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IIoDT: Industrial Internet of Digital Twins for Hierarchical Asset Management in Manufacturing

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***Abstract*—The Internet of Things (IoT) and digital twins (DT) are emerging technologies in the industry 4.0 landscape. Both technologies offer the capabilities of collecting and analyzing large quantities of data and utilizing this data for intelligent decision-making. These technologies together form the Industrial Internet of Digital Twins (IIoDT). Currently most works on DTs in literature focus on a single level of the manufacturing hierarchy without considering the interactions among levels. It is important to understand how these different scales of DTs can interact together in order to create a scalable system. The various assets in a manufacturing environment exist in a hierarchy with information flowing up from the lowest level to the highest. Additionally, information flows from various levels to a central database and data processing center. DTs connected in an IoT network can provide various services for asset management in manufacturing such as condition monitoring, health assessment, simulation, forecasting, and visualization. It is important to understand the various capabilities and interactions between the various DTs. This work examined DTs at multiple levels along the manufacturing hierarchy, what value they can provide, examples in the literature of DTs at each level, and how they can interact with other DTs along the hierarchy. This IIoDT system can be used to analyze both vertically along the hierarchy and horizontally across assets of the same level. This framework can help bridge link the various levels of DTs that exist to better integrate them in a manufacturing system.**

***Index Terms*—asset management, digital twin, internet of things, manufacturing**

I. Introduction

Digital twins (DTs) are an important emerging technology in the Industry 4.0 landscape. DTs are virtual representations of physical objects, systems, and processes. They utilize heterogeneous data streams to update one or more models at a high frequency. DTs have been successfully leveraged in other industries but manufacturing is thus far the most popular field of research for their use. DTs have seen use in applications such as condition monitoring, control, simulation, visualization, and modeling in a manufacturing environment.

The Internet of Things (IoT) and Industrial Internet of Things (IIoT) are other important technologies. IIoT enables the connection and collaboration of various devices and assets in a manufacturing environment. Data collected via the sensors in an IIoT system enables and supports many useful services such as condition monitoring, data analysis, and visualization.

These two technologies can be leveraged to enable better asset management in an industrial environment. Integrating DTs into an IIoT requires some consideration as to how DTs can be constructed and organized within an IIoT system. DTs can be classified as unit level, system level, or system of system level based on their structure [1]. This paper proposes a framework for organizing DTs in an IIoT system to enable effective communication and utilization of information. An effective flow of information will enable robust asset management in an industrial environment.

There are a few previous works which have investigated the relationship between IoT and DTs and the possible advantages as well as challenges. Souza et al. proposed a DT architecture which was based on the IIoT [2]. Their model has three main components: The physical twin, an IIoT gateway, and an internal server which hosts the DT. Users within the workplace such as technicians and engineers would have access to this system, as well as users outside the workplace such as management and other support roles. They demonstrated their system using a didactic assembling plant DT. An important consideration when designing a DT or IoT system is the various standards that exist for IoT. In a paper by Jacoby et al. [3], they examined various standards that could be applied to both IoT and DT and the various advantages and disadvantages of each. One important conclusion is that there are multiple standards with overlap and there is a need for cooperation and consolidation. Liu et al. [4] discussed a semantic model based on ontology for modelling of a machine tool DT to address the issue of multi-source heterogeneous data from sensors, machines, and persons. Delfino et al. [5] described an overview of the DT architecture and how it relates to the IIoT.

Additionally, there has been some previous work which has examined hierarchical modeling of DTs. In their framework for hierarchical modeling of a mechanical product DT [6] describes the process of developing a hierarchical structure for a mechanical system. In their work, they use the case study of a helicopter. They describe a hierarchical structure of a mechanical product consisting of an assembly which has various sub-assemblies and parts underneath that. Shangguan et al. created a hierarchical model for DTs [7]. Their model contained four layers: the Interface layer, the components layer, the sub-system layer, and the scenarios layer. Each of these layers contained several sub-components. They applied their framework to an industrial robot in a case study. Jia Et al. [8] presented their modeling method for a complex multi-scale DT. They identified different contexts that DT exists among each layer such as the shop floor, unit, and part. They also identified four key characteristics in DTs: scalability, interoperability, expandability, and fidelity.

This work intends to build upon previous works examining hierarchical relationships of Dts and IoT. The proposed framework is called the Industrial Internet of Digital Twins (IIoDT). Implementing IIoDT can enable factory owners and operators to obtain maximum value from the various assets along the manufacturing hierarchy. It can enable the implementation of the following: predictive and prognostic maintenance to maximize equipment availability and reliability, simulation to best plan and predict future outcomes and to optimize various processes, and gathering and analyzing large data streams to enable intelligent decision making in complex environments.

