Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 52 (2020) 38–43

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

5th International Conference on System-Integrated Intelligence

Data-driven Context Awareness of Smart Products in Discrete Smart Manufacturing Systems

Juergen Lenz[a], Valerio Pelosi[b], Marco Taisch[b], Eric MacDonald[c], Thorsten Wuest[a]*

[a]Benjamin M. Statler College of Engineering and Mineral Resource, West Virginia University, Morgantown, WV 26506, United States
[b]Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Piazza Leonardo Da Vinci 32, 20133 Milano, Italy
[c]Advanced Manufacturing Research Center, Youngstown State University, Youngstown, OH 44555, United States

* Corresponding author. Tel.: +1-304-293-9439; fax: +304-293-4970. *E-mail address: thwuest@mail.wvu.edu*

Abstract

Traditionally, smart-connected products are predominantly utilized during the usage phase of the product lifecycle. However, we argue that there are distinct benefits of system-integrated sensor systems during the beginning of life, more specifically in manufacturing and assembly. In this paper, we analyze the ability of a smart-connected product with an integrated sensor system to recognize and label different manufacturing processes, generating a distinct process fingerprint within a discrete smart manufacturing system. The ability of the smart-connected product to detect distinct manufacturing process patterns ('process fingerprint') enables the production planner and operator, e.g., to optimize the scheduling, improve part quality, and/or reduce the energy footprint. The experimental setup is based on a *FestoDidactics CPlab* with eight different manufacturing processes. The smart-connected product is equipped with a sensor system providing data from eight different sensors (e.g., temperature, humidity, acceleration). We used an Artificial Neural Network (ANN) algorithm to create a model to detect specific events/patterns within the dataset after labelling it manually over the course of a complete production cycle. The focal manufacturing process was the heating tunnel where the smart-connected product was exposed to a heat treatment process and sequence. The results of this prototypical implementation indicate that a smart-connected product can reliably recognize specific process patterns with a system-integrated sensor system during a simulated manufacturing process. While this work is only a first step, the potential applications and benefits are promising and further research should focus on the potential quality implications within smart manufacturing of product-integrated sensor readings compared to machine tool-based sensors, both of which monitored during the beginning of life. Smart products' integrated sensor systems provide the means to obtain measurements relevant for smart manufacturing systems that are not obtainable with common external sensor systems today.

Keywords: Smart Manufacturing; Machine Learning; Sensor Integration; ANN; PLM

1. Introduction

Industry 4.0 and Smart Manufacturing are changing the manufacturing industry and data is the lifeblood of these paradigms. Today, significant research focus is placed on monitoring and analyzing manufacturing data from sensors using machine learning and artificial intelligence. Most of the manufacturing data is captured either at the machine tool [1], during in-situ or ex-situ quality inspections, or at the planning level, e.g., ERP, CAD/CAM, etc. With sensor systems becoming cheaper, more powerful, smaller, and more mobile, we also see an increase of sensor data stemming from products equipped with sensors themselves - so-called smart, connected products. However, these smart, connected products are only beginning to capture and communicate data during their field usage after manufacturing and assembly are completed.

This paper evaluates two research questions related to this issue. The overarching question that arises is whether 'smart-

10.1016/j.promfg.2020.11.008

connected products can add value during manufacturing processes (beginning of life - BOL)?', followed by a more technical question of whether 'smart-connected products today are capable of detecting the distinct manufacturing process patterns based on sensor data analyzed via machine learning'. The experimental setup to answer the latter question comprises integrating a sensor system into a smart product and recording the sensor data during the complete manufacturing and assembly program. This recorded data is subsequently fed into an artificial neural network (ANN) to detect the execution of the manufacturing processes. This paper presents the initial results and performance of the ANN to identify a selected process based on smart-connected product-based sensor input.

The paper is structured as follows: Section 2 briefly highlights the current state of the art and background relevant for this research. Section 3 presents the research methodology including how data was acquired and analyzed. In section 4, the findings are presented, discussed, and evaluated. Section 5 concludes the paper with a summary and an outlook on further research.

