation level with the ability to process information, enhance the yield of production (Zhang, Mehta, Desai, & Higgs, 2017), visualize the performance in real-time (Xu, Mei, Ren, & Chen, 2017), enable intelligent predictive maintenance system (K.-S. Wang, Li, Braaten, & Yu, 2015), and match service providers with customer demands.

There were some suggestions to implement the control system for a smart factory including a combined system composed of virtual reality and rapid prototyping (Zawadzki & Żywicki, 2016) and a dynamic algorithm for the simultaneous selection of machine structure and job assignment (Ivanov, Dolgui, Sokolov, Werner, & Ivanova, 2016). The architecture of the most decentralized control system is fitted to a dynamic environment with the ability to quickly adapt to change. However, coordinating a single machine that attempts to pursue its objective

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and at the same time pursuing the global objective of the system remains a challenge for the control system. As such, most of the control systems are a mixture of centralized and decentralized architectures (Brennan, 2000) that cannot fully address the requirement of Industry 4.0 (Meissner, Ilsen, & Aurich, 2017). Also, there is no concrete information on how it can enable the management, interoperability, and control of data inside a smart factory. Most of the previous research studies focus on the control system and communication of a smart factory based on cyber-physical systems (CPS) and cloud-computing platforms (Liu, Shahriar, Al Sunny, Leu, & Hu, 2017) and little attentions to the technical enabling of machines in a smart factory.

Additive Manufacturing (AM) is a crucial component of the smart manufacturing system to enable flexible configuration and dynamic changing processes (Scholz-Reiter, Weimer, & Thamer, 2012), quickly adapt the products to new demands, and eventually change traditional supply chains. AM has tremendous potential to make a customdesigned part on-demand with minimal material, but it is hampered by poor process reliability and throughput due to lack of the condition-awareness of the AM process and automation. The parts built using current state-of-the-art AM machines have noticeable unpredictable mechanical properties.

Currently, almost all AM machines have only limited sensing capabilities that are mostly inaccessible to the users, or completely "open-loop" system operating without any feedback measurement systems for correction during the process. However, future AM machines must be a smart system that can perform self-monitoring, self-calibrating, and quality self-controlling in real-time. The gap between the smart factory and existing manufacturing systems can be bridged concerning the automation, flexibility, and reconfigurability of AM machines in an interactive distributed network as a natural way of scaling up learning algorithms.

Machine learning can play an important role to create multi-level of predictive models for both individual AM machine operation (Zhang et al., 2017) and the system-level smart factory management. However, a few ML models have been explored in existing studies and the application of ML algorithm for improving the AM process has been limited to powder quality, specific processes, and applications. For instance, Chen et. al. (Chen & Zhao, 2015) developed a ML model to optimize parameters of a Binder Jetting (BJ) process without a comprehensive understanding of why the ML model would work better for some particular processes. Some papers are only focused on controlling powder quality using ML model: Zhang et. al (Zhang et al., 2017) trained a machine learning model using computational data of the discrete element method to introduce a powder spreading map for the metal AM process. Decost et. al. (DeCost, Jain, Rollett, & Holm, 2017) used computer vision and machine learning methods to characterize, compare, and analyze powder feedstock materials and micrographs for metal AM process. Stoyanov et al.

(Stoyanov & Bailey, 2017) used a ML algorithm to control the quality of 3D inkjet printing for electronic circuits. In this paper, we propose the application of machine learning for controlling AM machines (D. Wang, Khosla, Gargeya, Irshad, & Beck, 2016) and managing a smart factory. Smart 3D printers need to keep track of the AM process to manage AM operations and optimize the procedure by adjusting the process parameters as they sense certain properties of a build. We describe how a distributed ML algorithm can quickly and dynamically adapt to the change in the manufacturing environment, coordinating a single machine for its objective and pursuing the global objective of the system at the same time. The rest of the paper is organized as follows. Section 2 presents the proposed ML model for improving the AM process in 3D printers. Section 3 presents the attribute and properties of the distributed ML model in a smart factory and explains how this model fulfils the requirements of Industry 4.0 including self-organization, distributed control function, communication between the smart components, and realtime decision-making capability. The section also discusses how the model benefits a smart factory focusing on product performance, security, reliability, scalability, and cost-efficiency. Section 4 draws summarizing conclusions.

