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SMART MANUFACTURING: STATE-OF-THE-ART REVIEW IN CONTEXT OF CONVENTIONAL & MODERN MANUFACTURING PROCESS MODELING, MONITORING & CONTROL

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ABSTRACT
With the advances in automation technologies, data science, process modeling and process control, industries worldwide are at the precipice of what is described as the fourth industrial revolution (Industry 4.0). This term was coined in 2011 by the German federal government to define their strategy related to high tech industry [1], specifically multidisciplinary sciences involving physics-based process modeling, data science and machine learning, cyber-physical systems, and cloud computing coming together to drive operational excellence and support sustainable manufacturing. The boundaries between Information Technologies (I.T.) and Operation Technologies (O.T.) are quickly dissolving and the opportunities for taking lab-scale manufacturing science research to plant and enterprise wide deployment are better than ever before. There are still questions to be answered, such as those related to the future of manufacturing research and those related to meeting such demands with a highly skilled workforce. Furthermore, in this new environment it is important to understand how process modeling, monitoring, and control technologies will be transformed. The aim of the paper is to provide state-of-the-art review of Smart Manufacturing and Industry 4.0 within scope of process monitoring, modeling and control. This will be accomplished by giving comprehensive background review and discussing application of smart manufacturing framework to conventional (machining) and advanced (additive) manufacturing process case studies. By focusing on process modeling, monitoring, analytics, and control within the larger vision of Industry 4.0, this paper will provide a directed look at the efforts in these areas, and identify future research directions that would accelerate the pace of implementation in advanced manufacturing industry.

1. INTRODUCTION
Various manufacturing industries are constantly improving the efficiency and consistency in their

operations by reducing the extant of manual labor tending to advanced manufacturing equipment. This reduction happens with the increased level of integration of advanced controls into manufacturing processes. This control spans from manufacturing preparation tasks, material handling, logistics, material removal, additive manufacturing operations, assembly, quality control, and packaging. Some global companies have introduced lights-out facilities and are moving towards a more distributed approach of process control and monitoring. However, recent advances in computing capabilities are not always easy to implement since not all advanced manufacturing equipment has up to date embedded systems that would enable network connectivity. Utilization rates could vary greatly across the different parts of the manufacturing systems and many of these systems could have long life cycles. Typical advanced manufacturing systems will have machines that have interfaces and controllers that can be from different generations, or they could be from different manufacturers. They can vary greatly in what kind of data storage capabilities they have, as well as in network accessibility and security systems. Due to the sensitive nature of advanced manufacturing systems and various worst-case scenarios that may occur during the non-proficient operation of these, many of the equipment manufacturers limit access to modifying and adapting control units and processing systems, aside from also limiting local data storage. These limitations inhibit more integrated and connected manufacturing systems of the future. In fact, to some extent, many of these advances in the possible use of cloud-based computing and on-demand data analytics in industrial processes are effectively being hindered by such restrictions imposed by advanced manufacturing equipment manufacturers.

This state of the art review discusses smart manufacturing in the context of conventional and modern manufacturing process modeling, monitoring and control. To facilitate the discussion, the first few sections of the paper present the state of industrial automation in the 21st century, laying down the terms of the automation pyramid in smart manufacturing pyramid. The upcoming and ongoing revolution in industry (Industry 4.0) is then discussed with its various aspects. The discussion then diverts to state of modeling, monitoring and control for conventional processes, as an example. Then, the Additive Manufacturing process is presented as a representative of the modern manufacturing process, which is evolving in the smart manufacturing environment, along with current and future developments. The paper concludes with a brief discussion of challenges and opportunities.

1.1 State of Industrial Automation in 21st Century

One paradigm of digital manufacturing (DM) is related to the design and development of manufacturing systems that would support the whole product lifecycle. This view of DM emphasizes the importance of a digital thread, which would enable accurate and real-time data sharing among different lifecycle stages. As per the report by McKinsey (2015), the fourth industrial revolution is marked by digitalization of manufacturing operations, assets and integration of design, manufacturing, life cycle tracking and eventual recycle/reuse of the materials towards the next product lifecycle [2]. Towards the end of the third industrial revolution, the rapid growth in computer technology led to moving from manual control to automatic control; further, the advances in information technology allowed growth of business intelligence applications that streamline product design, development and manufacturing. However, the development of all these systems were done in isolated environments.

The second paradigm of digital manufacturing is related to the data exchange in real-time on the shop floor. It is applicable to previously defined concepts of Computer Integrated Manufacturing (CIM). In 2010, the International Society of Automation launched a standard (ANSI/ISA95) that outlines and assigns “levels” to constitute an automation pyramid, as shown in Figure 1, and described subsequently [3]. It is important to mention that the ideology that ANSI/ISA95 is built on has been around in traditional metal manufacturing since 1990’s. Levels 0 through 3 have been existing for manufacturing control, but with ANSI/ISA95 it has been formalized and propagated across other industries.

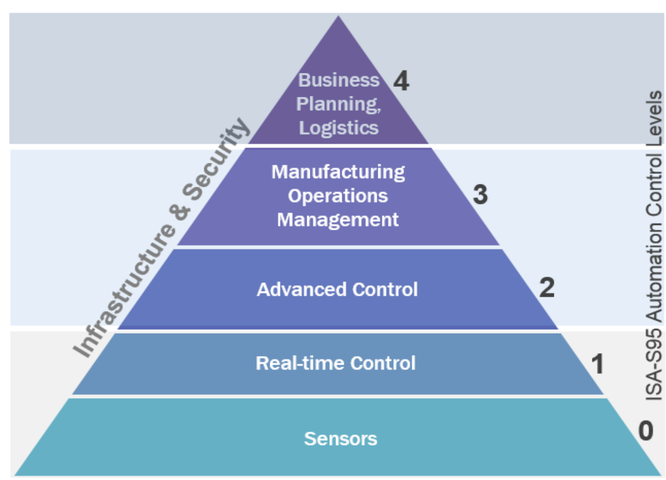

Figure 1: ISA Automation levels

The anticipated benefits claimed by Industry 4.0 can only be achieved if there is a robust framework to allow interaction between all these automation layers, minding the efficiency, cost, and security.

Levels 0 & 1: Sensors, Actuators and Real-time Controllers

Sensors and actuators in manufacturing process are the foundational layer of the ISA95 automation pyramid. These include position, velocity, acceleration, temperature, pressure, humidity sensors, etc. and pneumatic/hydraulic actuators, servo motors actuators, etc. Over time the sensors and actuators have evolved in terms of the task delivery accuracy, as well as reporting their own health. Across different industries, the standard used for Level 1 is a combination of microcontrollers and Programmable Logic Controllers (PLC); however, while PLCs are known for their fast execution (~5-10 ms deterministic loop rate), they fall short on reporting, trending, and data historian tasks. For some of the time-critical applications, advanced microcontrollers are also used as a level 1 controller. Over last few years, the trend in the process industry has gravitated towards combined Level 0/Level 1 solution systems. This makes sense because it decreases the maintenance requirements for the manufacturing plants, as well as provides a means to connect to the higher automation layers.

