# Factory 4.0 Toolkit for Smart Manufacturing Training

**Dr. Joseph Dennis Cuiffi, Pennsylvania State University, New Kensington**

Dr. Joseph Cuiffi is the Program Coordinator for the Electro-Mechanical Engineering Technology program at Penn State New Kensington. He is a graduate of Penn State with an honors B.S. and a Ph.D. in the Department of Engineering Science and Mechanics, focused on semiconductor processing. His current interests are in Smart Manufacturing education and workforce development.

**Prof. Haifeng Wang, Pennsylvania State University, New Kensington**

Dr. Haifeng Wang has received degrees of Doctor of Philosophy in Electrical Engineering (2014), Masters of Science in Control (2006) and Bachelors of Science in Electrical Engineering (2002). Currently, he is an IEEE member and IEEE Pittsburgh Section Executive and Administrative Committee Secretary. His expertise includes control system, power electronics, embedded system, image processing and machine learning.

**Josephine Heim, Pennsylvania State University, New Kensington**
**Dr. Brian W. Anthony, Massachusetts Institute of Technology**

Brian Anthony is the Director of the Master's of Engineering in Manufacturing Program and Co-director of the Medical Electronic Device Realization Center at MIT. He has more than 20 years of product realization experience, including instrumentation and measurement solutions for manufacturing systems and medical diagnostics and imaging systems.

**Mr. Sangwoon Kim**
**Dr. David Donghyun Kim, Massachusetts Institute of Technology**

David Donghyun Kim received a Bachelor of Applied Science in Mechanical Engineering with Management Science Option from the University of Waterloo and received Master of Science and Ph.D. degrees in Mechanical Engineering from MIT. He is interested in mechanical design for robotic systems. His fundamental research background in CAD/CAM, mainly focusing on 5-axis CNC milling, allowed him to design with manufacturing in mind. He invented and developed multiple mechatronics systems pushing the limits on the current industrial standards.

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## Abstract

The rapid pace of technology development in the field of smart manufacturing has left educational systems scrambling to keep pace and adapt learning outcomes, resulting in inadequate preparedness and readiness of workforce at all levels. Often, smart manufacturing training materials are either broad and conceptual or a specific technical deep dive with little context. We have developed an educational toolkit that leverages an inexpensive, bench scale extrusion platform to provide lab activities and feature-rich data to explore fundamental concepts of smart manufacturing in a production context for an audience of both undergraduate engineering students and current manufacturing workforce members. Through investigation of the mock production platform and associated data, concepts and applications of modern data-driven tools are explored in the topic areas of data collection and the industrial internet of things, data analytics and predictive modeling for production data, simulation and digital twinning, and process and manufacturing systems optimization. The activities culminate in the exploration of advanced feedback control algorithms and optimization of operating conditions, balancing throughput, quality, and power consumption, using digital twins.

The combination of overview conceptual materials along with in-depth activities on an actual process allows us to tailor the scope of the specific training to the intended audience. Select modules of the Factory 4.0 toolkit were delivered in an undergraduate course and in a training workshop for manufacturing personnel. Pre- and post-attitude surveys, along with participant comments, were used to assess the training approach and content. We found that the proper technical scope is critical for a given audience and that all types of manufacturing personnel, from technicians and engineers to operations and management, benefit from foundational smart manufacturing concepts and examples. We also found that for technical materials, student audiences required more of the fundamental instrumentation and statistical analysis topics, while current technical practitioners desired specific deep dives into data analytics, digital twinning, and process optimization after introductory overviews. Both educational experiences exposed a need for preparedness in programming and statistical analysis software tools to take advantage of these smart manufacturing concepts.


## Introduction

Manufacturing and industrial process systems are evolving at a relatively rapid pace due to the digitalization and data centric transformations occurring in many aspects of the economy [1]. As applied to manufacturing, this wave of transformation is generally referred to as Industry 4.0 or Smart Manufacturing, and in the U.S. our efforts to modernize manufacturing are less centrally led than in other countries [2]. By its very nature, Smart Manufacturing is a data driven, highly integrated enterprise, bridging multiple levels within a traditional automation environment and the cyber-physical space. The interdisciplinary technology nature of Smart Manufacturing as noted in [3] and the business, innovation, and teamwork skills noted by [4] have caused both manufacturers and educational institutions to develop new programs to educate the current and future workforce.

