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Intelligent Accuracy Control Service System for Small-Scale Additive Manufacturing

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Abstract:

Ensuring the geometric accuracy of 3D printed parts has proven to be a significant challenge. A recent body of work has developed strategies for using statistical modeling and machine learning to learn from shape accuracy data of past prints to predict and compensate for errors in future prints. Unfortunately, this approach faces a number of challenges that make it difficult to translate from theory to industrial practice. This paper addresses these challenges by proposing a framework for a distributed system through which this modeling methodology could be deployed in an industrial setting. Further, a prototype of this system is illustrated.

1. Background

While the prevalence of additive manufacturing (AM) in industry has seen significant growth in recent years, one persistent challenge is the presence of significant geometric deviations between the part that a manufacturer intended to produce and the object that was obtained [1–3]. These geometric deviations can frequently lead to a part being scrapped, or necessitate rework, both of which can be costly. One complicating factor in the effort to understand, model and prevent the formation of these geometric deviations is the heterogeneity inherent to AM. Today, manufacturers utilize a wide range of AM methods, printer manufacturers, printer models, slicing software, materials, and print settings/parameters. A further complicating factor is the emerging manufacturing paradigm that centers on niche markets and production of small batches of highly customized items. Examples of this include on-site design and manufacturing of medical protective equipment to meet demand, or 3D printing of personalized dental models during a single dental visit to cut treatment cost. Because of this "mass customization", efforts to improve geometric accuracy must also contend with a high degree of shape heterogeneity.

As manufacturers transition to Industry 4.0, there is a growing desire for advanced cyber-physical systems (CPS) that can collect and leverage data to increase manufacturing efficiency and quality [4–8]. Rajkumar, et al. define cyber-physical systems as "physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core" [9]. In the context of additive manufacturing, this could potentially include everything enabling the relevant workflow, including design software, preprocessing tools, 3D printers, *in situ* monitoring hardware, scanners and software used for quality control, any tools used for data analysis, and more. A recent body of work has sought to address the problem of shape accuracy through a predictive compensation approach that would be deployed in the context of a CPS [2,3,18–21,10–17]. The first step in this approach is to generate predictions for the geometric deviations across the surface of the shape to be printed. Methods for accomplishing this can be divided into subgroups, including works that seek to generate predictions using physics-based models [16,17], and those that use data-driven models [2,3,20,21,10–15,18,19]. Once predictions are generated by a model, the shape of the object is then modified in a manner that is anticipated to eliminate the predicted deviation. To address the challenge of process heterogeneity, a recent line of work has focused on methods for transferring knowledge from one printing process to another [22,23]. This means that data from one process could be leveraged to reduce the amount of data necessary to train an effective model for a semi-related process.

2. Challenges

Unfortunately, there are a number of significant barriers that have hampered translation of this line of research into industry. First, there are reasonable limitations in the domain knowledge possessed by those managing an AM workflow. Producing an effective data-driven model for an AM process using the methods mentioned above currently requires advanced knowledge in fields such as statistical modeling or machine learning. Second, there is a significant cost in both time and money to generate these modeling tools in-house for a specific AM process. Small organizations with a limited number of AM machines, or for whom AM is not a main focus might not deem the effort worthwhile. Further, the amount/quality of data generated by a smaller manufacturer might prove to be a challenge for generating the models that they desire. Finally, such a manufacturer might not have access to the measurement equipment or sensors that are needed to train a specific model.

These challenges point to the need for a CPS for AM architecture that can centralize this effort to overcome the knowledge gap and resource constraints, allowing small-scale makers and manufacturers to outsource modeling to domain experts and automated processes. Further, with such a system, AM geometric accuracy data could be pooled among users, reducing the cost of generating this data for each new model that is desired, and lowering the barrier to entry for new users. While the benefits of this approach are significant, the need for manufacturers to maintain the privacy of large swaths data presents a major challenge. One example of this would be a manufacturer that produces proprietary parts, and would be hesitant to send CAD files and geometric accuracy data for those parts to a 3rd party, let alone share that data with its peers. For this reason, a system that allows for some geometric accuracy data to be shared, while preserving the security of proprietary information and still allowing modeling to be outsourced to a third party is needed.