2. State of the Art

Smart manufacturing emerged due to increased computing and networking capabilities within manufacturing equipment. It can be described as "a data intensive application of information technology at the shop floor level and above to enable intelligent, efficient and responsive operations" [2]. Smart Manufacturing Systems (SMS) are complex Cyber Physical Systems (CPS) that integrate operational technology (OT) and information technology (IT) to improve manufacturing operations through sensor systems and advanced data analytics [3]. Alternatively, smart products, in essence, rely on these computing and networking capabilities, however at the product level [4]. The majority of today's smart product are utilized during the middle of life (MOL) phase of the product lifecycle to provide the basis for advanced services and/or product service systems (PSS) for the consumer [5]. However, when considering the opportunity from a manufacturing-centered perspective, smart products are often interpreted as intelligent and connected machine tools [6]. Machine learning in general can be defined as programming computers to optimize a performance criterion using example data or past data [7]. A subgroup of machine learning algorithms is Artificial Neural Networks (ANN). ANNs try to simulate neurobiology and fabricate networks to solve computational problems [8]. Adapting this machine learning approach to manufacturing lead to improved yield, lower scrap rates, and reduced supply chain forecasting errors [9]. Machine tool interfaces enable connectivity for advanced data analytics [1]. This data can be utilized, e.g., for deep learning in smart manufacturing systems [10]. This paper aims to further expand the current state of the art by developing a model for data analytics in smart manufacturing on the basis of data solely captured by a smart-connected product during the BOL.

3. Methodology and Experimental Setup

The methodology is split into two distinct phases (Figure 1). The first phase is focused on collecting data and generating the manufacturing data set for the experimentation. The smart product's integrated sensor system continuously records the sensor readings during the processing on the SMS test bed. The second phase focuses on data analytics and identifying patterns ('process fingerprints') in the generated data set. The recorded manufacturing data is i) pre-processed to prepare the machine learning application (including labelling), ii) visualized to enable feature engineering within the data set, and iii) ultimately the machine learning algorithm was executed.

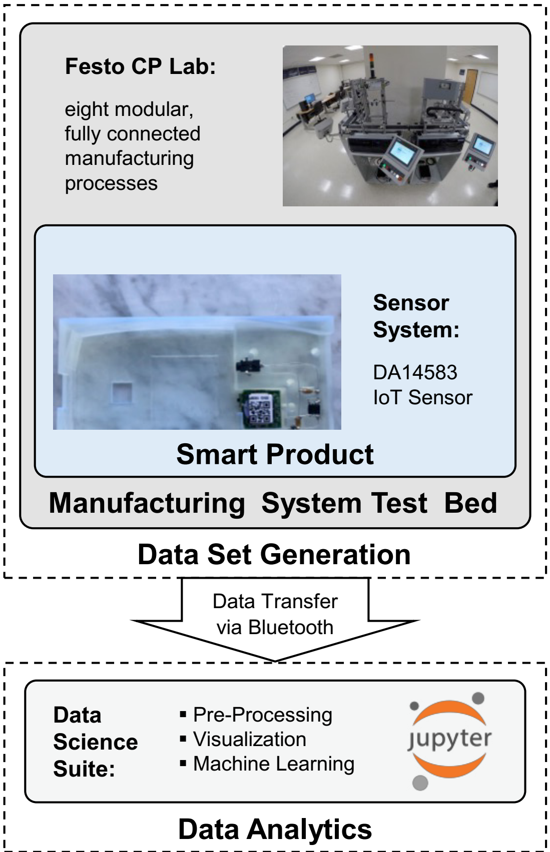

Fig. 1. Methodology and experimental setup.

The experimental setup builds on three core systems: the SMS test bed (*FestoDidactics* CPlab), the sensor system, and the data analytics suite (see Figure 1).

3.1. Manufacturing System Test Bed

The SMS is a state of the art *FestoDidactics* Cyber-physical Lab (CPlab) with eight modular, fully connected manufacturing processes located at WVU's Smart Manufacturing lab. The CPlab system's eight modular manufacturing processes include for example a drilling process, heat treatment process, and muscle press process that are all connected via an automated conveying belt system.

