A Survey of Cybersecurity and Resilience of Digital Manufacturing

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Abstract—Recent efforts towards industry 4.0 promote a digital manufacturing (DM) paradigm that can enhance quality and productivity, reduce inventory and the lead-time for delivering custom, batch-of-one products based on achieving convergence of 3D printing and hybrid machine tools, Automation and Robotic Systems, Sensors, Computing, and Communication Networks, Artificial Intelligence, and Big Data. A DM system consists of embedded electronics, sensors, actuators, control software, and inter-connectivity to enable the machines and the components within them to exchange data with other machines, components therein, the plant operators, inventory managers, and customers. This paper will outline the cybersecurity risks and threat vectors in the emerging DM context, assess the impact on manufacturing, and identify approaches to secure DM.

Index Terms—Digital Manufacturing

I. INTRODUCTION

DIGITALIZATION of manufacturing aided by advances in sensors, artificial intelligence, robotics, and networking technology, is revolutionizing the traditional manufacturing industry by rethinking manufacturing as a service. Concurrently, there is a shift in demand from high volume manufacturing to batches-of-one, custom manufacturing of products [1]. While the large manufacturing enterprises can reallocate resources and transform themselves to seize these opportunities, the medium and small scale enterprises (MSEs) with limited resources need to become federated and proactively deal with digitalization. Many MSEs essentially consist of general-purpose machines that give them the flexibility to execute a variety of process plans and workflows to create one-off products with complex shapes, textures, properties, and functionalities. One way the MSEs can stay relevant in the next generation digital manufacturing (DM) environment is to become fully interconnected with other MSEs by using the digital thread and becoming part of a larger, cyber-manufacturing business network [2]. This allows the MSEs to make their resources visible to the market and continue to receive work orders [3].

Digitization will also enhance compliance with the larger industry and customers in terms of technology standards and practices, and access resources and services available through the inter-connected digital supply chain (DSN) network.

In the emerging DM, timeliness of information is important for lean production, as well as quality and productivity assurance. Digitization creates communication channels across vendors and OEMs on one hand and between the various machines inside an MSE on the other. DM requires the integration of cyber (computing and communications) resources with the physical resources in the manufacturing process and supply chain. Continuous streaming of data from sensors at various locations in the manufacturing plant (e.g., individual machines and the network of machines) informs the data-driven decision making that guides design modifications, calibrates manufacturing methods, and programs the robot tasks and paths that they navigate the manufacturing floor. Securing such a distributed and connected cyber-physical system against cyberattacks requires developing novel approaches that are tailored to the threats faced by such systems. The cyberattacks can range from sabotage of product quality and intellectual property theft to ransomware. The attack surface, threat vectors, and solutions need to be analyzed to enable a secure, resilient, and scalable next generation DM.

Traditionally, manufacturing plants have been siloed and naturally create air gaps making them secure [4]. On one hand, DM exploits the information from the various sensors and devices to streamline the process and material flow. On the other hand, the distributed and collaborative nature of DM exposes it to risks that come with the connectivity required to implement DM. A typical DM process workflow is illustrated in Figure 1. A large part of the process before the actual manufacturing step is completely digital and relies on computational resources and computer networks for design, simulation, and programming the controllers of the manufacturing machines. The DM system may consist of additive, subtractive, and hybrid manufacturing machines. This process flow requires connectivity throughout the process chain. However, connectivity poses a security risk, which needs to be addressed by traditional and novel cybersecurity solutions that are applicable to various steps of the process flow. This paper is focused on analyzing the cybersecurity risks, developing an attack taxonomy and proposing novel solutions designed for the DM cyber-physical system.

This paper is organized as follows: Section 2 will present a hybrid manufacturing cell, a building block of DM, and uses it to discuss vulnerabilities. A taxonomy of threats for DM and attack case studies are discussed in Section III. Section IV will demonstrate how novel manufacturing-unique defenses can mitigate the attacks. Section V discusses lessons learned from state-of-the-art in DM security and research challenges.
II. HYBRID MANUFACTURING CELL: A DM BASIC BLOCK

Hybrid manufacturing cells are a prime example of a DM building block. Hybrid manufacturing combines traditional and advanced manufacturing technologies with state-of-the-art DM to work in tandem to produce the desired part. A traditional manufacturing cell has resources to process and produce parts efficiently and economically. Key components of a hybrid manufacturing cell include classical manufacturing machines retrofitted with sensors and connectivity, emerging digitally-enabled manufacturing machines (e.g., additive, subtractive and hybrid machines), autonomous robots, and quality-control/inspection instrumentation.

Connectivity and computational infrastructure are key enablers of hybrid manufacturing cells, and set them apart from a traditional manufacturing cell. Connectivity includes the feedback loops within the machines based on the machine state and feedback loops based on the observations of the process from an observer external to the machine. It also refers to the communication channels among the manufacturing resources within the manufacturing cell. The computational infrastructure supports data collection, storage, analysis, and decision making elements of manufacturing. While connectivity and computational infrastructure improve the utilization of the manufacturing resources, they can be attack vectors for both internal and external adversaries. Thus, vulnerable nodes in these supporting infrastructures must be identified and secured to realize the economic and efficiency benefits of DM. In the following sub-sections we discuss applications of the hybrid machine tools, describe key components in a cell, feedback loops within a cell and the vulnerabilities.

A. Applications of Hybrid Machines

While metal additive manufacturing processes are costly and inefficient for creating certain part features such as surface texture, subtractive manufacturing processes are expensive for certain designs because of the tooling and material costs. Hybrid machines bring synergy in these complementary processes (by including both additive and subtractive manufacturing capabilities within a single machine) especially for manufacturing custom components, resulting in reduced setup times, material costs and error in handling. Hybrid machines satisfy the quality and accuracy requirements for industrial applications and are able to replace process chains spread across multiple machines (possibly located at different enterprises) to just a single machine, reducing any logistical inefficiencies.