Level 2: Advanced Control Solutions

ISA95 defines the second level of automation as the advanced control layer [4]. This is the level at which the process setup control (feed forward/predictive), which is within the process control (model-based control, adaptive control), as well as run-to-run control (product-to-product adaption and control) are deployed. The Level 2 control provides set points for the Level 1 control hardware. This is important since the process knowledge (physics-based models, process experience and recipes, and data driven knowledge) can be embedded in a control strategy at this layer. The control execution loop rate is in the order of 100 ms and up to the duration of the manufacturing cycle. Such control is typically hosted on industrial computers running real time Linux or Windows Operating systems.

Level 2 is also a platform for leveraging the process modeling solutions. Over time, there have been tremendous advances in creating manufacturing process models. These are typically first principles-based models coupled with experimental and/or numerical simulated data. Due to advances in High Performance Computing (HPC), it is possible to embed intelligence of these models in process monitoring and control. When this is 'perfected,' Level 2 would be the host for such solutions.

Level 3: Manufacturing Operations Management Systems

For any modern manufacturing facility, the actual manufacturing process is only a subset of the activity performed. In the manufacturing flowpath, there are multiple non-manufacturing process related activities that need to be performed for efficient production. Manufacturing Operations Management (MOM) refers to the infrastructure that encompasses raw material acquisition and preprocessing, scheduling, and resource planning. This requires interchange of information between various process databases and historians, and user interfaces for engineers and managers to execute activities required for production. Level 3 is the first instance where operation intelligence and business intelligence interface drives process optimality.

At Level 3, process solutions, such at line balancing, predictive process setup, and flowpath optimization can be deployed since it has an overarching view of the process, as well as business goals. Although current MOM systems mostly focus on driving the basic performance metrics, such as an Overall Equipment Efficiency (OEE) and Downtime and Scrap rate, there are opportunities for more profitable solutions.

Level 4: Business Planning and Logistics

Enterprise Resource Planning (ERP) and other logistics applications are hosted at Level 4. At this level the variation in the system is only based on the type of manufacturing *viz*: continuous, semi-continuous or discrete. There is limited influence on the type of system deployed (for example, the ERP systems for glass manufacturing and chemical manufacturing would have similarities due to both being continuous manufacturing processes, but MOM systems would be drastically different). Such solutions are well developed and deployed widely in various industries.

1.2 KEY COMPONENTS OF INDUSTRY 4.0:

Industry 4.0, being an emerging phase/trend in the digitization of manufacturing, naturally has a number of evolving definitions; however, all these descriptions include certain key technological components briefly outlined next. Among the current descriptors of the fourth industrial revolution, many of which were coined by consultancies predominantly based in the United States and Germany, perhaps McKinsey [2, 5] captures best the overarching disruptions that inevitably gave birth to and essentially constitutes Industry 4.0 – "*(i)* the rise in data volumes, computational power, and connectivity; *(ii)* the emergence of analytics and business-intelligence capabilities; *(iii)* new forms of human-machine interaction; and *(iv)* improvements in transferring digital instructions to the physical world."

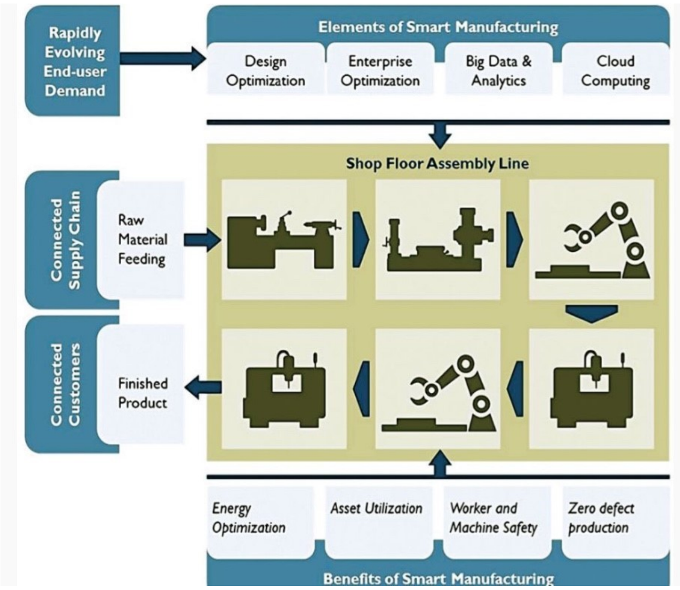

Figure 2: Key Elements and Benefits of Smart Manufacturing

Figure 2 shows some of the key elements of Smart Manufacturing / Industry 4.0 framework along with the benefits. The connected enterprise enables operational excellence focused benefits such as energy optimization, asset utilization, process insights and health monitoring. At the same time, promoting sustainable manufacturing as shown in Figure 3.

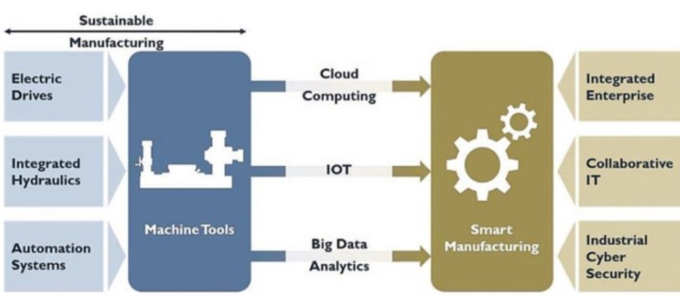

Figure 3: Smart manufacturing benefits promoting sustainable manufacturing

It is important to note that while Smart Manufacturing is a framework for enterprise operations, the focus of the current state of the review is based on modeling, monitoring and process control. To that end, the following discussion will focus on elements that enable the same.

Rise in Data Volumes, Computational Power, and Connectivity – Big Data, Cloud Computing, Industrial Internet of Things (IIoT)

Big Data: Big Data is termed as massive datasets having large, varied, and complex structure with the purposes of storing, analyzing, and visualizing for further process improvements [6]. For data generated in manufacturing, this takes a slightly different flavor while retaining some of the major characteristics, typically known as "3V"s of Big Data [7]. These are – Volume: disk space occupied, Variety: different forms of data (SQL databases, text files, video logs, web files, documents), and Velocity: sampling frequency of data. Note that there have been extensions of these characteristics to Veracity (replication of same data and filtering through the same) and Value (the extent to which big data generates economic value [8-10]. Big Data research is an active area in the fields of computer science and technology [11]. However, Big Data, as it applies to manufacturing, must be considered in its own context. A large manufacturing facility typically generates data that satisfies the definition of Big Data (has "5V" characteristics). Retention and processing of data is not only valuable from a process efficiency point of view, but also a regulatory standpoint in certain cases. This requires a large enterprise level of data architecture leveraging advances in database technology. Data infrastructure of this scale is termed Data Warehousing [12]. A typical data warehousing architecture has data collection and related functions (ETLR – Extraction, Transform, Load & Refresh), physical storage and servers to serve analytics, reports and data mining.