3.2. Sensor System

The smart product's sensor system in this experimental setup is a *DA14583* IoT Sensor by *Dialog Semiconductor* [11]. The sensor system is a low power 12-degree-of-freedom wireless sensor module, which combines a low power ARM processor with *Bosch Sensortec* sensors. The integrated Bosch sensors are BMI160 (Inertial Sensor-Gyroscope), BMM150 (Geomagnetic Sensor), and BME280 (Environmental Sensor). The BMI160 gyroscope sensor combines an accelerometer and gyroscope and offers low-noise 16-bit inertial measurements. The BMM150 geomagnetic provides 3-axis digital geomagnetic readings. The BME280 is an environmental sensor for temperature and relative humidity with a high accuracy and response time. The whole sensor package can operate in sleep mode only consuming 11uA (average). While active the average consumption reaches up to 560uA.

3.3. Data Processing and Data Analytics

Data analytics was performed in a *Jupyter Notebook* by a *Jupiter Project* [12]. The data analytics steps were pre-processing (including labelling), data visualization and feature engineering, and finally machine learning. In the pre-processing phase the retrieved data is transformed from a CSV file into an array with data type correction per variable, and then split into individual production runs through the SMS by marking the initial time t_0 and end time t_f for each run. The different processes were manually labeled based on the recorded timestamps entering and leaving each station and aligned with an even split across the production run. For data visualization the *matplotlib* library was utilized in order to identify anomalies and grasp a visual clue of the offsets between the individual runs. Furthermore, the visualization allowed for selection of relevant features for the modeling phase. The machine learning phase consisted of the model design, model parameter selection, model training, model execution, and evaluation of the model prediction performance.

4. Results

The cleaned and pre-processed data was plotted, and the data analytics implemented by feature engineering, model design, model training, model execution, and model evaluation.

4.1. Data Set and Plots

The resulting manufacturing data set includes the variables temperature, humidity, magnetic field (3-axis) with a resolution of one reading per second for every production run. One production run is defined as utilizing all eight manufacturing stations to manufacture a complete product. A total of 15 runs throughout the SMS test bed were recorded and make up the data set. The start of each production run was defined by releasing the raw material into the conveying container marking 0 seconds on the timescale. Each production run is built with five variables and 1,000 data points per variable. The runs were then divided into a test data set and a training data set. Data from 11 production runs are allocated for training (73.33%) and 4 for testing (26.67%).

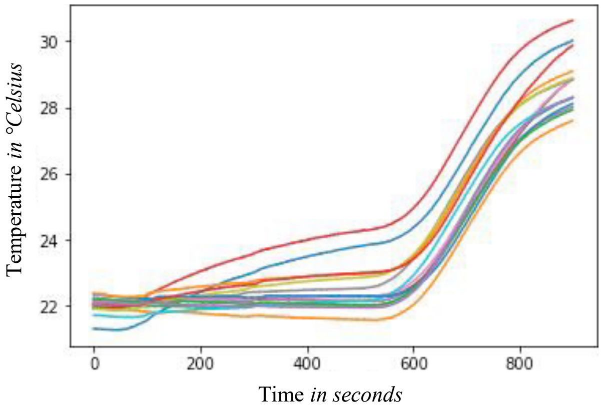

Fig. 2. Temperature trend.

Figure 2 illustrates the temperature progression during the production runs. The plot shows 15 completed recordings and the resulting temperature increase during the heat treatment process can be identified with a linear temperature increase around the 600 second mark. Regarding the two outliers with early temperature increase, we were able to identify the use of preheated conveying container from previous runs as the cause.

