evaluating artificial intelligence effects on additive manufacturing by machine learning procedure

Kubura Motalo [1], Lolade Nojeem [1], Vivian Lotisa [2], Mike Embouma [2], Ibrina Browndi [2]
[1] Department of Computer Science, Rivers State University, Port Harcourt, Nigeria
[2] Department of Urban and Regional Planning, Rivers State University, Port Harcourt, Nigeria

ABSTRACT
Additive manufacturing of three-dimensional objects are now more and more realised through 3D printing, known as an evolutional paradigm in the manufacturing industry. Artificial intelligence is currently finding wide applications to 3D printing for an intelligent, efficient, high quality, mass customised and service-oriented production process. This paper presents a comprehensive survey of artificial intelligence in 3D printing. Before a printing task begins, the printability of given 3D objects can be determined through a printability checker using machine learning. The prefabrication of slicing is accelerated through parallel slicing algorithms and the path planning is optimised intelligently. In the aspect of service and security, intelligent demand matching and resource allocation algorithms enable a Cloud service platform and evaluation model to provide clients with an on-demand service and access to a collection of shared resources. We also present three machine learning algorithms to detect product defects in the presence of cyber-attacks. Based on the reviews on various applications, printability with multi-indicators, reduction of complexity threshold, acceleration of prefabrication, real-time control, enhancement of security and defect detection for customised designs are seen of good opportunities for further research, especially in the era of Industry 4.0.

KEYWORDS: additive manufacturing, machine learning, powder bed fusion, feedback loop

1.0 INTRODUCTION
Today 3D printing (3DP) is known as one of the advanced manufacturing technologies and also a revolutionary progress for the next-generation manufacturing industry. It refers to the layer-basis additive manufacturing of three dimensional object using digital data. The prefabrication stage aims to enhance the reliability and feasibility of 3DP. A 3D printable model designed through Computer-Automated Design (CAD) or 3D scanning is presented as triangle meshes in Stereolithography (STL) format and then converted into sliced layers with G-code to instruct a 3D printer. The prefabrication of image based slicing, path planning, support generation, orientation, repairing and packaging can significantly speed up the construction time and reduce the cost and material waste. Throughout the printing process, a typical 3D printer implements fabrication of a physical object according to G-codes. The “ink-jet” printing nozzle and platform move respectively in horizontal and vertical directions to construct each layer which is composed of massive segments along the predefined path. The process typically uses the binder, laser or electron beam to solidify materials such as polymer, metal, and ceramic. Meanwhile, the extruder wheel can control the flow rate of material [1-13]. At present, 3DP has been widely used in numerous domains including medical, architecture, food, mechanics, aeronautics, chemical industry, education and social culture, etc. Nevertheless, the limitations hindering the popularisation of 3DP still exist in the nowadays manufacturing industry. The excessive time consumption, shortage of real-time control, potential security hazard and transform from mass production to mass customisation are principal problems that require being solved by computational intelligence, so-called artificial intelligence (AI). To date, AI has been developed in various forms and applied successfully in a wide range of fields, including aviation, computer science, finance, education, healthcare, medicine, transportation, industrial manufacturing and so on [14-28]. It provides various algorithm, theories, methods and offers great potential to transform the current manufacturing technique under the situation of ever- increased data repository. For example, machine learning (ML) is one representative of AI, which enables machines to learn and improve autonomously. Applying ML in manufacturing can derive the useful information out of existing data sets, so that provides a basis for approximations or predictions to operate machines with future behaviours such as decision-making and

automatic system improvement. It is also beneficial to detect certain patterns or explore regularities in a dynamic manufacturing environment [29-38]. In this paper, a comprehensive survey of various AI methods applied throughout 3DP are presented with analyses in Section 2. It includes AI in printability checking, slicing acceleration, nozzle path planning, cloud service platform, service evaluation and security of attack detection. Moreover, future directions are discussed in Section 4 based on the reviews of above methods and applications. Finally, conclusions are drawn in Section 5.

2.0 LITERATURE REVIEW

AI is described as indicated intelligence performed by machines, typically aims to enable computers to construct intelligent systems for learning and solving problems like human brain [9]. Same as most sciences, AI is divided into several subdisciplines, sharing an essential approach to solving problem but applied in different areas, ranging from Game Playing to Expert Systems, from Machine Learning to Neural Nets and Genetic Algorithms. In this section, several kinds of AI methods and potential directions for further researches are presented throughout different stages of 3DP. Printability is the capability to closely reproduce a 3D model via 3D printer [1-13]. Theoretically, the 3DP technique is expected to print any three-dimensional object. However, compared with traditional manufacturing methods, the promotion and employment of 3DP are still limited due to the geometrical attribute, time consumption and specific material requirement. To reduce the complexity of product fabrication and ensure the 3D model can be made in an optimal way, Lu proposed the Printability Checker (PC) scheme to judge whether an object is suitable to be 3D printed or produced through other ways [14-19].

