SMART: A System-level Manufacturing and Automation Research Testbed

Ilya Kovalenko, Miguel Saez, Kira Barton, and Dawn Tilbury

Mechanical Engineering Department, University of Michigan, Ann Arbor, MI.
{ikoval, migsae, bartonkl, tilbury}@umich.edu

Abstract

Manufacturing testbeds are used to develop, test, and analyze technologies that address some of the current challenges facing the manufacturing sector. This paper provides a classification of manufacturing testbeds and categorizes existing testbeds based on each category specification. In addition, this paper introduces the System-level Manufacturing and Automation Research Testbed (SMART), a multidisciplinary testbed used for manufacturing research and education at the University of Michigan. SMART consists of a physical serial-parallel line equipped with sensors to collect data at both the machine and system level. Various tools are used to aggregate, analyze, and display this data in a cloud infrastructure. The system set-up allows for the discovery, testing, implementation, and analysis of new technologies. In addition, different simulations of SMART have been developed to augment and study the testbed at the machine and system levels. A number of ongoing projects utilize SMART's physical and virtual capabilities. These projects cover a wide variety of areas, including centralized and decentralized control of manufacturing systems and performance monitoring and analysis.

Keywords: System-level testbeds, Manufacturing Systems, Manufacturing Automation, Simulations

1. Introduction

A common approach for realizing advancements in the manufacturing sector is through the use of manufacturing system testbeds that simulate the industrial environment on a smaller scale. In the literature, there have been several surveys that outline metrics that must be met for specific categorization of manufacturing system testbeds. Each of these categories helps specify the manner in which an industrial testbed could be used for various types of manufacturing system research and education. In this work, we compile these surveys and provide example testbeds that fulfill the requirements for these categories with different combinations within a given testbed. In addition, we present a unique testbed installed at the University of Michigan that meets the requirements of several categories and is used for both research and educational purposes.

The manufacturing sector is an integral part of the global economy, accounting for 16% of the global Gross Domestic Product (GDP) [1]. In the US, the manufacturing sector employs nearly 12 million workers, while accounting for 13% of the US GDP [2]. It has the largest multiplier effect of any sector in the US, supporting many other services and sectors across the entire economy [2]. For every nation, it is imperative that the manufacturing sector remains as productive as possible.

To stay competitive in this global market, manufacturers must work to face growing challenges in production and distribution of their products. These challenges can include integrating and implementing new technologies, addressing security concerns, dealing with system malfunctions, and accounting for varying customer demands. To tackle these challenges, research regarding new manufacturing system strategies must be validated and analyzed before being implemented in industry. Manufacturing system testbeds provide a place where new ideas can be developed and tested without the need to disrupt the production or distribution capabilities of an industrial plant. In addition, these testbeds provide a way to showcase and disseminate novel manufacturing technologies and ideas. One such testbed is the System-level Manufacturing and Automation Research Testbed (SMART) at the University of Michigan, described in this paper.

The main contributions of this paper are: *first,* a compilation of categories that can be used to classify manufacturing system testbeds, *second,* an identification of requirements necessary for cloud manufacturing testbeds, *and third,* a description of a specific testbed with unique capabilities. This paper presents several examples of how SMART is used to study different aspects of manufacturing.

The remainder of this paper is organized as follows. To begin, a variety of system-level testbed categories are identified and specified in Sect. 2. A comprehensive description of SMART, including an overview of the hardware and software installed in the testbed, is provided in Sect. 3. Current simulation environments available for manufacturing system research with the testbed and to augment the testbed are discussed in Sect. 4. Sect. 5 outlines how the physical and cyber components of SMART make it a unique system-level testbed by comparing it to other example testbeds. Sect. 6 overviews current research problems that are being addressed using SMART. Concluding remarks are provided in Sect. 7.

2. Manufacturing Testbed Classifications

Testbeds are frequently used to demonstrate manufacturing innovations. Based on a literature review, we have identified five categories that can be used to classify manufacturing testbeds. These categories are specified regarding the capabilities of a system to address challenges in various manufacturing related areas. The five manufacturing testbed categories include: reconfigurable manufacturing testbeds, learning factories, industrial control system testbeds, Internet of Things testbeds, and cloud manufacturing testbeds. Surveys have been previously presented regarding reconfigurable manufacturing testbeds [3], learning factories [3], industrial control system testbeds [4], and Internet of Things testbeds [5]. The recent interest in the utilization of cloud services in manufacturing [6] has incentivized the need for testbeds in the area of cloud manufacturing. These categories have been chosen based on the state of manufacturing system technology research and education today. Descriptions of these categories, including the category requirements, are specified below. Note that the identified requirements are the necessary conditions for each category.

Reconfigurable Manufacturing Testbeds:

Reconfigurable manufacturing systems define a class of systems capable of responding to market variability by changing the system level structure, machine configuration or task, and control strategy. Requirements for reconfigurable manufacturing testbeds were identified in [3, 7, 8]. In [3], the authors present a survey of testbeds based on the necessary attributes of reconfigurable manufacturing systems. In this survey, the testbeds are compared using parameters of change-enablers. The necessary characteristics of reconfigurable manufacturing testbeds include [7]:

- Customization: Flexibility to work with different parts with distinct features of a single product family
- Convertibility: Ability to change machine functionality to produce new parts
- Scalability: Ability to scale-up or -down the production capabilities of the system based on demand

Learning Factories:

Over the past few years, the term "learning factories" has been used to refer to manufacturing testbeds that serve educational goals [9]. The purpose of these testbeds is to create an environment to communicate theoretical knowledge utilizing practical applications such as automation, control, and manufacturing processes. In addition to this goal, these testbeds serve as developmental and validation facilities for novel technologies in a controlled industrial setting [3]. The necessary characteristic of a learning factory is [10]:

- A practical manufacturing environment that provides teaching opportunities to students and industry personnel in the field of manufacturing system technology

Industrial Control Systems Testbeds:

Various types of Industrial Control Systems (ICS), such as programmable logic controllers, need to be tested to determine the vulnerability of the control systems. Testing cybersecurity on a working ICS could affect performance. Thus, testbeds that copy ICS architectures provide good alternatives to perform cybersecurity testing without the risk of causing a negative impact on an actual system [4]. In [4], a number of ICS testbeds are identified and briefly described. The four identified requirements for ICS testbeds are [4]:

- Fidelity: Similar representation to an actual manufacturing system
- Repeatability: Ability to reproduce results from studies
- Measurement accuracy: Ability to monitor the testbed without interference
- Safety: Ability to perform testing without compromising safe operation of machine or personnel.

Internet of Things Testbeds:

The Industrial Internet of Things (IoT) enables extensive data collection from machines and sensors [11]. Since IoT is still a developing research area, testbeds are needed to evaluate various IoT devices and data extraction and processing algorithms before implementation in real-world scenarios. In [5], a number of IoT testbeds were surveyed and a few of the testbeds were compared over a set of the identified necessary requirements for IoT research. These identified requirements include the following [5, 12]:

- Scale: 1000s of IoT enabled devices
- Heterogeneity: A variety of IoT devices
- Repeatability: Ability to reproduce results from studies
- Federation: Ability to connect with other IoT testbeds
- Concurrency: Ability to have multiple experiments running at the same time
- Experimental environment: Similar representation of the actual environment
- Mobility: IoT devices can be moved to other locations
- User Involvement and Impact: Ability to evaluate user response to IoT technology

Cloud Manufacturing Testbeds:

Cloud manufacturing, the utilization of cloud computing in the manufacturing sector, provides a platform to improve the performance of industrial processes [13]. Over the past several years, cloud manufacturing has been defined in two different ways. The first implementation of cloud manufacturing is to use cloud computing with a set of distributed services throughout different phases on the manufacturing process life cycle. The second definition of cloud manufacturing is to use cloud computing capabilities to process large amounts of data obtained on the factory floor for improving machine and system level performance [6]. For the second definition of cloud manufacturing, research in the utilization of the cloud, including data processing and analysis, is required to understand the possibilities of using cloud manufacturing technologies. Since companies might be reluctant to test and evaluate new cloud manufacturing capabilities due to possible downtime or loss of data, manufacturing testbeds with cloud capabilities can be used to initially validate new data processing and analysis methods using cloud computing.