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2.   Machine Learning Model For Improving Additive Manufacturing Process

Additive manufacturing plays a critical role to produce high-quality industrial parts, but its application for large-scale finished goods is minuscule due to the challenges in scaling down the AM process. A smart AM machine improves the geometry and mechanical properties as shown in Fig.1 (fotografie). AM machines can be empowered by the ML model to fabricate miniaturized builds with complex geometry that are usually difficult to be fabricated by the subtractive- or deformation-based manufacturing processes. For instance, hollow objects with thin-shell structures seem more suitable for hybrid fabrication because AM processes can overcome accessibility limitations to the internal features. Figure 2 shows the two-step strategy to establish the closed-loop ML algorithm for AM machines: the offline training of an ML system for identifying multi-model correlation and representative sensor and the use of the offline trained ML model for real-time AM process control.
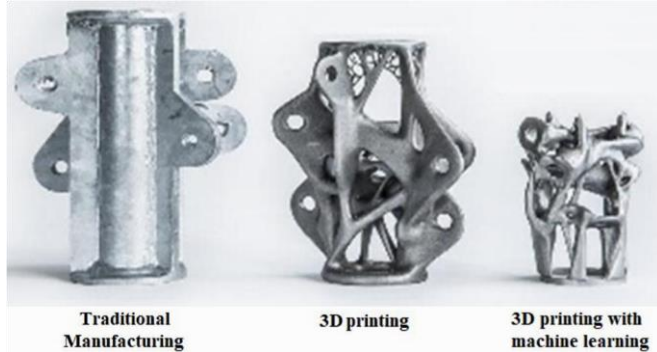

Figure 1: Example of three structural nodes that all support the same weight, but the part on the right that manufactured by 3D printing and machine learning algorithms weight 75% less and is 50% smaller than the original part on the left (fotografie).
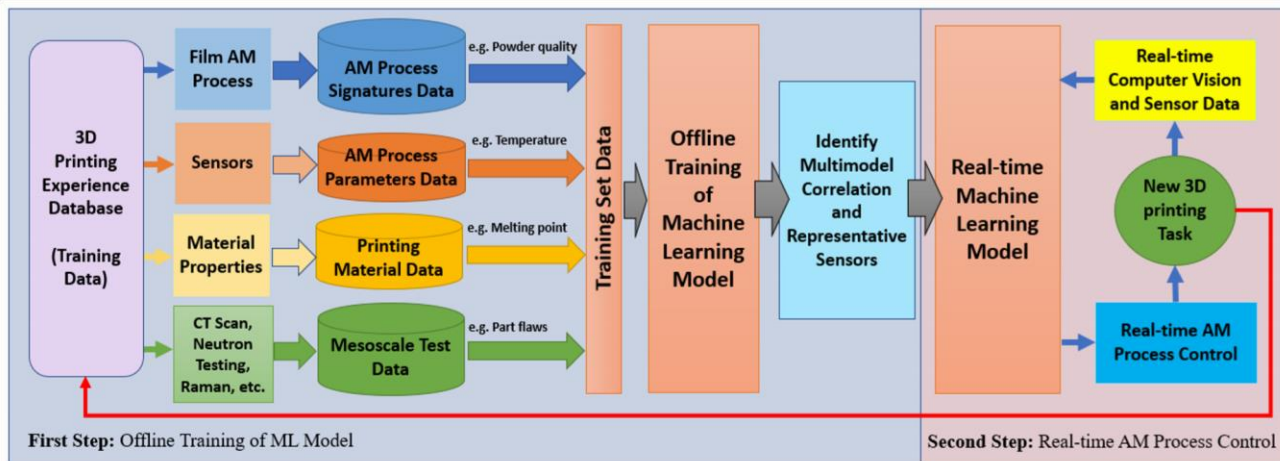

Figure 2: Two-step strategy to establish the closed-loop ML algorithm for AM process control.

2.1. Offline ML Model

Offline Training of ML Model is the first step to establish the closed-loop ML algorithm for AM machines as shown in Fig.2. The procedure includes four sub-steps as follows:

2.1.1. Filming AM Process: *By filming the AM process, one can understand what characteristics would lead to a good build by observing the behavior of each powder layer before, during, and after laser scanning. Powder spreading (Perret, Graf, & Sagmeister, 2004) and laser scanning (Jia & Gu, 2014) are important factors for the*

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quality of the final part. This includes filming the build of every layer in printing simple geometric shapes like flat bars and cylinders and record any streaks, pits, divots and other patterns in the powder layer that are practically invisible to humans.