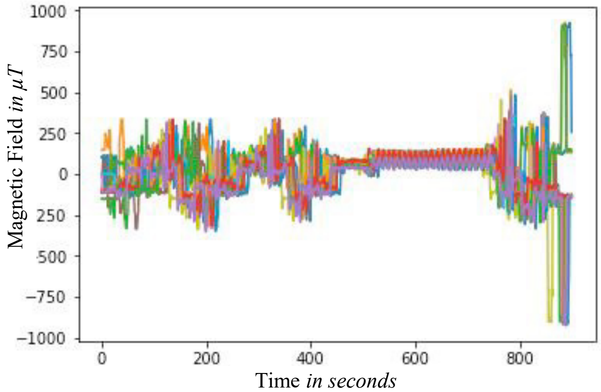

Fig. 3. Magnetic field trend (Y-axis).

The plot shows the distinct pattern across all different processes employed in the manufacturing program. Geomagnetic field readings are used for spatial orientation and also identify if any ferro-magnetic material is within a close proximity of the product during manufacturing. Identifying a magnetic signature could provide insights to the ANN as to which sub-process is underway. In the plot, for instance, between second 500-700 the convey container remains stationary inside a closed chamber. Furthermore, the starting point and end point of each run can be clearly identified, which is important for precise automated labeling of these events.

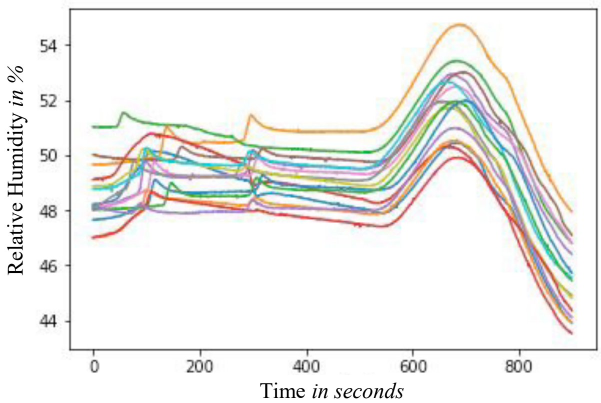

Fig. 4. Relative humidity trend.

Figure 4 highlights the relative humidity progression during each production run. The relative humidity initially rises, then drops when process heat is applied during the heat treatment sequence. Similar to the temperature values, the humidity values are subjected to lag at the beginning of the process.

4.2. Model Design

Five different ANN models have been built and used for this research project. It has to be noted that the objective is not to optimize the machine learning model but to showcase the potential of smart products adding value during the BOL. Therefore, we focused on basic ANNs with little variations to showcase the further potential for improvement in the analytical space for such applications. Table 1 summarizes the five models, which were designed using the *scikit-learn* library.

Table 1. Machine learning models.

Model No.	1	2	3	4	5
Color Scheme	black	blue	green	red	yellow
Hidden Layers	5	7	3	3	3
Neurons per Layer	50	100	50	20	10

The machine learning models differentiate themselves by the number of neurons per layer and the number of hidden layers. The idea behind this approach is to choose suitable parameters to achieve an acceptable trade-off between performance and accuracy of the ANN.

4.3. Feature Engineering

Feature engineering incorporates knowledge from the real world (such as laws of physics) and manufacturing domain knowledge (e.g., from data labeling by manufacturing experts aka 'a teacher' in machine learning terms) into the application of the machine learning algorithm. Data exploration was used to contextualize the sensor readings for the individual manufacturing processes of the SMS. The temperature reading (mainly relevant for identifying the heat treatment process step) was selected to be most suitable for the experiment. The humidity readings were not used for this study since they were regarded as not an independent variable from the temperature reading. The geomagnetic field readings were discarded as too noisy after a visual inspection of the data plots. A block design was used (8-block division) to split the production runs into smaller segments.

4.4. Model Training

The machine learning model was trained to detect one of the eight manufacturing processes. The heat treatment module was selected as the proof of concept process for this experiment.

Figure 5 details the loss curves of the five models (see Table 1 for color scheme). A loss curve shows the error vs. epochs. An epoch is a measure of the number of times all of the training data is used to update the weights. For each of the five different ANN models we performed a batch training. This means the training data pass through the learning algorithm simultaneously in one epoch, then the weights are updated.