Based on previous cloud computing requirements and our observations, we have developed a list of requirements for cloud manufacturing testbeds. A cloud manufacturing testbed should meet the following requirements:

- Contain a cloud architecture that meets the cloud deployment, security, data migration, interoperability, and scalability requirements [14]
- Utilize cloud computing capabilities to analyze data from the plant floor at both machine and system levels
- Include user interface and data visualization capabilities for data analysis using the cloud

3. SMART Overview

The University of Michigan has developed the System-level Manufacturing and Automation Research Testbed (SMART) shown in Fig. 1. First built within the University of Michigan's Engineering Research Center for Reconfigurable Manufacturing Systems in the early 2000s [8], the testbed has been used for a variety of manufacturing research projects including: the development and validation of a framework for logic control of a manufacturing system [15], testing a novel anomaly detection method [16], and implementing a Factory Health Monitoring system [17], among other things [18, 19, 20]. Recently, in partnership with Rockwell Automation, the testbed has been upgraded and equipped with the latest control system technologies. The long-term goals of SMART are:

- To create an environment for identifying, developing, and testing new manufacturing system technologies. For these purposes SMART has been equipped with the latest control technology currently used in manufacturing production facilities.
- To create an environment where industrially relevant research can be performed. New ideas and technologies can be tested on SMART without the need to disrupt production. Using both the real and virtual environments of SMART, multiple real-world scenarios can be studied. These scenarios can mimic challenges faced by the manufacturing sector today.
- To foster collaboration between academia and industry so that new research ideas can be developed and validated before putting them into practice.
- To consolidate the work of different fields: The research conducted in collaboration with SMART is multidisciplinary. Examples of current research directions are discussed in Sect. 6.
- To provide educational opportunities for students in different areas of manufacturing. The testbed can be used to engage and educate people in emerging industrial technology. The transfer of knowledge regarding state-of-the-art technological advancements is vital for creating a highly skilled workforce for the continued improvement of the manufacturing sector.

The testbed consists of a physical serial-parallel manufacturing line, a network of sensors that perform data acquisition from the testbed, and a cyber network that stores and analyzes the data for future use. The three subsystems of SMART are discussed in more detail below.

3.1 Physical Serial-Parallel Line

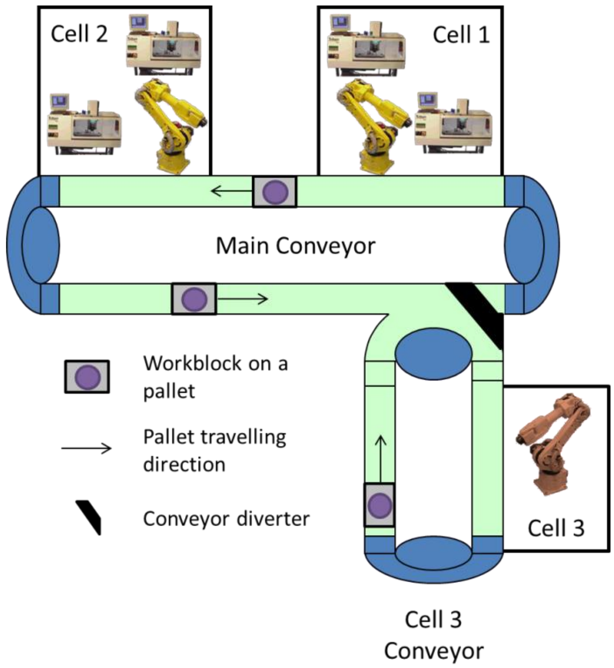

Fig. 1: The SMART Serial-Parallel Line. The workblocks are moved between each cells using a conveyor system.

Fig. 2: Various views of the components of SMART. The pictures are of: (a) the main conveyor line (b) Cell 1 (c) CNC and robot from Cell 1 (d) robot from Cell 2

Currently, SMART is focused on producing discrete products that can be formed through the machining and assembly of multiple parts (e.g. a small car made using three separate wax parts). To produce those types of products, SMART has three industrial robots and four CNC milling machines connected by a conveyor system, as shown in Fig. 1 and Fig. 2. The robots and CNCs are split into three cells. Pallets carrying the parts move around the testbed using the conveyor system. The main conveyor line handles the movement between Cells 1 and 2, while Cell 3 has its own conveyor line. The main conveyor and the Cell 3 conveyor are each run by an AC motor (Sew Eurodrive DFT71D4 and Rockwell Automation CM220, respectively). To program and control a variety of conveyor line speeds a variable frequency drive (Allen-Bradley PowerFlex 525 VFD) runs each motor with an output frequency range of 0-500 Hz. The speed at which the parts move between cells is dependent on the electric frequency of the VFD. The pallets are routed between the two lines using a controllable, pneumatic diverter. A total of 6 radio-frequency identification (RFID) transceivers (Rockwell Automation 56RF-TR-8090) and 7 proximity sensors (Rockwell Automation 871TM) are installed along the conveyor line to identify the location of parts in the system. The locations of these components are shown in Fig. 3. A pneumatically actuated stopper (FlexLink XKPD-32X15-A) is located next to each proximity sensor. The choices of sensor locations are discussed in Sect. 3.2.

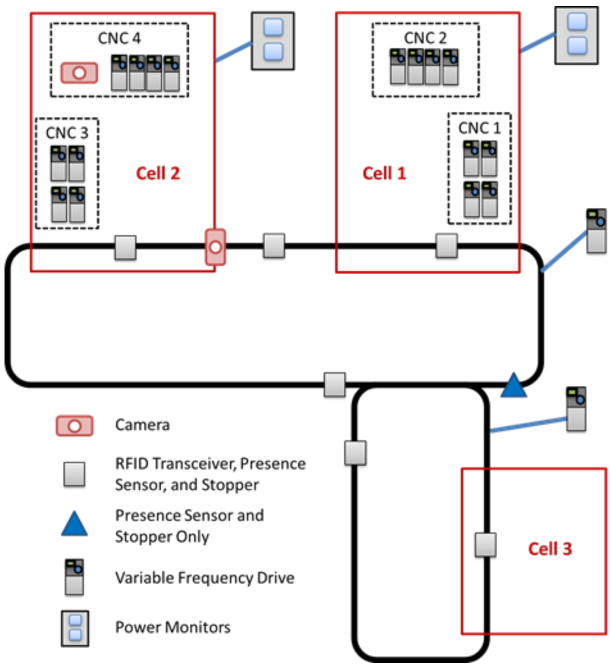

Fig. 3: Sensor and stopper locations around SMART's conveyor system.

Cells 1 and 2 each have a six degree of freedom robotic arm (Fanuc M-6iB). The robots are controlled using the controller and teach pendant from the robot manufacturer. The teach pendant is used to program pick and place actions (conveyor to CNC and CNC to conveyor) for each robot. The robots have a reach of 1373 mm, a payload at the wrist of 6 kg, and custom made gripping tools. The two robot gripping tools that move parts between the conveyor and the CNCs are a mechanical clamp and a pneumatic suction gripper. The robot clamp is used to move heavier, bulkier parts, while the suction gripper is used to move smaller, harder to grasp parts. These gripping tools are automatically interchanged by the robot based on the type of part that needs to be moved. Cell 3 has a single six degree of freedom robotic arm (ABB IRB 140) for part handling. Similar to both the Cell 1 and Cell 2 robots, the Cell 3 robot is controlled via a controller and a teach pendant provided by the robot manufacturer. The robot has a reach of 810 mm and a 6 kg handling capacity.

Additionally, Cells 1 and 2 each have two four axis CNC milling machines (Denford Triton Pro). The control system of the CNCs has been updated to allow for easier access to real-time and historical CNC data. Each CNC is controlled using a programmable logic controller (1769 CompactLogix 5370 PLC). Each CNC PLC has safety, input, and output modules for control of the CNC. Four variable frequency drives (Rockwell Kinetix 5500 S2 VFD) are integrated with the PLC. The VFDs are controlling four servo motors (Rockwell Kinetix VP Low Inertia Servo Motors) that are used to move the table and spindle in the coordinate planes, and rotate the spindle. These CNC machines have a working table size of 500 mm x 160 mm and a spindle speed of up to 3500 rpm. Utilizing this setup, the CNCs can cut wax, plastic, acrylic, copper, aluminum, and steel workpieces. Each of the CNCs has been pre-programmed to perform a number of manufacturing operations based on the inputs to the CNC controller.