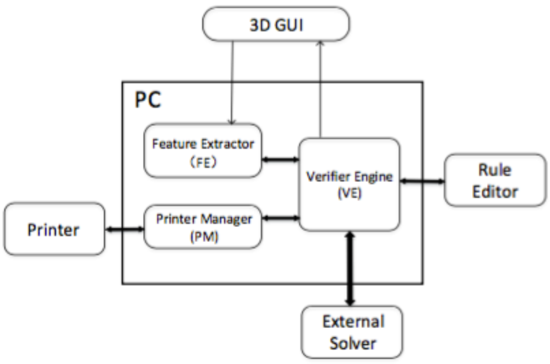

Figure 1. Architecture of Printability Checker [12]

In, a service-oriented printability problem composed of feature extractor (FE), printer manager (PM) and verifier engine (VE) is modelled. As shown in Figure 1, PC implements decision based on the findings of complexity values out of criteria. The calculation of complexity depends on the selection of different indicators such as tested runtime. With the assist of External Solver to decode the constraint rules coded in VE, three components can realise the information transfer and cooperation each other. Specifically, FE is to extract the decidable features of a given 3D object. PM is to manage printers by utilizing the relevant constraints and then send the printer profiles to VE. Meanwhile, VE can match the features and constraints from FE and PM so that tests the printability of the 3D object based on the final complexity results [20-27]. Though the experiments prove the PC scheme has achieved the capability of checking printable model, the practical implementation is still the lack of feasibility and reliability, especially when meeting plenty of various features or data. Hence Lu proposed to apply the ML method into automatic rule adjustment, especially the parameters used to verify the printability. Different from the above method, the estimation model can be trained for printability prediction by using the Support Vector Machine (SVM) instead of predefining any rules. In this way, the optimal decision function could be obtained for further classifications by using the same parameters [28-34]. This method was also proved by experiments, which effectively reduced the feature extraction time of 3D models without any negative impact on product precision. In practical manufacturing industry, the printability or complexity calculation is not only based on a single indicator but an integration of multiple indicators such as time, cost, raw material, model size and geometry, etc. The problems about how to test and determine multi- indicators and what effect proportion each indicator has should be converted into an optimisation problem solved by genetic algorithms (GA) and genetics-based ML method to achieve the optimal effect proportion and the minimum complexity value. The reason is GA is designed especially for large spaces or data that could be expressed in binary string format. Compared to other methods, this probabilistic search method only requires few assumptions to build objective functions. Furthermore, the PC scheme is developed on the basis of the current level of 3DP. To popularise 3DP, further research should focus on the optimisation of printing technique to lower the complexity threshold under multi- indicator environment [35-44]. By combining the improved printing method with the assist of printability checker, more and more products are possible to be classified from unprintable to printable. With the increasing design complexity, the optimisation of computational prefabrication, also known as process planning, has become a hot issue of 3DP. At present, lots of researchers have proposed their methods to accelerate prefabrication. For instance, R. M. et al. proposed an asymptotical algorithm for adaptive slicing problem. Wang et al. presented a method to accelerate the slicing through parallel computing. Vatani et al. optimised the slicing algorithms to reduce the STL file sizes and computer memory by using nearest distance analysis. Zhou et al. presented a hybrid slicing process by integrating the laser-based vector scanning and mask projection. Fok et al. proposed a path optimizer to search for the optimal printing trajectory. To convert the sliced 3D model into a set of slicing planes in z-coordinates, the layer information requires being extracted from triangular mesh by using slicing algorithm. In projects, Wang et al. presents a slicing algorithm composed of three kernel modules, i.e. ray-triangle intersection (TRI), trunk sorting (TS) and layer extraction (LE) [45-57]. Wherein TRI enables the slicing algorithm to calculate the intersection points between vertical rays on 2D image pixel centres and triangle meshes in STL format. A similar approach in utilises the plane- triangle intersection to calculate the intersection point. TS is to sort the intersection points in the order in the trunk. According to the layer height and point position, LE is to calculate the binary value of each pixel and then generate the layer images for printing. Though the slicing algorithm has established the foundation of subsequent layer-based addictive manufacture, it has a few weaknesses in computational complexity and difficulty of parallel implementation. In today's big data era, parallel computing has become a great potential for alleviating the computational demands of AI in the aspects of image processing, production rules, mechanisation of logic, data filtering and data mining, etc. Hence, Wang et al. proposed two Graphic Processing Unit (GPU) schemes to accelerate this prefabrication process with the assist of pixel-wise parallel slicing (PPS) and fully parallel slicing (FPS) methods [58-66].

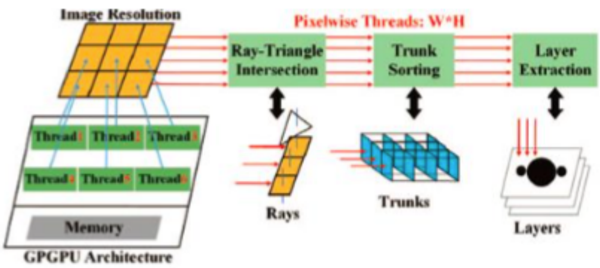

Figure 2. Pixelwise Parallel Slicing [13]