Cloud Computing: Also called the "cloud," this is another key enabler of Industry 4.0. As defined by the National Institute of Standards and Technology (NIST), it is essentially "…a model for on-demand network access to a shared pool of configurable computing resources (*e.g.*, networks, servers, storage, applications, and services)" [13]. Together with high-performance computing (HPC) and high-throughput computing (HTC) capabilities, which are rapidly increasing in computing power/efficiency, this combination provides a very powerful and decentralized data/computing resource.

Industrial Internet of Things (IIoT): Internet of Things is a paradigm in which the pervasive presence around us are of a variety of things or objects, which through unique addressing schemes, can interact with each other and cooperate with their neighbors to achieve common goals [14]. This paradigm rose out of maturity of multiple communication technologies like wireless communication, Near Field Communications, and Wireless Sensor and Actuators. One of the many sub-paradigms is the Industrial Internet of Things, which is the information networks of physical objects (sensors, actuators, machines) that allow interaction and cooperation towards achieving a synergistic goal [15]. The IIoT can be thought of as a bridge between the real and digital counterparts [3].

In this context, one can understand the importance of data infrastructure architecture, as detailed by the ISA95 automation pyramid. Having data infrastructure in place that can connect between Level 2 (advanced modeling and control solutions) and Level 3 (PLM) enables seamless integration of smart objects across the factory floor. As shown in Figure 4, the Industrial Internet of Things acts as a connecting layer between physical and cyber counterpart.

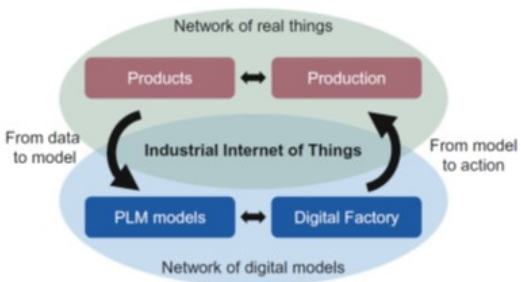

Figure 4: Industrial Internet of Things

Representative examples of IIoT deployment at the customer/consumer-level include equipment health and status updates/alerts provided to consumers of machinery (*e.g.*, Caterpillar), HVAC systems (both commercial and residential), mobility avenues (*e.g.*, traffic, monitoring of commercial fleets, telemetry for farming, fuel efficiency), and infrastructure (building security, climate control, elevators). It should be noted that, often, a third-party entity proficient in data analytics is tasked with collecting the data and managing notifications. Further, though the majority of these actions lead to an eventual manual intervention to investigate or remedy a potential problem, growing levels of automated decision making and control are being implemented in these scenarios. These decision making and control actions are more prevalent in the digital factory. For instance, parts are tracked through the inventory, retrieval, processing, assembly and quality testing/control stages by RFID and other means in integrated factory setups to address production bottlenecks or other failures in leading players like BMW, Zeiss, Siemens and Airbus. In these instances, real-time data is collected through an array of sensors, quality management accomplished through automated decision making, tangible actions/tasks conducted through control to move along the production process, and the data points, and information and analytics recorded in a time-historied cloud-database for future use. Some examples include [16]:

- The German chemical giant BASF at a pilot smart factory, “is producing fully customized shampoos and liquid soaps. When a customer inputs an order, RFID tags attached to empty soap bottles on the assembly line communicate to production machines what kind of soap, fragrance, and labeling is required,” leading to highly customizable products.
- A global tech firm, CGI, “has teamed-up with Microsoft to deliver a predictive maintenance solution for elevators manufactured by ThyssenKrupp, by securely connecting thousands of sensors and systems within elevators, which monitor everything from motor temperature to shaft alignment, to Microsoft’s cloud-based Azure Intelligent Systems Service, enabling technicians to use real-time IIoT data to spot a repair before the breakdown occurs.”
- AGCO, headquartered in the U.S., is “tackling the pending food shortage of the projected increase in the world population by using AgCommand, a precision agriculture telemetry tool to enable users to better understand their operation’s performance through an interface that farmers and dealers could understand.”

Emergence of Business-Intelligence – System Integration, Analytics

Business Intelligence is defined as the collection of decision support technologies that enable knowledge workers to make better decisions [12, 17]. Some of the most promising advantages of Industry 4.0 include leveraging data generated inside the smart factory, decisions related to the product and process quality, flowpath optimizations, as well as operational excellence. To fulfill this vision, the systems, operating at different levels of automation pyramid, must be integrated in cohesive manner. Table 1 shows how the automation levels, analytics tasks, and data sampling requirements are related.

Table 1: Automation levels, analytics tasks and supporting data sampling requirements

Automation Level	Modeling/Monitoring/Analytics task	Data Sampling period
0	Real Time Signal processing/ Feature Extraction	Milliseconds
1	Supervisory Control/ Simplistic Models / Visualization	Seconds
2	Advanced Analytics Models / Advanced Control	Minutes/hours
3	Process Optimizations/Predictive Models/ Simulations/BI tools	Hours/days
4	Plant/Enterprise Optimizations/Predictive Models	Months

At the lower levels of automation, more real time and low computationally expensive tasks are performed; at higher levels, both complexity of models and the amount of data rises. It is also important to note the data sampling needs at each level. For instance, Level 0-1 systems operate at millisecond time intervals for fast data operations. The fidelity required for operations at higher levels allow for either summary data or features extracted on higher frequency data.

In addition to the vertical integration of different levels (0-4) within the automation pyramid, as described above, horizontal integration across all aspects of the supply chain, both within and external to the factory, is an essential aspect of Industry 4.0. Note that the analytics and reports are typically used with the explicit information available in the data (production volume, sales, downtime, overall equipment efficiency (OEE), etc.). Data mining, on the other hand, is used to generate knowledge out of the implicit information in the data [12, 18-20].

Forms of Human-Machine Interaction and, Connecting the Digital to the Physical World

Other key components of Industry 4.0 include novel forms of human-machine interaction through interfaces such as touch and feature/voice recognition. The use of virtual reality (VR) and augmented reality (AR) interfaces, sometimes in combination with haptic, visual or audio feedback, further refine the capabilities and efficiency of such interactions. The ability to embed (simple) knowledge-based algorithms within the setup to predict process outcomes for simple perturbations in input process parameter makes this even more powerful. Finally, the drastic improvements in transferring digital instructions to the physical world through mature cyber-physical systems, such as in advanced robotics systems and on-demand additive manufacturing, help complete the loop for translating concepts/needs to functional products.

1.3 Focus Topics of this Review

With this background on Smart Manufacturing infrastructure, automation levels, and interaction with the IIOT, we can review process modeling, monitoring, and control. The goal of this review is to show the historical context of the process modeling/monitoring/control methodology for conventional processes, as well as a few recent developments. Then, the Additive Manufacturing process modeling, monitoring and control use case will be discussed to put it in the context of Industry 4.0.