A centralized control system makes the material handling and processing decisions for SMART. The testbed is outfitted with an industrial programmable logic controller (Allen-Bradley ControlLogix PLC) that is responsible for the automation of SMART. The PLC includes the following components: a control module (Logix5571S), a safety module (Logix55L7SP), two Ethernet/IP modules, and a motion control module (Logix5550) for conveyor movement. The PLC was initially programmed by Rockwell Automation using standard industrial methods in ladder logic. Any updates to the logic algorithms (e.g. new tags, rungs, or ladder programs) are programmed via a software program (Rockwell Automation Studio 5000) on a separate workstation computer and uploaded to the PLC during SMART downtime. PLC and machine/robot data collected during operation can be sent to the cloud using an IoT adapter. Additional details regarding the data path and the cloud infrastructure are discussed in Sect. 3.3. Further, a human machine interface (HMI) touch-screen panel (Allen-Bradley PanelView Plus 6 1500 Terminal) provides an easy-to-use platform from which to operate SMART. The sensors, controllers, HMI, programming workstation, and adapter are connected over a single Ethernet/IP network. The network, shown in Fig. 4, has a hybrid ring-star topology.

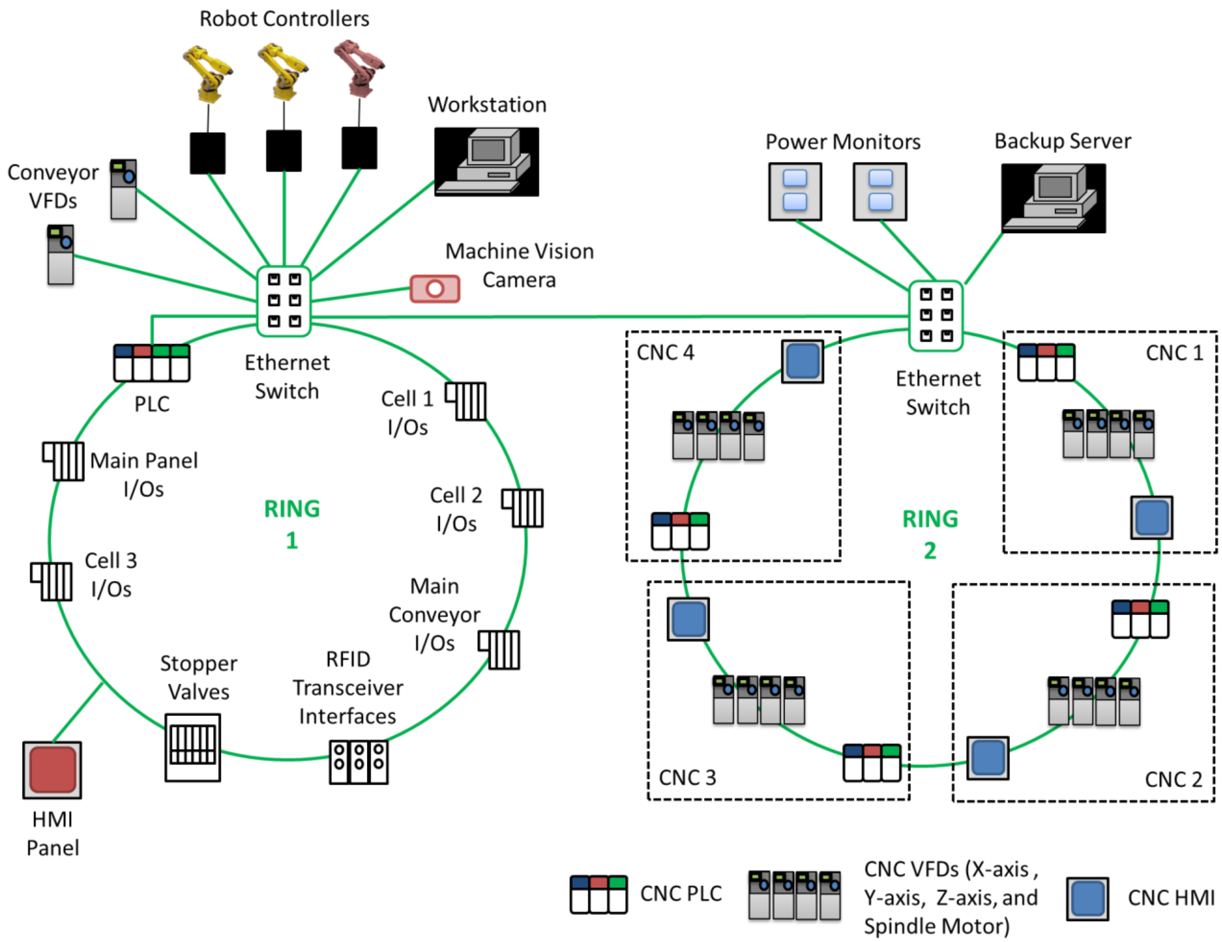

Fig. 4: The SMART Network. The components are connected in a hybrid ring-star topology using an Ethernet/IP Network.

SMART is configured to be a hybrid serial-parallel line. The parts can go through all the machines in sequence (serial configuration), or through some of the machines based on availability and process requirements (parallel configuration). The decision of which of the CNCs to use is programmed in the PLC logic. The serial-parallel configuration provides a variety of combinations for research in planning and scheduling of production line tasks.

3.2 Data Acquisition from the Testbed

The testbed is equipped with the latest sensing technology to obtain real-time data from components, machines, and parts by monitoring different types of signals. Each workpiece is outfitted with an RFID tag with re-write capabilities. The six RFID transceivers placed around the testbed are able to read and write data for each workpiece tag. The locations of these transceivers are shown in Fig. 3. The transceivers can send/receive information from the workpiece prior to entering each cell, before and after going through the machining process, and before changing conveyor lines.

In addition to the RFID system, a camera (National Instruments 1752 Smart Camera) with machine vision capabilities has been installed in SMART. It has a built-in lighting controller, a resolution of 640 x 480 pixels, and an acquisition rate of 60 frames per second. The camera, located at the entrance of Cell 2, is able to capture an image of the work-part in between machining processes. The PLC compares part dimensions obtained from the camera image to preset part tolerances for quality control of the various parts in the system.

Information about the CNCs and robots is captured by tapping into the controllers of each of the machines. For each CNC, the position of the motor along each respective axis and the percentage load on the motor is obtained. For each robot, the position of the three joints and the position and angle of the end effector are obtained by tapping into the Fanuc robot controller (via the Fanuc PC development kit PCDK).

The energy consumption of SMART is also captured. The conveyor system's VFD drives monitor the energy usage of each of the conveyor lines. Additionally, four power monitors (Allen-Bradley PowerMonitor 5000) have been installed to measure the voltage, current, power, and energy consumption of SMART. Each monitor is responsible for measuring the energy usage of one machine. Both of the robots and 1 CNC from each cell are monitored. Finally, the percentage load output by the CNC VFDs provides information regarding the energy consumption of each of the servo motors in the CNC.

3.3 Data Processing and Storage

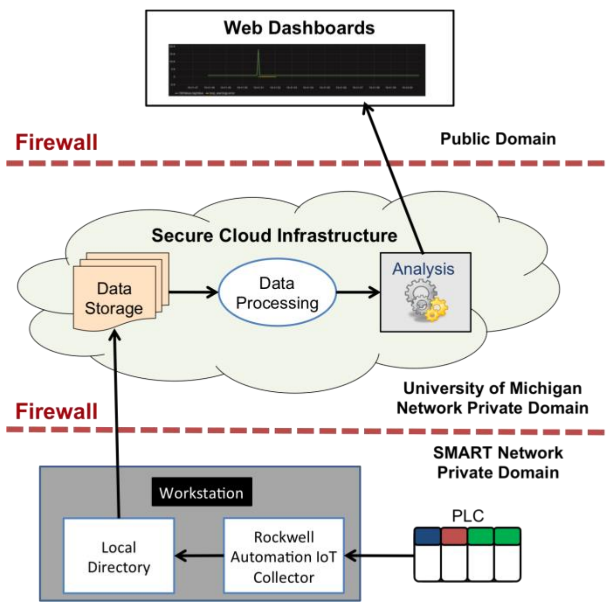

Fig. 5: The path of the data from the testbed to the cloud.