The PPS aims to achieve the parallelism of slicing algorithm. As shown in Figure 2, it enables GPU to support the threads and allocate them to each pixel ray, which means all rays are operated by their specific threads. Also, the threads can help to store the intersection points and sorting results in a shared memory in GPU, which significantly reduces the time consumption. FPS further develops the parallelism of RTI, TS and LE especially for solving the large size slicing problems. Compared to PPS, FPS enables the multi-thread concurrency to operate three independent modules in a fully parallel method [67-72]. A feasible printing trajectory can not only direct the nozzle to form the desired shape but also significantly shorten the computational and printing time. During the printing process, a printing nozzle basically spends time on traversing two types of segments, including print segment and transition segment. Therefore, it is necessary to seek for an optimal path in the shortest traversing time or distance. Similar to Travelling Salesman Problem (TSP), Fok et al. proposed a relaxation scheme of 3DP path optimizer to compute the nozzle traversing time. The path optimisation problem is formulated as TSP by comparing each print segment to a city and finding the fastest or shortest tour to visit the whole country [71-78]. In each layer, TSP implements optimisation at inter-partition level (print area) and intra-partition level (blank area) based on the boundaries of these areas. Between each inter- partition, TSP can compute the visit order and start the tour to visit each area. Then the Christofides algorithm is used to find the shortest time of this visit. The transition segment in intra-partition level is the connection of two nearest end points located in two adjacent print areas. Though the computational simulation has verified that the scheme which is capable of simplifying and accelerating the printing process, there still exists a few defects which may affect the printing precision and optimal solution [1-9]. Firstly, the Christofides algorithm utilising the distance as a criterion can only prove that the nozzle traversing distance or time is optimal. But it fails to prove the total time consumption is the shortest under the circumstance of neglecting the retraction time. In study, it points out that the retraction method has to be considered due to the generation of excess filament leaking, which usually happens for a typical printer. It requires time to retract the filament back when the nozzle traverses between segments. Thus, this retraction time should not be simply regarded as a constant due to its positive correlation with the number of segments, which requires simulation and physical experiment to verify [10-17]. Secondly, to reduce the computing and printing time, researchers proposed a simplified method to consolidate the small connected print segments into integrated segments based on the consolidation threshold value. However, this approach is a lack of an optimal threshold control. Because a large threshold is possible to effect the boundary shape of the print area, causing wrong transition segment between two adjacent inter-partitions and even the precision problem of the final 3D object. Thus how and what degree the threshold control has that can achieve the optimal printing speed without negative impact on precision are key directions in future [18-26]. Finally, many researches have proved that parallel slicing acceleration and path optimisation may offer an efficient performance. But there is few research on the integration of printability checking, slicing and path planning. According to the layer-based printing process, the parallel computing to both convert the 3D model into layer image and automatically form an optimal path is reliable to further accelerate the prefabrication. Service-oriented architecture (SOA), known as a core part of cloud manufacturing, refers to a computing paradigm that provides enabling technologies and services to fulfil the client requirements in an efficient and fast manner. A feasible SOA is able to intelligently realise the high flexibility, integration and customisation of 3DP. To date, several researchers have studied the problem of correlation among virtual services under multiple demands and constraints [27-39]. For example, Li et al. proposed the impact of service-oriented cloud manufacturing and its applications. Ren Lei et al. presented the resource virtualisation and allocation for cloud manufacturing. Wu proposed the 3DP technique in cloud-based design and manufacturing system. Y. Wu et al. also developed a conceptual scheme of 3DP service-oriented platform and an evaluation model on the basis of cloud service. The cloud platform is an on-demand computing model composed of autonomous, hardware and software resources. As an example, it provides clients with a convenient on-demand access to a shared collection of resources and then integrates the resources and capabilities into a virtualised resource pool [40-4]. The assist of service evaluation and demand matching algorithm enables the platform to intelligently make a comprehensive evaluation of terminal printers, providing an optimal resource allocation based on printing precision, quality, cost and time. Similarly, W. Wang et al. proposed the resource allocation algorithms to build a flexible and agile collaborative scheduling and planning of resources. Based on above content, the method to evaluate and select the services of terminal printers was further developed by using ML method. Y. Wu et al. presented a service evaluation model using principal indexes including time, cost, quality, trust, ability and environment. With the help of fuzzy number different quantization based on Hamming Distance algorithm, the optimisation algorithm is able to quantify the service quality and improve the accuracy of service selection. Similarly, Dong, Y. F et al. also presented a quality of service acquisition method and a trust evaluation model for cloud manufacturing service using the genetic algorithm. A comprehensive cloud platform is not only a collection of abundant resources [49-56]. Most researches still focus on the technical innovation, resulting in the lack of attention to system security and safety for future deployment and adoption. Though the sharing platform may highly improve the resource usage and provides the opportunity to middle or small scale manufacturers to accomplish their production. It also leads to the malicious attacks from side-channel, causing the risks of information steals or losses in the nowadays competitive environment. For enhancing users' privacy, F. Tao et al. proposed the establishment of a private cloud platform, offering benefits and services from public platform environment but self-managed [57-65]. Although it may lower the risk to some extent, the specific criteria and standard to implement still require further research and simulation. In addition, in spite of service and manufacturing intelligence, the cloud platform is still a lack of real-time control during a printing process. Once a printing task begins, it will be difficult to interrupt or terminate the task already in progress, especially when connected with the online Cloud platform. To reduce the massive time and material wastes, what intelligent method should be used is a principal objective to research. Security problem in manufacturing industry has gained more attention in recent years. The cyber-physical attack, a new vulnerability to a cyber-manufacturing system including 3DP, may cause several defects of products including change of design dimensions, void infill, nozzle travel speed, heating temperature and so on. To real-time detect the malicious attacks in 3DP, Wu et al. proposed an ML method on physical data, covering k- Nearest Neighbours (kNN) algorithm, random forest algorithm and anomaly detection algorithm. Specifically, each layer-based image with defects is converted into a greyscale plot [66-72]. Based on extracted features, the ML algorithms will real-time detect the outliers in defect areas and trigger alerts to the administrator. Wherein kNN is to determine the classification of defect areas when the probability density of some parameters are unsure. The anomaly detection is to detect unusual outliers that do not conform the predefined or accepted behaviours, such as increase of mean value, standard derivation and number of pixels larger than a threshold. Similarly, in a cyber- physical system, this unsupervised learning method is also applied to detect anomalies with low false rate by using a Recurrent Neural Network and Cumulative Sum method. The random forest can not only classify the defects by estimating the posterior distribution of each image layer but also build process-based patterns and use proximities to detect outliers according to the images. Through simulation and experiment, the anomaly detection algorithm was found to achieve the highest accurate detection [73-78].

