BUILDING FUTURE FACTORIES: A SMART ROBOTIC ASSEMBLY PLATFORM USING VIRTUAL COMMISSIONING, DATA ANALYTICS, AND ACCELERATED COMPUTING

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ABSTRACT

Modern manufacturing platforms are defined by the quest for increased automation throughout the production cycle. This continuing pressure towards automation dictates that emergent technologies are leveraged towards this goal. Unfortunately, this increasing automation brings additional complexity and production issues. To address these challenges, this paper discusses the methods developed and deployed by our team (USC neXt) to employ (1) large-scale simulation, (2) system health monitoring sensors, and (3) advanced computational technologies to establish a life-like digital manufacturing platform and to capture, represent, predict, and control the dynamics of a live manufacturing cell. A machine learning based Digital Engine will be used to dynamically control and schedule operations in the live manufacturing cell, based on simulation results and real time data. Sensors, such as load cells, accelerometers, robot monitors, and thermal cameras will connect to digital twin systems, collecting and sharing accurate real-time plant descriptions between stakeholders. By creating our future factory using an Industrial Internet of Things (IIoT) platform, we will present data-driven science and engineering solutions to our industrial partners, accelerating the Smart Manufacturing Innovation. Future work will focus on applying the proposed methodology on more diverse manufacturing tasks and material flow, including collaborative assembly jobs, visual inspection, and continuous movement tasks.

Keywords: future factories, robotics, virtual commissioning
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1. INTRODUCTION

The manufacturing sector is currently reinventing itself by embracing the opportunities offered by digital transformation, industrial internet, automation, and machine learning among other innovations. This development is commonly referred to as the Fourth Industrial Revolution (Industry 4.0) or Smart Manufacturing. Smart Manufacturing can be seen as the cognitive counterpart of automation of physical processes, thus being understood as cognitive automation. While physical automation relieves human operators of unergonomic, dangerous, repetitive, and heavy workloads, cognitive automation attempts the same for mental tasks that are both stressful and repetitive or require significant processing power for large dataflows. Overall, Smart Manufacturing incorporates advanced data acquisition, analysis, and utilization through visualization. The convergence between virtual and physical manufacturing systems has been pursued as a goal of data-driven smart manufacturing. However, Smart Manufacturing systems are constrained by the methods used to connect factories to control processes in a more dynamic and open environment [8]. One of the most common problems with physical smart manufacturing systems is that direct process quality measurements are often unavailable [4]. The potential capability of adopting available industrial tools to develop plant predictions and smart manufacturing policies is expected to demonstrate the easy applicability of Smart Manufacturing (SM) to industry without requiring specific expertise for practitioners. One of the more recently available industrial digital transformation tools, Virtual Commissioning (VC), intends to verify and validate manufacturing systems and associated control programs through simulation before the physical implementation by enabling the connection between a virtual plant model and a real controller [9].

In our work, establishing connections with virtual environments is proposed to further overcome these outstanding bottlenecks in the evolution of SM. This research demonstrates that the implementation of Virtual Commissioning as one of the steps to industrial digital twinning will accelerate the training, testing, and validation of smart control systems. The method to pursue VC employs large-scale simulations, sensors, and computation technologies to establish a life-like digital manufacturing platform to capture, represent, and predict the dynamics of a live manufacturing cell. By creating an Industrial Internet-of-Things (IIoT) platform, this work presents data-driven science solutions to the current industrial applications while moving towards accelerated Smart Manufacturing Innovation. As a result of this work, the conceptual outline towards an AI-driven robotic manufacturing cell proposed by our preliminary proof of concept [18] is further enhanced by illustrating more detailed implementations and key technologies along with some preliminary results using our methodology. On this basis, the foundation of a dynamic scheduler agent, termed the Digital Engine (DE), is developed as a smart process optimization tool utilizing virtual platform data. The ideation of such a platform optimization tool through the DE concept coupled with a true Virtual Commissioning platform fits directly under the SM umbrella and has the potential to evolve into a number of advances in smart systems. These advances include higher throughput, safer human intervention, self-monitoring manufacturing cells, and more autonomous operation control and scheduling.