Hybrid machines have been successfully used in re-manufacturing and repair of high-value components and in manufacturing parts that require complex process chains. Pipe casings for offshore oil extraction have several features (Boss, Fins, Flange and Spiral coatings) on the surface critical for the target patient. Hybrid machines can create innovative injection molds which provide improved cooling performance over the traditional fabrication methods. Other applications of hybrid machines include surface patching in mold and die repair and turbine blade repair.

B. The Hybrid Machine Tool

Figure 2(a) illustrates a hybrid machine tool with its three key elements: the hybrid process element, the controller, and the smart element. The hybrid process elements include the milling tools, the coordinate measuring touch probe, grinding tools, and the laser engineered net-shaping process that employs a directed energy deposition printing head. These tools support consecutively running the additive and subtractive manufacturing cycles within a process cycle. The control element allows the user to interface with the hybrid process element and the execution of process cycles. It acts as an...
internal observer that observes the internal state of the machine (e.g., position, feed rate, laser power, and spindle speed) and sends actuation signals based on the instructions specified by the operator. The smart elements include sensors (e.g., accelerometer, acoustic emission sensor, dynamometer, and a high-speed camera) with supporting hardware. Hardware and software that enable data acquisition from the sensors are termed the sensor wrapper [11], [12]. The sensor wrapper implementation is composed of high-resolution sensors, Data Acquisition system (e.g., CompactDAQ from the National Instruments), signal conditioning elements such as filters and amplifiers (e.g., AE2A Amplifier from Mistras), and human machine interface (e.g. LabView from National Instruments). The sensors include the acoustics sensors (e.g., WSA wide-band AE sensor from Physical Acoustics, accelerometer (e.g., K-Shear 8728A500 from Kisler) and a dynamometer (e.g., MFS15050 tri-axis dynamometer from CNIC Electric Co.). The sensor wrapper also has high-speed camera (e.g, Mini AX 200 high-speed camera from Photron). The sensor signals allow the process states to be estimated for feedback control [13] as well as for providing observations from the perspective of an external observer (e.g., the operator) [14]. During the process cycle, the sensors collect acceleration, force, acoustic emissions and camera recordings of the process. The three elements of the hybrid machine tool work in harmony to enable refined control over the process. Such harmony is possible due to the coordination among process hardware and IoT devices in the computing and the communication channels.

C. Process Control Based on Feedback Loops

The hybrid machine tool can produce parts with complex geometries and functionalities. These capabilities of the machine create complexities in the process cycles and allow for faults to creep into the process. While process faults are inevitable for any complex system, one needs to execute corrective measures to mitigate the effects of these faults. Monitoring the process as an external observer is therefore essential in operating the hybrid machine tool. The hybrid elements can allow the operator to take corrective actions when a fault is observed. For example, a defect created in the part during the additive manufacturing cycle can be undone by executing a subtractive cycle over the layer with the defect before resuming the additive cycle. Taking corrective measures after a fault occurs leads to loss in manufacturing lead time and the physical resources. The smart elements can intervene to save time and resources by informing the operator about an imminent fault. This is possible by using the information that the sensor wrapper collects. Figure 2(b) illustrates the time synchronized data stream for an additive manufacturing cycle collected over 120 seconds. The Data stream for the force signals are densely packed, therefore an adjacent plot represents the force plot for a 0.05 second window. The information generated from the sensor wrapper is voluminous. Data is sampled at a rate of 100 KHz, 50 KHz and 10 KHz for the acoustic emissions, the accelerometer, and the force transducers, respectively. Each of these data streams over a 120 second period generate 89.5 MB, 44.7 MB and 8.92 MB of data, respectively. The High-speed camera captures images at a maximum of 1000 frames per second amounting to 110 GB over the 120 second period.

The controller (internal observer) observes and controls the hybrid machine tool based on the machine state. The external observer however, observes the process and takes corrective measures. This establishes two feedback loops. The controller sends actuation signals to the hybrid machine tool based on instructions within the G-code (subject to change...
Cloud service providers (e.g., Amazon Web Services and Rackspace) have integrated the enabling shop-floors may be limited in their capacity to cater to such requirements efficiently, cloud computing infrastructure could be economical and efficient. Cloud-based computing infrastructure is mature and reliable for application in the hybrid manufacturing cells. Cloud service providers (e.g., Amazon Web Services and Rackspace) have integrated the elements of storage, computation and communication. Amazon provides storage services (namely, the Elastic Block Store) and hosts well-known services (R, Matlab, Mathematica) as Virtual Machines (VMs) in the cloud. All computations can be visualized on the cloud VMs with software like Tableau and the workflow in the cloud orchestrated by scientific workflow management software such as Kepler.

Figure 4 illustrates the cloud as being central to online and offline quality control for the hybrid manufacturing cells. Signals collected by the sensors from the plant are stored in a local historian (storage for the data stream) and is then uploaded to the cloud for storage. From this point, the scientific workflow management software handles the flow of data. The computing VM is activated to receive the data, to analyze the data, and to calculate new control signal outputs, which are downloaded onto the controller closing the loop. For offline quality control, scanning electron microscopes and 3D profilometers in the hybrid manufacturing cell inspect the part after the process cycle. These instruments download process-related data streams from the cloud storage and identify anomalies in the process to explain defects in the part.

D. Vulnerabilities in a Hybrid Machine Tool

Although the hybrid machine tool is only one of the multiple resources of a digital manufacturing process workflow, this critical resource has multiple vulnerable nodes. Figure 5 summarizes eight vulnerable nodes in the closed loop control diagram illustrated in Figure 3.

1) The first class of vulnerabilities can be used to manipulate the instructions sent to the controller/plant. The adversary can intervene at nodes 1 and 2. At node 1 the adversary modifies the instruction (typically a G-code) sent by the operator. The adversary may intervene at node 2 and tamper with the actuation signal sent to the plant.