TABLE 1. SUMMARY OF AI METHODS FOR 3D PRINTING

3D Printing Process	Status	Application	Method	Problems &Future Work
Printability Checking (Design & Preparation)	Offline	Original printability checker	PC scheme (FE, PM, VE)	1. Multi-indicator test and optimal effect proportion using GA. 2. Lower complexity threshold.
		Automatic checking	ML (SVM)	
Prefabrication (Planning)	Offline	Slicing acceleration	Slicing Algorithm (TRI, TS, LE) GPU (PPS and FPS parallelism)	1. Evaluation of time consumption closed to a practical situation. 2. Consolidation of print segments and threshold control. 3. Parallel computing of printability checking, slicing and path planning.
		Path Optimiser	TSP based optimisation Christofides algorithm	
Service Platform & evaluation (Design & Printing &Service& Control)	Online	Cloud Service Platform	Demand matching algorithm Resource allocation algorithm	1. Security enhancement. 2. Real-time control. 3. Design for printing.
		Evaluation Model	ML (Multi-criteria fuzzy decision based on Hamming Distance algorithm; GA)	
Security (Control)	Online	Attack Detection	kNN, anomaly detection, random forest	Defect detection for mass customisation.

The features of grayscale mean, standard derivation and number of pixels larger than the threshold are all extracted according to the greyscale value distribution. Based on extracted features, the ML algorithms will real-time detect the outliers in defect areas and trigger alerts to the administrator. Wherein kNN is to determine the classification of defect areas when the probability density of some parameters are unsure. The anomaly detection is to detect unusual outliers that do not conform the predefined or accepted behaviours, such as increase of mean value, standard derivation and number of pixels larger than a threshold [1-17]. Similarly, in a cyber- physical system, this unsupervised learning method is also applied to detect anomalies with low false rate by using a Recurrent Neural Network and Cumulative Sum method. The random forest can not only classify the defects by estimating the posterior distribution of each image layer but also build process-based patterns and use proximities to detect outliers according to the images. Through simulation and experiment, the anomaly detection algorithm was found to achieve the highest accurate detection. The experiment has indicated the feasibility of ML in 3DP security. However, the research only works on the component surface with regular shapes or patterns. Because the construction of 3D model depends on the requirements from clients in an actual printing process. For a complex construction, it is unable to guarantee the detection system will never identify a correct component as a defect by mistake. Hence the current research on defect detection is only feasible for standardised components in mass production, requiring further development to fit into mass customisation only with the capability to classify the defects accurately [23-37].