2. LITERATURE REVIEW

Negri et al. (2017) summarized the roles of the Digital Twin (DT), which are still mostly applied in product predictive maintenance and condition-based monitoring related research in the fields of Aeronautics and Space [11]. However, it is worth noting that the DT usage is emerging in the fields of manufacturing and robotics, where the emphasis on Virtual Commissioning and automation system optimizations are in demand. In 2013, the first works reporting research on DT in advanced manufacturing sector considered DT to be the virtual counterpart of production resources, and not only of the product [10]. An interesting application of applying real-time synchronized simulation of the production system as a part of a highly responsive and modular production control system

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is proposed, named Synchro-push [2], which continuously updates inventory status and performs adaptive scheduling of production orders and transfer management in prompt response to the changes in the production mix.

The definition of a Digital Twin has been non-uniform and ambiguous depending on the application areas. Scientific researchers tend to look for high-fidelity reference models to improve predictive capabilities of digital twins, where interactive optimizations can occur on both physical and virtual parts. Schleich et al. proposed a concept of utilizing Skin Model Shape [12], an abstract model of the physical interface between a workpiece and the environment, as a reference model to predict the product physical properties [13]. The transient data feed between objects requires safer and more efficient communication protocols to key DT technologies, such as MQTT [5] and OPC-UA [15], which is a more practical industrial approach. In the aspect of system optimization, a comparison between the conventional process optimization tool of Value Stream Mapping and Digital Twin was made [17] and the potential near real-time data acquisition and simulation capabilities of DT were demonstrated. Furthermore, Virtual Commissioning is another well-developed technology for testing systems through simulations to evaluate the safety, feasibility, and efficiency of scheduling and manufacturing approaches before physical deployment. An overview by Hoffmann et al. (2010) [6] demonstrated the implementation of VC necessitates a Computer-Aided Engineering (CAE) simulation tool environment and object-oriented databases containing simulation models of manufacturing system components, by which several recent attempts [1][3] were made in realizing VC with the same philosophy using different tools to construct virtual plant, hardware/software architecture, communication pathways, etc.

The implementation of Digital Twin is centered around data and interfacing communications since mass customization and flexible production emphasize the need for an easier high-level data storage and model exchange between different systems connected to the DT [14]. In this work, an object-oriented paradigm (XML/JSON) and IoT middleware are used for an easier exchange of data. The following are identified as the future research trends on DT-driven design and manufacturing: (1) Intelligent perception and connection technology, (2) Digital twin data construction and management, (3) Smart service analysis method based on digital twin data, and (4) More applications on DT-driven Product Lifecycle Management (PLM) [16]. The data-driven approach to Smart Manufacturing was further outlined in three essential steps: (1) Establish networks to define problems, (2) Develop platforms for modelling, sharing, and innovation, (3) Enact smart manufacturing policies. Kritzinger et al. attempts to distinguish between recent applications by the level of data integration among digital and physical objects [7]. The Digital Model method implements bi-directional manual data flow while Digital Twin enables bi-directional automatic data flow. Digital Shadow only feeds one-way automatic data flow from the physical object into the digital object, while data flow from digital object to physical object is manual. Based on this categorical method, most of the investigated publications are based on Digital Shadow and Digital Model classifications. The case studies that fit the definition of two-way data streaming Digital Twin applications are very scarce. In such a study, three kinds of data are being exchanged: real-time perception data, production process data, and production activity plan data. These are highlighted and their linkage to resource deployment and optimization are depicted under an event-driven assembly line [19]. To that end, three levels of DT components need to be modelled: element, behavior, and rule, which can be interpreted as system components, predictive responses, and control policies.