A learning environment for manufacturing concepts typically uses demonstration equipment and processes for hands-on exercises, which can often be expensive. This is exemplified by learning factory environments, which allow for an immersive educational experience that demonstrates a system-wide enterprise [5][6] or a digital design experience [7]. In addition, Smart Manufacturing education further requires data collection and management systems that allow for exploration of data analysis and feedback as demonstrated by [8]. In order to provide a relatively low-cost training platform for a relatively challenging control problem, D. Kim and B. Anthony demonstrated a benchtop fiber extrusion system for educational training [9]. This FibeR Extrusion Device, FrED, provided a process that would benefit from complex process control, while also being straightforward to analytically model and test. Recently, S. Kim et al. showed how deep reinforcement machine learning could even be applied to the feedback control for this device for improving fiber quality [10]. These properties of FrED have led to its use in the Smart Manufacturing Professional Education program at MIT [11], where statistical process control, data-decision thinking, and advanced control techniques are applied to improving machine operation.

Our goal was to adapt the FrED system to serve undergraduate engineering education as well as add to the learning activities possible with the platform. To accomplish this, activities for Internet of Things (IoT), digital twin creation, and digital twin use in the optimization of manufacturing process, were developed to create a Factory 4.0 Toolkit. Materials from this toolkit were presented to undergraduate students and current workforce members in order to assess and organize an overall approach to Smart Manufacturing training.

**Course Objectives and Design**

Given the broad landscape of technologies and business practices under the umbrella of Smart Manufacturing, it is important to scope the topics carefully for curriculum development. In an attempt to convey the core concept of data-centric thinking, we decided to focus the Smart Manufacturing topics on collecting and using data to develop digital models and improve manufacturing processes. This led to the following Factory 4.0 Toolkit overall learning objectives:

1. <u>Data Collection - Industrial Internet of Things (IIoT):</u> Students will be able to develop a data collection strategy for industrial networks, including non-traditional IoT data streams and cloud-based data storage.
2. <u>Data Analytics and Predictive Modeling for Production Data:</u> Students will be able to visualize, analyze, and predict relevant production outcomes based on process data.
3. <u>Simulation - Digital Twinning:</u> Students will be able to create and use digital twins of factory processes.
4. <u>Process and Manufacturing Systems Optimization:</u> Students will be able to optimize factory processes using digital twins, data analytics, and predictive modeling.

Our goal was to develop educational materials including presentations, videos, and lab materials as a general Factory 4.0 Toolkit for both undergraduate students and current workforce members. Therefore, the materials were not designed to fit within a specified training plan, such as a 15 week college course. Instead, we took an approach to develop overall learning objectives and subsequent supporting materials, a Factory 4.0 Toolkit, that could be drawn from to create a specified training course. The developed materials range from fundamental (definitions and concepts) to hands-on activities based on an example manufacturing process, fiber extrusion with the FrED system. The topic and activities are organized to support the learning objectives, as shown in Table 1, and include 35 slide decks with audio recordings, 12 videos, and 10 lab activity guides.

Table 1. Topic Outline of Factory 4.0 Educational Materials

| **I. Introduction and Overview** | **IV. Digital Twinning** |
|---|---|
| I.a Factory 4.0 Introduction | IV.a Approaches to Digital Twinning |
| I.b Smart Manufacturing Essentials | IV.L Developing a FrED Analytical Process Model |
| I.c Example Extrusion Process – FrED | IV.b Data Preparation for Empirical Modeling |
| **II. Data Collection** | IV.bL FrED Data Preparation for Empirical Modeling |
| II.a IIoT Fundamentals | IV.c Introduction to Machine Learning |
| II.b IoT Retrofitting | IV.cL FrED Machine Learning to Develop Time-Invariant Models |
| II.bL Adding Power Monitors to FrED | IV.d Developing Time-Variant Models |
| II.c Fundamentals of Data Acquisition | IV.dL FrED Time-Variant Heater Modeling |
| II.d Data Communication Protocols | IV.e Packaging and using Digital Twins |
| II.dL FrED Data Communication and Collection | IV.eL Packaging and Deploying FrED Digital Twin Models |
| II.e Data Integration | **V. Process Control Optimization** |
| II.f Cloud Storage | V.a Optimizing Process Control |
| **III. Data Analytics for Production Data** | V.aL FrED Process Control Optimization |
| III.a Statistical Exploration | V.b Using a Neural Network Time-Variant model with Feed Forward Process Control |
| III.aL FrED Statistical Exploration | **VI. Manufacturing Systems Optimization** |
| III.aSup Python for Engineers | VI.a Multi-Objective Optimization using Digital Twins |
| III.b Data Visualization | VI.aL FrED Optimization of Run Conditions |
| III.c Data Contextualization | VI.b Digital Twin Assisted Process Monitoring |
| III.cL FrED Data Visualization and Contextualization | VI.bL FrED Smart Monitoring |
| | VI.c Digital Twin Assisted Scheduling |