3.0 FUTURE DIRECTIONS

Based on the above survey, the developments and analyses of different methods for 3DP are simply outlined in Table 1. The directions to further improve the performance of 3DP are given as follows, In path planning process, the evaluation of time consumption should closely conform to a practical situation, which may provide the clients with high-quality services and optimal solutions for actual manufacturing. Due to the limitations of current printing technique, the time spent on nozzle traversing, printing and filament retracting should all be considered. It also requires simulations and physical experiments to determine the correlation between time consumption and the number of print segments. In project, it points out that the retraction method has to be considered due to the generation of excess filament leaking, which usually happens for a typical printer. It requires time to retract the filament back when the nozzle traverses between segments. Thus, this retraction time should not be simply regarded as a constant due to its positive correlation with the number of segments, which requires simulation and physical experiment to verify. Secondly, to reduce the computing and printing time, researchers proposed a simplified method to consolidate the small connected print segments into integrated segments based on the consolidation threshold value. However, this approach is a lack of an optimal threshold control. Because a large threshold is possible to effect the boundary shape of the print area, causing wrong transition segment between two adjacent inter-partitions and even the precision problem of the final 3D object. Thus how and what degree the threshold control has that can achieve the optimal printing speed without negative impact on precision are key directions in future. Finally, many researches have proved that parallel slicing acceleration and path optimisation may offer an efficient performance. But there is few research on the integration of printability checking, slicing and path planning. According to the layer-based printing process, the parallel computing to both convert the 3D model into layer image and automatically form an optimal path is reliable to further accelerate the prefabrication. Service-oriented architecture (SOA), known as a core part of cloud manufacturing, refers to a computing paradigm that provides enabling technologies and services to fulfil the client requirements in an efficient and fast manner. A feasible SOA is able to intelligently realise the high flexibility, integration and customisation of 3DP. To date, several researchers have studied the problem of correlation among virtual services under multiple demands and constraints. For example, Li et al. proposed the impact of service-oriented cloud manufacturing and its applications. Ren Lei et al. presented the resource virtualisation and allocation for cloud manufacturing. Wu proposed the 3DP technique in cloud-based design and manufacturing system. Y. Wu et al. also developed a conceptual scheme of 3DP service-oriented platform and an evaluation model on the basis of cloud service. The cloud platform is an on-demand computing model composed of autonomous, hardware and software resources. As an example, it provides clients with a convenient on-demand access to a shared collection of resources and then integrates the resources and capabilities into a virtualised resource pool. The assist of service evaluation and demand matching algorithm enables the platform to intelligently make a comprehensive evaluation of terminal printers, providing an optimal resource allocation based on printing precision, quality, cost and time. Similarly, W. Wang et al. proposed the resource allocation algorithms to build a flexible and agile collaborative scheduling and planning of resources. age recognition is an essential application of Neural Nets in deep ML of AI, inspired by human eyes of neurology to implement recognitions from boundary to angle, from complex construction to final object. By applying ML in 3DP area, the recognition of defects or specific construction could be more accurate for customisation production in future. To enhance the manoeuvrability, the Intelligent control method is a sound solution to automatic and real-time control the printing progress, especially when connected with the online Cloud platform. It should be developed throughout whole 3D printing from the offline prefabrication to the accomplishment of physical printing. Instead of spending time on checking printability, design for printing should be considered as an efficient and convenient approach, which means all models will be designed to match 3DP in particular. Thus clients will not consider the printability but only follow the 3DP criteria to design with the help of intelligent algorithms and CAD. Although it seems to be a long way to realise, especially under the comparable situation with traditional manufacturing industry, it requests both improvements of 3DP techniques and also the conversion to a digitised and personalised production mode which is integrated with products and services, so called Industry 4.0. The reason is GA is designed especially for large spaces or data that could be expressed in binary string format. Compared to other methods, this probabilistic search method only requires few assumptions to build objective functions. Furthermore, the PC scheme is developed on the basis of the current level of 3DP. To popularise 3DP, further research should focus on the optimisation of printing technique to lower the complexity threshold under multi- indicator environment. By combining the improved printing method with the assist of printability checker, more and more products are possible to be classified from unprintable to printable. With the increasing design complexity, the optimisation of computational prefabrication, also known as process planning, has become a hot issue of 3DP. At present, lots of researchers have proposed their methods to accelerate prefabrication. For instance, R. M. et al. proposed an asymptotical algorithm for adaptive slicing problem. Wang et al. presented a method to accelerate the slicing through parallel computing. Vatani et al. optimised the slicing algorithms to reduce the STL file sizes and computer memory by using nearest distance analysis. Zhou et al. presented a hybrid slicing process by integrating the laser-based vector scanning and mask projection. Fok et al. proposed a path optimizer to search for the optimal printing trajectory. To convert the sliced 3D model into a set of slicing planes in z-coordinates, the layer information requires being extracted from triangular mesh by using slicing algorithm. Wang et al. presents a slicing algorithm composed of three kernel modules, i.e. ray-triangle intersection (TRI), trunk sorting (TS) and layer extraction (LE). Wherein TRI enables the slicing algorithm to calculate the intersection points between vertical rays on 2D image pixel centres and triangle meshes in STL format. A similar approach in utilises the plane-triangle intersection to calculate the intersection point. TS is to sort the intersection points in the order in the trunk. According to the layer height and point position, LE is to calculate the binary value of each pixel and then generate the layer images for printing.

4.0 Conlusion

Additive manufacturing (AM), also known as 3D printing, has been increasingly adopted in the aerospace, au- tomotive, energy, and healthcare industries over the past few years. While AM has many advantages over subtractive manufacturing processes, one of the primary limitations of AM is surface integrity. To improve the surface integrity of additively manufactured parts, a data-driven predictive modeling approach to predicting surface roughness in AM is introduced. Multiple sensors of different types, including thermocouples, infrared temperature sensors, and accelerometers, are used to collect temperature and vibration data. An ensemble learning algorithm is introduced to train the predictive model of surface roughness. Features in the time and frequency domains are extracted from sensor-based condition monitoring data. A subset of these features is selected to improve computational efficiency and prediction accuracy. The predictive model is validated using the condition monitoring data collected from a set of AM tests conducted on a fused filament fabrication (FFF) machine. EXperimental results have shown that the proposed predictive modeling approach is capable of pre- dicting the surface roughness of 3D printed components with high accuracy. A comprehensive survey of AI methods in 3DP has been presented, ranging from various algorithms to the design of the service-oriented platform. While current challenges have also been discussed, covering the real-time control, parallel computing, attack detection for mass customisation and conceptual scheme of design for printing. Although many researches and tests have proved that 3DP is expected to become the mainstream mode of production, further developments on AI in this domain are necessary to accelerate the realisation of this prospect in the future Industry 4.0.

REFRENCES

[1] Wang, Chengcheng, et al. "Machine learning in additive manufacturing: State-of-the-art and perspectives." Additive Manufacturing 36 (2020): 101538.

[2] Zhu, Zuowei, et al. "Machine learning in tolerancing for additive manufacturing." CIRP Annals 67.1 (2018): 157-160.