2.1.2. Collecting Sensory: *Multiple sensors can be used to capture certain properties of the printed build from different perspectives. Different types of sensors measure certain characteristics of every layer of the samples. For instance, the thermal images of selective fusing can be captured using IR cameras as the process parameter data (e.g. process temperature), which can significantly affect the mechanical properties of the final metal part (e.g. residual stress, strength, porosity and microstructure due to poor thermal gradients in metal AM processes). In the case of noisy sensor data, data pre-processing techniques such as temporal-spatial smoothing, convolutional filtering, and clustering can be used to refine online sensing data, which are critical in real-time monitoring.*

2.1.3. Collecting Mesoscale Information: *The final builds will be examined using neutron testing (Gnäupel-Herold, Slotwinski, & Moylan, 2014), Raman (Beard, Ghita, & Evans, 2011), or a powerful CT scanner (Karme, Kallonen, Matilainen, Piili, & Salminen, 2015)to hunt for flaws in the printed part. The powder-bed 3D printers are optimized to work only with a handful of powders and the parts built using such printers have a rough exterior and porous interior. Collecting and analyzing the optical scan imaging data of the 3D printed metal parts provides mesoscale information that we either can't see or may not know what to look for(Brooks et al., 2018).*

The training ML algorithm interpolates between the observed mechanical performance in the final sample and process signatures in the powder layers during the laser scanning process. The well-trained ML correlates defects in the final parts with powder layer patterns and other AM process parameters. Once the comprehensive sensing data are correlated with mechanical properties and printing qualities, and a couple of simple sensors have stood out as representatives, one can use the correlation to control multiple tasks in the AM process in real-time.

2.2. Real-Time AM Process Control

As the smart AM machine creates a large amount of real-time data, it warrants the effective use of online ML techniques so that the smart control system learns and adapts while the AM machine is operating. Given a collection of training samples with ground truth labels from human experts, multi-modal multi-task learning can be developed to correlate measurements from different sensors and techniques to identify a few representative instruments such as mechanical properties prediction and defect detection. The selected sensors will be used to collect real-time data, and input to the correlation function obtained from the offline DNN model to predict the mechanical properties and possible defects in real-time. The ML model will observe the real-time behavior of the powder layers and other realtime sensory data to predicts and flag system failures before they happen, leading to a better chance of getting to the 100 percent yield. The system will decide on "go" or "no go" and suggest potential remedial actions.

The smart 3D metal printers track the repetitive spreading of powder and selective fusing to automatically modify the AM parameters to generate layers with desirable roughness and porosity. The ML model extracts the physical variations in powders, classify powders with different distributions of particle size, shape, and surface texture, and relate these microstructural features of powders to processing parameters (flowability and spreadability) and build outcomes (porosity and flaws).

A closed-loop ML model in a smart 3D printer can manage AM operations and optimize the procedure autonomously by adjusting the process parameters as they sense certain properties of a build. The more often we print samples, the smarter the ML model gets and eventually have enough training to automatically predict a problem, and in real-time, suggest changes to reach a flawless build. This turns 3D metal printers into essentially their inspectors by eliminating the need to inspect parts after they are completely built. As such, the machine

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makes better products, faster, with fewer errors, resulting in a breakthrough in productivity. The new AM task can be used to increase the 3D printing database so that AM machine trains over time to recognize any issues with the process itself and make proper adjustments and corrections itself. The ML model eventually has enough training to automatically predict a problem, provide the derived insights immediately and suggest changes in real-time to reach a flawless build. AM machine empowered by machine learning can observe new and different scenarios, takes in new part build data, learns from experience, becomes smarter and more capable, continuously improve the manufacturing process, automatically selfcorrect/compensate the deficiencies, thereby adds another layer of quality control. This enhances the process and quality of the AM process, thereby produce better parts with fewer quality hiccups, limiting waste of time and materials.