2. Modeling, Monitoring, Analytics and Control of Traditional Manufacturing Processes

2.1 Material and process modeling

Modeling has typically been used as a tool to gain an understanding of the machine-process-material interaction. The objective is to determine the list of key sub-processes and phenomena dominating the behavior of the processed material. In essence, the physical model and associated mathematical model are built to construct the virtual process, where the input of processing (in terms of tunable parameters) is mapped to output quantities (part performance predictions). The primary goal of material and process modeling is to design, monitor, predict, and control the interactions between work materials and processes. At a high level, the material and process modeling can be divided into two major categories – physics-based modeling and data driven modeling. Physics-based modeling methods rely on mathematical representation of the physical phenomena that occur during the processing of material. The primary modes for model building are analytical and numerical within the physics-based process modeling. A summary of the modeling approach examples is shown in Table 2. As a use case(s), Machining process and Rolling process modeling have been chosen due to the volume of industrial products these two conventional processes generate. It is important to note that the list of references is representative and not exhaustive.

Table 2: Modeling Methodology for use cases of conventional manufacturing processes.

Modeling Method	**Machining Process Modeling**	**Rolling Process Modeling**
Analytical	Orthogonal Machining Theory [21, 22] Single DOF chatter [23] Nonlinear regenerative Chatter [24] Shear zone deformation theory [25] Ploughing process theory [26] Elastic contact deformation and friction effects [27] Tool chip interface theory improvements [28]	Primary roll force model based on static equilibrium [29] Roll pressure equivalence to strip stress [30] Simplified & usable Orowan model [31]
Numerical	Thermal finite element analysis of machining [32] Cutting model based on plane strain assumption [33] Viscoelastic model to predict chip geometry [34] Incremental elastic-plastic finite element model [35]	Numerical Integration of Orowan's equations [36] 2D finite element model [37] 2D model including thermal effects [38]

Need for Surrogate Models of Physical Processing in Manufacturing

In the previous sections, we discussed the conventional methods of process modeling, which has been a traditional approach in the last few decades. However, as the complexity of the manufacturing increases, the modeling of all stages and phenomena becomes challenging due to high computational cost. A traditional modeling effort is typically used for process optimization in terms of processing variables (e.g. deposition speed, temperature or laser power in AM) to determine the optimal processing window. Very often these tasks can be performed off line, where computational cost is less important. However, when any real time autonomous correction is required (Level 2), there is a need for reliable models that can provide almost instantaneous response to, and suggestion for, the corrective action.

Typically, the accuracy of the reliable model is correlated with the complexity of the physics-based model and associated high cost of the prediction. With the advances of data driven approaches, there is a need for wider adoption of these techniques to build statistical surrogate models of manufacturing that could accelerate the online process control schemes without sacrificing the accuracy of modeling (Level 2). Moreover, the surrogate models should be adaptable for reuse when new specification arrives. This is of high importance in the context of shifting manufacturing from mass production to model customization.

2.2 Diagnostics/Prognostics Approaches for Model-Based vs. data-Driven models

The diagnostics are mainly classified into either model-based or data-driven approaches. Model-based techniques rely on an accurate dynamic model of the system and are capable of detecting even unanticipated faults. They use the actual system and model outputs to generate a ''discrepancy'' or residual, between the two outputs to indicate a potential fault condition, then a bank of filters is used to identify the actual faulty component. On the other hand, data-driven techniques often address only anticipated fault conditions, where a fault ''model'' is a construct or a collection of constructs, such as neural networks or expert systems that must be trained first with the known prototype fault patterns (data) and then employed online to detect and determine the faulty component's identity. The Pros and Cons of different fault diagnosis approaches are summarized in Table 3.

Table 3: Comparisons on Different Fault Diagnosis Approaches

Approaches		Pros	Cons
Data-Driven Approach	Expert system	Suit for systems that are difficult to model, i.e. systems involving subtle and complicated interaction whose outcomes are hard to predict	A considerable amount of time may elapse before enough knowledge is accumulated to develop the necessary set of heuristic rules for reliable diagnosis, very domain dependent, difficult to validate
	Neural network	Able to implicitly detect complex nonlinear relationships between dependent and independent variables, able to detect possible interactions between predictor variables, and the availability of multiple training algorithms.	Black box nature, great computational burden, proneness to overfitting, and the empirical nature of model development.
	Fuzzy logic	Easily understood linguistic variables, allows imprecise inputs, reconciles conflicting objectives, rule base or fuzzy sets easily modified, simplify knowledge acquisition and representation, a few rules encompass great complexity	Hard to develop a model from a fuzzy system, no systematic approach to fuzzy system designing. Instead, empirical ad-hoc approaches are used. Require more fine tuning and simulation before operational
	Hidden Markov Model	Can easily be extended, because in the training stages, HMMs are dynamically assembled according to the class sequence. Smaller models are easier to understand, but larger models can fit the data better.	The Viterbi algorithm is expensive, both in terms of memory and compute time. For a given set of seed sequences, there are many possible HMMs, and choosing one can be difficult.
Model-Based Approach	Fault tree	Easy to read and understand, can be synthesis automatically	Difficult to include information about ordering and timing information of events in fault tree. No way to treat common-cause failures resulting from fault propagation.
	Model based analytical redundancy	Mostly for continuous system, is able to detect abrupt faults and incipient fault	Computation load for detailed online modeling of process, the sensitivity of detection process with respecting errors and measurement noise
	Finite state automaton	Easy to set up the component and system model, mostly for DES	Model complexity explosion by explicitly listing all possible states and events, lack of readily available software packages
	Petri net	Mathematical capability and graph description of DES	Lack of readily available software packages

Prognostics focuses on understanding the failure modes, detecting precursors to failure, tracking degradation mechanisms, and predicting the remaining useful life of components and systems. Prognostics is still an emerging field, and much of the published work has been exploratory in nature. Current prognostics technology is considered to be immature due to the lack of uncertainty calculations, validation, and verification methods, as well as risk assessment for Prognostics and Health Management (PHM) system development [39].

The prognostics methods are largely classified in three types [40]. Type I: Reliability data-based (population), which considers historical time to failure data used to model the failure distribution. They estimate the life of an average component under average usage conditions. Type II: Stressor data-based (population), which also considers the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions. Type III: Effects-based (individual), which also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions. The pros and cons for these three approaches are summarized in Table 4.

Manufacturing-related prognostic and health management (PHM) research work is divided into machine-level and system-level studies, which highlights the greater emphasis found in the literature on the machine-level, such as machine tools PHM. These machine tool PHM studies include the machine tool spindle, cutting tool wear or breakage [41-45] and the machine tool feed-axis system [46-48].

The PHM in the system level starts from the overall equipment efficiency (OEE) to the overall throughput effectiveness [49].