[3] Shafaie, Majid, Maziar Khademi, Mohsen Sarparast, and Hongyan Zhang. "Modified GTN parameters calibration in additive manufacturing of Ti-6Al-4 V alloy: a hybrid ANN-PSO approach." The International Journal of Advanced Manufacturing Technology 123, no. 11 (2022): 4385-4398.

[4] Meng, Lingbin, et al. "Machine learning in additive manufacturing: a review." Jom 72.6 (2020): 2363-2377.

[5] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Experimental and finite element investigation of high-speed bone drilling: evaluation of force and temperature." Journal of the Brazilian Society of Mechanical Sciences and Engineering 42, no. 6 (2020): 1-9.

[6] Li, Zhixiong, et al. "Prediction of surface roughness in extrusion-based additive manufacturing with machine learning." Robotics and Computer-Integrated Manufacturing 57 (2019): 488-495.
[7] Jin, Zeqing, et al. "Machine learning for advanced additive manufacturing." Matter 3.5 (2020): 1541-1556.
[8] Jiang, Jingchao, et al. "Machine learning integrated design for additive manufacturing." Journal of Intelligent Manufacturing (2020): 1-14.
[9] Sarparast, Mohsen, Majid Ghoreishi, Tohid Jahangirpoor, and Vahid Tahmasbi. "Modelling and optimisation of temperature and force behaviour in high-speed bone drilling." Biotechnology & Biotechnological Equipment 33, no. 1 (2019): 1616-1625.
[10] Baumann, Felix W., et al. "Trends of machine learning in additive manufacturing." International Journal of Rapid Manufacturing 7.4 (2018): 310-336.
[11] Gu, Grace X., et al. "Bioinspired hierarchical composite design using machine learning: simulation, additive manufacturing, and experiment." Materials Horizons 5.5 (2018): 939-945.S
[12] Bahrami, Javad, Mohammad Ebrahimabadi, Sofiane Takarabt, Jean-luc Danger, Sylvain Guilley, and Naghmeh Karimi. "On the Practicality of Relying on Simulations in Different Abstraction Levels for Pre-Silicon Side-Channel Analysis."
[13] Qi, Xinbo, et al. "Applying neural-network-based machine learning to additive manufacturing: current applications, challenges, and future perspectives." Engineering 5.4 (2019): 721-729.
[14] Johnson, N. S., et al. "Invited review: Machine learning for materials developments in metals additive manufacturing." Additive Manufacturing 36 (2020): 101641.
[15] Sadi, Mehdi, Yi He, Yanjing Li, Mahabubul Alam, Satwik Kundu, Swaroop Ghosh, Javad Bahrami, and Naghmeh Karimi. "Special Session: On the Reliability of Conventional and Quantum Neural Network Hardware." In 2022 IEEE 40th VLSI Test Symposium (VTS), pp. 1-12. IEEE, 2022.
[16] Qin, Jian, et al. "Research and application of machine learning for additive manufacturing." Additive Manufacturing (2022): 102691.
[17] Caggiano, Alessandra, et al. "Machine learning-based image processing for on-line defect recognition in additive manufacturing." CIRP annals 68.1 (2019): 451-454.
[18] Bahrami, Javad, Mohammad Ebrahimabadi, Jean-Luc Danger, Sylvain Guilley, and Naghmeh Karimi. "Leakage power analysis in different S-box masking protection schemes." In 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), pp. 1263-1268. IEEE, 2022.
[19] Yao, Xiling, Seung Ki Moon, and Guijun Bi. "A hybrid machine learning approach for additive manufacturing design feature recommendation." Rapid Prototyping Journal (2017).
[20] Bahrami, Javad, Viet B. Dang, Abubakr Abdulgadir, Khaled N. Khasawneh, Jens-Peter Kaps, and Kris Gaj. "Lightweight implementation of the lowmc block cipher protected against side-channel attacks." In Proceedings of the 4th ACM Workshop on Attacks and Solutions in Hardware Security, pp. 45-56. 2020.
[21] Sing, S. L., et al. "Perspectives of using machine learning in laser powder bed fusion for metal additive manufacturing." Virtual and Physical Prototyping 16.3 (2021): 372-386.
[22] Ahmadinejad, Farzad, Javad Bahrami, Mohammd Bagher Menhaj, and Saeed Shiry Ghidary. "Autonomous Flight of Quadcopters in the Presence of Ground Effect." In 2018 4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS), pp. 217-223. IEEE, 2018.
[23] Ko, Hyunwoong, et al. "Machine learning and knowledge graph based design rule construction for additive manufacturing." Additive Manufacturing 37 (2021): 101620.
[24] Hadiana, Hengameh, Amir Mohammad Golmohammadib, Hasan Hosseini Nasabc, and Negar Jahanbakhsh Javidd. "Time Parameter Estimation Using Statistical Distribution of Weibull to Improve Reliability." (2017).
[25] Jiang, Jingchao, et al. "Achieving better connections between deposited lines in additive manufacturing via machine learning." Math. Biosci. Eng 17.4 (2020): 3382-3394.
[26] Zavareh, Bozorgasl, Hossein Foroozan, Meysam Gheisarnejad, and Mohammad-Hassan Khooban. "New trends on digital twin-based blockchain technology in zero-emission ship applications." Naval Engineers Journal 133, no. 3 (2021): 115-135.
[27] Li, Rui, Mingzhou Jin, and Vincent C. Paquit. "Geometrical defect detection for additive manufacturing with machine learning models." Materials & Design 206 (2021): 109726.
[28] Baturynska, Ivanna, Oleksandr Semeniuta, and Kristian Martinsen. "Optimization of process parameters for powder bed fusion additive manufacturing by combination of machine learning and finite element method: A conceptual framework." Procedia Cirp 67 (2018): 227-232.
[29] Bozorgasl, Zavareh, and Mohammad J. Dehghani. "2-D DOA estimation in wireless location system via sparse representation." In 2014 4th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 86-89. IEEE, 2014.
[30] Gobert, Christian, et al. "Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging." Additive Manufacturing 21 (2018): 517-528.
[31] Amini, Mahyar, Koosha Sharifani, and Ali Rahmani. "Machine Learning Model Towards Evaluating Data gathering methods in Manufacturing and Mechanical Engineering." International Journal of Applied Science and Engineering Research 15.4 (2023): 349-362.
[32] Paul, Arindam, et al. "A real-time iterative machine learning approach for temperature profile prediction in additive manufacturing processes." 2019 IEEE International Conference on Data Science and Advanced