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3. BUILDING FUTURE FACTORIES

To address these challenges, this paper discusses the methods developed and deployed by our team (USC neXt) to employ (1) large-scale simulation, (2) system health monitoring sensors, and (3) advanced computational technologies to establish a life-like digital manufacturing platform and to capture, represent, predict, and control the dynamics of a live manufacturing cell. A machine learning based Digital Engine (DE) will be used to dynamically control and schedule operations in the live manufacturing cell, based on simulation results and real time data. Sensors, such as load cells, accelerometers, optical slip detection sensors, and thermal cameras will connect to digital twin systems, collecting and sharing accurate real-time plant descriptions between stakeholders. By creating our future factory using an IIoT platform, we will present data-driven science and engineering solutions to our industrial partners, accelerating Smart Manufacturing Innovation. Future work will focus on applying the proposed methodology on more diverse manufacturing tasks and material flows, including collaborative assembly jobs, visual inspection, and continuous movement tasks.

3.1 Large-Scale Simulations

In this work, the Digital Twin is based on one of the key technologies of Digital Transformation, Virtual Commissioning (VC). Current implementations of VC still require manual construction of the virtual system and definition and tuning of system components. However, the development of industrial software solutions to VC has greatly improved the accuracy and user-friendliness of offline programming of robotic systems and verifying control logic over the traditional commissioning process. The VC solution used to build the virtual cell for this work was Siemens Tecnomatix Process Simulate. Process Simulate provides advanced simulative functions such as importing CAD models, kinematics definition and simulation, collision detection, and Teach-Type Robot Programming. A functioning virtual robotic cell can be designed, from which possible robot configurations can be defined, simulated, and translated to robot programming languages, given proper robot dimensions and critical frames such as the Tool Center Point (TCP). This is normally referred to as offline programming. A functional virtual cell depends on accurate definitions of system components. While CAD models and definitions of well-developed products can be retrieved from manufacturers, some components require manual definition before being imported to Process Simulate. For example, the kinematics of an in-house manufactured robot gripper from our stage 1 platform had to be defined (see Figure 1). In defining the kinematics of this device, first a CAD model was created in another software and exported with all the components in an assembly folder; second, the kinematics of the gripper base, gear rod, connecting rod and gripper finger were grouped as a crank, which consists of a fixed link, input link, output link and coupler link; third, the defined components were linked and their relative translations were specified; finally, the kinematic definitions were tested by jogging the joints. The gripper positions and join values were configured for the OPEN, CLOSE, SEMIOPEN poses for simulation uses.

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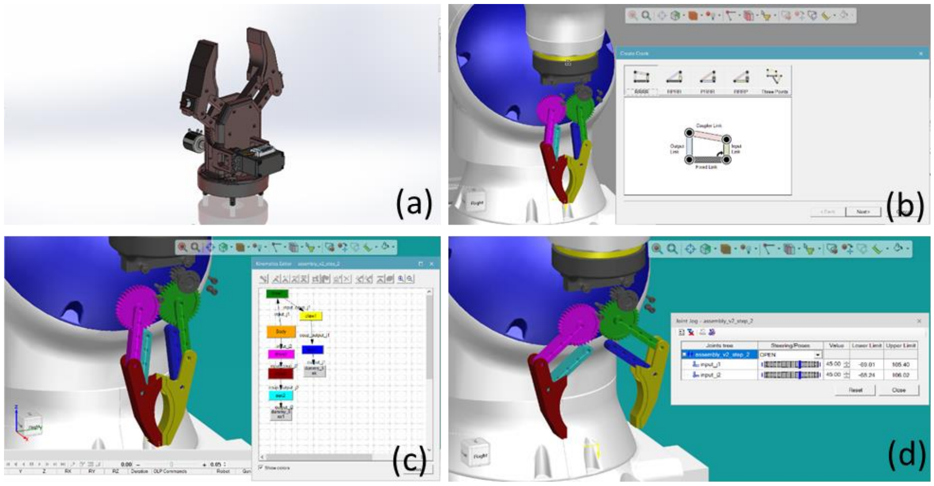

Figure 1: Gripper kinematics definition in Process Simulate: (a) Create CAD model; (b) Define component kinematics; (c) Link components; (d) Jog joints and verify kinematic definitions

Beyond object kinematics definitions, a successful virtual cell construction requires accurate definitions for object locations, mounting or attachment information about gripper or any other end effector mounted on robot end, object collision detection to verify there are no dynamic intrusions between objects, robot reachability checking to see if the path locations are within the possible configured reach, etc. Process Simulate provides a simple user interface, allowing the user to simulate object dimensions to avoid collisions, plan potential physical cell setups, and smart locate objects (Figure 2). Benefiting from Process Simulate capabilities, our stage 1 platform setup was constructed with high fidelity to the physical cell (Figure 3) ensuring all the robot paths are valid and safe within reachable and collision-free regions.