The data path for the information that is collected from SMART is shown in Fig. 5. In addition to being utilized for configuring the PLC logic, the workstation computer is used to transfer data from SMART to a University of Michigan cloud server. The workstation computer contains a Rockwell Automation (RA) Internet of Things collector (IoT collector agent) and a Kafka producer. The RA IoT Collector obtains data from the PLC based on a manifest. This manifest identifies the tags that should be processed and analyzed in the cloud and the timing frequency of the data file generated by the RA IoT Collector. For example, a manifest could be written to collect the VFD voltage and current readings every 50 ms. The RA IoT Collector will then create a file every 50 ms with the VFD voltage and current readings at that time. Then, the Kafka data messaging service producer pulls the data collected by the RA IoT Collector and pushes it to a Kafka broker in the cloud. If the connection between the workstation and the cloud is lost, the data is temporarily stored locally in the RA IoT collector until the connection to the cloud is reestablished. This approach prevents any data losses in the case of an interruption in the internet connection. The workstation computer is located behind a firewall in a private domain.

Data is stored and processed utilizing two methods for real-time and historical data analysis. For real-time analysis, InfluxDB is used to store the data and Grafana is used to visualize it. A Kafka consumer written for InfluxDB immediately pulls the data from the Kafka broker and stores it in the InfluxDB database. The server for the InfluxDB database is located at the Flux high-performance computing (HPC) cluster run by the University of Michigan's Advanced Research Computing Technology Services (ARC-TS) [21]. The University of Michigan servers are also located behind a firewall in a private domain. Grafana is used to obtain the InfluxDB data to create dashboards for real-time data visualization. These dashboards are pushed to a public domain and they can be used by people with the required credentials. In addition, the Hadoop Distributed File System (HDFS) is used to store historical data. A Kafka consumer for HDFS immediately pulls the data from the Kafka broker and stores it in a working directory. After a user-defined amount of time (e.g. one day), the Kafka consumer for HDFS pushes all the collected data to the HDFS. The HDFS server is also located at the Flux HPC cluster. The data stored in the HDFS server can later be compiled to analyze historical trends and identify long-term time horizon performance capabilities.

3.4 SMART Extensions

SMART's flexible cyber-physical architecture allows for easier extensibility of SMART in all the previously mentioned areas. New hardware can be added to the testbed and integrated into the Ethernet network. Various types of products can be manufactured by utilizing the different capabilities that this testbed offers. There is space on the line and the network for various types of stations, such as assembly and loading and unloading cells. Sensors, control equipment, and data retrieval tools can be added, integrated, tested, and analyzed with SMART. To improve system communication and information sharing, protocols, standards, and control strategies can be tested and demonstrated using various equipment installed on the testbed. Extensions to the cloud architecture will include the ability to analyze and display historical data. The flexibility of the cloud infrastructure allows for various types of data to be processed and analyzed on other computers or mobile devices. In addition, the described cloud infrastructure is easily scalable as the University of Michigan ARC-TS servers are meant to store a large amount of data.

4. Simulations

Simulations have been extensively used in conjunction with SMART for a variety of purposes. A new framework that merges signals from the physical components of SMART and from a simulation of the testbed has been implemented in the testbed to improve system productivity. Continuous and discrete time simulations of SMART have been developed to analyze system performance and virtually extend the testbed to mimic a real manufacturing plant floor. These models allow for more effective testing and analysis of novel technologies utilizing both the real and virtual domains.

4.1 Simulations Augmenting the Testbed

The integration of virtual models in each stage of the manufacturing system's life-cycle has the potential to yield system productivity and performance improvements. During the implementation phase, virtual commissioning helps detect and solve problems before equipment installation takes place in the plant floor. Having a virtual environment that emulates the physical system is a useful tool to model and evaluate the control logic.

Hybrid Process Simulation (HPS), based on Hardware In the Loop (HIL), can separate the essence of a component from its effect [20]. Implementation of HPS at a machine level enables the replacement of real components with a virtual model, and allows the addition of equipment and cells in the virtual environment to be tested, and the control validated, before the physical change is made. HPS can be used to evaluate different machines and system configurations in a mixed virtual-real environment that is higher-fidelity than a pure simulation. Using a filter, a virtual model of the workpiece emulates the effect on the physical part in the system [22]. By decoupling the essence and effect of the workpiece, this virtual part can trigger action on the physical manufacturing system without being physically present. The virtual model of the part allows the entire physical system to be running, with the final control system, without risking damage to expensive parts.

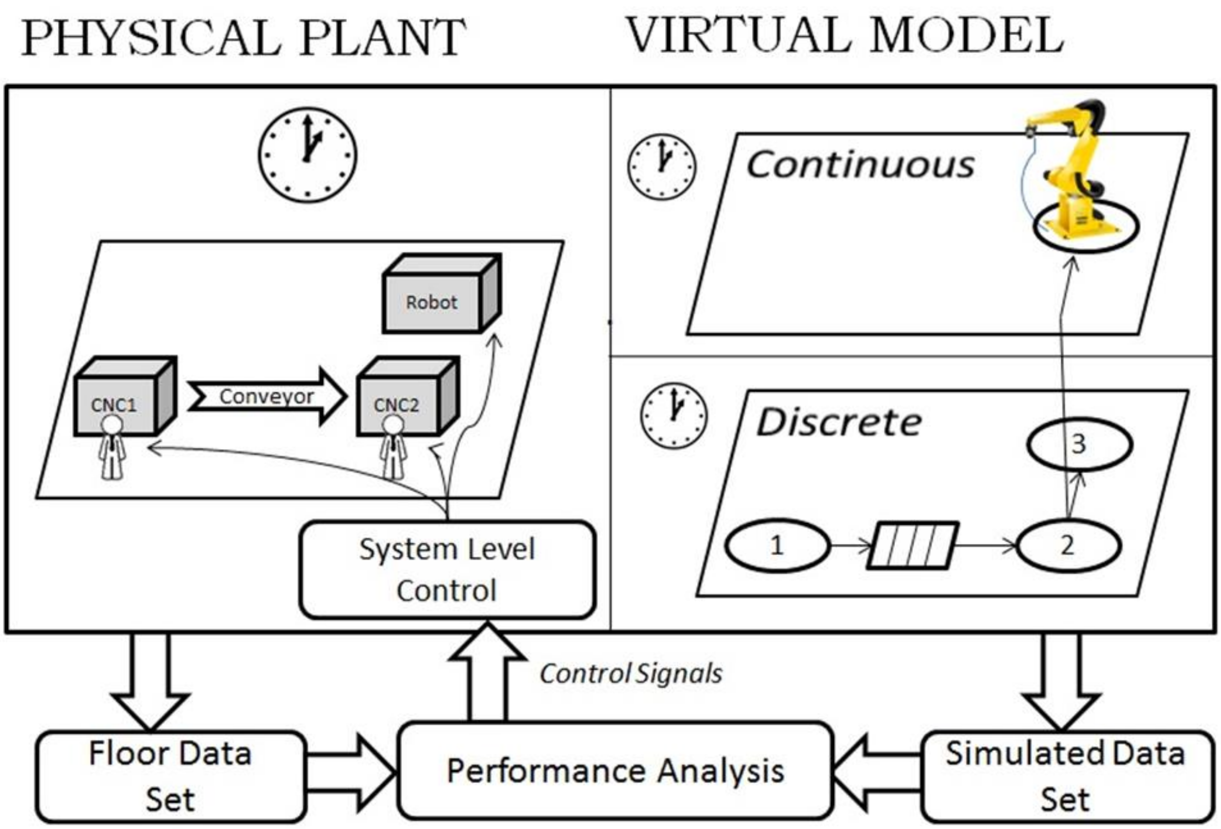

Fig. 6: Real and virtual environment interaction [24]

Utilizing this framework, the testbed has simulation models that are run in parallel with SMART [22]. Synchronization of the real and virtual environments via SimKit [23] allows the simulations to run using the time step of the PLC. This real-time hybrid simulation allows for the comparison of performance indicators from SMART and a simulation of the testbed at any point in time, as shown in Fig. 6. The results can be used to evaluate the performance and detect anomalies of SMART [24].

4.2 Simulations of the Testbed

Different simulation strategies can be used to model a manufacturing system during each phase of its life-cycle at both the machine and system level. At the machine level, simulations can evaluate technology prior to utilization, analyze the performance of individual components, and predict future failures. At the system level, simulations can help examine new machine integration, analyze the performance of the system, and develop optimal production plans. The integration of both types of simulations results in high fidelity models of the system that can provide extensive information regarding its performance. These types of simulations can lead to better understanding and improvement of the production and distribution capabilities of a system in a cost-effective manner. A few simulations have been developed for SMART as a reference for studying manufacturing system performance. Additionally, these simulations serve as tools for manufacturing education.