Analytics (DSAA). IEEE, 2019.
[33] Amini, Mahyar, and Aryati Bakri. "Cloud computing adoption by SMEs in the Malaysia: A multi-perspective framework based on DOI theory and TOE framework." Journal of Information Technology & Information Systems Research (JITISR) 9.2 (2015): 121-135.
[34] Mahmoud, Dalia, et al. "Applications of Machine Learning in Process Monitoring and Controls of L-PBF Additive Manufacturing: A Review." *Applied Sciences* 11.24 (2021): 11910.
[35] Amini, Mahyar. "The factors that influence on adoption of cloud computing for small and medium enterprises." (2014).
[36] Khanzadeh, Mojtaba, et al. "Quantifying geometric accuracy with unsupervised machine learning: Using self-organizing map on fused filament fabrication additive manufacturing parts." *Journal of Manufacturing Science and Engineering* 140.3 (2018).
[37] Amini, Mahyar, et al. "MAHAMGOSTAR.COM AS A CASE STUDY FOR ADOPTION OF LARAVEL FRAMEWORK AS THE BEST PROGRAMMING TOOLS FOR PHP BASED WEB DEVELOPMENT FOR SMALL AND MEDIUM ENTERPRISES." Journal of Innovation & Knowledge, ISSN (2021): 100-110.
[38] Liu, Rui, Sen Liu, and Xiaoli Zhang. "A physics-informed machine learning model for porosity analysis in laser powder bed fusion additive manufacturing." *The International Journal of Advanced Manufacturing Technology* 113.7 (2021): 1943-1958.
[39] Amini, Mahyar, et al. "Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.10 (2014): 129-135.
[40] Nojeem, Lolade, et al. "Machine Learning assisted response circles for additive manufacturing concerning metal dust bed fusion." International Journal of Management System and Applied Science 17.11 (2023): 491-501.
[41] Golmohammadi, Amir-Mohammad, Negar Jahanbakhsh Javid, Lily Poursoltan, and Hamid Esmaeeli. "Modeling and analyzing one vendor-multiple retailers VMI SC using Stackelberg game theory." Industrial Engineering and Management Systems 15, no. 4 (2016): 385-395.
[42] Motalo, Kubura, et al. "evaluating artificial intelligence effects on additive manufacturing by machine learning procedure." Journal of Basis Applied Science and Management System 13.6 (2023): 3196-3205.
[43] Fu, Yanzhou, et al. "Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review." *Journal of Manufacturing Processes* 75 (2022): 693-710.
[44] Amini, Mahyar, et al. "The role of top manager behaviours on adoption of cloud computing for small and medium enterprises." Australian Journal of Basic and Applied Sciences (AJBAS) 8.1 (2014): 490-498.
[45] Stathatos, Emmanuel, and George-Christopher Vosniakos. "Real-time simulation for long paths in laser-based additive manufacturing: a machine learning approach." *The International Journal of Advanced Manufacturing Technology* 104.5 (2019): 1967-1984.
[46] Amini, Mahyar, and Nazli Sadat Safavi. "Critical success factors for ERP implementation." International Journal of Information Technology & Information Systems 5.15 (2013): 1-23.
[47] Petrich, Jan, et al. "Multi-modal sensor fusion with machine learning for data-driven process monitoring for additive manufacturing." *Additive Manufacturing* 48 (2021): 102364.
[48] Amini, Mahyar, et al. "Agricultural development in IRAN base on cloud computing theory." International Journal of Engineering Research & Technology (IJERT) 2.6 (2013): 796-801.
[49] Snow, Zackary, et al. "Toward in-situ flaw detection in laser powder bed fusion additive manufacturing through layerwise imagery and machine learning." *Journal of Manufacturing Systems* 59 (2021): 12-26.
[50] Amini, Mahyar, et al. "Types of cloud computing (public and private) that transform the organization more effectively." International Journal of Engineering Research & Technology (IJERT) 2.5 (2013): 1263-1269.
[51] Akhil, V., et al. "Image data-based surface texture characterization and prediction using machine learning approaches for additive manufacturing." *Journal of Computing and Information Science in Engineering* 20.2 (2020): 021010.
[52] Amini, Mahyar, and Nazli Sadat Safavi. "Cloud Computing Transform the Way of IT Delivers Services to the Organizations." International Journal of Innovation & Management Science Research 1.61 (2013): 1-5.
[53] Douard, Amélina, et al. "An example of machine learning applied in additive manufacturing." *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*. IEEE, 2018.
[54] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Heuristic Solution For IaaS Cloud Placement Problem Without Migration." International Journal of Computer Science and Information Technologies 6.11 (2014): 25-30.
[55] Ding, Donghong, et al. "The first step towards intelligent wire arc additive manufacturing: An automatic bead modelling system using machine learning through industrial information integration." *Journal of Industrial Information Integration* 23 (2021): 100218.
[56] Amini, Mahyar, and Nazli Sadat Safavi. "A Dynamic SLA Aware Solution For IaaS Cloud Placement Problem Using Simulated Annealing." International Journal of Computer Science and Information Technologies 6.11 (2014): 52-57.
[57] Zhang, Wentai, et al. "Machine learning enabled powder spreading process map for metal additive manufacturing (AM)." *2017 International Solid Freeform Fabrication Symposium*. University of Texas at Austin, 2017.