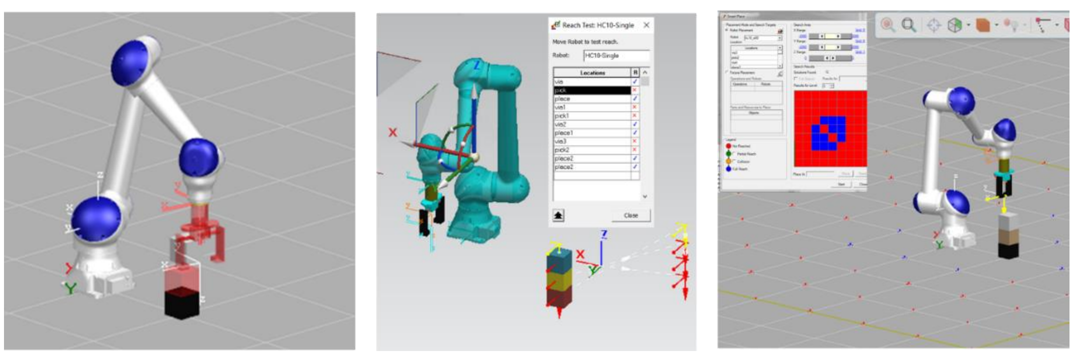

Figure 2: Proposed virtual cell capabilities. Left: predict object collisions; Middle: test path location reachability. Right: Smart locate objects

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Figure 3: Stage 1 Platform. Left: virtual cell in Process Simulate. Right: physical setup.

To ensure the feasibility of the proposed system, the path accuracy of Process Simulate offline programming (OLP) was investigated. Virtually commissioned paths were tested on Stage 1 platform physical setup (Figure 3 right), which includes a human collaborative robotic manipulator, Yaskawa Motoman HC-10, the YRC1000 OEM robot controller, and a SIMATIC S7-1516F Siemens Programmable Logic Controller (PLC). The robot program generated by Process Simulate OLP was directly transferred to YRC1000 using a Siemens CP1616 Profinet adapter card and successfully interpreted by the HC10 with the proprietary Yaskawa programming language, INFORM III. Stage 1 platform experiments were performed in the following procedures: (1) virtual path planning in Process Simulate, (2) generation of the INFORM III code within Process Simulate platform, (3) physical experimentations with generated robotic code. Three different robot tasks were virtually commissioned and then physically tested: pick and place, water pouring, capping and assembly. These tasks were accomplished with high precision with defined kinematics, path locations, and robot configurations. Moreover, under the option of 1:1 real-time simulation speed, the simulation and real robot programs were executed near synchronously. Therefore, it is concluded that Process Simulate is a relatively powerful tool for the virtual commissioning of robot motions and paths. Given the simulation accuracy, robot manufacturing virtual cell proposed in this work is based in Process Simulate virtual environment shown in Figure 3. Additionally, the system communication pathways depicted in Figure 4 were used to facilitate the required communication between system components.

This completes the system data flow proposed by our previous work and implies that the simulation-based digital twin of production systems can be used as an augmented tool to commission robotic manufacturing cells with significantly reduced safety and cost concerns by constructing virtual cell environment and enabling the communication pathways between system components.