The purpose of continuous variable simulations is to study the temporal response of a component or machine to a specific input. Roboguide and SimMechanics have been used to create continuous simulations for the study of SMART's robots. Roboguide is Fanuc proprietary software that has been used to create a hybrid simulation process along with the Fanuc PC development kit (PCDK) [25]. This physics-based modeling simulation offers a high level of accuracy and fidelity since both the physical robot (Fanuc M-6iB) and its virtual representation were developed by Fanuc. The virtual model interface and inputs replicate the parameters used to control the physical robot (e.g. robot coordinates, speed, and type of trajectory). Simulation outputs include the time, trajectory, and possibility of collision situations in the robot workspace for any programmed actions. These outputs can be used to assess the feasibility and efficiency of potential robot programs. Importantly, a continuous variable simulation can be used to validate the robot's operation before implementing the program on the physical robot.

In addition to the Fanuc Roboguide simulation, continuous simulations were developed using MATLAB's SimMechanics environment and Robotics toolbox. A simulation program was used to study the dynamics of each robot joint and link for a variety of programmed paths [24]. Using a CAD file from Fanuc, a robot specification sheet, and measurements of the robot, the geometry and mass distribution of each robotic link was modeled. These links were then combined to create a 3D model of the system. This type of simulation can be used to provide insight on the status of the robot during point-to-point movements with different trajectories and varying torque and speed profiles.

System-level manufacturing performance has typically been investigated using discrete event simulations (DES). The goal of DES with SMART is to analyze the operations and control of the manufacturing system based on the cycle times and reliability of each machine. Virtual representations of SMART have been developed using the SimEvents and ProModel software. The underlying analysis used for models developed in both software packages is based on queuing theory. Thus, the model inputs and simulation environments of these models are similar. Machines are modeled as servers with a capacity and a cycle time distribution. Buffers are modeled as queues with fixed capacity and a processing rule (Fist-In-First-Out or First-In-Last-Out).

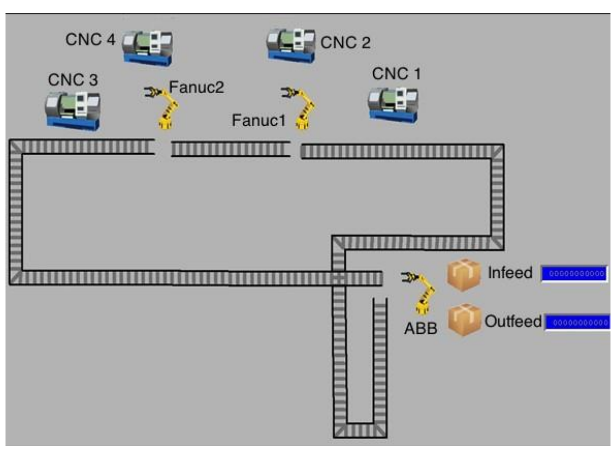

Fig. 7: DES model using the ProModel software package [26]

The ProModel software was used to develop models, such as the one shown in Fig. 7, for analyzing, optimizing, and visualizing the system-level performance of various configurations of SMART. The model was constructed using output data regarding the time it took for the material handling and machining operations to be performed on SMART. Additionally, the model was used to virtually extend the testbed beyond its physical constraints by adding extra conveyor lines, machines, and robots to mimic a factory floor. Virtually extending the testbed provides a link for SMART to generalize any findings to a larger industrial setting. A number of scenarios (e.g. varying processing times, different layout and cell configurations, the effect of machine failures, etc.) were tested on both the original simulation and the extended version of the testbed utilizing this software. The scheduling, production, and reliability of SMART and its virtual extensions were then analyzed based on the data obtained from the models built by this software [26, 27].

Another DES model built to model SMART uses SimEvents and StateFlow. Similar to the ProModel software, this model was used to analyze and optimize the performance of SMART [24]. Unlike the ProModel simulation, this model is able to synchronize with a virtual PLC using the Rockwell SimKit. While ProModel is able to visually represent the manufacturing system, the SimEvents model does not have the same visualization capabilities. Extendable versions of SMART have not been built or analyzed using this software even though the SimEvents model is scalable for the purposes of studying larger, full-scale manufacturing systems. Alternative DES simulation software tools have been explored to extract, analyze, and utilize system performance data from SMART [28, 29].

5. Classification of Manufacturing Testbeds

The categories presented in Sect. 2 can be used to classify existing manufacturing testbeds. In this section, SMART and selected manufacturing testbeds are evaluated using the requirements specified in Sect. 2. Table 1 shows the results of this comparison.

5.1 SMART Classification

SMART has been integrated with a variety of technologies as described in Sect. 3 and Sect. 4. Those components make SMART a unique multidisciplinary testbed with a wide array of extensions. With its cyber, physical, data processing, and simulation capabilities, SMART is a testbed that satisfies the requirements for most of the identified categories of testbeds. The only requirement not satisfied by SMART is the scale aspect for IoT testbeds, which currently include only network-based testbeds and hence contain a significantly large scalable requirement not seen in manufacturing testbeds. Thus, when compared to other testbeds shown in Table 1, SMART is shown to be unique manufacturing systems testbed.

Reconfigurable Manufacturing Testbed:

SMART was initially designed as a reconfigurable factory testbed [8]. The infrastructure of SMART satisfies the requirements of Reconfigurable Manufacturing Testbeds in the following manner:

- Customization: The CNCs can make various parts from either the same or different product families. The interchangeable grippers and the conveyor lines allow for a variety of parts to be moved around the system.
- Convertibility: The CNCs and robots can be reprogrammed to handle and machine different parts, in different sequences if necessary.
- Scalability: The parameters of the various machines can be changed to alter system throughput (e.g. reroute parts, change speed of conveyor or robot operation, etc.). In addition, machines can be added and integrated into the system, if necessary.

Table 1: Summary of Representative Manufacturing Related System-level Testbeds.
(*Partially in the IoT testbed category indicates that the scale is less than thousands of IoT nodes, but the other criteria are met)

Testbed	Reconfigurable Manufacturing Testbed	Learning Factory	ICS Testbed	IoT Testbed	Cloud Manufacturing Testbed
SMART (this paper)	Yes	Yes	Yes	Partially*	Yes
SmartFactory KL [30, 31]	Yes	Yes	Unknown	Partially*	Yes
iFactory [35, 36]	Yes	Yes	Unknown	Partially*	No
MSU SCADA Testbed [37, 38]	No	Yes	Yes	Partially*	No
TWIST [39]	No	No	No	Yes	No
Smart Manufacturing Lab Testbed [40, 41]	Yes	Unknown	Unknown	Partially*	No

Learning Factory:

SMART serves as both a research facility and an educational tool at the University of Michigan. Some of the ongoing research that utilizes SMART is discussed in Sect. 6. The physical, cyber, and simulation components are maintained with the help of the Secure Cloud Manufacturing Multidisciplinary Design Program project team, which consists of undergraduate and graduate students who gain hands-on manufacturing experience. The students gain industry relevant experience in robot, CNC, and PLC programming, machine and system-level modeling, and cloud analytics, among a number of other topics. Thus, this testbed satisfies the requirement of being a learning factory.

Industrial Control Systems Testbed:

The network and controllers of SMART, described in Sect. 3.2, satisfy the requirements of ICS Testbeds, as described below.

- Fidelity: SMART contains industry-level control and security that was set-up and programmed by Rockwell Automation using industrial standards to replicate a realistic manufacturing system.
- Repeatability: SMART has been used to run a variety of repeatable studies regarding the control network
- Measurement accuracy: The testbed has been set-up to be non-invasive for measurements of the network during testing.
- Safety: A safety protocol has been embedded in all the controllers to protect machines and personnel while the system is operating. Industrial-level safety equipment such as light curtains and emergency stops have been installed in SMART.

Internet of Things Testbed:

SMART's physical and cyber components, described in Sect. 3, satisfy most of the IoT Testbed requirements, except for scale. Each of the requirements is described in detail below.