The FrED system, as noted above and shown below in Figure 1, provides a benchtop-style, relatively inexpensive platform for running the learning activities. The philosophy of using FrED within the Factory 4.0 Toolkit is to improve and explore the fiber extrusion process by retrofitting sensors and improving the process through data learning and modeling. This provides a relevant learning platform not only for students, but also for current industry participants dealing with upgrading legacy equipment and developing data-centric processes in their facilities.

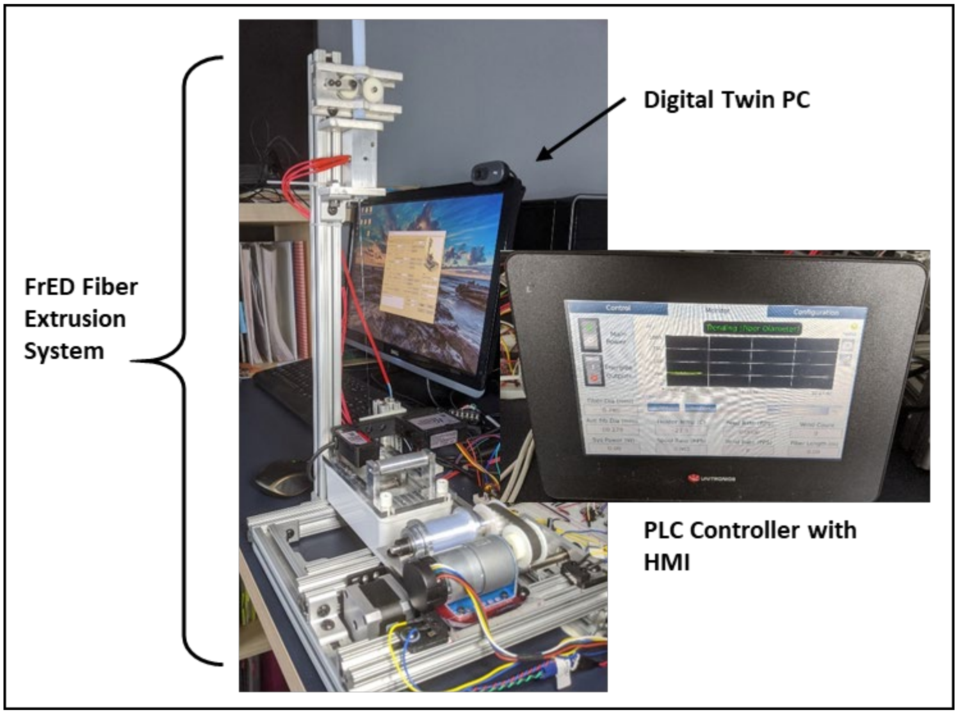



Figure 1. FrED benchtop extrusion system showing the control Programmable Logic Controller (PLC) with Human Machine Interface (HMI) and a PC running a FrED Digital Twin.

A critical component in running the activities in the Factory 4.0 toolkit is the data information network. Figure 2 shows the overall architecture of the data flow and the interconnected devices. The FrED system is controlled locally with a PLC (microcontroller and PC control is optional). A centralized Data Server PC handles the data communication through the network and can be run simply with an MQTT Broker or optionally with an OPC UA Server for a more industrially relevant setup. The Data Sever PC is also setup with a Node-RED dashboard for Smart Monitoring and programs to log data in data files or through a historian database. The power monitoring sensors added to FrED communicate directly with the Data Server to mimic sensor retrofitting using an IoT style configuration, where the data is not collected at the PLC level but transmitted directly to the information network. The Digital Twin PC is setup with python programs that run a FrED digital twin and advanced control algorithms that can be used to control FrED, bypassing the PLC control algorithms. All of the data generated by FrED and the FrED Digital Twin are accessible by Trainee PCs on the network. This allows trainees to analyze data, create their own dashboards, and perform modeling and machine learning using Excel, python or MATLAB®. A GitHub repository (jcuiffi/pyhton-fred) contains the software used to setup the Factory 4.0 Toolkit along with sample data and data analysis scripts that align with the learning activities.