2) The second class of vulnerabilities is the replay attack. At node 4, since the actuation signal is monitored, the replay attack can trick the external observer into thinking that the instructions are executed as per specifications.

3) The third class of vulnerabilities arise due to the feedback loops. The internal observer (controller) and the external observer use the machine state and process information to send new instructions. The adversary may intervene at node 3, 5 and 6 to relay false information on the machine state and process resulting in erroneous feedback control. This sabotages the process of online quality control.
The outer feedback loop tracks the process and serves the purpose of minimizing the process deviation and averting any process anomaly. Attacks on the outer feedback loop have a direct consequence on the inner feedback loop, since instructions generated by the outer feedback loop are direct inputs to the inner feedback loop. Man-in-the-Middle attacks carried out at nodes 4, 5 or 6 yield incorrect process state estimations and therefore wrong prognosis leading to generation of incorrect instructions to the controller. Injection attacks at node 1 serve the effect of controllers in the inner feedback loop tracking reference signals generated from the adversary’s instructions, obviating the efforts of the prognosis-based instructions from the external feedback loop.

Side channel attacks at node 7 involve adversaries monitoring the footprint generated by the process. These footprints, for example, can be captured using a microphone that collects the acoustic sounds produced by the machine when in operation [19] or by tapping into the sensor data and other signals in the outer feedback loop. Adversaries that track these footprints from un-monitored channels could reverse engineer the product and create counterfeits which could find their way into the supply chain of critical components. Although the effect of a counterfeited product is not as pronounced in the manufacturing of low volume, high-value customizable parts as is the case where these hybrid machines are put to use, existence of such threats cannot be overlooked. Counterfeit products do not qualify the strict quality standards causing devastation in critical applications. They also sabotage brand reputation. Counterfeiting practices threaten the entire hybrid machine tool that is meticulously put in place with its feedback loops to ensure strict part quality and highlighted as node 8.

III. Digital Manufacturing: Taxonomy of Threats

Cyber-enablement and interconnectivity of digital supply chain networks introduce threats including financial theft and theft of IP. Some of the threats are unique to DM including digitally printing dangerous or illegal components, stealing competitor IP (e.g., the design files), modifying them and digitally printing dangerous or illegal components, stealing the product and creating counterfeits which could find their way into the supply chain of critical components. Although the effect of a counterfeited product is not as pronounced in the manufacturing of low volume, high-value customizable parts as is the case where these hybrid machines are put to use, existence of such threats cannot be overlooked. Counterfeit products do not qualify the strict quality standards causing devastation in critical applications. They also sabotage brand reputation. Counterfeiting practices threaten the entire hybrid machine tool that is meticulously put in place with its feedback loops to ensure strict part quality and highlighted as node 8.

4) The last class of vulnerabilities are identified at nodes 7 and 8. Node 7 corresponds to the side channel attacks leading to IP theft. Node 8 represents an indirect sabotage of the system in place due to counterfeit production.

The block $H_2(s)$ within the innermost feedback loop is a transfer function block that estimates the machine state (e.g., spindle speed, bed and tool position, laser power) based on the measurements from built-in sensors, such as optical scales and other motion trackers. The controller is continually tracking the error between the reference signal (generated from the hybrid machine tool) and the feedback signal of the estimated machine state from the hybrid machine tool. The reference signal specifies what the machine state should be at any given point in time as per the instructions. The controller sends actuation signals to the hybrid machine tool that nullifies this error and thereby bringing the machine state to the reference state. Injection attacks performed at node 2 include false actuation signals that drive the machine to undesirable states resulting in process faults. In case of a Man-in-the-Middle attack (replay attack) carried out at node 3, the transfer function block receives incorrect observations (contrary to the actual observations made by the optical scales within the machine) leading to a trail of miscalculations of the estimate of the machine state, error and therefore the actuation signal itself. Therefore, again resulting in the machine being driven to undesirable states and thus eventually faults in the process.

The block $H_3(s)$ in the outer feedback loop estimates the state of the process, based on information from a sensor wrapper [15] and generates new instruction sets as required. Typically, the transfer functions tend to be nonlinear operators to fuse information on the nonlinear and nonstationary dynamics underlying the measured signals to detect changes for corrective actions [16] or anticipate anomalies for prognostication and anticipatory control [17]. The state of the process is defined in terms of the thermo-mechanical state variables that capture the process that determines transformation of the geometry, morphology, and the microstructure of the part as it is being realized, as well as the health of the machine and its components. Information derived from the sensor wrapper may include thermal history, acoustic emission, and vibrations. The new set of instructions generated based on the estimated process state include reduction of laser power for the DED process if desired melt-pool geometry, thermal history and/or micro structure are not realized, re-manufacturing of layers due to part distortions, and stopping the machine for preventive maintenance due to tool wear. Information on thermal history can be used to predict part deformation during additive manufacturing cycles [18]. Vibrations in a grinding process can predict surface quality [19]. Acoustic emission signals can be used to predict the cutting conditions for orthogonal cutting experiments [19]. Such applications of the sensory information from the process allow for generation of prognosis-based instructions to the controllers.
insiders. The motivation of the attacker, resources available, and the damage caused in each category can be different and should be a part of the threat analysis.

A. Taxonomy of threats

Figure 6 shows a taxonomy of attacks, attack goals, attack targets and the countermeasures using the DM process chain in Figure 1. It also shows how an attacker can choose their attack methods based on their goals and targets. This taxonomy is used to develop defenses presented in Figure 6. For example, to prevent an attacker from tampering with the design files (e.g., STL files), a defender can embed identification codes in the design to physically authenticate the printed product. If the design has been tampered with or reverse engineered, the embedded code will be impacted, and therefore will not match with the correct one.