One existing issue in the literature and industry is that DTs are often complex and costly to develop. For this reason it is necessary to understand the capabilities of the various levels of DTs. Before venturing to developing various DTs it is important to understand what information and value is desired, as well as what resources are available for development, and what sort of DT is best suited for these criteria.

This work has identified and described five key asset layers in an IIoDT system. Each asset DT has the opportunity to provide unique value to the system as a whole. Each asset layer's interaction with other layers, potential DT services, and existing examples in the literature have been examined. In addition, this work presents a discussion on the various consideration when designing and developing an IIoDT network. Using this information and framework it it easier to develop a plan for implementation of an IIoDT.

The remainder of this paper will be organized as follows: Section II covers the five identified hierarchies in the IIoDT, section III describes some other design considerations when building an IIoDT system, finally the work is concluded in section IV and future research directions are discussed.

II. Digital twins at different levels in the hierarchy

In an IIoT there will exist DTs at various levels of complexity. These levels from the highest level to the lowest are the following:

1) Factory
2) Manufacturing line
3) Machine
4) Sub-system
5) Component

They can be seen in the Figure 1 and are described in the following subsections. Generally higher levels exist as a collection of the level below them, however, it may be the case that a DT contains DTs of objects or systems 2 levels lower than it. For example, a factory DT consists of various manufacturing line twins as well as various machines which do not belong to a particular manufacturing line. The reverse of this is not true however, it would never be the case that a higher level DT be a component of a lower level DT, such as a manufacturing line digital twin being a component of a machine DT. Information cascades from the lowest levels of the hierarchy up to the largest overall level of it. Information from lower levels on the hierarchy can be used for decision making in higher ones. The following subsections describe each level in the hierarchy as well as a few examples of DTs in the literature.

A. Component Digital Twin

The component level DT is for the critical components that make up the various sub-systems. This includes components such as motors, ball screws, and bearings. It would not include things such as washers, bolts, covers, and panels as a DT of these objects would provide little to no value. Sensors such as accelerometers, thermometers, and dynamometers could be utilized to take measurements of the various components and perform various types of analysis such as machine learning, and vibration analysis to make estimations on the condition of the various components [9], [10]. This level would not have any data storage or computational capabilities. Data collected at this level would be stored and analyzed at higher levels. Determining the condition of these parts can be useful in determining a holistic view of the overall condition of the system in which they are a part of.

Some forms of DT analysis that can be performed include developing degradation models of the components using both model-based and data-based predictions. DTs have been successfully developed for various components including bearings where they have been used for fault detection, crack identification [11], and defect detection [12]. It has also been applied to electric motors for the estimation of the remaining useful life of a permanent magnet [13].

B. Sub-System Digital Twin

The sub-system level DT would include the main subsystems of the various manufacturing assets, in the case of a machine tool this would include things such as the spindle, the linear and rotary feed drives of each axis, and the tool changer. It would draw upon both component-based condition estimates as well as sub-system-level sensors to make an overall estimation of the health of the sub-system [9]. Again,