3. Proposed solution: a distributed system architecture for CPS for AM

Previous work in the area of data analysis for CPS for AM has looked at systems for pooling machine data for tasks such as process settings selection [24]. Further work has looked at challenges and opportunities inherent to CPS for AM [25], as well as potential security vulnerabilities in CPS for AM [26]. This paper proposes a distributed system architecture for addressing the modeling needs of manufacturers while also enabling the separation of proprietary data. In this system, there are three main components. First, the 3rd party service maintains a set of software tools for generating statistical or machine learning models based on geometric accuracy data. Second, a manufacturer client runs software that can take models generated by the 3rd party and use them to generate accuracy predictions and compensated CAD files. Third, both the manufacturers and the 3rd party service utilize a cloud-based app in order to transfer manufacturing data and trained models. The client can manufacture non-proprietary objects using an AM process that they desire to generate a model for. The data from these parts can be sent to the 3rd party service, which generates a trained model based on the data and sends it to the client. Then, the client can deploy the models on their local system, which can handle proprietary and otherwise confidential CAD designs. This system is illustrated in Figure 1. Each component of the system will be discussed below, and illustrated through a case-study.

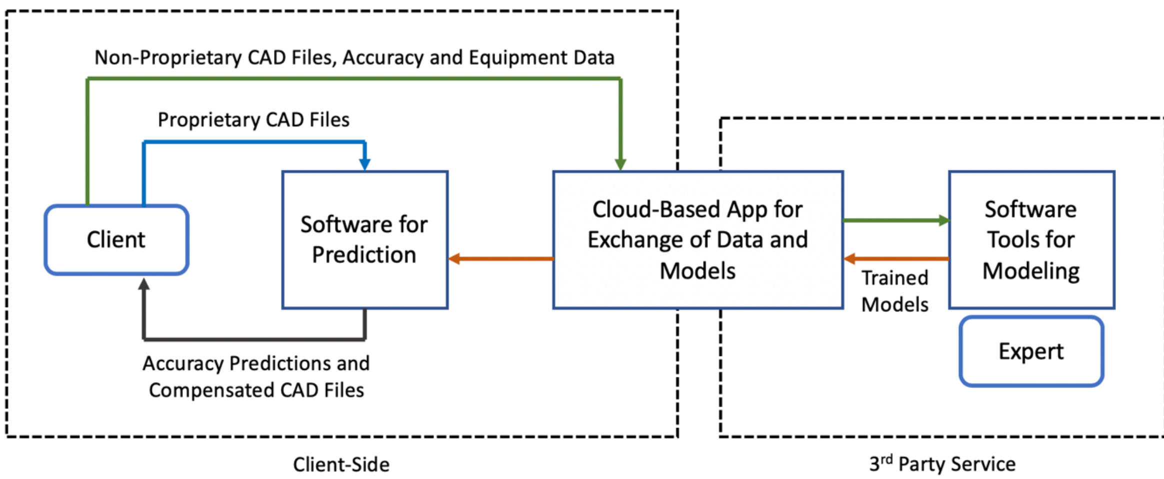

Figure 1. Diagram of the proposed system.

4. Proposed solution: a distributed system architecture for CPS for AM

3.1. Client-side software

In the proposed system, software that runs locally on a client's computers handles deployment of trained models for predicting geometric deviations and modification of CAD files, as well as collection of the relevant manufacturing data that will be used for modeling. Because of this, all private information is retained by the client. This software also offers the ability to visualize errors and perform analysis to determine whether a part is likely to fall within required tolerances.

A prototype of this software that was developed by the authors is shown in Figure 2. It allows for the visualization of errors across the surface of the part in 3D, while also providing tools for quantitative analysis of the predicted deviations. It takes in a STL file of a part, as well as a trained model for a given process, and can output a modified STL file of the compensated part.