According to this taxonomy, we classify recent related works in Table I. We first classify the papers based on whether they focus on attacks or defenses or both. Then the threat models that they consider are identified. In the case that the paper is a survey that covers a variety of threat models, we will leave the threat model field blank. Lastly, we categorize all papers based on the attack methods they presented or based on the defenses. It is not surprising that most papers are focused on presenting possible defenses. However, in order to develop a defense scheme, the threat model that it targets overwhelmingly indicates that sabotage is the main attack goal and the attacks are launched either to tamper the files or for IP theft. IP theft is a major concern in DM because the design of hardware parts remains the same for many years, even decades. Revision to the designs that have been in place for so long, due to design theft becomes expensive and taxing exercise. A related issue in manufacturing sector is that a legitimately obtained part can be used to reverse engineer the part design which is then used for unauthorized production leading to IP theft. The deterrence in such cases lies in the production method that cannot be easily copied or decoded. Although DoS attacks are a major concern in financial and technology sectors, they are not a major concern in the manufacturing sector. This is because in many large manufacturing enterprises, the manufacturing machines are maintained on a separate, protected internal network, which is then securely connected to the internet for software or firmware updates only under supervision when the production activity is not taking place. A growing concern is the manufacturing-unique side channels (e.g., acoustics) and side channel attacks aided by machine learning used to uncover patterns in data obtained from the multiple sensing sources such as the acoustic, thermal, smart power meter and security camera sensors.

The threats in our taxonomy apply to all type of manufacturing machines including the hybrid machines. The complexity of the hybrid machine tool opens up possibilities for attackers to sabotage or steal secrets. Attackers can sabotage the products by tampering the control signals, or instructions (e.g., the G-Code) from the operators. Attackers can steal design secrets from side channel leaks from the hybrid machine tool. To explain the attacks and potential impact of the attacks on various aspects of DM process chain, we present five case studies shown as red rows in Table I.

B. Case Study 1 DrOwned attack on AM [24]

Informed by taxonomy of Figure 6, the goal of this attack was sabotage. The attack was conducted to reduce reliability of the part, and the attack target was design files. This attack on a 3D printer deliberately introduced defects into the part during printing [24]. The controller PC connected to the 3D printer was compromised by exploiting an un-patched vulnerability in WinRAR. The attack decreased the fatigue life of a quadcopter propeller causing a mid-flight failure by manipulating the part geometry (an example shown in Figure 7(b)). The attack was executed in three stages: The attacker compromises the Controller PC, developed a counterfeit design similar to the
TABLE I
Categorization of DM security studies. “DoS”, “Rev. Engg.”, “Tamper”, “Unreliable”, Cov. channel” stand for “Denial of Service”, “Reverse Engineering”, “Tampering data”, “Reduce reliability”, and “covert channel”, respectively. Red rows are attack case studies in Section III blue rows are defense case studies in Section IV.

| Papers                  | Attacks | Defenses | Attack Goals | Attacks |
|-------------------------|---------|----------|--------------|---------|
| Gupta et al.            | ✓       | ✓        | ✓            | ✓       |
| Strum et al.            | ✓       | ✓        | ✓            | ✓       |
| Ranabhat et al.         | ✓ ✓     | ✓        | ✓            | ✓       |
| Belikovetsky et al.     | ✓ ✓ ✓   | ✓        | ✓            | ✓ ✓ ✓   |
| Yampolski et al.        | ✓ ✓     | ✓        | ✓            | ✓ ✓ ✓   |
| Wu et al.               | ✓ ✓     | ✓        | ✓            | ✓ ✓ ✓   |
| Chhetri et al.          | ✓ ✓     | ✓        | ✓            | ✓ ✓ ✓   |
| Desmit et al.           | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chen et al.             | ✓ ✓ ✓   | ✓        | ✓            | ✓ ✓ ✓   |
| Elhabashy et al.        | ✓ ✓     | ✓        | ✓            | ✓ ✓ ✓   |
| Moore et al.            | ✓ ✓     | ✓        | ✓            | ✓ ✓ ✓   |
| Bracho et al.           | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Graves et al.           | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Yampolski et al.        | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chhetri et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Belikovetsky et al.     | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chhetri et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Baumann et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Wu et al.               | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Gupta et al.            | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Moore et al.            | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Tsotsos et al.          | ✓ ✓ ✓   | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Belikovetsky et al.     | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Zarre et al.            | ✓ ✓ ✓   | ✓ ✓ ✓    | ✓            | ✓ ✓ ✓   |
| Miller et al.           | ✓ ✓      | ✓ ✓     | ✓            | ✓ ✓ ✓   |
| Chaudhery et al.        | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Raman et al.            | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chen et al.             | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Yu et al.               | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Hoffman et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Abdulhameed et al.      | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Padmanabhan et al.      | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Prinsloo et al.         | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chhetri et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Calzado et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Yampolski et al.        | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Ivanova et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Bridges et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Holland et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Chhetri et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Wei et al.              | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Wu et al.               | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Vincent et al.          | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Riel et al.             | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Ren et al.              | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| He et al.               | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Wu et al.               | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Fey et al.              | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Elhabashy et al.        | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Slaughter et al.        | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Satchidanandan et al.   | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Satchidanandan et al.   | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Woollaston              | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| INCIBE [73]             | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Satchidanandan et al.   | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
| Behera et al.           | ✓ ✓     | ✓ ✓      | ✓            | ✓ ✓ ✓   |
original design, and replaced the original design file on the victim's PC with the counterfeit design file with the manipulations shown in Figure 7(c). A reverse shell backdoor was installed on the PC, which was used to submit jobs to the 3D printer. This allowed the malicious software to take over the 3-D printer and execute commands by the hacker. According to our taxonomy, a variety of defenses can be applied to this scenario. Although the attacker exploited a software vulnerability, the detection of sabotage was possible by more rigorous testing of the part.