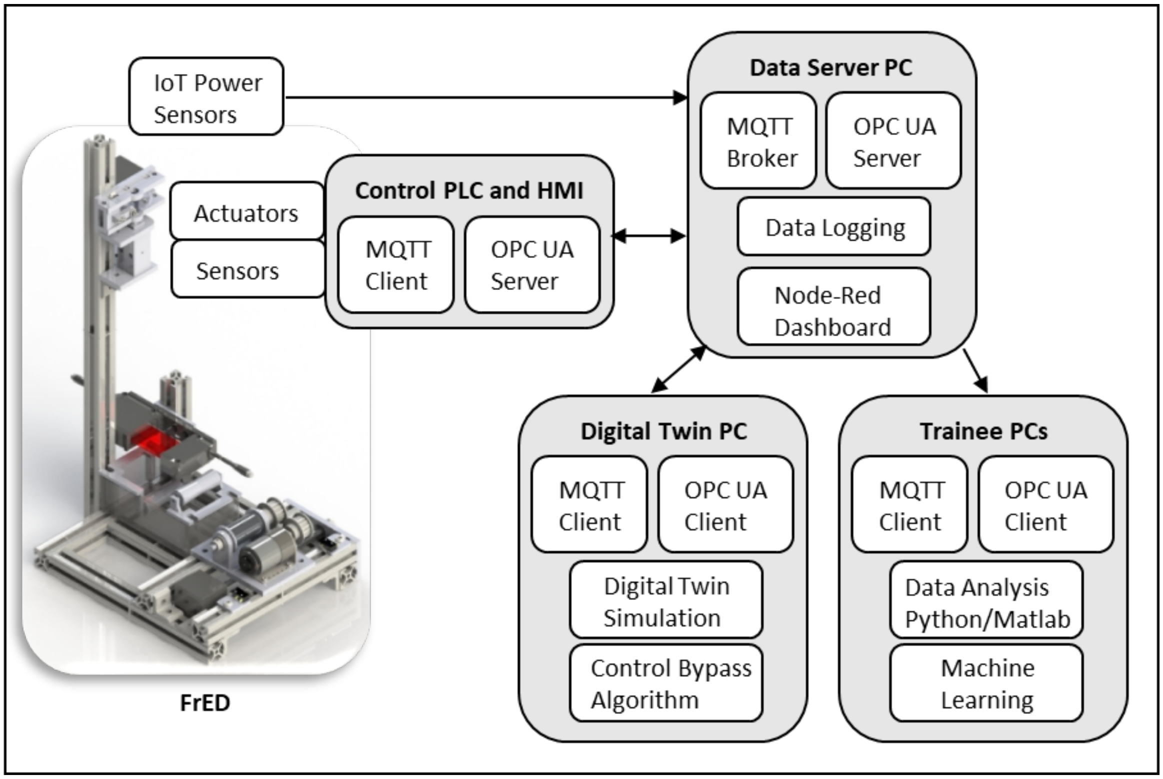


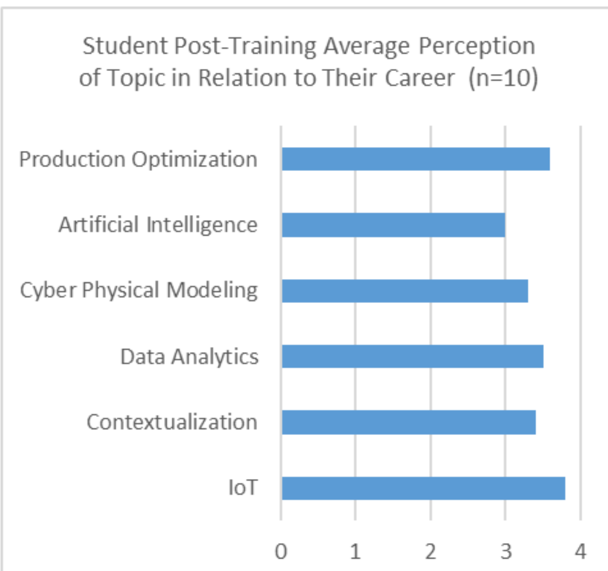

Figure 2. Factory 4.0 data flow architecture showing a central data server (MQTT or OPC UA) communicating with the control system, add-on sensors, a Digital Twin PC, and any number of Trainee PCs.