- Scale: SMART is made up of less than 20 IoT nodes and, thus, does not satisfy the scale requirement
- Heterogeneity: The testbed has RFID transceivers, CNC PLCs, and central PLCs with IoT capabilities
- Repeatability – see the ICS repeatability requirement
- Federation: This testbed can be integrated with other, similar IoT testbeds
- Concurrency: The SMART network and physical setup can perform concurrent experiments during run-time
- Experimental environment – see the ICS fidelity requirement. Simulations can extend the environment to study larger manufacturing systems
- Mobility: The testbed mirrors the mobility of parts and devices in a manufacturing setting
- User Involvement and Impact: The HMI and cloud interface provide local and remote user interfaces that can be used during experimentation

Cloud Manufacturing Testbed:

The cloud infrastructure of SMART, described in Sect. 3.3, satisfies the requirements of Cloud Manufacturing Testbeds in the following manner:

- The SMART cloud infrastructure satisfies the cloud architecture requirements. The cloud deployment requirement is satisfied through the community cloud architecture provided by the University of Michigan ARC-TS service. The security and data requirements are met with the layered architecture shown in Fig. 5. The interoperability requirement is satisfied through the use of commonly used platforms (e.g. InfluxDB and Hadoop). The testbed is readily scalable, as described in Sect. 3.4.
- The cloud infrastructure is set-up to obtain and store the manufacturing data obtained from SMART in the community cloud provided by University of Michigan.
- The data pipeline and cloud infrastructure is able to analyze and display meaningful data either streaming or batching from the manufacturing floor, as described in Sect. 3.3.

Thus, SMART can be classified and utilized in various types of research and educational activities.

5.2 Other Example Testbeds

A literature review of selected manufacturing testbeds around the world was compiled. In Table 1, these testbeds are compared to SMART based on their capabilities as learning factories and reconfigurable manufacturing, ICS, IoT, and cloud manufacturing testbeds.

One testbed focused on validating new manufacturing technologies is the SmartFactoryKL in Kaiserslautern, Germany. This testbed focuses on developing modular, plug-and-play equipment for manufacturing facilities. Three types of production lines have been developed at this facility to test and demonstrate novel manufacturing systems technologies [30]. The modules used in these production lines include assembly stations, a mill for engraving, and machines used for mixing, dispensing, and labeling a liquid [31, 32]. Academic and industrial partners use the factory for individual and joint research projects. These projects focus on creating a blueprint for a future "factory-of-things" with novel Internet of Things technologies such as RFIDs and wireless networks [31]. Some sections of the line are controlled by a centralized PLC [32], while other sections use microcontrollers based on a Service-oriented Architecture (SOA) framework [33]. Operators for the testbed have access to some of the SmartFactoryKL data analytics performed in the cloud [34]. Thus, the SmartFactoryKL is a reconfigurable manufacturing testbed, a learning factory, and a cloud manufacturing testbed. Similar to SMART and iFactory, this testbed does not have enough IoT nodes to be considered an IoT testbed. However, the ICS testing capabilities of SmartFactoryKL are unknown.

One example of a prototypical learning factory is the iFactory at the University of Windsor, Canada. This testbed was set up in 2011 to study the challenges associated with a reconfigurable manufacturing system. Its modular layout consists of automated and manual assembly cells, inspection cells, and material handling machines, among a number of other smaller cells. In addition to the physical components, the testbed includes design (iDesign), as well as planning and simulation (iPlan) environments. The iFactory testbed provides students with an opportunity to participate in all aspects of the product life cycle [3, 35]. Each of the stations is connected with an Ethernet network and controlled using a SCADA (supervisory control and data acquisition) controller with a number of sensors that identify neighboring cells [36]. The iFactory is a reconfigurable manufacturing testbed and a learning factory. Similar to SMART, it does not have enough IoT nodes to be considered an IoT testbed. Based on the available literature, it does not appear to have the cloud infrastructure that makes it a cloud manufacturing testbed. Finally, the ICS testing capabilities of iFactory are unknown.

One testbed that focuses on the testing of industrial controls systems is found in the Mississippi State University Supervisory Control and Data Acquisition (SCADA) security laboratory and Power and Energy Research laboratory. This testbed consists of seven industrial control systems that are responsible for a variety of physical processes and are controlled using remote terminal units, programmable logic controllers, and other types of common industrial automation technology. ICS testing is performed for systems in a number of industrial areas such as electric power transmission, gas distribution, and manufacturing, among others [37, 38]. In addition, this testbed has been integrated into the learning environment at Mississippi State University [37]. Thus, the MSU SCADA testbed is a learning factory and an ICS testbed. The testbed has some infrastructure that can be used for IoT testing, but it has not been used to perform any tests in that area. Finally, the MSU SCADA testbed does not meet any of the requirements of reconfiguration nor does it have a cloud infrastructure. Thus, it is neither a reconfigurable manufacturing testbed nor a cloud manufacturing testbed.

Telecommunication Networks Group’s TKN Wireless Indoor Sensor network Testbed (TWIST) is a testbed developed at the Technische Universität Berlin. It is meant for testing Wireless Sensor Networks, as a basis for the Internet of Things. The testbed consists of a few hundred nodes that communicate over an Ethernet network. The purpose of this testbed is to test the effectiveness of Wireless Sensor Networks architectures in deployment, testing, and reconfiguration of the nodes [4, 39]. TWIST is an IoT testbed, but it does specifically target manufacturing research. Thus, it is not a reconfigurable manufacturing testbed, a learning factory, an ICS testbed, or a cloud manufacturing testbed.

The automated production line in the State Key Laboratory for Manufacturing Systems Engineering at Xi’an Jiaotong University is a testbed used for manufacturing system research. It has four cells connected by a conveyor line. The machines in this testbed include a CNC lathe, two CNC mills, and a Kuka robot. A number of sensors, including RFID transceivers, are present in the testbed [40]. This testbed has been used for research in creating a smart manufacturing job shop [40, 41]. This testbed can be classified as a reconfigurable manufacturing testbed due to the presence of CNC machines. Similar to SMART, iFactory, and SmartFactoryKL, this testbed does not have enough IoT nodes to be considered an IoT testbed. It does not have a cloud infrastructure, thus it is not a cloud manufacturing testbed. In addition, the ICS testing capabilities of this testbed and the educational opportunities offered by this production line are unknown.

This survey represents a sample of some of the system-level research testbeds that are located around the world. A number of learning factories, ICS, and IoT testbeds can be found in the previously mentioned surveys [3, 4, 5]. In addition, other research testbeds are currently being developed across the world. For example, in the United States, a recent emphasis on manufacturing has resulted in the development of several National Network for Manufacturing Innovation (NNMI) institutes. Many of these institutes have manufacturing testbeds that aim to fill the gap between academic research and industrial implementation in the US manufacturing sector [42]. Another example of manufacturing testbeds in development is the Industrial Internet Consortium (IIC) testbeds. This consortium, launched in 2014, oversees designing and building of testbeds that will explore the advantages and challenges associated with the integration of the Industrial Internet across a variety of industries, including manufacturing. The proposed testbeds will range from a Trace and Track testbed for locating and managing tools in a factory to an Industrial Digital Thread testbed to collect, analyze, and distribute data on the industrial floor [43].

Even though testbeds exist that are similar to SMART, its multidisciplinary nature allows it to occupy a unique niche in the manufacturing system research community. In fact, some of SMART's unique physical and simulation capabilities serve as technological enablers for the ongoing work described in Sect. 6.

6. Ongoing Research with SMART

In this section, current research activities that incorporate SMART are outlined.

6.1 Cloud Manufacturing Performance Monitoring and Analysis

In a large production environment, information collected from the wide array of sensors can be used to model different key performance indicators. In discrete manufacturing, monitoring processing time at a component, machine, and system level will support early detection of under-performance. The monitoring of continuous signals (vibration, pressure, temperature, energy) from different machines aids root cause analysis. The collected data could be stored in a cloud environment for analysis purposes. This data-intensive monitoring approach has the potential to improve maintenance scheduling and reduce downtime. SMART and its cloud architecture provide a platform in which the utilization of these services has been implemented and analyzed [24]. The sensors in SMART can provide real-time data for analysis. Quality inspection using the cameras in the testbed, energy usage for the conveyor line, robots, and CNCs, and data obtained from the robot and CNC controllers can be used to detect and diagnose anomalies in the system.

6.2 Centralized Control of Manufacturing

Due to the large amount of data collected on the manufacturing shop floor, there is a lot of information about the system in both the physical (robots, machines, etc.) and cyber (RFID, Ethernet Network, etc.) domains. This information, when utilized properly, can be used to analyze and improve the performance and productivity of the manufacturing system. By utilizing a global view of the entire manufacturing system and high fidelity system models, a central controller should have the ability to detect, classify, and respond to abnormal behavior in a manufacturing system. Abnormal behavior can consist of a machine wear or failure, network loss, or even a cyber-attack [44]. SMART and its simulations are being used to test a novel central decision maker that can integrate model and system information to asses and improve the system performance.