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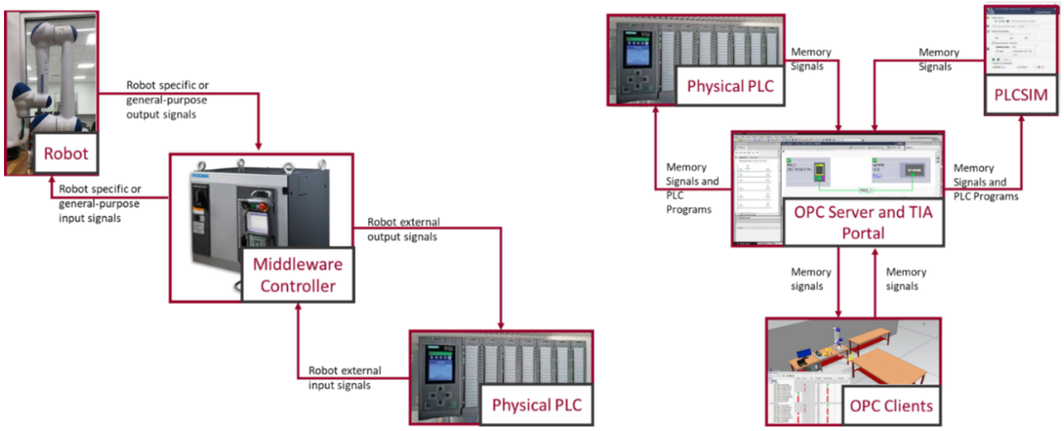

Figure 4: Control loops of physical and virtual robot platform. Left: Robot signals hardware control loop. Right: Virtual Cell Control Loops by Hardware-in-the-loop (PLC as controller) and Software-in-the-loop (PLCSIM as controller).

3.2 System Health Monitoring

The convergence between cyber and physical manufacturing systems has been pursued as a goal of data driven smart manufacturing (SM). However, SM systems are constrained by the gap between connecting factories and control processes in a more dynamic and open environment. Moreover, previous research on data-driven manufacturing intelligence mainly focuses on data collected from the physical model instead of the virtual model. The most common problem with physical manufacturing systems is that direct process quality measurements are often unavailable. Therefore, establishing connections with virtual environments is proposed to further overcome these outstanding bottlenecks in the evolution of SM. This research demonstrates that the implementation of Virtual Commissioning (VC), as one of the steps to industrial digital-twinning, will accelerate the training, testing, and validation of smart control systems.

This section describes the design an application for health monitoring of an assembly line. A senior engineer/manager or a maintenance engineer using the developed application will be able to access health data of any assembly line through their personal device. Their device will display the health of system components and the statistics of sensors embedded within the line. The goal of such an application is to have a better real-time representation of the system's health and to be able to act proactively. Augmented Reality (AR), a data visualization tool, can be used in manufacturing industries where real time reports are essential for the decision-making process. AR technology displays Key Performance Indicators (KPI) of each workstation inside an assembly line, gathered from measuring devices; this information is transmitted to a mobile device wirelessly. The implementation of such a system would result in a dynamic tool that allows users to reduce audit times.

3.2.1 Sensors for condition monitoring

This section defines the data acquisition and processing systems that will be used to monitor and assess the condition of a robotic assembly line by extracting data from sensors installed on the robot gripper and pair this data with a live stream video feed of the robotic cell for the overall purpose of health monitoring. This implementation can be divided into four main clusters:

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1. Sensor positioning and installation: the first cluster is data acquisition through the sensors on the gripper. These five sensors will relay vital information from the robot that will be used to assess the overall health of the robotics functions. Figure 5 shows the gripper, where all sensors' location is depicted. The temperature sensor is attached directly on the motor, the potentiometer is attached to the motor shaft, the load sensor is attached on the inner side of one of the fingers, the optical slip detection sensor is attached on the inner side of the other finger, and the accelerometer is attached to the upper section of one of the arms.