Table 4 Comparisons on Different Prognostics Approaches

Type	Pros	Cons	Typical algorithm(s)
Reliability data-based	Estimate failure density functions with parametric or non-parametric models: A population of components is tracked and their failure times are noted. Components that have not failed are called censored data, which is also useful in predicting the failure density.	Failure modes cannot be random, it must be related to measurable stressors for historical data to be beneficial. Without consider the operating condition of the component.	Weibull Analysis
Stressor data based	Use covariates to control or predict reliability model on the failure distribution parameters	Environmental effects that drive the failure modes must be measurable	Proportional Hazards Model
Effects-based	Use degradation measures to form a degradation path for prognostic prediction	Degradation severity must be related to a measurable parameter such as tread depth or bearing vibration level or temperature	Cumulative Damage Models General Path Models

2.3 CASE STUDY (TRADITIONAL MANUFACTURING) – MACHINING PROCESSES

With connected enterprise, model based manufacturing provides a concept of using a digital twin as a basis to plan the processes before they are being implemented with minimal downtime. A digital factory provides an option to use simulations of assembly and manufacturing processes to determine assembly tasks and tool paths in a digital environment. Figure 5 shows an example of digital thread in a machining process centered manufacturing. The main machine controller captures all necessary parameters for a machine controls such as spindle speed, material feed, cutter shape, cutting, depth and such. The cell with the CNC machine is connected through the data acquisition module to the network. This enables two way communication : from the cloud and database with control programs related to different parts and their machining operations to the machine controller, and from the connected transducers to the cloud and database. The main machine network at the shop floor is connected through ethernet cards and connectivity modules to the main digital thread data pathway. Internet of Things serves is furthermore connected to the office network through the web based enterprise resource tier. The Client Tier is providing staff access through the office network to all Computer Aided Engineering Applications, such as Computer Aided Design, Computer Aided Manufacturing applications, applications used for process planning and simulation, converters of files to neutral data exchange files, and furthermore to the external customer access through the rich or thin clients.

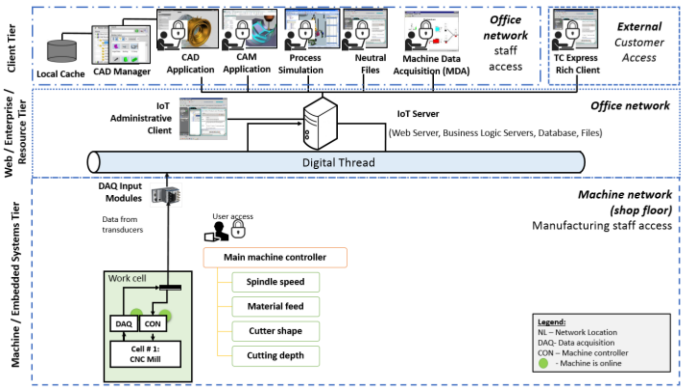

Figure 5:: Example of Digital Thread/Digital Twin framework

Albeit demonstrated for a single machine, the same concept can be extended for entire machining facility. Such framework enables advanced monitoring and control of machining processes.

3. MODELING, MONITORING, ANALYTICS AND CONTROL OF ADVANCED MANUFACTURING PROCESSES

3.1 PARADIGM SHIFT IN PHYSICS-BASED MODELS OF MANUFACTURING

Traditionally modeling has been used as a prefabrication tool to gain a fundamental understanding of machine-process-material interaction [50, 51], and ultimately to optimize the fabrication process in terms of identifying the optimal processing window. In general, the focus has been centered around key sub-processes and phenomena dominating the fabrication of interest [50, 52]. Significantly less attention has been paid to multi-scale models that couple the manufacturing level with the material behavior [53, 54]. However, as process automation increases, the modeling must be expanded towards multiple steps up to the entire production line. Moreover, Industry 4.0 will heavily rely on real time autonomous response to unexpected events like failure or process drifts. In this context, there is a need for reliable models that can provide almost instantaneous response in terms of the recovery or corrective actions. Finally, the models should be tunable towards mass customization, small production series, and personalized products at relatively low costs. All together the requirements for simulation tools posed by Industry 4.0 need to reshape the physics-based simulations. In particular, a new paradigm for modeling tools is highly needed -- customizable, high fidelity, multiscale models up to system level with low computational costs seamlessly coupled with the sensors to enable autonomous actions.

To provide a more detailed perspective, we focus here on additive manufacturing as the new emerging technology. However, the discussion included below is applicable to other processes, as well. In general, we highlight four main critical needs: (i) co-simulation, (ii) model adaptation, (ii) model validation (iv) computational cost, along with their interrelationships.

<u>Co-simulation</u>: Simulations are used in many areas in industry with varying level of details and focus, ranging from behavior of individual beads in direct energy deposition processes up to supply chain modeling. Interoperability between specialized tools and different simulations becomes more and more important. Taking additive manufacturing as an example, a designer creates the project in STL format using one software, e.g. Autodesk. The file is then sliced using another tool, for example Slic3r [55], Cura [56], Slimplify3d [57]. If any physics-based analysis is to be performed the STL file, along with the generated G-code, needs to be converted into the computational mesh that is gradually activated using the birth and death method [58-60]. At this stage, the choice of software is limited and dictated by the choice of modeling tool used. Simulation software, such as NetFabb [61] (integrated with Autodesk) or 3DSim [62] (recently acquired by Ansys), begin to offer end-to-end solutions, where physics-based models are integrated with the design process. The focus of these tools is mostly on metal printing processes and thermomechanical behavior of the built part [63], such as the prediction of distortion accumulation or microstructure evolution [64]. Even within the metal additive manufacturing practices, the physics-based simulators are yet to be fully adopted. The choice of deposition parameters, design of supports, or any trouble shooting are still predominantly made using trial and error approaches. Other technologies in the additive manufacturing family still largely lack the physics-based simulators integrated with the design tool to optimize the fabrication process. For example, aerosol jet printing [65] or fused filament fabrication [66-70] received significantly less attention, most likely due to lower business benefits. Nevertheless, to fully capitalize on the advent of Industry 4.0 there is a need to advance physics-based modeling and integrated simulation tools for other technologies. Outside of the AM domain, the progress is being made around Functional MockUp Units [70, 71] along with workflows, where the goal is to facilitate the seamless [71, 72] integration of various software by interface design and data sharing.

<u>Model adaptation</u>: Static simulation model is currently the dominant mode of physics-based simulation. In particular,

the specifics of the design are translated into the input parameters of the model, with the specific question targeted. For example, in metal, AM engineers seek to design the supports for structural stability [72-74]. Although some design rules can be drawn to facilitate the decision-making process, the intricacies of the part geometry may hamper the process necessitating geometry-specific queries [75]. Moreover, very often several versions of the models are constructed as a result of optimization or customization. In such cases, significant savings can be gained by the smart reuse of previous results without manual interventions, for example during slicing step [76]. AM is a highly repetitive process with high level redundancy and high potential for model adaptation in terms of part geometry. Recently, neural network has been successfully harnessed to capture the thermal behavior of several layers, building a data driven surrogate a model and subsequently adapting it to predict temperature field for another geometry [77]. The progress in this field is highly needed [51, 52]. Although some design rules can be drawn to facilitate the decision-making process, the intricacies of the part geometry may hamper the process necessitating geometry-specific queries.
Another challenge emerges in the relation to the Materials Genome Initiative [78]. We witness growing effort to accelerate the discovery of new materials. The goal is to deploy them twice as fast at the fraction of cost [78]. Manufacturing is an important ingredient of this ambitious goal. Consequently, the progress made around "Industry 4.0" needs to be ready for the vast expansion of the materials to be manufactured. The modeling effort in the area needs to be refocused into understanding the parameters of materials, and expanding their ranges, to facilitate manufacturing or leveraging the current technologies. Hence, there is a need for computationally inexpensive surrogate models for manufacturing processes, where the input is extended to include the design variables of materials, as opposed to materials properties.