C. Case Study 2: Cyberattack on the Honda automotive physical plant [72]

Honda’s Tokyo-based automotive production plant was forced to go offline by the self-propagating malware WannaCry impacting the production of about 1000 vehicles [72]. The WannaCry malware infected hundreds of thousands of computers worldwide by exploiting vulnerabilities in unpatched legacy systems [76]. The plant was shut down for 48 hours to recover operations and data, as both the ICS and IT networks were impacted [72]. As shown in Figure 8, the ransomware got deployed in the plant computer network using a backdoor in an older un-patched version of the Windows OS and then infected all systems in the network. According to our taxonomy in Figure 6, the attacker in this case launched a denial of service attack on the automotive plant by infecting and tampering their controller computers in the control network.

D. Case Study 3: Cyberattacks on the physical power grid [73]

Attackers may want to sabotage DM machines by tempering with their power supplies. Idaho National Laboratory demonstrated Aurora Vulnerability, where a connected generator was subjected to cyberattack on the control processors to open and close the breakers out of sync [73]. This stressed the mechanical systems inside the power generator, destabilizing it and causing it to explode. This and other similar attacks can damage the physical infrastructure in a manufacturing plant. Nation-scale attacks have been launched on the Ukrainian power grid leading to country-wide power outages affecting 230,000 citizens [77]. Three power distribution companies were affected as a result of this coordinated cyberattack that lasted for several hours. This attack exploited credentials and infected the network and SCADA systems using phishing emails with malware [77]. Absence of network monitoring and rules for remote access led to this attack. Disruption in the power supply even momentarily can damage the part that is being manufactured and some of the damages may go undetected because of their small size or location. As per taxonomy Figure 6, these attacks have the goal of sabotaging the product or the machine and the target can be any system connected to the power supply, ranging from power grid and smart meters (side channels) to the printer power supply.

E. Case Study 4: Additive Manufacturing Firmware Attack [31]

Attackers may set their attack target to be the firmware of 3D printer. If the firmware is compromised, attackers can sabotage the system by either modifying the control or deny the service of the machines. The attacker’s strategy is to exploit the firmware in order to selectively affect the integrity of printed artifacts; this approach is particularly effective in case random sample testing is applied after the artifact is printed, as it increases the chance of bypassing detection. Furthermore, any intervention to the printer firmware (especially at the bootloader level) can make the attack persistent.

There are different tactics an attacker can employ to infect the printer firmware. Most 3D printers and hybrid manufacturing platforms support Internet connectivity to allow remote management or troubleshooting from the manufacturer, as part of a service-level agreement with the end-users. In this case, attackers can exploit vulnerabilities in the network services running on the printer and eventually escalate their privileges on the printer. This privilege escalation can be exploited to update the printer with infected firmware, in case signed firmware updates are not supported. Another attack vector that may be exploited, is the input file parser within the printer. In cases where the firmware directly processes tool path input files (e.g., G-code files), any input sanity vulnerability may allow memory corruption and execution flow hijacking. In this case, attackers can inject malicious routines through input files, or reuse existing code within the firmware memory space.

As soon as an attacker has infected the printer firmware, they can easily control the actuators of the printer (e.g., print head motors, extruder valves or laser operation). By controlling these actuators in a judicious fashion, attackers can inject physical property attacks [31]. Furthermore, attackers can also perform a Denial of Service (DoS) attack to the printer so that legitimate users can no longer use the 3D print service.

Fig. 7. (a) Two 3D printed propellers. One of is defective. (b) CAD model of the design. (c) Design is compromised at the joints causing in-service failure. [24]
F. Case Study 5: Dissolvable support material

This attack is applicable to multihead/multimaterial printers, where support material can be printed in addition to the build material. Typically, the support material is dissolvable and as soon as the part is printed, it is submerged into an oxidizer (e.g., acid) to separate it from the build material. The attack consists of maliciously replacing build material in the interior of the 3D part with support material, allowing narrow channels for oxidizer to enter inside. Then, as soon as the print is complete and the solvent removes all support material, it would also carve hollow spaces within the part, where original build material was replaced. The effect of this attack is to reduce the structural integrity of the part, since the internal structure will no longer be solid. According to our taxonomy in Figure 6, this attack is classified as sabotage on DM machine in order to reduce the reliability of the products.

IV. Digital Manufacturing: Cyberphysical Defenses

This section presents five case studies of manufacturing-unique defenses spanning watermarking of controllers used in a range manufacturing settings, design obfuscation, part identification and provenance checking using embedded codes, authentication of designs in the signal processing domain, and an epidemiological approach to manufacturing IoT device security by leveraging their inherent diversity.

A. Securing Manufacturing Controllers via Dynamic Watermarks

Manufacturing may be broadly subdivided into discrete manufacturing and process manufacturing. Discrete manufacturing is concerned with manufacture or assembly of discrete units. In contrast, in process industries, the production processes are continuous and batches are indistinguishable. Examples are manufacturing plants such as chemical refineries and paper mills. The production process depends critically on maintaining the compositions, temperatures, pressures, etc., of relevant chemical reactions, the levels of tanks, or flow rates, etc. The regulation of all the required variables is done through a feedback control loop that senses the relevant output variables and calculates what actuation commands to apply.

Therefore the sensors, actuators and control laws play a critical role in the manufacturing process. The measurements made by the sensors typically travel over a communication network. The measurements may also be processed at nodes in the network either for fusing information or for performing computations to support the control law. The problem of cybersecurity arises since sensor measurements or other information traveling over the communication network may be intercepted en route and altered. It is also possible that in distributed control systems, the sensors may be compromised to report false measurements. Therefore, for securing the manufacturing processes, it is critical to address the security of the overall distributed control system. Figure 9 depicts a manufacturing plant with some compromised nodes in the feedback loops.

One can unify all the cases via a simple abstraction where just sensors are compromised, as indicated in Figure 10. Whenever the corruption of the measurements may have taken place, one can just suppose that the sensor has been compromised.