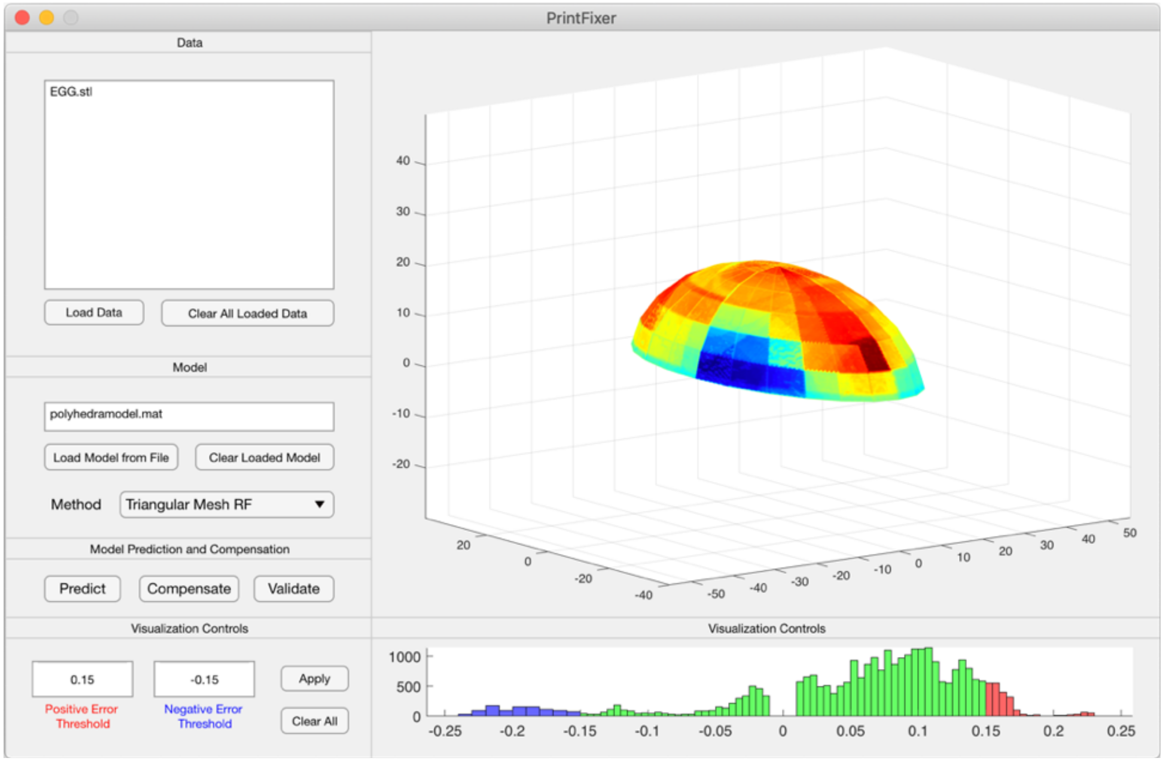

Figure 2. Screenshot of a prototype of the client-side software program.

3.2. Expert-side software

A broader set of tools are required on the expert side in order to process accuracy measurement data, AM process data, generate predictor variables that can be used to generate a model, and finally to train the required model. These tools might vary as a result of the data that is available from a client, as well as their specific needs. For this reason, a one size fits all approach is likely not possible. Further, because of the significant variability in process conditions and measurement data that is produced by and sent from users, expert judgment and domain knowledge will likely be difficult to fully remove from this process.

3.3. Cloud-based app for exchange of data and models

The final component of this system is a cloud-based app that facilitates the exchange of non-proprietary process accuracy measurement data from users to the 3rd party service, and trained models in return. Screenshots from a prototype of this app developed by the authors are shown in Figure 3. This app also allows users to organize their measurement data from each of their printers, printing processes, and products. This enables manufacturers to track AM accuracy across their resources while giving them a complete inventory of the data they have available for modeling.