<u>Computational cost</u>*:* The ability to predict the behavior of material, one step of the production line, or the system of factories is at the core of any optimization or adoption within a cyber physical system. However, the accuracy of the reliable model is typically correlated with the complexity of the physics-based model and the associated high cost of the prediction. With the advances of data driven approaches, there is a need for wider adoption of these techniques to build statistical surrogate models of manufacturing that could accelerate the online process control schemes without scarifying the accuracy of modeling (Level 2). Moreover, the surrogate models should be adaptable for reuse when new specification arrives. This is of high importance in the context of shifting manufacturing from mass production to model customization. In the context of AM, the current computational cost of physics-based models is still very high. There are various approaches to reduce the cost. The reduction can be achieved either at the model level by simultaneous deposition of several layers, instead of gradual deposition according to the path. Another reduction can be achieved at the numerical solver level [79, 80] or by mesh coarsening whenever processes are less dynamic [80, 81]. Finally, the surrogate models are yet to be advanced with high impact on the design for closed loop process control.
<u>Model validation</u>*:* Physics-based models are still to be thoroughly validated if they are to be routinely used in the industrial application, especially in the context of advances towards Industry 4.0. This is certainly true if these models are to be used as a virtual counterpart of the physical process to suggest corrective action due to unexpected event. In an ideal case scenario, a so called "Digital Twin" [82-84] would use physics-based models to predict the nominal behavior of the system of interest, with the goal to identify potential issues of the real machine counterpart and suggest corrective action. In the context of AM, model validation is typically performed post-production. Due to high computational costs associated with the high-fidelity physics-based models, in situ validation has been limited with recent attempts [84, 85]. As indicated in the previous section, there is a need for surrogate models that shadow the high-fidelity models to enable detection of potential issues during the deposition. Self-awareness of the machine is of high importance for AM processes, where the part properties may be impaired by the local defects that occurred and remained uncorrected during the printing process. Finally, models need to be validated across multiple levels in terms of uncertainty stacking.

3.2 CASE STUDY (ADVANCED MANUFACTURING) – ADDITIVE MANUFACTURING PROCESSES

The advent of additive manufacturing (AM) promises to revolutionize the reach and possibility of manufacturing. Hod Lipson's book *Fabricated* makes the case for AM as a disruptive technology in terms of 10 different principles; a deeper examination of these principles behooves the following freedoms to AM from the constraints of traditional manufacturing [86].

- Freedom of infinite complexity – it takes the same effort, for instance, to make a square hole versus a round hole. Indeed, there is no need to restrict to simple Euclidean shapes to ease manufacturing.

- Freedom from assembly – the number of component parts can be reduced by several orders of magnitude. For example, the oft-cited General Electric LEAP engine nozzle has zero sub-assemblies, compared to over 20 parts in the earlier design, while being 25% lighter.
- Freedom of variation in size – the manual effort to scale a part is negligible, as no new fixtures need to be made if the size of the part is decreased or increased.
- Freedom from material constraints – there is a significantly reduced burden on determining the recipe for different materials; a part can be made from stainless steel or titanium by changing a few parameters (laser power, scan speed, etc.), as opposed to perhaps changing the tooling.
- Freedom from expensive, skilled labor and experience-driven knowledge – AM processes run almost entirely on their own, irrespective of the material and shape being produced.
- Freedom from waste of energy and materials – the amount of material and energy needed is magnitudes smaller, for instance, the buy-to-fly ratio in AM, viz., the ratio of material processed to the final weight of the part is as small as 7:1 compared to 20:1 with traditional machining [87-89].
- Freedom from specialized tooling, fixtures, and waste from wear – there is no special tooling or different type of die or tooling required. Because AM does not require the tool to be harder than the material of the part to be produced there is no wear or possibility of stoppage due to broken dies.
- Freedom from waste of movement and logistics – All parts required for a product can conceivably be made under the same roof without having to source from different suppliers.
- Freedom of production flexibility, and breaking of batch size scheduling constraints and inventory – the batch size and product mix can be varied at will to match to demand. Hence, given adequate resources, the production rate can be made to match the takt time with zero buffer inventory needed. Furthermore, in an AM-oriented facility, because all machines are identical, there are no bottleneck machines (in the parlance of theory of constraints [90]) that dictate production. If a machine breaks down, there are other identical machines to take the load without having to adjust production.
- Freedom from variability due to breakdowns and maintenance – because there is no variability due to tooling, controlling the input material is sufficient to reduce variability. Furthermore, the uniformity of machines regardless of part design has a great impact on the reliability and maintainability aspects of the production line. Instead of maintaining several service parts and employing repair technicians for various types of machines, a small group of personnel and replacement items is sufficient to keep production at pace.

These freedoms afforded by AM, make it an apt vanguard technology to implement in the emerging paradigm of smart and digital manufacturing (Industrie 4.0), as pointed out in the 2011 Whitehouse report on advanced manufacturing [91]. Despite these revolutionary possibilities, recent roadmap reports by federal agencies and national labs emphasize the need for fundamental research in the following areas in additive manufacturing [92-97]:

a) Advanced and novel materials customized to the application.
b) Process development to increase the speed and volume of the part produced.
c) Design rules and support structure optimization.
d) Efficient and accurate process modeling and simulations to anticipate potential problems.
e) In-process sensing, monitoring, and control to ensure parts are produced to specification.
f) Non-destructive evaluation and post-process quality assurance.
g) Post-process finishing to improve surface and geometric integrity of free-form surfaces and aid in the removal of supports.
h) Standardization of test procedures, geometric dimensioning and tolerancing (GD&T) and metrology of AM parts, standardization of best practices, such as post-process cleaning, and safety benchmarks for handling powders.
i) Logistics and supply chain implications of AM.
j) Cyber security to defend against intrusion of the digital thread in AM, and protection of design intellectual property.

From a technical vista, the current lack of fundamental understanding of causal process mechanisms, the microstructure of the part produced, and its relationship with the property of the part, i.e., the process-structure-property relationship, is at the heart of the current repeatability and reliability-related challenges in AM. Unlike machining and forming operations, wherein the surface and near-surface is of concern, and the bulk of the part can be assumed to remain unchanged, in AM the mechanics of surface generation is contingent on each individual layer. A defect at any layer, if not detected and averted before the next layer is deposited, is liable to be permanently sealed in and, thus, affect the property of the part.