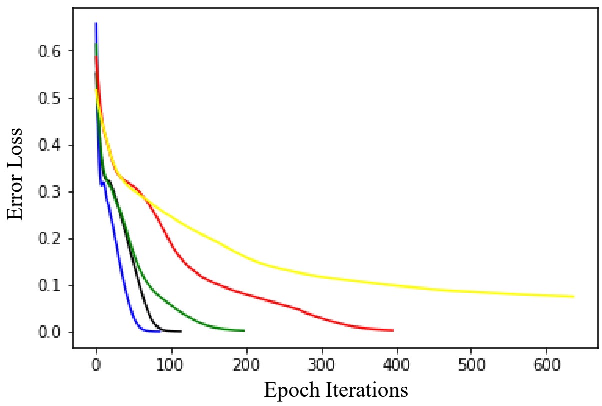

Fig. 5. Loss curves of the 5 models.

Table 2 depicts the number of iterations until convergence or the epoch limit is reached. Given the size of the data set, more neurons and hidden layers are needed for faster learning. The model 2 performed best among the five.

Table 2. Number of epoch iterations of all models.

Model No.	1	2	3	4	5
Iterations	113	85	197	395	636

The performance of models 1 and 3 were surprisingly low given the low number of neurons. This may mean that when the dataset works well, then regular shapes of the loss curves with number of iterations proportional to the size of the model are expected.

4.5. Evaluation

The trained models were executed using the remaining test data set and evaluated with the help of the metrics module of the *scikit-learn* library. A successful detection is defined as the model prediction being able to detect the correct state (or correct non-state) within the manually pre-labeled test data set. The data-set was labeled by an expert based on the eight-block split of each production run and whether a block was covering the heat treating process or not.

Table 3. Confusion matrix of all models.

		Actual Case									
Model No.		1		2		3		4		5	
		True	False	True	False	True	False	True	False	True	False
Predicted Case	True	32	0	32	0	32	0	32	0	32	0
	False	0	4	0	4	1	3	1	3	1	3

Table 3 presents the confusion matrices of the different models. The confusion matrix is presented as n*n table where n is the number of cases that are binary in this scenario (true and false). Since this is a case of binary classification, reading clockwise from row 1 column 1, the categories are: 1) true positive (TP) - the model predicts the positive class correctly; 2) true negative (TN) - the model predicts the negative class correctly; 3) false positive (FP) - the model mistakes the negative class as a positive one; and 4) false negative (FN) - the model predicts the negative class incorrectly as false. The sum of the matrix represents the total number of predictions carried out by the machine learning model. The number of predicted cases in this case is 36 given that there are four complete production runs dedicated solely for testing the prediction model (test data set) that were each split in eight labeled time blocks. For instance, looking at model 5, we can observe 35 correct predictions regarding the heat treatment fingerprint (32 'no heat treatment' & three 'heat treatment' blocks) and one instance where a heat treatment block was incorrectly predicted to be a heat treatment block.

Table 4. Accuracy of all models.

Model No.	1	2	3	4	5
Accuracy	1.0	1.0	0.97	0.97	0.97

The confusion matrix can be summarized in an overall accuracy for each of the models. Table 4 shows that all cases (process prediction and detections of a different process) were correctly detected by model 1 & 2 resulting in a perfect accuracy of 100 %, while Models 3 - 5 reach an accuracy of 97 % in this case.

4.6. Limitations

This research is an explorative study to show the potential value-add of expanding the active use of smart-connected products form the usage phase (MOL) to the beginning of life (BOL) by correctly identifying a manufacturing process in an SMS production run solely based on a smart product's integrated sensor data. Despite the prototypical state, a few limitations of the study exist that need to be mentioned. Firstly, in this study, the production runs were manually split in blocks that were manually labeled. However, to provide real value in an industrial production process continuous monitoring and analytics are more desirable. This is an area where further research is necessary. Secondly, the data set is rather unbalanced (which is a common problem of manufacturing data). This can cause issues with some machine learning algorithms. Thirdly, we focused on only one process out of a total of eight - heat treatment - for the prototypical study. We chose the process due to the fact that it is rather unique and thus most likely to be correctly classified as a proof of concept. However, in a real production environment, in order to provide true value, all processes need to be correctly predictable rendering this problem to be not only a multi-class problem but also a problem requiring the introduction of additional clusters that are more noisy and less well defined. Fourthly, for the study we used identical smart products, sensors, SMS, and manufacturing programs. Thinking ahead, the challenge will be to correctly identify a process when it is manufacturing a variety of products (with different parameter settings etc.).