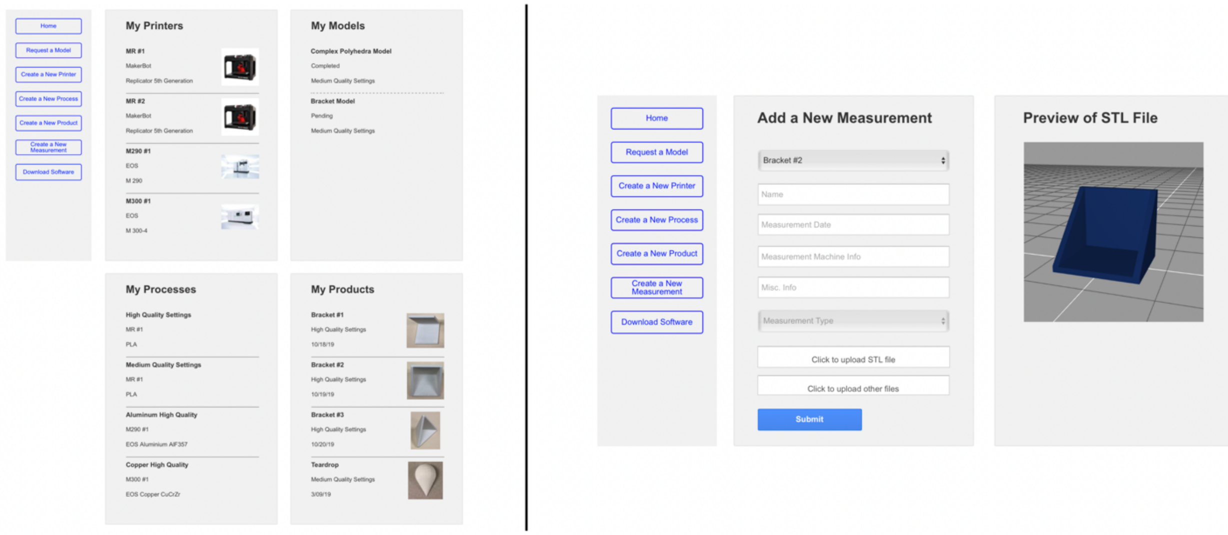

Figure 3. Screenshots of a prototype of the cloud-based exchange.

4. Case-Study

A short case study is provided to illustrate the functioning of the prototyped system. Geometric accuracy data (shown in the bottom left corner of Figure 4) is collected for several objects printed with a desktop FDM printer. In the figure, blue indicates areas of the part with dimensions that are too small, while red indicates areas that are too large. In this case, the printer used was a MakerBot Replicator 5th Generation, and the parts were scanned for accuracy using a Romer Absolute Arm. This data, as well as the corresponding CAD/STL files for the prints is uploaded to the cloud-based app and associated with the printer used, as well as the set of process parameters and materials used, referred to here as simply a 'process'. It is important to note that these shapes will likely be non-proprietary, since they will have to be shared outside the manufacturer's organization. The app keeps records of each printer and process used by the manufacturer, as well as the types of parts they have produced and the corresponding accuracy data for each. The manufacturer can then request a predictive model for a given process using the form shown in Section 2 of Figure 4. This request is sent to the 3rd party service, along with all non-proprietary data that is associated with the process. A model is then trained by the service according to a method such as [2,15,21] and returned to the user with any needed instructions and information. This is illustrated in Section 3 of Figure 4. Finally, when the manufacturer desires to print a proprietary design that the model has not seen, they can use the proposed client-side software tool in order to generate predictions of deviation and compensation via the new model. This is shown in Section 4 of Figure 4. The accuracy of the new part is shown in the bottom right hand corner of Figure 4. For this part, there was a 44% reduction in the mean absolute error of dimensions at each vertex across its surface.