Given the putative lack of confidence in the consistency of AM processes, industries such as aerospace and biomedical, therefore, demand extensive post-process inspection of AM parts, such as X-Ray computed tomography (XCT) [98-100]. This is cumbersome and expensive, and will inhibit the drive to incorporate the use of AM for mission-critical parts. This challenge is further compounded by the need for materials testing and process databases to qualify parts for critical components, particularly, for aerospace applications. Because, the sample sizes available in AM are small due to the relatively slow and, oftentimes, highly specialized nature of the part design, manufacturers do not have the advantage of material performance datasets, as in machining and forging, which have been developed over the last several decades [98, 99].

For instance, Gorelik *et al.* cite the example of a crash of a F/A-18 aircraft in 1981 that was attributed to the premature and catastrophic failure of a turbine disk made using a powder metallurgy process [100]. This accident led to a 5-year decline in powder metallurgy components in the defense industry. Given that AM processes favored for metal parts, such as powder bed fusion (PBF) and directed energy deposition (DED), rely on powder raw material, there is hesitancy on the part of defense manufacturers to adapt AM processes for mission-critical components.

A solution to overcome these quality-related impediments in AM is to qualify the integrity of the part in-process using in-situ sensor data. For instance, SigmaLabs has recently trademarked the phrase in-process quality assurance (IPQA). In a 2013 NSF workshop in AM, Huang *et al.* suggest the term, *certify-as-you-build*, wherein the integrity of the part is ascertained as it is being built via the sensor signature patterns [94, 95]. A slight caveat to the phrase certify-as-you-build is the use of the word certify; certify typically relates to a third party involvement. A slightly different term *qualify-as-you-build* can be used instead to skirt the unsuitable connotations associated with the former.

The crux of the challenge towards realizing the *qualify-as-you-build* paradigm is to establish sensor signature-based process maps, wherein specific sensor signatures are intimately tied to specific types of defects. To build these sensor signature-based process maps requires fundamental understanding of each link in the following AM process chain.

Process Conditions → Process Phenomena → Process Signatures → Part Microstructure (Defects) → Process Control (Rectification) → Part Performance.

Each of these aspects is listed herewith and exemplified in Figure 6.

- Process conditions (e.g., parameter settings, material contamination, part design, machine errors).
- Process phenomena (e.g., vaporization, incomplete fusion, meltpool instability, thermal gradients).
- Sensor data signatures (e.g., meltpool thermal profile, meltpool shape, spatter pattern) extracted from heterogeneous in-process sensors (e.g., thermal and high-speed cameras, photodetectors).
- Part microstructure/defects (e.g., pinhole pores, acicular pores, distortion) caused by the above phenomena.
- Process control (e.g., changing the process parameters, scan strategy, part design, and support structures to compensate for defects)
- Part performance or quality, such as the fatigue life and surface finish.

The progress towards sensor-signature based process maps can be put in historical perspective in terms of four phases, with each phase often overlapping with the others. We note that none of the following phases can be considered to have been finished; they continue to remain avenues for active research, given the pace at which new materials, processes, and applications are being introduced in AM.

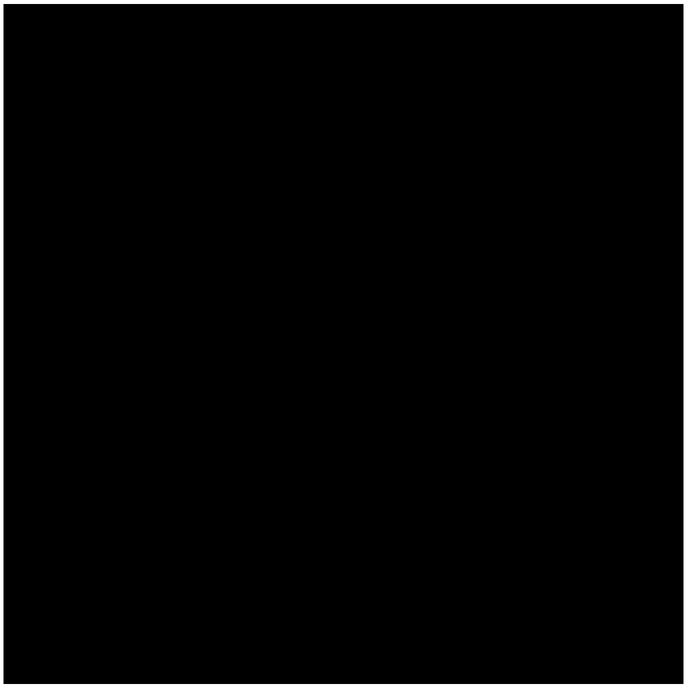

Figure 6: Schematic Stratification of the AM Process chain

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Phase 1: Process Conditions → Process Phenomena

In the earlier stages of AM, the emphasis was to establish the link between the process conditions and process phenomena through empirical process variable-based maps for AM processes [101-103]. For instance, in the context of L-PBF this meant relating the areal energy density (E_A) in terms of the laser power, scan velocity, and hatch spacing to the structure of the meltpool. To explain further, an inordinately high energy density leads to a phenomena called balling, wherein the meltpool separates into discrete parts due to changes in the surface tension and wetting characteristics [104]. Concomitantly, the laser can enter the so-called keyhole mode, and instead of fusing the powder particles it may vaporize material, leading to pinhole-shaped spherical pores, called gas porosity in the range of 10 µm. In contrast, at low E_A the energy required to fuse the powder particles is inadequate, and the material fails to consolidate properly, leading to large (~ 30 µm to 100 µm) acicular porosity.

Phase 2: Process Phenomena → Process Conditions → Part Microstructure → Part Performance.

Research in this phase seeks to establish the process-structure-property relationship in AM by creating a fundamental understanding of the causal phenomena in AM, and its impact on the functional integrity of the part [105-107]. Staying within this context, the multi-scale nature of AM defects and their dependence on specific process phenomena still remains a significant barrier. For instance, the particle size and laser power used in laser powder bed fusion (L-PBF) is significantly different than blown powder DED. Hence, this phase of process mapping is a tedious and difficult process that involves process modeling, empirical design of experiments, and, finally, materials characterization and testing. Each of the links in the process chain, summarized above, is fraught with challenges.

For example, in L-PBF there are over 50 independent process variables [108]. Investigating the so-called statistical main effects, let alone the interactions, of these variables is cumbersome, and perhaps beyond the scope of traditional design of experiments schemas. Next, the causal phenomena itself occurs at different levels, for instance, in L-PBF the fusion of powder and dynamics of the meltpool has a distinctive effect on porosity. At the higher-scale, the temperature distribution of the part and the heat flux, owing to part design, is an important aspect influencing the residual stresses in the part. King *et al.* have used powder-level dynamics and elucidated the effect of laser power, scan speed, and hatch spacing on the meltpool shape and splatter pattern [93, 109, 110]. These so-called powder-level models require tracking each particle in and around the meltpool, and require several days to complete on a supercomputer. The higher-level modeling of residual stresses though more tractable, is not easy either, and currently, simulations are reported for a few layers of simple geometries [105].

Phase 3: Process Conditions → Process Phenomena → Process Signatures → Part Performance.