The resulting threat model is shown in Figure 11. One or more sensors/communication/computational nodes in the cyberphysical system may be compromised, as indicated in Fig. 9. A compromised sensor node can report any false data at any time, as shown in Fig. 11. We do not restrict the
range of false-data attacks. With this abstraction in hand, it is possible to develop an active defense based on the idea of “dynamic watermarking” [74]. The basic idea is illustrated in Figure 12. Consider the problem of verifying if a sensor is being truthful in reporting its plant output measurements. The actuation nodes superimpose a small secret random “excitation signal” onto their nominal actuation command.

This secret excitation can be regarded as a form of “watermarking” in the signal domain for the dynamical (control) system and hence the name dynamic watermarking. This excitation applied into the plant manifests itself in a transformed way in the outputs of the plant – it is indelible just like a watermark on a sheet of paper. The manner in which it is transformed depends on the dynamics of the pathway from the actuator to the particular output. In model-based control, design engineers have a good model of this pathway. If a sensor reports measurements that do not contain the transformed watermark, then the actuator can deduce that the sensor measurements have been compromised somewhere. One can conclude that an attack is happening and act appropriately.

The tests to determine whether the sensor measurements contain the appropriate watermark are statistical in nature. They rely on the fact that noise is normally present in the sensor measurements, and that the attacker cannot separate this ambient noise from the superimposed private excitation applied by the actuator. The statistical tests that can be conducted in various scenarios are described in [74], [79]. To illustrate the core of the idea, consider the following example.

Example: Consider a fully-observed linear scalar Gaussian controlled dynamical system described by the equation:

\[ x[t + 1] = ax[t] + bu[t] + w[t], \]

where \( x[t] \) is the state of the system and \( u[t] \) is the control input at time \( t \). \( w[t] \sim \mathcal{N}(0, \sigma_w^2) \) is i.i.d. noise with a Gaussian distribution. We suppose that \( a, b, \sigma_w^2 \) are known to the control system designer. Let \( z[t] \) be the measurement reported by the sensor. A truthful sensor reports \( z[t] = x[t] \), but a malicious sensor reports \( z[t] \neq x[t] \). We assume an arbitrary history-dependent feedback control policy \( g \) is in place, so that the control policy-specified input is \( u_{\text{nominal}}[t] = g(t(z^t)) \), where \( z^t := (z[1], z[2], \ldots, z[t]) \) denotes the reported measurements up to time \( t \). This results in a closed loop system, \( x[t + 1] = ax[t] + bu_{\text{nominal}}[t] + w[t] \). Suppose that the actuator superimposes a Gaussian noise unknown to the sensor on its control input: \( u[t] = u_{\text{nominal}}[t] + e[t] \), where \( e[t] \sim \mathcal{N}(0, \sigma_e^2) \) is a “dynamic watermark.” The true state therefore satisfies:

\[
\begin{align*}
x[t + 1] - ax[t] - bu_{\text{nominal}}[t] & \sim \mathcal{N}(0, \sigma_e^2), \\
x[t + 1] - ax[t] & \sim \mathcal{N}(0, b^2 \sigma_e^2 + \sigma_w^2).
\end{align*}
\]

The intuition behind dynamic watermarking is that by superimposing the private excitation that is unknown to the sensor, the actuator forces the sensor to report measurements that are correlated with \( \{e[t]\} \), lest it be exposed. In particular, for this scalar system, the following two “Attack Detector Tests” can be done by the actuator to detect if the sensor is malicious:

**Attack Detector Test 1:** Actuator checks if the reported sequence of measurements \( \{z[t]\} \) satisfies

\[
\lim_{t \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} (z[t + 1] - az[t] - bu_{\text{nominal}}[t] - be[t])^2 = \sigma_e^2.
\]

**Attack Detector Test 2:** Actuator checks if the reported sequence of measurements \( \{z[t]\} \) satisfies

\[
\lim_{t \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} (z[t + 1] - az[t] - bu_{\text{nominal}}[t])^2 = b^2 \sigma_e^2 + \sigma_w^2.
\]

If the sensor is honest and reports truthful measurements \( z[t] \equiv x[t] \), it passes both Tests. If either test fails, the actuator can declare the presence of a malicious sensor in the system.

The more difficult question is: If the signal \( z[t] \) passes both...
Tests 1 and 2, then what guarantees can we provide on the CPS? Rather strong guarantees can be provided if the signal passes both Tests. Let \( v(t+1) := z(t+1) - a z(t) - b u_{\text{nominal}}(t) - b e(t) - w(t) \). It has the interpretation as the additive distortion sequence introduced by the malicious sensors to the process noise present in the system. If \( z(t) \equiv x(t) \), then \( v(t) \equiv 0 \).

**Theorem 1** [74]: Suppose that the reported sequence of measurements passes the two tests. \( \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} v^2(t) = 0 \). That is, \( \{v(t)\} \) is a zero power signal.

It states that if the malicious sensors wish to remain undetected by passing the above two tests employed by the actuators, then the only attack that they can launch is to distort the process noise present in the system by adding a zero power signal to it. This in turn allows the dynamic watermarking method to provide powerful guarantees on the overall closed-loop performance of the Physical Plant even under attack. Suppose, for example, that \( |a| < 1 \) and a closed-loop linear control law has been designed to maintain stability, \( u_{\text{nominal}}(t) = f x(t) \) with \( |a + b f| < 1 \), with the control gain \( g \) chosen to yield good quadratic regulator performance.

**Theorem 2** [74]: The malicious sensor cannot compromise the mean-square performance if it is to remain undetected through the above two tests: \( \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} x^2(t) = (\sigma_w^2 + B^2 \sigma_\epsilon^2)/(1 - |a + b f|^2) \).

System metrics such as the quadratic regulation cost cannot be degraded by the malicious sensors, no matter what attack strategy they employ, without being detected.