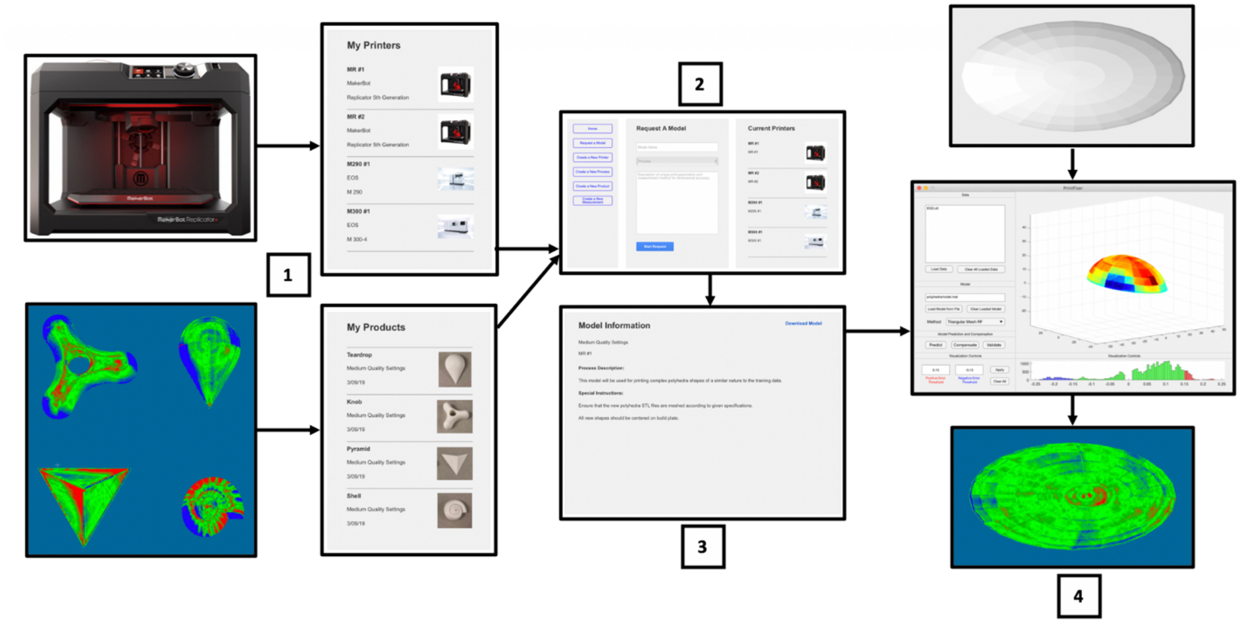

Figure 4. Illustration of the case-study.

5. Discussion

A system that balances the need for data privacy with outsourced expertise is necessary to facilitate the translation of research into shape deviation modeling and compensation from academia to widespread industrial use. The distributed system architecture proposed here offers a step in this direction. Such a system might be put into place by a large AM machine manufacturer as a service that would be offered to customers. This would fit with the industry-wide pivot to software as a service (SaaS) and recurring revenue streams to compliment large one-time purchases. This would further serve as a step in facilitating the necessary transition of disconnected printers into an Industry 4.0 framework. One significant downside to the proposed approach is that due to controls on which data is shared, knowledge generated using proprietary parts, which could be the most relevant to a manufacturer's needs, can't be utilized for model training and improvement. An additional limitation to the approach that should be acknowledged is the fact that while it can generate predictions for previously unseen designs, they must possess somewhat similar geometric features to the training data used in the model, so as to limit the degree to which the model must extrapolate.

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References

[1] Dimitrov D, Van Wijck W, Schreve K, De Beer N. Investigating the achievable accuracy of three dimensional printing. Rapid Prototyp J 2006;12:42–52. https://doi.org/10.1108/13552540610637264.

[2] Huang Q, Zhang J, Sabbaghi A, Dasgupta T. Optimal offline compensation of shape shrinkage for three-dimensional printing processes. IIE Trans (Institute Ind Eng 2015;47:431–41. https://doi.org/10.1080/0740817X.2014.955599.

[3] Huang Q, Nouri H, Xu K, Chen Y, Sosina S, Dasgupta T. Statistical Predictive Modeling and Compensation of Geometric Deviations of Three-Dimensional Printed Products. J Manuf Sci Eng 2014;136:061008. https://doi.org/10.1115/1.4028510.

[4] Lee J, Bagheri B, Kao HA. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett 2015;3:18–23. https://doi.org/10.1016/j.mfglet.2014.12.001.

[5] Krugh M, Mears L. A complementary Cyber-Human Systems framework for Industry 4.0 Cyber-Physical Systems. Manuf Lett 2018;15:89–92. https://doi.org/10.1016/j.mfglet.2018.01.003.

[6] Ahuett-Garza H, Kurfess T. A brief discussion on the trends of habilitating technologies for Industry 4.0 and Smart manufacturing. Manuf Lett 2018;15:60–3. https://doi.org/10.1016/j.mfglet.2018.02.011.

[7] Lee J, Lapira E, Bagheri B, Kao H an. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 2013;1:38–41. https://doi.org/10.1016/j.mfglet.2013.09.005.

[8] Colosimo B, Huang Q, Dasgupta T, Tsung F. Opportunities and Challenges of Quality Engineering for Additive Manufacturing. J Qual Technol 2018;50:233–52.

[9] Raj R. Cyber-Physical Systems : The Next Computing Revolution 2010:731–6.

[10] Tong K, Lehtihet EA, Joshi S. Software compensation of rapid prototyping machines. Precis Eng 2004;28:280–92. https://doi.org/10.1016/j.precisioneng.2003.11.003.