The aim of this phase is to capture the process phenomena as it evolves and links them to specific defects through sensor-signatures [91, 96]. This phase is tied to development of new sensor hardware and data analytics to synthesize the sensor signatures into process decisions. Process decisions imply deducing the type, severity, and location of an impending defect based on the sensor signatures. Sensing and monitoring in AM can be stratified per the scale into the following aspects [109]:

1. Monitoring of the machine condition, such as the vibration of the recoater, clogging of the nozzle, and the condensation of residue over the optical system.
2. Meltpool-level monitoring, such as tracking the temperature distributions and the shape of the meltpool, and relating these characteristics to process conditions.
3. Hatch or scan-level monitoring, such as tracking the temperature distribution of each hatch.

4. Layer-level monitoring, such as imaging of the integrity of the powder bed using an optical camera or the thermal distribution of the layer.
5. Part-level monitoring, such as obtaining the thermal image of the part, or its ultrasonic signature.

These five different sensing strategies are each geared towards detecting a specific type of defect, for instance, meltpool monitoring uncovers porosity in the part, which occurs in the range of 10 µm to 100 µm, whereas, imaging of the powder bed with optical sensors are focused on detecting the onset of delamination and distortion. This detection of multi-scale phenomena mandates heterogeneous sensing, and concomitantly there is a need for efficient methods to synthesize the sensor signatures, and furthermore, to integrate this data with real-time decision-making algorithms. While the sensor hardware is continually improving, the data analytics and decision-making aspect, which must be seamlessly integrated with the data acquisition protocol, are currently lagging.

Phase 4: Process Conditions → Phenomena → Process Signatures → Microstructure (Defects) → Process Control (Rectification) → Part Performance.

In the final phase, once the type of defect is pinpointed, a corrective action must be suggested. The corrective action can take several different forms, including continuing to build with the changed process parameters or stopping the build to prevent further waste of material. With the advent of hybrid additive manufacturing systems, such as the Maatsura's Lumex series L-PBF system, DMG Mori-Seiki's Lasertec DED system, Optomec's Hybrid LENS system, wherein subtractive machining heads are incorporated within the AM machine, it is possible to entirely remove a layer instead of discarding the print. This new development offers the possibility to extend the qualify-as-you-build concept to a *correct-as-you-build* paradigm, wherein, the part can be guaranteed to be defect-free. This development of hybrid AM techniques can be foreseen as akin to an undo command, whereby mistakes in previous layers can be rectified.

Additive Manufacturing in the context of Smart Manufacturing / Industry 4.0

Table 5: Additive manufacturing in context of Smart Manufacturing Framework

Automation Level		Modeling	Monitoring	Control
	0-1	Meltpool measurements, process environment sensors	Multivariate monitoring models	Laser power & scan speed correction
	2	Layer deposition, cooling and distortion	Deposition anomalies,	Layer deposition control,
	3	Part deposition and thermal modeling	Geometry monitoring	Deposition process setup parameter
	4	Support structure and orientation modeling	-	Geometry optimization – part design

After review of the Additive Manufacturing process modeling, monitoring and control, it is important to view it in the Smart Manufacturing framework. Table 5 shows an example of how various modeling, monitoring, and control methodologies can be placed at various automation levels. Additive manufacturing technology is ripe for taking advantage of all aspects of Smart Manufacturing framework, as shown in Figure 7.

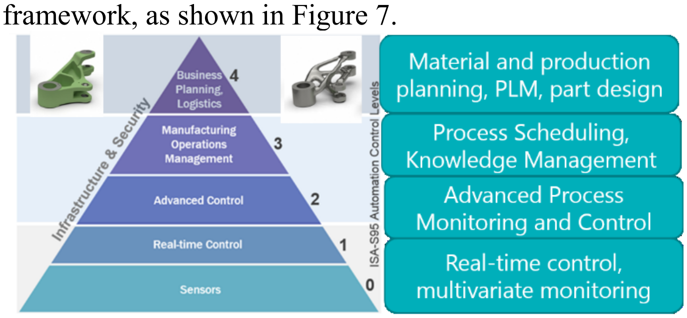

Figure 7: Smart Infrastructure for leveraging AM

As shown in Figure 4. the Smart infrastructure can be leveraged right from the part design in digital space to part production in physical space.

4. Challenges and Opportunities

4.1 Data communication and Interoperability

The biggest challenge in adapting the ISA 95 automation strategy is that although the process solutions for individual levels exist, it is extremely difficult to find one system that can communicate between all the levels in a cost effective way. A complementary challenge is that such a framework can be cost prohibitive for small or medium scale manufacturing industries. Given the premise that the production management system will be amalgamation of heterogeneous systems at different levels (different technologies, different vendors and OEMs etc.), the connecting system should be able to communicate between these system in an interoperable way.

4.2 Make vs Buy Decision & Long term maintainability

Suppose that a small or medium size manufacturing facility wants to leverage the promise of a connected shop. One such option is to develop a home grown system that takes advantage of the open source protocols (MT Connect standard, open computing platforms, etc.), by managing the scope and organically developing a staff that can maintain and operate such a solution. The upside of this approach is a targeted solution that can grow with the company, with a possible downside of not leveraging the best practices, as well as reinventing some of the functionalities. An alternative is to hire an automation contractor, who can deliver a solution ready to use. This approach can deliver a tactical solution without having to hire and develop a software organization, with the risk of the automation contractor not being able to sustain support over a long period of time. In either case, a manufacturing facility is faced with the challenge of keeping up with the pace of computer technology development and obsolescence.

4.3 Time and Cost of deployment of Advanced Solutions

The investment of Smart Manufacturing infrastructure can only be justified if, through the use of advanced process scheduling, modeling, monitoring and control, the manufacturing process can be done faster, cheaper, and safer. As the smart systems are being deployed at plant level, the time and cost of deployment of such advanced solutions cannot be overlooked. To reduce the time to deployment, one of the major factors is availability of the relevant data in the analytics ready format. This aspect will be discussed further in detail in the following sections. Secondly, there should be a platform to rapidly develop process solutions and deploy in a "shadow-mode" with the production facility to fine tune the model parameters and make it ready for deployment. Finally, there should be rigorous testing protocol to ensure the deployed solution will not cause any adverse effect on process of people operating it.

5. Conclusions and Future Trends

The fourth industrial revolution has brought opportunities to understand manufacturing processes better and control them to serve the business purpose. Out of the 4 levels of the automation pyramid, Level 2 serves as the brains of the smart system. While commercially off the shelf (COTS), solutions are available for Level 0, 1, 2, and 4, and Level 2 remains highly specialized to particular industry, process and manufacturing facility. With large amounts of data generated from Level 0/1, Level 2 systems will be able to compress, summarize, contextualize and visualize data for visual analytics, engineering analytics and prognostics/diagnostics. Academic research performed in fundamental physics based process modeling will need to be fused with this enhanced data to get process insights, predictive process and part quality, and process control. Smart systems will also be able to perform high fidelity process simulations for process set up using High Performance Computing (HPC). With these revolutionary trends, the manufacturing industry of tomorrow is certainly well posed to respond to the challenges of energy efficiency, sustainability, and ever growing demand.

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