The dynamic watermarking is only designed to detect an attack. What is to be done after an attack is detected depends on the context. In some plants, one may be able to switch to manual control. In others, one may be able to replace the sensor, or reboot the system. Dynamic watermarking is an active defense in which the actuators inject secret excitation in order to monitor the system and detect any adversarial presence. This idea was introduced in [80] to detect replay attacks, and extended in [81] to detect other attacks. The papers [74], [79], [82] develop detectors that provably detect arbitrary attacks that introduce non-zero power distortion. Dynamic Watermarking is a general methodology that can apply in a variety of contexts. It has been implemented in a laboratory process control system [83]. A laboratory demonstration showing the efficacy of dynamic watermarking in an automation transportation testbed [84] was followed by an implementation on a real autonomous vehicle driven in autonomous mode [85]. It holds potential to be deployed as a general purpose attack detection strategy in digital and continuous manufacturing plants, and in IoT and manufacturing systems with sensors and actuators.

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**B. Security of Design files: Obfuscating Designs** [40]

One of the major concerns in the DM is to ensure the security and authenticity of CAD files. These files are designed to provide incredible capabilities and information to the designers. For example, some design software programs save the entire workflow as a feature tree that the designers can use to conveniently recall a previous design step by a single click. However, such capabilities are also major security risks because these files can reveal not only the design but also the entire design process. Hence, embedding security in the design files may compromise some of the functionalities [86].

Recent studies have shown the possibility of embedding a layer of security in the form of design features. These features can be developed with design elements such as overlapping surfaces, curvatures, and scaling functions. A part 3D printed from the design file containing such security features will appear to be different than the onscreen representation of the geometry unless the security key is applied. An example of such secure CAD file is shown in Figure 13 where a stolen CAD file will print with a different gear geometry if the file is not sliced and printed in the prescribed orientation. A combination of slicing orientation, slicing resolution, printer resolution and other manufacture-time processing parameters can be used for designing such security features.

**C. Securing Manufactured Parts by Embedding Codes** [47]

Parts manufactured by subtractive or formative manufacturing rely on surface markings for identification or authentication. Serial number, bar code, QR codes, and other forms of identifications are stamped or embossed on the parts. Additive manufacturing presents a unique possibility of encoding information inside the part during manufacturing because the part is printed layer by layer. Either conventional or bespoke identification marks can be encoded in the product. These internal markings can be read by imaging methods such as tomography, radiography, and ultrasonic imaging. We have demonstrated the possibility of embedding a QR code inside the part [86]. The method of embedding the internal identification codes depends on the AM technology. For example, sintering temperature can be changed locally to generate a feature that provides a different signature when the
A novel encryption method is proposed where a lossless transform converts the CAD files to frequency domain audio files [75]. The frequency domain files are saved as a spectrogram, which is used to generate the fingerprints of the design in the form of (time, frequency) pairs for the amplitude peaks. These fingerprints can be used as an alternate modality for file authentication at any step in the manufacturing process chain.

Figure 15 shows a CAD model of a wheel hub, which is transformed into the frequency domain spectrogram. The red dots in the spectrogram mark the fingerprints identified for the model. The number of fingerprints depend on a designer specified threshold level or automatically determined based on the security level. If the entire spectrogram is saved or the threshold level is low enough, the spectrogram can be converted back to the CAD model without any distortion or loss of geometry. Such spectrograms are sensitive to change in the design file. Even changing a dimension to the limit of resolution of the CAD file will generate significant perturbations in the fingerprints that can be detected.

E. Securing Manufacturing IoT Networks by Device Population Diversity

The manufacturing industry is adopting Internet-of-Things (IoT) devices at 40% annual growth rates for enhanced asset management and increased productivity [87]. The proliferation of IoT and other non-compute devices is increasing the diversity of devices connected to the network in the next-generation manufacturing system [88]. The number and diversity of IoT devices is expected to grow over time as sensors and controllers are deployed widely [89]–[95].

Due to the increasing diversity in IoT devices, their ease in connecting to networks, weak default password configurations, and general lack of ability to automatic upgrade of firmware, they are an easy target for cyberattacks [96]–[100]. While efforts to deal with vulnerability of a particular equipment or a unit in manufacturing system has been reasonably addressed, assuring cybersecurity in the presence of a diverse “population mix” of IoT sensors and other non-compute devices deployed in the next-generation manufacturing plants or across the enterprise has not received much attention.

As a proxy to studying the device population mix in a real world manufacturing enterprise, we carried out a measurement campaign of types of devices on a large-scale campus network [95]. We carried out a census of devices connected to the campus network, and classified them based on their function. The results are shown in Figure 16(a). The devices connected to the network included desktops, laptops, mobile phones, VOIP phones, printers, TV displays, AV equipment, science appliances, and building automation gear among others. While

D. Intellectual Property Protection by Fingerprinting in the Acoustic Domain [75]

CAD files are used as inputs for 3D printers in AM methods. These files are not designed for mere visualization of the part design but are designed to manufacture the part. This poses a limitation on encryption and compression methods that can be applied to such files. Any algorithm that causes a loss of information will not be useful for such application and only lossless methods are required.

A novel encryption method is proposed where a lossless algorithm converts the CAD files to frequency domain audio files [75]. The frequency domain files are saved as a spectrogram, which is used to generate the fingerprints of the design

Fig. 14. Two QR codes are sliced into 300 parts each and embedded as interpenetrating codes. The correct slicing will retain only the authentic code. Incorrect slicing will retain points that will not produce any scannable code.
the importance of keeping the computing equipment patched and up-to-date has for obvious reasons been recognized for quite some time, only recently the security of non-compute IoT devices has started receiving attention \cite{101}. Our study showed that over 71\% of devices on the campus network are non-compute. Among these, \sim 59\% of the printers on the network had out-of-date firmware (see Figure 16(b)) and over half of the printers had no password. In a manufacturing plant, the percentage and diversity of non-compute devices is expected to be higher.

Current network security approaches and tools are device agnostic and ignore the diversity of the networked IoT devices. However, not all the devices are created equal and not all the devices are updated and maintained at the same level of network hygiene. In the campus network that we studied, while the computers are managed, patched, and secured by the IT team, the printers are maintained by graduate students, the VOIP phones are managed by the communications department, and the building automation devices are maintained by the facilities department. This leads to inconsistencies in the hygiene and health across devices. We advocate enhancing security tools to consider the diversity of the device populations.