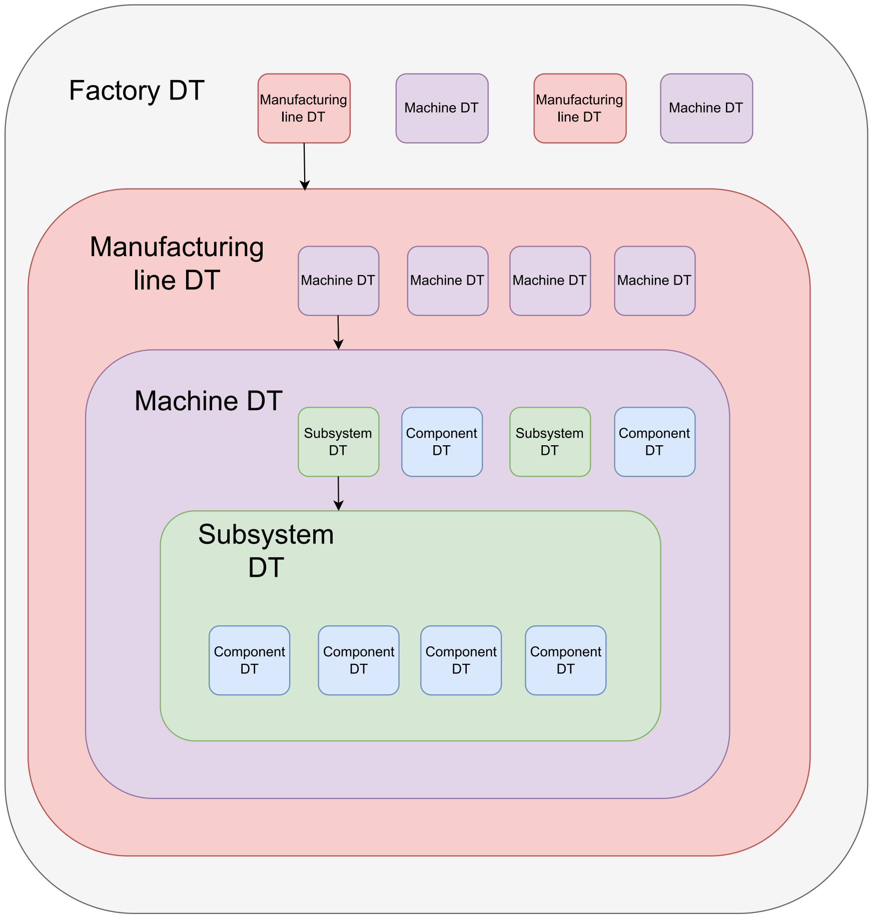

Fig. 1. Data streams in an IoT DT sub-system

this level would not have any data storage or computational capabilities. Data collected at this level would be stored and analyzed at higher levels. The health and condition of these sub-systems can help form an overall estimate of the condition of the machine of which they constitute.

Some DT-based analysis that could be performed at this level include simulating the dynamics of a feed drive to estimate levels of vibration and surface finish, this could then be compared to accelerometer data and actual measured part surface finish to determine modeling accuracy. DTs for sub-systems are not as popular as the other levels of the hierarchy but have been utilized for machine tool spindles in a few instances. They have been used to model and estimate the thermal characteristics of a spindle [14]. They have also been used to monitor the performance of a spindle via measuring and monitoring stiffness and vibration using both models and experimental results [15].

C. Machine Digital Twin

The machine level will include large manufacturing machines such as robot arms, machine tools, conveyor belts, and gantry cranes. This level would likely be equipped with some computing and data storage capabilities. Underneath them in the hierarchy would include both sub-systems as well as component DTs. Data received from these DTs can help create a holistic view of the health of the machine. This level of DT would be connected to both the manufacturing line above it and a centralized data warehouse / computing center. The machine would be responsible for collecting and transmitting data from its sub-systems and components.

DT-based analysis at this level may require integrating the DTs lower on the hierarchy. Some examples of analysis could be simulating the dynamics of the various sub-systems working together to avoid collisions. It could also be used to estimate power usage and torque requirements for various movements. Various examples exist in the literature of applying DTs to manufacturing machines such as machine tools and robot arms. Tong et al. [16] created a DT framework for a machine tool for the purpose of data analysis, optimization and decision making, and data visualization. They applied their framework to a 5-axis machine tool and created a monitoring interface dashboard, they were able to optimize their tool path and improve surface finish. Armendia et al. [17] evaluated the application of DTs to machine tools. They found that some of the key purported advantages of applying digital twins were the following: Increasing overall equipment efficiency, validating simulated results with actual results using sensors, reducing tool cost with improved tool selection, reducing scrap, and increasing uptime. Matulis et al. created a DT of a robot arm. This robot arm was trained using reinforcement learning in a virtual space to perform a task. This training was then mapped to the physical counterpart [18].

D. *Manufacturing Line Twin*

The manufacturing line level would include all the manufacturing assets that work together towards a certain goal. In the case of a car transmission manufacturing plant, this may include a line for manufacturing transmission cases, one for manufacturing the gears, and one line for assembly. Underneath this would be the various assets that are part of the line. Generally, it would just be assets, as components or sub-systems would not exist independently from their assets.

A common DT service that would be utilized at this level would be simulating and estimating reliability and throughput. Vachálek et al. created a DT of an assembly line including material flow, a mock-up of the production line, and the interaction of the various manufacturing facilities. This DT gave additional insight into the dynamics of the system [19]. Zheng et al. created a DT of a manufacturing line and mapped real production data to it [20]. Their DT included real-time connection and interaction between the model and real production line. They utilized several different models such as geometric model, physical model, and kinematic model. Data was transmitted via OPCUA to map the models to the physical system.

E. *Factory Digital Twin*

The Factory DT is the highest level of DT in the manufacturing environment. Theoretically, an organization could have higher levels such as a manufacturing group DT or an enterprise-level DT but that is beyond the scope of this work. The Factory DT consists of various manufacturing lines and manufacturing asset DTs. The health, condition, and performance of the factory level DT can be determined based on the DTs below it.

Levels of performance and health at this level could be measured by overall throughput, levels of inventory, and average availability and utilization of its various assets and production lines. Guo et al. created a flexible DT for factory design. They applied their framework to a paper cup factory [21]. Constructing a DT enabled the optimization of the manufacturing process by discovering bottlenecks and other design flaws. Park et all created and implemented a DT-augmented micro smart factory [22]. Their system utilized an IIoT-based DT to collect data and monitor the system which was used to track past data, monitor current conditions, and support future decision making. They tested their system on a micro factory which contained components such as a material handling robot, 3D printers, an inspection station, and a packing robot.