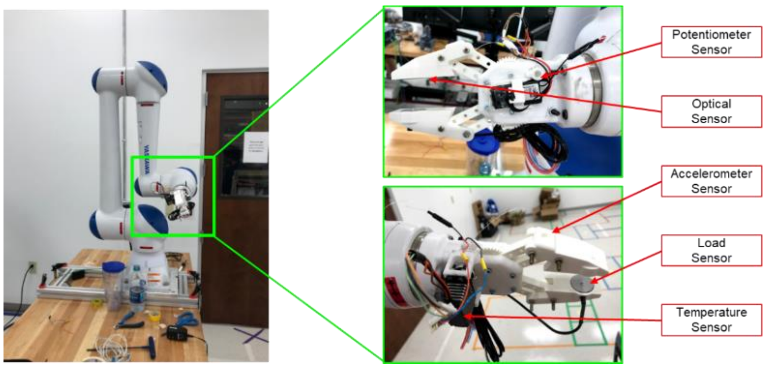

Figure 5: Sensors used to monitor the robotic gripper

2. Collecting data through a single-board computer: data will be acquired through a small, industrial single-board computer. Data will be acquired in real time with minimal latency.
3. Integration: data will be transferred to a server in order to be displayed. This cluster will receive, process, and ultimately distribute the information.
4. Display: this cluster provides the information in an organized manner while making sure all vital information is readily available for the user, whether he/she is a senior manager or a maintenance engineer. This final cluster is the display modulus that will be used to showcase the processed information gathered from the server.

Each cluster in the architecture will integrate with the cluster after to ensure all data is being acquired, transferred, and displayed successfully.

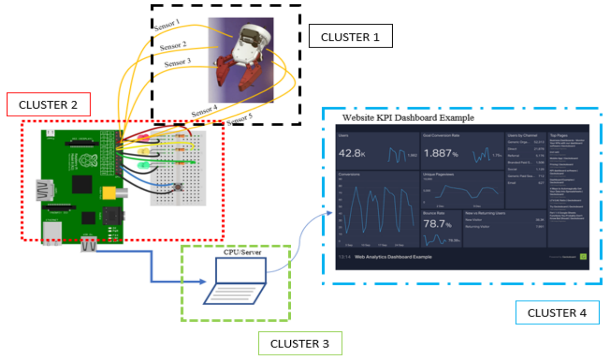

Figure 6: Data management

Figure 6 summarizes the connections between major components of the system. Yellow lines represent wired connections between the sensors and the single-board computer. The number of wires depends on the sensor type. The purple connection between the ethernet port on the single-board computer (SBC) and the main computer represents a wireless connection between the SBC

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and the server accessed from the main computer. From the main computer, all incoming data is processed and sent to a website, where the resulting information can be accessed from any device.

3.2.2 Monitoring of robotic health deterioration

Robot precision deterioration detection, monitoring, and evaluation are crucial activities in numerous manufacturing applications, particularly when it comes to the high precision processes that may include assembly, welding, material removal, drilling, and riveting. The deterioration of robot precision can increase the probability of unpredicted stoppages and influence manufacturing quality and production efficiency.

3.3 Accelerated Computing

One of the principles in robust automation involves the rapid evaluation of the state of the manufacturing platform and the interjection of new actions into said platform. In more precise words, future factories will thrive on speed. The importance of this axiom is twofold: (1) the faster data is processed and utilized, the faster the production cycle, and (2) fast actions in physical systems correspond to a safer environment. In service of this principle, each area of the Future Factories platform will be augmented with advanced computing hardware.

Hardware devices capable of significant performance increases above traditional CPU-bound platforms have recently begun to gain popularity in the consumer and industrial markets. In particular, the culmination of breakthrough technologies in the Graphical Processing Unit (GPU), Application Specific Integrated Circuit (ASIC), and Field Programmable Gate Array (FPGA) spaces makes each device attractive as solutions for the acceleration of applications. GPUs are hardware devices consisting of many general-purpose processing units that operate in parallel. While not possessing a lower latency for individual computations than a CPU core, the many parallel arrangements of each processing unit creates a computing paradigm that dramatically increases the run time of certain operations such as matrix multiply and search. While parallel architecture of the GPU offers a counterbalance to the tradeoff between flexibility and speed in general purpose processors, individual computations and logic operations are still somewhat slow compared to dedicated hardware. ASICs and FPGAs remove the general computing paradigm in order to further increase speed, embedding algorithms and computations on physical hardware. The speed increases come with the price of an explicit and limited instruction set. FPGAs, in response to this, are composed of a series of reconfigurable logic blocks, allowing for the hardware to be reprogrammed for new operations. However, because FPGAs are not custom devices such as ASICs, they have a set footprint, and thus a set amount of hardware components, limiting the size of the operation they can efficiently perform.