[58] Sharifani, Koosha and Amini, Mahyar and Akbari, Yaser and Aghajanzadeh Godarzi, Javad. "Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model." International Journal of Science and Information System Research 12.9 (2022): 20-44.
[59] Du, Y., T. Mukherjee, and T. DebRoy. "Physics-informed machine learning and mechanistic modeling of additive manufacturing to reduce defects." *Applied Materials Today* 24 (2021): 101123.
[60] Sadat Safavi, Nazli, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 70-75.
[61] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." *Virtual and Physical Prototyping* 16.1 (2021): 50-67.
[62] Sadat Safavi, Nazli, Nor Hidayati Zakaria, and Mahyar Amini. "The risk analysis of system selection and business process re-engineering towards the success of enterprise resource planning project for small and medium enterprise." World Applied Sciences Journal (WASJ) 31.9 (2014): 1669-1676.
[63] Yaseer, Ahmed, and Heping Chen. "Machine learning based layer roughness modeling in robotic additive manufacturing." *Journal of Manufacturing Processes* 70 (2021): 543-552.
[64] Sadat Safavi, Nazli, Mahyar Amini, and Seyyed AmirAli Javadinia. "The determinant of adoption of enterprise resource planning for small and medium enterprises in Iran." International Journal of Advanced Research in IT and Engineering (IJARIE) 3.1 (2014): 1-8.
[65] Chen, Lequn, et al. "Rapid surface defect identification for additive manufacturing with in-situ point cloud processing and machine learning." Virtual and Physical Prototyping 16.1 (2021): 50-67.
[66] Safavi, Nazli Sadat, et al. "An effective model for evaluating organizational risk and cost in ERP implementation by SME." IOSR Journal of Business and Management (IOSR-JBM) 10.6 (2013): 61-66.
[67] Guo, Shenghan, et al. "Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm." Journal of Manufacturing Systems 62 (2022): 145-163.
[68] Khoshraftar, Alireza, et al. "Improving The CRM System In Healthcare Organization." International Journal of Computer Engineering & Sciences (IJCES) 1.2 (2011): 28-35.
[69] Ren, K., et al. "Thermal field prediction for laser scanning paths in laser aided additive manufacturing by physics-based machine learning." Computer Methods in Applied Mechanics and Engineering 362 (2020): 112734.
[70] Abdollahzadegan, A., Che Hussin, A. R., Moshfegh Gohary, M., & Amini, M. (2013). The organizational critical success factors for adopting cloud computing in SMEs. Journal of Information Systems Research and Innovation (JISRI), 4(1), 67-74.
[71] Zhu, Qiming, Zeliang Liu, and Jinhui Yan. "Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks." Computational Mechanics 67.2 (2021): 619-635.
[72] Amini, Mahyar and Ali Rahmani. "Agricultural databases evaluation with machine learning procedure." Australian Journal of Engineering and Applied Science 8.6 (2023): 39-50-10.
[73] Newiduom, Ladson, et al. "Machine learning model improvement based on additive manufacturing process for melt pool warmth predicting." International Journal of Applied Science and Engineering Research 15.6 (2023): 240-250.
[74] Jackson, Keypi, et al. "Increasing substantial productivity in additive manufacturing procedures by expending machine learning method." International Journal of Mechanical Engineering and Science Study 10.8 (2023): 363-372.
[75] Opuiyo, Atora, et al. "Evaluating additive manufacturing procedure which was using artificial intelligence." International Journal of Science and Information System 13.5 (2023): 107-116.
[76] Amini, Mahyar, and Ali Rahmani. "Machine learning process evaluating damage classification of composites." Journal 9.12 (2023): 240-250.
[77] Yun, Chidi, et al. "Machine learning attitude towards temperature report forecast in additive manufacturing procedures." International Journal of Basis Applied Science and Study 9.12 (2023): 287-297.
[78] Shun, Miki, et al. "Incorporated design aimed at additive manufacturing through machine learning." International Journal of Information System and Innovation Adoption 16.10 (2023): 823-831.