III. Design considerations and value of system

There are a few considerations that need to be made when building an IIoDT. One of the primary considerations is the modularity and extend-ability of the system. The system must be able to accommodate the addition and removal not of just DTs but also the capabilities of DTs. To accommodate this change an exponentially increasing level of computational power, data storage, and data throughput will be necessary. These IIoDT systems will generate a great deal of data which needs to be properly handled [23].

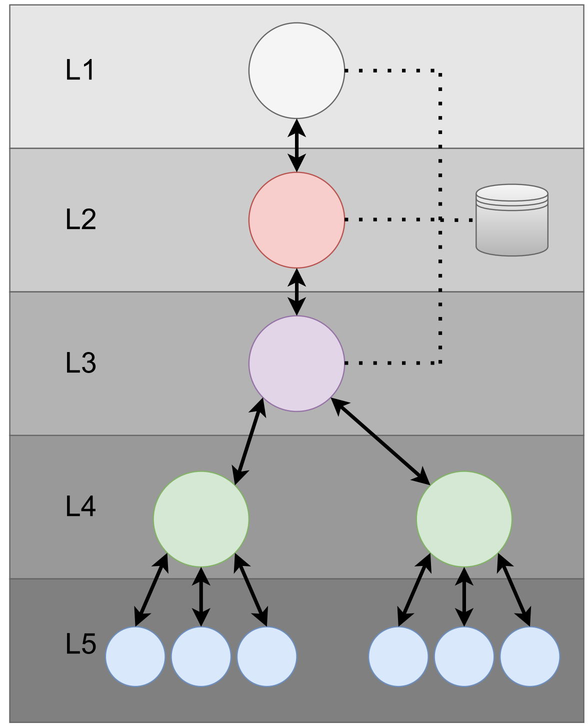

Fig. 2. One possible network hierarchy for IIoDT

It must be considered how the network nodes will be organized and connected. There are several options of network topology that exist and can be considered. Different topologies may be preferable depending on the vertical and horizontal scale of the systems. Star or tree topology may be useful for the sub-system and machine level for communication as the various sensors and sub-systems would only need to communicate directly with the level above them [9]. For the levels of machine to factory, it may be ideal to utilize a tree, star, or hybrid of the two topologies to create a hierarchical structure and interconnection to a central database. This network topology can be seen in Figure 2, with dotted lines representing the connection to a central database and the arrows the connections between layers.

When beginning to develop an IIoDT a decision needs to be made about the starting point of building the various DTs along the hierarchy. There are a few questions that need to be answered before proceeding. How much value will building this DT provide? And what services can be utilized? How difficult and how long will it take to develop this DT? Is it better to build many DTs with limited capabilities or fewer with greater capabilities? Answering these questions is essential before beginning the process of developing an IIoDT network.

Information gathered from the IIoDT can be leveraged for analysis in both horizontal and vertical directions of the hierarchy. Vertical analysis would be the analysis from some starting point and proceeding down the hierarchy. One example of this might be examining the state of a manufacturing line. You could get an estimate of the performance by examining the assets below it which could in turn be evaluated by a sum of their sub-systems and components. Horizontal analysis would be analyzing the same components, sub-systems, machines etc along different vertical streams in the hierarchy. One example of this would be examining how one model or manufacturer or motor used in spindles is performing in many different machine tools. This information can be used to predict maintenance scheduling and inform future purchasing decisions.

IV. Conclusion

Existing literature on DTs in manufacturing often focuses on creating a DT for a single level of the manufacturing hierarchy. There exists successful examples in the literature of implementing DTs at each of the five levels discussed in this work. Additionally, given that DTs require a great deal of resources it is often only possible to develop at a single level at any given time. With this constraint on mulit-level DT development it is important to develop a framework for a modular framework to implement them in an IIoT system.

This work has presented a framework for implementing a hierarchical IIoT for DTs. Considerations about the connection between each level in the hierarchy, what sort of data will be collected and analyzed at each level, and the complexity of the analysis performed at each level are discussed. This work can help to provide a reference framework for those who wish to develop a hierarchical IIoDT, whether that would be linking just two layers or the entire five layers that have been discussed.

There did not seem to be any examples in the literature of developing and connecting more than one DT in a hierarchical structure that went beyond a framework or theoretical case study. Work that would involve the development and linking of multiple DTs such as a ball screw DT and feed drive DT, or a machine tool DT with a manufacturing line DT could be interesting and novel research. Additionally, future works could expand on the topics explored in this paper and cover more examples of DTs at each level of the hierarchy.

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