3.   **Distributed Machine Learning Model of Additive Manufacturing Process in a Smart Factory**

In this section, we describe how ML models of AM machines can be distributed to comply with a smart manufacturing system. The product quality, system productivity and sustainability can be improved through fully connected manufacturing machines (e.g. 3D printers) that are monitored by sensors and controlled by an advanced computational intelligence. The unprecedented volumes of manufacturing data can be analyzed by data-driven intelligence to model the complex multivariate nonlinear relationships among data and extract actionable and insightful information for smart manufacturing. The manufacturing is experiencing an unprecedented increase in available sensory data from manufacturing equipment, manufacturing process, production line, environmental conditions, and labor activity. To establish manufacturing intelligence, the huge collected data is essential to be handled and processed in real-time by big data modelling and analyzing methods (Kusiak, 2017). Data modelling and analysis is an essential part of smart manufacturing to fulfil the current and future needs for efficient and reconfigurable production (Vogl, Weiss, & Helu, 2016). Monitoring machinery conditions is crucial for a smart factory to identify the incipient defects and thereby avoid the failures caused by degradation or abnormal operating conditions, resulting in lower operating costs, higher productivity, less disqualified part waste, and less unexpected downtime (Park, Kwon, Park, & Kang, 2016). Manufacturing intelligence enables precise insights for better decision making and thereby improves product designs, processes, operations, fault detection, maintenance, and quality (Harding, Shahbaz, & Kusiak, 2006).

In future smart factories, not only the components (e.g. 3D metal printers) are smart to make local decisions, but also the system is smart and context-aware resulting in two layers of smart decision-making system. In this scenario, we need a distributed machine learning (DML) model as an interactive learning procedure among AM machines and a natural way of scaling up ML algorithms. The trained ML model represents a hypothesis for a single AM machine, but the DML model is not necessarily contained within the hypothesis space of the models from which it is built, showing more flexibility in the functions. AM has tremendous potential to make a custom-designed part ondemand with minimal material, but it is hampered by poor process reliability and throughput, especially in metal printing. The 3D printers equipped with sensors and communication capabilities can further improve the conditionawareness of AM processes and the level of automation resulting in a quality product with the potential to dynamically changing with customer demands (Lalanda, Morand, & Chollet, 2017; Tao & Qi, 2017). An adaptive ML algorithm for 3D printers can be developed with the ability to learn from printing experience commanded by users. However, there might be a circumstance that the machine performance is low for printing new build because of no data and experience. To develop better ML algorithm that incorporates these experiences, one may collect more data by printing the build with such types of AM features or by obtaining AM data from other 3D machines and store in a hub to analyze by centralized unit and make a very comprehensive all-purpose ML algorithm for all the AM machines in the smart factory. However, a unique comprehensive ML algorithm is not efficient since it deviates from the specific kinds of AM task for a machine.

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In a very limited case, a machine needs learning many experiences, e.g. printing unique geometries or materials. Also, this method means a huge data collection and transmission to the hub and far away from the goal of industry 4.0. The DML model could employ the pre-trained ML model from a relevant task for its initialization. Finetuning is possible by transferring the data for new printing experience through closed-loop structure that enables knowledge updating and intelligence upgrading. This cyber-physical system empowered by ML algorithm monitors AM processes, creates a virtual copy of the physical process, and makes decentralized decisions based on selforganization mechanisms. The smart 3D printers will make decentralized decisions and communicate using a virtual copy of the DML system to achieve the goal of intelligent, resilient and self-adaptable components (Lee, Bagheri, & Kao, 2015) (see Fig. 3). The smart 3D metal printers are interconnectively synchronized with their corresponding modules in virtual space creating feedback loops in which physical processes affect its virtual model in real-time and vice versa (Hofmann & Rüsch, 2017; Lee, 2015). The aggregation of sensor data enables the creation of a virtual environment in which the design can be checked, modified, and tested prior to its order into the physical system (Zawadzki & Żywicki, 2016). This integrates computation, networking, and physical processes. In the DML model, the mind is in the individual machine with a certain degree of self-control to learn from its own experience and adapt the ML algorithm for the type of AM task 3D printers must do. The DML model enables not only a smart system to adjust the components for new demands and circumstances, but also each component of the system to act smart and communicates with each other to either request or offer functions. Each AM machine needs to process and learn separately from its own collected data, but also share and give access to some data for other AM machines. In this model, the raw collected data from all the machines will not be used to decide for every component of the system, but an individual AM machine has the authority to decide how to improve its task using its own collected data. The ML model is developed based on just its own experience without sharing raw data in the centralized hub while it makes the result of training experience available for other AM machines in the smart factory. The DML model fulfils the requirements of the smart factory as follows:

A.   **Self-organization:** *The ML models of smart AM machines are capable of managing the operations and optimizing the procedure autonomously by adjusting their parameters as they sense certain properties of a build. In a manufacturing chain, the modular structure of smart AM machines results in the improvements of the entire process due to the customization and personalization of smart machines for the types of builds that they are usually printing within the interconnected network. The distributed control function using smart AM machines is one of the main requirements for the modular and decentralized structure of Industry 4.0.*

B.   **Information on Workpieces:** *The local ML algorithm enables AM machine to extract the information from the*
current and targeted build (design in the CAD software) and thereby recognize if the available ML algorithm in the machine has enough AM experience to successfully print the build or it is new and different scenarios that need the AM experience of other machines available in the smart factory. The digital information is embedded into the build that can be shared with other smart AM machines via the proposed DML model as it moves along the production line. This information will be interpreted by a cyber-enabled DML model so that a machine knows if the AM task is in the domain of its high chance of success or an anomaly setting that are not experienced before and needs to use other resources or experience.

C.   **Communication with Other AM Machines**: *In the production line of a typical smart factory, many machines will be fully connected by a constant stream of data through the DML model to communicate with each other to either request or offer functions. The local smart AM machines who need more training experience must search for the machines with the better trained ML algorithm on the needed AM tasks and communicate with them to adapt its ML algorithm to other AM training without having to communicate with the central control*

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unit. The AM machines are independent of each other and central hub while autonomously communicating with each other, e.g. along the value chain, to obtain the required AM parameters and feature if there is a lack of local training experience for printing new build. All the AM machines can make intelligent decisions based on the data collected from their process, i.e. using various sensors, but communicate with each other to predict various supply chain scenarios.

D.   Real-Time Capability: *The smart AM machine is seamlessly integrated into the information network with the*

capability to collect and analyses its own AM data using the local ML algorithm and use the AM experience of other machines in the case of printing a build with a new scenario. The DML model eventually has enough training to automatically predict a problem, provide the derived insights immediately and suggest changes in real-time to reach a flawless build.
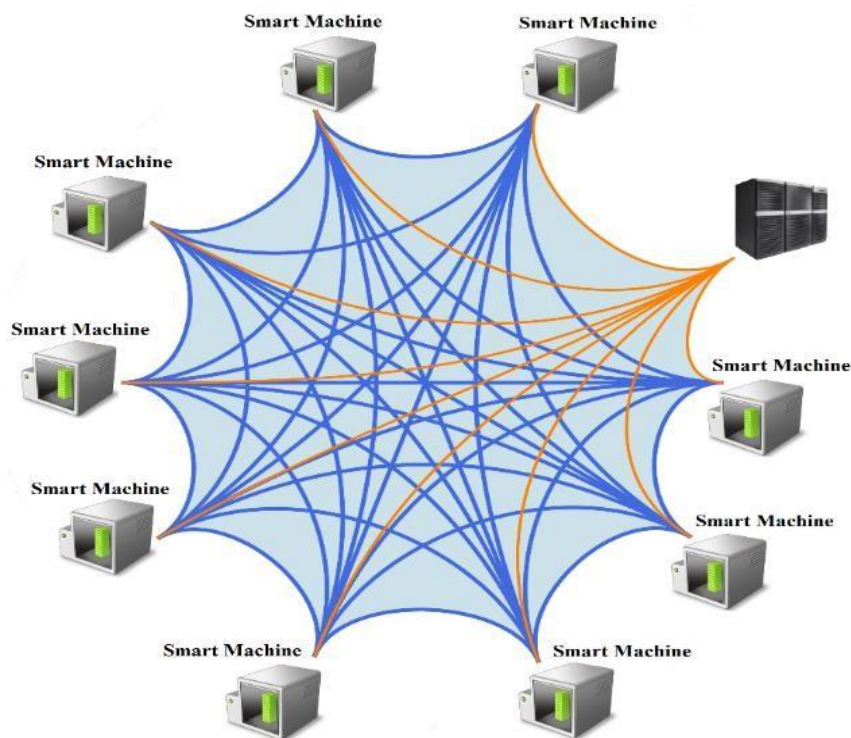

Figure 3 Conceptual schematics of a smart AM factory composed of modular and decentralized smart 3D printers that communicate the lesson of its own machine learning algorithm with each other.