6.3 Decentralized Control of Manufacturing Systems

One case of decentralization in the manufacturing system domain is at the supply chain level. As mass customization becomes a trend in global manufacturing [45], companies must adjust their production capabilities to appease customers desiring variable batches of customized products. One solution that can benefit both the manufacturing companies and the customers with specific requests is the use of a Production as a Service (PaaS) framework described in [46]. The PaaS framework consists of a front-end query interface for consumers and suppliers and a back-end analysis component for matching the consumer needs for supplier resources. By using the web based platform of the PaaS framework, companies may use some of their under-utilized resources to fulfill customized requests. This can lead to an increase in supplier's profits and the fulfillment of customized customer manufacturing orders [46]. SMART and its simulations are being used to test and analyze the PaaS framework.

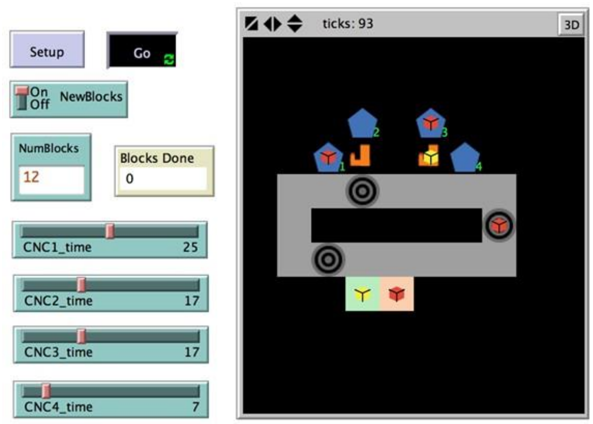

Fig. 8: Agent-based control simulation of SMART

Another use of decentralization is at the manufacturing system level. One type of decentralized architecture, multi-agent control, has been proposed to provide better flexibility and responsiveness to traditional hierarchical control methods [47]. A number of challenges need to be addressed before multi-agent systems can be used in an industrial environment. Some of these challenges include: development of a multi-agent control framework for manufacturing systems that provides guaranteed performance and robustness, integration of the multi-agent architecture with existing system components [48], demonstration of stable and effective performance when compared to current practices [49], and investigation of the advantages of learning to improve performance over time. Different scenarios can be tested using the agent-based framework and results can be compared to standard control methods using SMART. Previously, the NetLogo software [50] was used to create an agent-based simulation of SMART. This simulation, shown in Fig. 8, can evaluate agent-based schemes for controlling the testbed. In the simulation, the individual elements (four CNCs, two robots, three pallets, workpieces) are treated as separate agents. Communication and coordination between each agent is handled using a set of programmed rules.

7. Conclusion

This paper presents five categories that can be used to classify manufacturing system testbeds. Requirements for four of these categories were obtained from existing testbed surveys. Based on a literature review and the experience of the authors, the requirements for cloud manufacturing testbeds were introduced. Using these classifications, a number of testbeds around the world, including the System-level Manufacturing and Automation Testbed at the University of Michigan, were studied and categorized.

SMART is a unique testbed equipped with state-of-the-art technology. It consists of a physical serial-parallel line with robots, a conveyor system, machine tools, a network of data acquisition equipment, and hardware and software technology to process, analyze, and present the data. Moreover, virtual models of the testbed have been developed with different simulation environments. To align with current manufacturing trends, the testbed includes a wide array of sensors (cameras, power monitors, VFD, etc.) and control technologies (PLCs, safety equipment, etc.). These technologies are integrated into an Ethernet/IP network and a compatible central controller to make real-time decisions. To study the opportunities of IoT and cloud services in manufacturing, a data path has been linked to the cloud environment with capabilities of real-time and historical data analysis. Simulation models have been used with SMART to test algorithms for evaluating and improving system performance. The main limitation of the testbed, its small size, can be mitigated by extending SMART through high fidelity simulations. Solutions to challenges mentioned in Sec. 1, such as integrating and implementing new technologies, addressing security concerns, dealing with system malfunctions, and accounting for varying customer demands, can be addressed by utilizing both the physical and virtual environments of SMART. Its unique multidisciplinary nature allows it to address problems in a wide array of areas. It can be adapted for reconfigurable manufacturing, ICS, IoT, and cloud manufacturing research.

Acknowledgment

The authors would like to thank Bob Ulmer and Rockwell Automation for helping retrofit and providing operational support for the testbed, and the University of Michigan Secure Cloud Manufacturing Multidisciplinary Design Program Team for maintaining and continuously upgrading the physical testbed and its simulations. This work was funded in part by a Gift from Rockwell Automation, NSF grants 1544678 and 1462910, and an NSF graduate fellowship.

References

[1] Manyika, J., Sinclair, J., Dobbs, R., Strube, G., Rassey, L., Mischke, J., Remes, J., Roxburgh, C., George, K., O'Halloran, D., and Ramaswamy S., "Manufacturing the future: The next era of global growth and innovation," McKinsey Global Institute, Tech. Rep., November, 2012.

[2] Holdren, J. P., Lander, E., Press, W., Savitz, M., Bierbaum, R., Gates Jr., S. J., Cassel, C., Gorenberg, M., Jackson, S. A., Chyba, C., and Levin, R. C., "Report to the President on Capturing Domestic Competitive Advantage in Advanced Manufacturing," Advanced Manufacturing Partnership Steering Committee, Tech. Rep., 2012.

[3] Wagner, U., AlGeddawy, T., ElMaraghy, H., and Müller, E., "The state-of-the-art and prospects of learning factories," *Procedia CIRP*, vol. 3, no. 1, 2012, pp. 109–114.

[4] Holm, H., Karresand, M., Vidström, A., and Westring, E., "A survey of industrial control system testbeds," in *Proceedings of 20th Nordic Conference - Secure IT Systems*, vol. 9417, 2015, pp. 11–26.

[5] Gluhak, A., Krco, S., Nati, M., Pfisterer, D., Mitton, N., and Razafindralambo, T., "A survey on facilities for experimental internet of things research," *IEEE Communications Magazine*, vol. 49, no. 11, 2011, pp. 58–67.

[6] Xu, X., "From cloud computing to cloud manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 28, no. 1, 2012, pp. 75–86.

[7] Koren, Y, *The global manufacturing revolution: product-process-business integration and reconfigurable systems*. John Wiley & Sons, 2010.

[8] Moyne, J., Korsakas, J., and Tilbury, D. M., "Reconfigurable factory testbed (RFT): A distributed testbed for reconfigurable manufacturing systems," in *Proceedings of the Japan-USA Symposium on Flexible Automation*, July 19-21, 2004.

[9] Barton, H, and Delbridge, R., "Development in the Learning Factory: Training Human Capital." Journal of European Industrial Training, vol 25, no. 9, 2001, pp. 465–472.

[10] Seitz, K.F. and Nyhuis, P.,"Cyber-Physical Production Systems Combined with Logistic Models – A Learning Factory Concept for an Improved Production Planning and Control." *Procedia CIRP* vol. 32, 2015, pp. 92–97.

[11] O'Halloran, D. and Kvochko E., "Industrial Internet of Things: Unleashing the Potential of Connected Products and Services," World Economic Forum, Tech. Rep., 2015.

[12] Siaterlis, C., Garcia, A. P, and Genge, B., "On the use of emulab testbeds for scientifically rigorous experiments," IEEE Communications Surveys & Tutorials, vol. 15, no. 2, 2013, pp. 929–942.

[13] Huang, B., Li, C., Yin, C., and Zhao, X., "Cloud manufacturing service platform for small-and medium-sized enterprises," *International Journal of Advanced Manufacturing Technology*, vol. 65, no. 9-12, pp. 1261–1272, 2013.

[14] Rimal, B. P., Jukan, A., Katsaros, D., and Goeleven, Y., "Architectural Requirements for Cloud Computing Systems: An Enterprise Cloud Approach," *Journal of Grid Computing*, vol. 9, no. 1, 2011, pp. 3–26.

[15] Endsley, E. W., Almeida, E. E., and Tilbury, D. M., "Modular finite state machines: Development and application to reconfigurable manufacturing cell controller generation," *Control Engineering Practice*, vol. 14, no. 10, 2006, pp. 1127–1142.

[16] Allen, L. V. and Tilbury, D. M., "Anomaly detection using model generation for event-based systems without a preexisting formal model," *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, vol. 42, no. 3, 2012, pp. 654–668.

[17] Schroeder, K., Moyne, J., and Tilbury, D. M., "A factory health monitor: System identification, process monitoring, and control," in *4th IEEE Conference on Automation Science and Engineering*, Aug. 23-26, 2008, pp. 16–22.