In the context of the neXt manufacturing cell, FPGA and GPU-based acceleration is being used to dramatically increase the performance of the Digital Engine. Both FPGAs and GPUs have demonstrated significant speedups in the operation of neural networks. In the DE application, a GPU training loop interfaces with the software side of the DE, continuously updating network weights. GPU performance in floating point operations such as gradient calculations makes it ideal for this application. For the operation of the DE in the physical system, the network generated in the training loop is pushed to an FPGA and operated in a direct loop with the platform. The extremely fast bitwise operations, addition, and multiplication can be accomplished in fixed point on hardware, limiting hardware and RAM usage. Instancing a neural network consisting of a few thousand weights becomes the perfect application for this hardware configuration. Additional applications include having a high frequency data processor close to the source of sensor data. In the case of many digital sensor devices, the sample rate is far too high for most traditional platforms to process, requiring significant down-sampling. However, dedicated hardware devices, such as ASICs, have both the signal processing capabilities to perform the necessary computations while having a dedicated clock frequency that can keep up with extremely high sample rates. FPGAs have also been demonstrated to be a useful tool in the acceleration of solvers for ordinary and partial differential equations, though the area still has much room to be explored. With this in mind, a novel solution to dynamic path planning involving rapid inverse kinematics calculations accelerated on FPGA are currently being developed.

4. CONCLUSIONS

Filling the gaps between virtual and physical systems will open new doors on Smart Manufacturing. The scope of a smart automated manufacturing system is also limited due to the inability of manufacturing process measurements. Integrating Machine Learning algorithms into automated manufacturing control problems with a facile optimization environment will be a novel combination between data science and industrial manufacturing. The power of data analytics algorithms is greatly augmented by interfacing with industrial software for simulation and automation. This paper presented our efforts to incept a Digital Engine that supports the scheduling of a virtual commissioning platform. The DE and its subsequent application technologies represent a shift in how manufacturing is evaluated and completed (Figure 7).

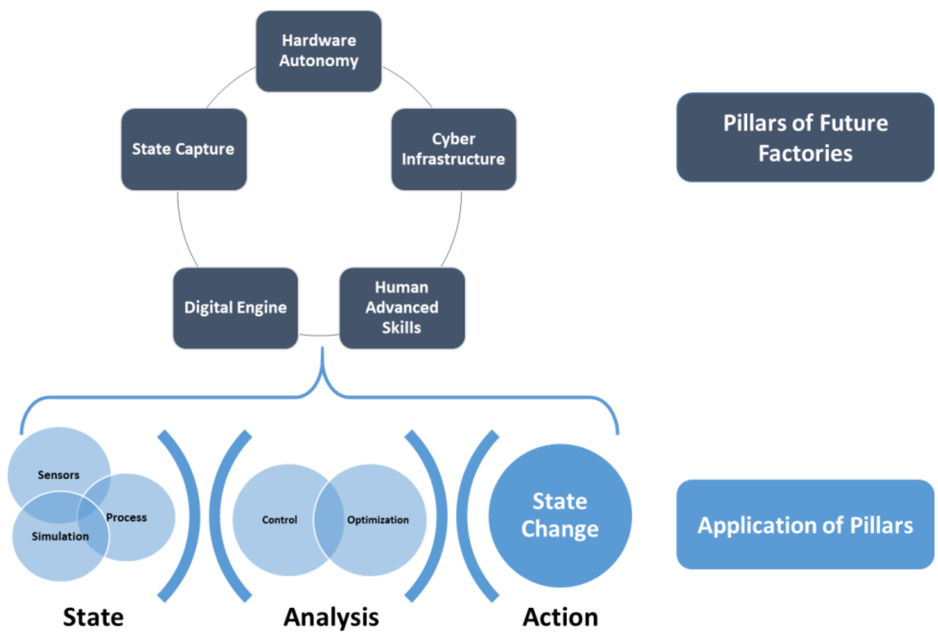

Figure 7: The pillars of Future Factories

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