The ML model leads to big efficiency gains by achieving just-in-time maintenance and near-zero downtime and significant time-to-market reductions. The DML model improves product performance, security, reliability, scalability, cost and prevent downtime and failure as follows:

A.   Improved Product Performance: *The ML computations and sensors are integrated into physical 3D metal printers allowing in-process detection of any areas of quality concern so that it is trained over time to recognize any issues with the build itself to make proper adjustments and improve the printing performance. The different AM machines can have the best learning algorithms of their data while the communication between different learning processes is an integration of different learning biases that compensate one another for their*

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inefficient characteristics and thereby increases the possibility of achieving higher accuracy, especially on a large-size domain.

B.   Improved Security: *The computations and sensors are integrated into physical 3D printers that are controlled by a local ML algorithm. Unlike classical could computing, the data is not collected and stored in a database for central processing (Erickson, 2009). In the proposed DML system, each smart AM machine maintains its dataset resulting in higher data protection and security.*

C.   Improved Reliability: Manufacturing resources are similar to a chain fashion; failure of one ring may cause downtime for the whole chain. The commands for all sensors and motors of an AM machine are being processed by a locally trained ML algorithm that leads to distributed control functions. The local ML algorithms analyze continuously acquired data from its sensors and forecast equipment status and information, enabling just-in-time maintenance and thereby improvement in the reliability of AM process.

D.   Improved Scalability: *Another advantage of distributed smart printers is that the size of a smart factory is scalable and the growing amount of data from additional 3D printers has a minor effect on the communication overheat. The local learning and global integration are the most promising solution to overcome the problems of centralized storage, resulting in accurate predictions based on multiple models. The DML algorithm makes AM machines precise and robust to be scaled up and used for commercial and industrialscale production.*

E.   Improved Cost-Efficiency: *The total cost of storing distributed data is much lower than the cost of storing the data in a central database. Similarly, the sum of the cost of analyzing subsets of data is lower than the computational cost of mining a central database. A distributed mining approach would make a better exploitation of the available resources. It is also unfeasible to transfer huge data volumes over the network to frequently update databases because it is costly and time-consuming to establish a high-bandwidth wireless network environment.*

4.   Summary and Conclusion

Additive manufacturing has tremendous potential to make a custom-designed part on-demand, but it is currently hampered by poor process reliability and throughput. Machine learning can play a critical role to ensure the continuous growth of AM technology. In this paper, a ML algorithm for controlling the AM process was proposed to continuously improve the AM standard in the 3D printers. Furthermore, a distributed machine learning algorithm was proposed an interactive learning technique among AM machines to scale up the ML algorithms in a smart factory. The DML model can fulfill the requirements of industry 4.0 and benefit a smart factory through product performance, security, reliability, scalability, and cost-efficiency.

References

Beard, M., Ghita, O., & Evans, K. (2011). Using Raman spectroscopy to monitor surface finish and roughness of components manufactured by selective laser sintering. Journal of Raman Spectroscopy, 42(4), 744-748.

Brennan, R. W. (2000). Performance comparison and analysis of reactive and planning-based control architectures for manufacturing. Robotics and Computer-Integrated Manufacturing, 16(2-3), 191-200.

Brooks, A. J., Hussey, D. S., Yao, H., Haghshenas, A., Yuan, J., LaManna, J. M., . . . Guo, S. (2018). Neutron interferometry detection of early crack formation caused by bending fatigue in additively manufactured SS316 dogbones. Materials & Design, 140, 420-430.

Original Article

Chen, H., & Zhao, Y. F. (2015). Learning Algorithm Based Modeling and Process Parameters Recommendation System for Binder Jetting Additive Manufacturing Process. Paper presented at the ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.

DeCost, B. L., Jain, H., Rollett, A. D., & Holm, E. A. (2017). Computer vision and machine learning for autonomous characterization of am powder feedstocks. JOM, 69(3), 456-465.

Erickson, J. (2009). Database Technologies: Concepts, Methodologies, Tools, and Applications: Concepts, Methodologies, Tools, and Applications (Vol. 1): IGI Global. Courtesy of ARUP, Davidfotografie (https://www.arup.com/projects/ additive-manufacturing)

Gnäupel-Herold, T., Slotwinski, J., & Moylan, S. (2014). Neutron measurements of stresses in a test artifact produced by laser-based additive manufacturing. Paper presented at the AIP Conference Proceedings.