5. Conclusion

The objective of this exploratory study was to investigate the potential of smart-connected products to add value during the manufacturing and assembly process. We postulated that the capability of a smart-connected product to create their own manufacturing history and production plan is valuable for a variety of reasons, including improved product quality, optimized scheduling, counterfeit resistance, energy optimization, and reduction of scrap. Furthermore, smart products with their integrated sensor systems augment the data picture with measurements that are otherwise not obtainable using common external sensors. For example, detailed internal temperatures and temperature curves during heat treatment.

To investigate the technical feasibility of a smart-connected product to identify the current manufacturing processes, we equipped a product with a sensor system and collected data on an eight-stage SMS and subsequently analyzed the data using an ANN algorithm with the goal of correctly identifying a selected manufacturing process (heat treatment) among the whole production run (eight manufacturing processes).

The results show that a smart-connected product can be employed to successfully identify process patterns ('process fingerprint') using machine learning. We were able to predict the correct class with an accuracy of 100% in this prototypical setup and distinguish production run blocks ('heat treatment' / 'no heat treatment'). The result is not surprising as we cautiously chose the process with the highest probability for successful detection. The objective of this study was not to develop an advanced algorithm for prediction, but a proof of concept that smart-connected products can provide useful and value-added information in an SMS environment during the beginning of life. Future applications are manifold, for example optimizing the exposure time in a heat treatment process based on the product itself in contrast to proxy data from outside the part. The geometry, material, and other conditions can impact the ideal exposure time. Too long can lead to material degradation and energy waste, while a too short exposure will impact the material properties of the final product.

5.1. Outlook and future research

The limitations already outline several areas worthy of investigation. Furthermore, there are several avenues that are interesting to explore further - both on the technical as well as the economic side. On the economic side, the question of what the break-even point of introducing a smart-connected product during the BOL. On the technical side, there are many open questions including the provision of connectivity and energy to the sensor system while the product is still being manufactured. Furthermore, the improvements to the sensor system itself can be investigated.

An exciting option emerging is the field of 3D printed electronics. The integration of electronics within geometrically-complex, additively-manufactured structures has been demonstrated since the 1990s [13–17]. 3D printing can be interrupted and components can be robotically placed and electrical interconnect can be realized with manifold methods including micro-dispensing, ink jetting and aerosol jetting of conductive inks [18–20] as well as by structural embedding of solid high-performance conductors directly into substrates [21,22]. One benefit of an integrated, in-envelope suite of manufacturing processes is access to the structure at intermediate layers during fabrication. This access can enable the next generation of products capable of providing sensing data from within the structure both during and after manufacturing. The in-product sensors can inform the manufacturing process of predictive maintenance and even support the qualification of smart-connected structures based on in situ validation/qualification. Figure 6 depicts recent progress made in printable electronics.

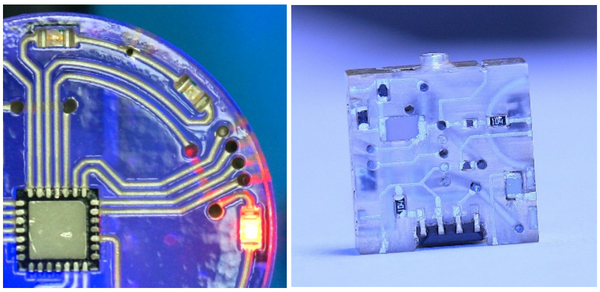

Fig. 6. Examples of previous 3D printed electronics with photocurable resins and conductive inks.