[11] Tong K, Joshi S, Lehtihet EA. Error compensation for fused deposition modeling (FDM) machine by correcting slice files. Rapid Prototyp J 2008;14:4–14. https://doi.org/10.1108/13552540810841517.

[12] Luan H, Huang Q. Predictive modeling of in-plane geometric deviation for 3D printed freeform products. IEEE Int Conf Autom Sci Eng 2015;2015-Octob:912–7. https://doi.org/10.1109/CoASE.2015.7294215.

[13] Luan H, Huang Q. Prescriptive Modeling and Compensation of In-Plane Shape Deformation for 3-D Printed Freeform Products. IEEE Trans Autom Sci Eng 2017;14:73–82.

[14] Huang Q. An Analytical Foundation for Optimal Compensation of Three-Dimensional Shape Deformation in Additive Manufacturing. J Manuf Sci Eng 2016;138:061010. https://doi.org/10.1115/1.4032220.

[15] Decker N, Huang Q. Geometric Accuracy Prediction for Additive Manufacturing Through Machine Learning of Triangular Mesh Data. Proc. ASME 2019 14th Int. Manuf. Sci. Eng. Conf., Erie, PA: 2019, p. 1–9.

[16] Chowdhury S, Anand S. Artificial Neural Network Based Geometric Compensation for Thermal Deformation in Additive Manufacturing Processes. Proc. ASME MSEC, June 27 - July 1, 2016, Blacksburg, Virginia, USA: 2016, p. MSEC2016-8784, p. V003T08A006. https://doi.org/10.1115/MSEC2016-8784.

[17] Chowdhury S, Mhapsekar K, Anand S. Part Build Orientation Optimization and Neural Network-Based Geometry Compensation for Additive Manufacturing Process. J Manuf Sci Eng 2018;140:031009-1-031009–15. https://doi.org/10.1115/1.4038293.

[18] Francis J, Bian L. Deep Learning for Distortion Prediction in Laser-Based Additive Manufacturing using Big Data. Manuf Lett 2019;20:10–4. https://doi.org/10.1016/j.mfglet.2019.02.001.

[19] Wang A, Song S, Huang Q, Tsung F. In-Plane Shape-Deviation Modeling and Compensation for Fused Deposition Modeling Processes. IEEE Trans Autom Sci Eng 2017;14:968–76. https://doi.org/10.1109/TASE.2016.2544941.

[20] de Souza Borges Ferreira R, Sabbaghi A, Huang Q. Automated Geometric Shape Deviation Modeling for Additive Manufacturing Systems via Bayesian Neural Networks. IEEE Trans Autom Sci Eng 2019;PP:1–15. https://doi.org/10.1109/TASE.2019.2936821.

[21] Huang Q, Wang Y, Lyu M, Lin W. Shape Deviation Generator (SDG) - A Convolution Framework for Learning and Predicting 3D Printing Shape Accuracy. IEEE Trans Autom Sci Eng 2020;17:1486–500. https://doi.org/10.1109/TASE.2019.2959211.

[22] Sabbaghi A, Huang Q. Model transfer across additive manufacturing processes via mean effect equivalence of lurking variables. Ann Appl Stat 2018;12:2409–29. https://doi.org/10.1214/18-AOAS1158.

[23] Francis J, Sabbaghi A, Ravi Shankar M, Ghasri-Khouzani M, Bian L. Efficient Distortion Prediction of Additively Manufactured Parts Using Bayesian Model Transfer Between Material Systems. J Manuf Sci Eng 2020;142:1–16. https://doi.org/10.1115/1.4046408.

[24] Amini M, Chang SI, Rao P. A cybermanufacturing and AI framework for laser powder bed fusion (LPBF) additive manufacturing process. Manuf Lett 2019;21:41–4. https://doi.org/10.1016/j.mfglet.2019.08.007.

[25] Cooper KP, Wachter RF. Cyber-enabled manufacturing systems for additive manufacturing. Rapid Prototyp J 2014;20:355–9. https://doi.org/10.1108/RPJ-01-2013-0001.

[26] Sturm LD, Williams CB, Camelio JA, White J, Parker R. Cyber-physical vulnerabilities in additive manufacturing systems: A case study attack on the.STL file with human subjects. J Manuf Syst 2017;44:154–64. https://doi.org/10.1016/j.jmsy.2017.05.007.