Harding, J., Shahbaz, M., &Kusiak, A. (2006). Data mining in manufacturing: a review. Journal of Manufacturing Science and Engineering, 128(4), 969-976.

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for industrie 4.0 scenarios. Paper presented at the System Sciences (HICSS), 2016 49th Hawaii International Conference on.

Hofmann, E., &Rüsch, M. (2017). Industry 4.0 and the current status as well as future prospects on logistics. Computers in Industry, 89, 23-34.

Ivanov, D., Dolgui, A., Sokolov, B., Werner, F., & Ivanova, M. (2016). A dynamic model and an algorithm for shortterm supply chain scheduling in the smart factory industry 4.0. International Journal of Production Research, 54(2), 386-402.

Jia, Q., & Gu, D. (2014). Selective laser melting additive manufacturing of Inconel 718 superalloy parts: Densification, microstructure and properties. Journal of Alloys and Compounds, 585, 713-721.

Karme, A., Kallonen, A., Matilainen, V.-P., Piili, H., & Salminen, A. (2015). Possibilities of CT scanning as analysis method in laser additive manufacturing. Physics Procedia, 78, 347-356.

Kusiak, A. (2017). Smart manufacturing must embrace big data. Nature News, 544(7648), 23.

Lalanda, P., Morand, D., &Chollet, S. (2017). Autonomic mediation middleware for smart manufacturing. IEEE Internet Computing, 21(1), 32-39.

Lee, J. (2015). Smart factory systems. Informatik-Spektrum, 38(3), 230-235.

Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18-23.

Original Article

Liu, X. F., Shahriar, M. R., Al Sunny, S. N., Leu, M. C., & Hu, L. (2017). Cyber-physical manufacturing cloud: Architecture, virtualization, communication, and testbed. Journal of Manufacturing Systems, 43, 352-364.

Meissner, H., Ilsen, R., &Aurich, J. C. (2017). Analysis of control architectures in the context of Industry 4.0. Procedia CIRP, 62, 165-169.

Park, J.-K., Kwon, B.-K., Park, J.-H., & Kang, D.-J. (2016). Machine learning-based imaging system for surface defect inspection. International Journal of Precision Engineering and Manufacturing-Green Technology, 3(3), 303310.

Perret, H., Graf, B.-F., &Sagmeister, U. C. (2004). Device for supplying powder for a device for producing a threedimensional object layer by layer. In: Google Patents.

Scholz-Reiter, B., Weimer, D., &Thamer, H. (2012). Automated surface inspection of cold-formed micro-parts. Cirp annals-manufacturing technology, 61(1), 531-534.

Stoyanov, S., & Bailey, C. (2017). Machine learning for additive manufacturing of electronics. Paper presented at the Electronics Technology (ISSE), 2017 40th International Spring Seminar on.

Tao, F., & Qi, Q. (2017). New IT driven service-oriented smart manufacturing: framework and characteristics. IEEE Transactions on Systems, Man, and Cybernetics: Systems.

Vogl, G. W., Weiss, B. A., &Helu, M. (2016). A review of diagnostic and prognostic capabilities and best practices for manufacturing. Journal of Intelligent Manufacturing, 1-17.

Wang, D., Khosla, A., Gargeya, R., Irshad, H., & Beck, A. H. (2016). Deep learning for identifying metastatic breast cancer. arXiv preprint arXiv:1606.05718.

Wang, K.-S., Li, Z., Braaten, J., & Yu, Q. (2015). Interpretation and compensation of backlash error data in machine centers for intelligent predictive maintenance using ANNs. Advances in Manufacturing, 3(2), 97-104.

Xu, P., Mei, H., Ren, L., & Chen, W. (2017). ViDX: Visual diagnostics of assembly line performance in smart factories. IEEE transactions on visualization and computer graphics, 23(1), 291-300.

Zawadzki, P., &Żywicki, K. (2016). Smart product design and production control for effective mass customization in the Industry 4.0 concept. Management and Production Engineering Review, 7(3), 105-112.

Zhang, W., Mehta, A., Desai, P. S., & Higgs, C. (2017). Machine learning enabled powder spreading process map for metal additive manufacturing (AM). Paper presented at the Int. Solid Free Form Fabr. Symp. Austin, TX.