Public health experts and epidemiologists consider population diversity and the differing impact of diseases on different groups in keeping the population healthy. Similarly, we advocate network security policies and mechanisms tailored to the population of devices in the manufacturing network. This has benefits over state-of-the-art device-agnostic approaches.

Dynamics of the device population has a significant impact on virus/attack epidemics in the network. For example, the Mirai attack targeted particular type of devices and networks with these devices had more compromises. Knowing the local device population allows one to mine CERT vulnerability database \cite{102}, \cite{103} to study vulnerabilities specific to the network. The CERT database is a repository of known vulnerabilities characterized by anticipated criticality. We can construct device population specific attack vulnerability profiles. Besides the CERT database, one could use internal information to augment the network monitoring tools. For example, a Programmable Logic Controller (PLC) controlling a boiler may need to be more carefully monitored and protected compared to a printer on the network. If additional information about the devices is available, this can be factored into allocation decisions on monitoring devices. Data from our study on campus devices revealed that the firmware in printers is not upgraded as frequently as in other devices (see Fig. 16(c)). While this knowledge is beneficial in deploying IT resources for updating/patching the device firmware to reduce the number of un-patched vulnerabilities, until that time these devices\footnote{e.g., devices with older firmware or vulnerabilities from CERT database.} are upgraded, extra resources maybe needed to monitor them.

It is important to study the vulnerabilities of the network device population and take steps to protect local device populations. Following are at least three ways.

1) Based on the number of local devices and the known vulnerabilities on these devices, network monitoring tools and resources can be optimally apportioned to maximize their effectiveness in detecting and containing the attacks. At the time of connection, the level of provided network service can be tailored to the known security vulnerabilities of the device requesting network service. The levels of service could include complete detail of service, limited access through security perimeters, requiring security patches or upgrades before full access could be provided etc. These approaches apply one device at a time at the time of connecting to the network.

2) Isolate similarly vulnerable devices on a Virtual LAN (VLAN) to provide suitable security for these devices. For example, the Windows8 devices for which no new security patches will be available could be isolated in a separate VLAN and protect them with a security device that carefully monitors Windows8 specific attacks. Similarly, IoT devices in a critical infrastructure could be put on a separate VLAN that only trusted users can access. Even if they are not perfect, such population specific isolation and protections will improve security.

3) Given the device population, network monitoring tools can aggregate anomalies based on device types to find patterns of attacks on specific types of devices. More information can be gleaned by aggregation based on device type. Observed anomalies can be checked against vulnerabilities in the CERT database to find attack vectors.

\section{V. Conclusion}

Adoption of DM requires companies to migrate to a Digital Supply Chain Network (DSN) as shown in Figure 17. The figure visually represents how a classical linear supply chain

Fig. 16. (a) Diversity in device population on a Network. (b) Printers with no passwords (c) Status of firmware updates on printers.
collapses into a set of dynamic networks due to digitalization. DSNs enabled by networking within and across organizations are integral to the DM. While integration of the social media may be a counter-intuitive component in the DSN, companies are adopting social media platforms to report service outages and system malfunctions and to provide customer support. As our study shows, the elements of the DM process chain open up a large attack surface and introduce numerous vulnerabilities making them susceptible to traditional cyberattacks and attacks that impact the physical plant and the quality of the manufactured products. The digital integration spanning the entire supply chain while making the production and movement of goods efficient, increases the attack surface and introduces new attack vectors.

Not all participants in a manufacturing supply chain may have the same level of resources to implement the most advanced defenses. The weakest links in a supply chain may besides compromising their own assets, may compromise the assets of all participants in the supply chain. This is especially true for the MSEs, who have limited resources, nevertheless have to embrace adoption of digital manufacturing. When the MSEs employ the digital thread as part of setting up the DM workflow and use the DSN to establish connectivity within their enterprise and across enterprises in the supply chain, they have to tackle the threats on all these multiple levels. The challenge for these MSEs is therefore to be judicious in using the limited resources to address these multi-level threats. The MSEs must prioritize which cybersecurity issues to address as they transition to a DM workflow.

While this study focused on cybersecurity of manufacturing—unique elements of DSN other elements such as the information, financial, and business networks are equally important. Some of these elements can be secured using well-known information security approaches such as encrypting data and communication. Side channel attacks and reverse engineering of products are threats that extend beyond the DM network and impact a company significantly. Reverse engineering of a product can lead to revenue loss, where the CAD models may be generated by skillful designers based on an actual part acquired from the OEM without any disruption or breaches to the connected supply chain. These additional risks need to be addressed when securing DM. Most IOT or DM technology components lack sufficient device activity logging capability. Insecure network protocols are typically used to connect DM components to the internet. Various methods can be used to assess the security posture of a manufactured product. Traditional systems have typically either been designed without security in mind, or with the explicit presumption that the system is isolated and so not subject to cyberattacks. The new generation of manufacturing sectors resulting from the adoption of the DM process workflow and migrating to the DSN would need special focus on securing complex systems that are integrated within the control network in the manufacturing plant. Hence, security controls should be designed from the inception of software development or hardware configuration in the control network.

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The provided text appears to be an abstract or a section of a journal article discussing the interplay between 3D printing and cybersecurity. It references various contributions and researchers on the subject of cybersecurity, 3D printing, and their intersections. The text includes references to publications, patents, and other scholarly works on topics such as secure control of networked systems, security in additive manufacturing, and how to ensure bad quality in metal additive manufacturing. The text is punctuated with specific years, indicating citations from different years, which suggests a comprehensive review of the literature on this topic. However, without the actual page numbers and specific lines, it is challenging to provide a more detailed summary. The abstract or section ends with a mention of cyber-physical systems and their impacts, hinting at ongoing research and development in this area.
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