Acknowledgements

This work was supported by the J. Wayne & Kathy Richards Faculty Fellowship in Engineering at West Virginia University and we would like to thank the Friedman Endowment for Manufacturing at Youngstown State University.

References

[1] Lenz J, Wuest T, Westkämper E. Holistic approach to machine tool data analytics. Journal of Manufacturing Systems 2018;48:180–91.
[2] Kusiak A. Smart manufacturing must embrace big data. Nature 2017;544:23–5.
[3] Xu LD, Duan L. Big data for cyber physical systems in industry 4.0: a survey. Enterprise Information Systems 2019;13:148–69.
[4] Porter ME, Heppelmann JE. How smart, connected products are transforming competition. Harv Bus Rev 2014;92:64–88.
[5] Wuest T, Schmidt T, Wei NA, Romero D. Towards (pro-)active intelligent products. International Journal of Product Lifecycle Management 2018;11:154.
[6] Bagheri B, Yang S, Kao H-A, Lee J. Cyber-physical Systems Architecture for Self-Aware Machines in Industry 4.0 Environment. IFAC-PapersOnLine 2015;48:1622–7.
[7] Alpaydin E. Introduction to Machine Learning. MIT Press; 2014.
[8] Hopfield JJ. Artificial neural networks. IEEE Circuits Devices Mag 1988;4:3–10.
[9] Forbes. 10 Ways Machine Learning Is Revolutionizing Manufacturing in 2018. Forbes 2018.
[10] Wang J, Ma Y, Zhang L, Gao RX, Wu D. Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems 2018;48:144–56.
[11] Dialog Semiconductor. DA14583 IoT Sensor; www.dialog-semiconductor.com/iotsensor (accessed December 1, 2019).
[12] Project Jupyter. Jupyter Notebook; https://jupyter.org/ (accessed December 1, 2019).
[13] Shemelya CM, Zemba M, Liang M, Espalin D, Kief C, Xin H, et al. 3D printing multi-functionality: Embedded RF antennas and components. 9th European Conference on Antennas and Propagation (EuCAP) 2015; 1–5.
[14] MacDonald E, Wicker R. Multiprocess 3D printing for increasing component functionality. Science. 2016;353.
[15] Mannoor MS, Jiang Z, James T, Kong YL, Malatesta KA, Soboyejo WO, et al. 3D printed bionic ears. Nano Lett. 2013;13: 2634–2639.
[16] Prinz FB, Weiss LE, Siewiorek DP. Electronic packages and smart structures formed by thermal spray deposition. US Patent. 5278442, 1994.
[17] Perez KB, Williams CB. Combining additive manufacturing and direct write for integrated electronics—a review. 24th International Solid Freeform Fabrication Symposium—An Additive Manufacturing Conference, SFF. 2013; 962–979.
[18] Mirzaee M, Noghanian S, Wiest L, Chang I. Developing flexible 3D printed antenna using conductive ABS materials. 2015 IEEE International Symposium on Antennas and Propagation USNC/URSI National Radio Science Meeting. 2015; 1308–1309.
[19] Rahman T, Renaud L, Heo D, Renn M, Panat R. Aerosol based direct-write micro-additive fabrication method for sub-mm 3D metal-dielectric structures. J Micromech Microeng. 2015;25: 107002.
[20] Paulsen JA, Renn M, Christenson K, Plourde R. Printing conformal electronics on 3D structures with Aerosol Jet technology. 2012 Future of Instrumentation International Workshop (FIIW) Proceedings. 2012; 1–4.
[21] Espalin D, Muse DW, MacDonald E, Wicker RB. 3D Printing multifunctionality: structures with electronics. Int J Adv Manuf Technol. 2014;72: 963–978.
[22] Kim C, Espalin D, Liang M, Xin H, Cuaron A, Varela I, et al. 3D Printed Electronics With High Performance, Multi-Layered Electrical Interconnect. IEEE Access. 2017;5: 25286–25294.