## Course and Workshop Demonstrations

Factory 4.0 materials were presented to two different audiences, undergraduate students and current manufacturing workforce members. The undergraduate demonstration was part of a Smart Manufacturing senior technical elective in an EMET (Electro-Mechanical Engineering Technology) program. EMET students are trained in automation engineering, and therefore, have a background in automation and control systems, with exposure to programming microcontrollers and PLCs, as well as basic data acquisition and analysis techniques. Ten students participated and were provided pre- and post-surveys as part of the class, and although this was a small initial sample size, there was value in assessing student interest in the exercises and materials.

The undergraduate course focused initially on gathering and collecting data with an internet of things style network. The students programmed microcontrollers to collect environmental data (ambient temperature, pressure, and humidity), and through MQTT and Node-RED, created dashboards and explored fundamentals in data collection and aggregation. This led to the introduction of FrED and adding power (current) monitors as a retrofit. The class exercises then focused on learning about FrED through analytical modeling and visualizing the data in Excel and MATLAB® (for complex plotting). The students were then led through developing more complex empirical models of FrED, starting with Excel and then moving to python demonstrations for data preparation, regression and machine learning. Although aspects of the data analysis and preparation were able to be performed with the students, more advanced data analysis with python was more demonstrative than interactive. The students were then shown how the models were used to build the FrED Digital Twin, which they could then interact with. The Digital Twin was used to demonstrate the power of multi-objective optimization, leading them through an exercise to balance fiber quality against energy consumption and cost with the digital model. Finally, a Smart Monitor activity was demonstrated to show how the Digital Twin can be used to compare against the physical process to detect anomalies.

Overall, the students were engaged with the material and found it relevant to their upcoming career. The post-training perception of the topics in relation to their career is shown below in Figure 3a. The average student change in perception is shown in Figure 3b. The post training data indicates that all of the topics appeared to be relevant to the students for their career. Artificial intelligence scored the least relevant, perhaps due to the approach taken to describe machine learning or the intimidation of the complexity of implementation with advanced computer programming. In the change in perception results, it was interesting and promising to see that Data Contextualization, providing meaning to data, rose to the top. This is a key learning activity for the course, where we are trying to stress data understanding and decision making.



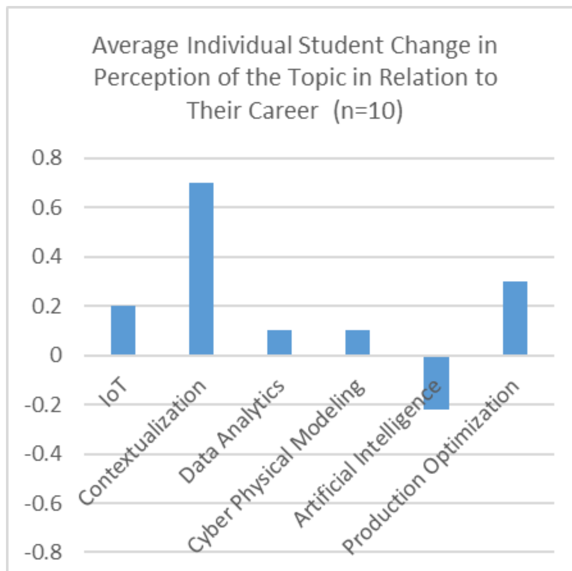
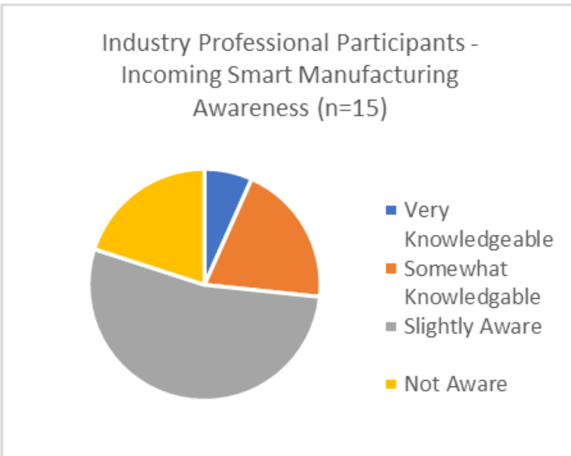




Figure 3. a) (left) Student final perception of the topics in relation to their career. b) (right) Average student change in perception. Each student's perception change was quantified and then averaged per topic. Scale: 4 – Very Important, 3 – Important, 2 – Slightly Important, 1 – Not Important.