[18] Luntz, J., Moyne, J., and Tilbury, D., "On-Line Control Reconfiguration at the Machine and Cell Levels: Case Studies from the Reconfigurable Factory Testbed," in *IEEE Conference on Emerging Technologies and Factory Automation*, vol. 1, 2005, pp. 641–648.

[19] Lucas, M. R. and Tilbury, D. M., "Methods of measuring the size and complexity of PLC programs in different logic control design methodologies," *International Journal of Advanced Manufacturing Technology*, vol. 26, no. 5-6, 2005, pp. 436–447.

[20] Harrison, W. S., Tilbury, D. M., and Yuan, C., "From hardware-in-the-loop to hybrid process simulation: An ontology for the implementation phase of a manufacturing system," *IEEE Transactions on Automation Science and Engineering*, vol. 9, no. 1, 2012, pp. 96–109.

[21] University of Michigan, "About ARC-TS," http://web.archive.org/web/20170227164044/http://arc-ts.umich.edu/about/ (accessed 27 Feb. 2017).

[22] Putman, N. M., Maturana, F., Barton, K., and Tilbury, D. M., "Virtual fusion: Integrating virtual components into a physical manufacturing system," *IFAC Proceedings Volumes*, vol. 48, no. 3, 2015, pp. 904–909.

[23] Maturana F.P., Kalolia M., Paredes P., "A Virtual Design Engineering Environment for Control System Design and Validation." In *Industrial Applications of Holonic and Multi-Agent Systems*, vol. 8062, 2013, pp. 118-127.

[24] Saez, M., Maturana, F., Barton, K., and Tilbury, D., "Real-Time Hybrid Simulation of Manufacturing Systems for Performance Analysis and Control," in *2015 IEEE International Conference on Automation Science and Engineering*, 2015, pp. 526–531.

[25] Viswanathan, J., Harrison, W. S., Tilbury, D. M., and Gu, F., "Using hybrid process simulation to evaluate manufacturing system component choices: Integrating a virtual robot with the physical system," in *Proceedings - Winter Simulation Conference*, 2011, pp. 2822–2833.

[26] Chou, W., Jin, Y., Shi, X., and Xu, D., “Simulation Subteam - Final Report,” Multidisciplinary Design Program, College of Engineering, University of Michigan, Tech. Rep., Apr., 2015.

[27] Xu, D., Lu, S., Duan, K., Liu, W., and Subramanian, G., “Simulation Subteam - Midterm Report,” Multidisciplinary Design Program, College of Engineering, University of Michigan, Tech. Rep., Oct. 2016.

[28] Manzocchi, D., and Mazzolini, M., “Design, implementation and validation of an IEC 61499-based optimized automation tasks supervisor for U-M RMST,” Department of Mechanical Engineering, University of Michigan, Tech. Rep., Oct., 2014.

[29] Chou, W., Jin, Y., Shi, X., and Xu, D., “Simulation Subteam - Final Report,” Multidisciplinary Design Program, College of Engineering, University of Michigan, Tech. Rep., Dec., 2015.

[30] Zuehlke, D. and Gorecky, D., “Case Study: A catalyst for smart manufacturing with Germany’s SmartFactory,” Control Design, 2016, http://web.archive.org/web/20170227161920/http://www.controldesign.com/articles/2016/case-study-a-catalyst-for-smart-manufacturing-with-germanys-smartfactory/ (accessed 27 Feb. 2017).

[31] Zuehlke, D., “SmartFactory - Towards a factory-of-things,” *Annual Reviews in Control*, vol. 34, no. 1, 2010, pp. 129–138.

[32] Zamfirescu, C.B., Pirvu, B.C., Loskyll, M. and Zuehlke, D., “Do not cancel my race with Cyber-Physical Systems.” *IFAC Proceedings Volumes*, vol. 47, no. 3, 2014, pp. 4346-4351.

[33] Loskyll, M., Heck, I., Schlick, J., and Schwarz, M., “Context-Based Orchestration for Control of Resource-Efficient Manufacturing Processes,” *Future Internet*, vol. 4, no. 3, 2012, pp. 737–761.

[34] Frank, H. and Heyer C., “Five Developments for Improved Data Exploitation,” 2017 https://web.archive.org/web/20170511233848/https://www.dfki.de/web/press/press-release/2017/HMI_4/ (accessed 11 May 2017).

[35] ElMaraghy, H. and ElMaraghy, W., “Learning Integrated Product and Manufacturing Systems,” *Procedia CIRP*, vol. 32, 2015, pp. 19–24.

[36] ElMaraghy, H. and ElMaraghy, W., “Smart Adaptable Assembly Systems,” *Procedia CIRP*, vol. 44, 2016, pp. 4–13.

[37] Morris, T., Vaughn, R., and Dandass, Y., "A testbed for SCADA control system cybersecurity research and pedagogy" In *Proceedings of the Seventh Annual Workshop on Cyber Security and Information Intelligence Research*, Oct. 12-14, 2011, p. 27.

[38] Vaughn, R. B., Morris, T., and Sitnikova, E., “Development & expansion of an industrial control system security laboratory and an international research collaboration,” in *Proceedings of the Eighth Annual Cyber Security and Information Intelligence Research Workshop*, Jan 8-10, 2013 p. 18.

[39] Handziski, V., Köpke, A., Willig, A., and Wolisz, A., “TWIST: A Scalable and Reconfigurable Testbed for Wireless Indoor Experiments with Sensor Networks,” in *Proceedings of the Second International Workshop on Multi-hop Ad Hoc Networks: From Theory to Reality*, May 26, 2006, pp. 63-70.

[40] Wang, C., Jiang, P., and Lu, T., “The Production Instruction System for Smart Job Shop,” in *IEEE International Conference on Mechatronics and Automation (IEEE ICMA),* Aug. 6-9, 2016, pp. 1850–54.

[41] Wang, C., Jiang, P., and Ding, K.. "A hybrid-data-on-tag–enabled decentralized control system for flexible smart workpiece manufacturing shop floors," in *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,* vol. 231, no. 4, 2017, pp. 764-782.

[42] National Network for Manufacturing Innovation (NNMI), “Institutes,” http://web.archive.org/web/20170227163204/https://www.manufacturing.gov/nnmi-institutes/ (accessed 27 Feb. 2017).

[43] Industrial Internet Consortium, “The industrial internet consortium: a global not-for-profit partnership of industry, government and academia,” http://web.archive.org/web/20170227163501/http://www.iiconsortium.org/about-us.htm (accessed 27 Feb. 2017).

[44] Dolan, M., “Michigan experts skip the man, turn to robots to boost productivity,” Detroit Free Press, Sep 10, 2016, http://web.archive.org/web/20170227165003/http://www.freep.com/story/money/business/michigan/2016/09/10/michigan-project-studies-boosting-manufacturing-productivity/89927438/ (accessed 27 Feb. 2017).

[45] Colliers International, “Manufacturers moving to be closer to consumers as new technologies and mass customization shift global trends in manufacturing,” *PR Newswire*, Sep 15, 2014, http://web.archive.org/web/20170227165335/http://www.prnewswire.com/news-releases/manufacturers-moving-to-be-closer-to-consumers-as-new-technologies-and-mass-customisation-shift-global-trends-in-manufacturing-275154201.html (accessed 27 Feb. 2017).

[46] Porter, M., Raghavan, V., Lin, Y., Mao, Z., Barton, K., and Tilbury, D., “Production as a Service: Optimizing Utilization in Manufacturing Systems,” in *ASME 2016 Dynamic Systems and Control Conference*, Oct. 12-14, 2016.

[47] Monostori, L., Váncza, J., and Kumara, S. R. T., “Agent-based systems for manufacturing,” *CIRP Annals - Manufacturing Technology*, vol. 55, no. 2, 2006, pp. 697–720.

[48] Leitão, P., Mařík, V., and Vrba, P., “Past, present, and future of industrial agent applications,” *IEEE Transactions on Industrial Informatics*, vol. 9, 2013, no. 4, pp. 2360–2372.

[49] Barbosa, J., Leitão, P., Adam, E., and Trentesaux, D., “Dynamic self-organization in holonic multi-agent manufacturing systems: The ADACOR evolution,” *Computers in Industry*, vol. 66, 2015, pp. 99–111.

[50] Wilensky, U., “NetLogo.” Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL., 1999, http://web.archive.org/web/20170227170154/http://ccl.northwestern.edu /netlogo/ (accessed 27 Feb. 2017).