For the current workforce manufacturer training, we held four sessions (2hrs each, 8 hours total) for 18 employees from local companies. The goal was to present overviews of Smart Manufacturing topics as well as deeper-dive demonstrations to showcase the possibilities of modern data collection and modeling. The mix of participants was interesting and reflected the interdisciplinary training needed to implement Smart Manufacturing techniques. Out of 15 that responded, 2 were in business operations, 4 were in engineering, 3 were in technical management, 2 were technicians, and 4 were in Information Technology. Their prior exposure to Smart Manufacturing also varied, as shown in Figure 4a.

The training focused initially on Smart Manufacturing definitions and then used the FrED example to walk the participants through advanced data collection, data analysis, and simulations to improve the process. All of the materials were simply demonstrated given the time constraints. The overviews and demonstrations appeared to resonate well with the audience, and post-training surveys indicated improved interest in pursuing Smart Manufacturing, see Figure 4b.



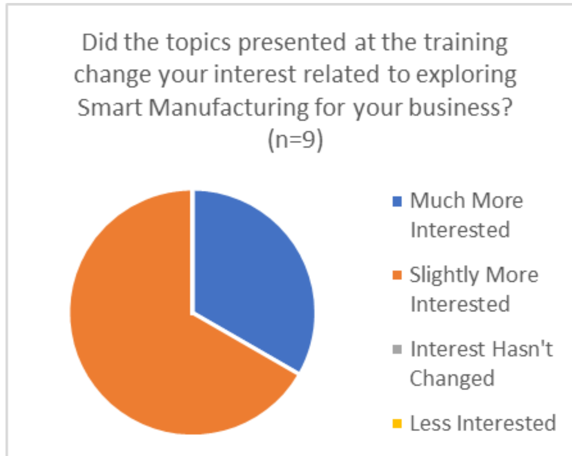




Figure 4. a) (left) Incoming participant Smart Manufacturing familiarity. b) (right) Post-training interest in exploring Smart Manufacturing further.

**Recommendations and Conclusions**

The integration of Smart Manufacturing topics in manufacturing education will continue to grow. The Factory 4.0 Toolkit demonstrations provided useful information as we develop the materials further for our programs. For dissemination, the materials described here are now available through CESMII – The Smart Manufacturing Institute (cesmii.org), which sponsored the effort. We note that other manufacturing processes, beyond the extrusion system that we used in our demonstration, can be adapted to present these materials and run hands-on exercises. Time-series data is important for presenting several concepts, so any type of continuous production process would be appropriate according to the machine availability at a given program. The data collection and analysis processes, which are at the core of the learning objectives, are relevant for many various production processes, both continuous and batch. In addition, the use of more industrial controllers (PLCs) and historians is also optional, as many of the data acquisition and control functions can be done with more educationally friendly systems, such as with microcontrollers or LabVIEW.

Regarding undergraduate education, the technical materials must be adjusted to student competencies, but the exposure to data-centric thinking and Smart Manufacturing concepts applies to all students. For the IoT exercises, which appear to be popular amongst students, a basic electrical background as well as exposure to microcontrollers are helpful, but not necessary. It is relatively easy to walk the participants through these types of exercises due to the ease of the Arduino platform and simplicity of the Node-RED environment. Most upper level industrial or manufacturing related engineering students have the electro-mechanical and automation background to explore the data generated from a production process. The data exercises require that the students are comfortable with Excel and basic statistical concepts. MATLAB® or python experience is preferable for the data visualization exercises. For our EMET undergraduates, the data processing and machine learning exercises are best demonstrated, as the programming skills and complexity of machine learning algorithms beyond regression are challenging. The culmination of using the Digital Twin to optimize and monitor processes is a great summary of the material and appears to bring the practicality of the concepts full circle.

The industry pilot was interesting and helped to scope future training. We were excited and surprised to see the variety of occupations represented. It was clear from the training that the introductory materials were useful to all the participants. It was, however, difficult to transition to more in-depth technical topics without losing interest of the less-engineering focused participants. In contrast to the student exercises, the participants here responded well to process improvement and overall systems topics more relevant to improving their manufacturing processes. The basic topics relating to data collection and aggregation were not as useful. These observations point to a strategy of starting with overview topics for all levels of occupations, then offering more in-depth technical topic coverage where applicable.

For all technical audiences, we note that Smart Manufacturing requires that engineers continue to develop data analysis tools as part of their skillset. As digital information becomes the key for driving process improvements, as it has in many other industries, manufacturing engineers need to keep up with modern data science tools and the programming environments to use them. We hope that the Factory 4.0 Toolkit helps to support undergraduate student exposure to these technologies and to provide learning experience for practicing engineers to improve and upgrade their current processes.

**Acknowledgment**

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