Digital Twin Enhanced Smart Assembly System Design and Analysis for Resilient Operations

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Abstract

The rapid evolution of customer demands has posed new challenges to manufacturing, leading to a shift towards mass customization and customer-centric approaches. This paradigm shift, driven by advancements in technologies such as additive manufacturing and digital technologies, has transformed assembly systems into smarter and more autonomous entities. However, the design and planning of assembly systems in this new context require greater speed and resilience. This paper proposes a digital twin-enhanced smart assembly system design for resilient operations to confront this challenge. The proposed design process leverages digital twin features and identifies several possible services enabled by digital twin. The paper also presents a framework for the digital twin-enhanced smart assembly system and discusses its implications and future directions.

Keywords
Digital Twin, Smart Assembly System, Manufacturing system

1. Introduction

The rapid-evolving customer demands have presented new challenges to manufacturing. The need to satisfy customer demands drives manufacturing companies to focus on mass customization, a more customer-centric approach. Mass customization recognizes the diverse needs and preferences of individual customers and aims to provide unique and tailored products at a scale (Jiao et al., 2003, Brettel et al., 2017). This paradigm shift involves remarkable advancements in various technologies, for instance, additive manufacturing, design technologies, and digital technologies. Driven by new needs and technologies, manufacturing systems have become smarter and more autonomous which reshapes product realization facilities (Gong, 2021).

In Industrial 4.0, the impact on manufacturing caused by linking new technologies such as Cyber-Physical System (CPS), Digital Twin (DT), Big Data, and Could Computing attracts lots of attention from both academia and industry (Zhang et al., 2021). New platforms and frameworks are proposed and aimed to achieve smart manufacturing by optimizing organizations, reducing production costs, and providing new services that satisfy individual customers' needs (Dos Santos et al., 2020). Assembly, as one of the significant processes in manufacturing, also evolves through the impact of new technologies and new challenges. With the vision of industrial 4.0, a smart assembly system is required to be flexible, adaptable, and can handle products with high varieties. The new requirements increase the complexity of assembly system design while the assembly system planning must be more rapid (EIMaraghy et al., 2016). Confronting the new challenges, assembly systems become modularized and standardized by deploying new information management systems, monitoring system, and control system and the integration of these new systems build foundations for the deployment of digital twin. The deployment of digital twins has a huge variety of applications in planning, maintenance, and process optimization with the scope of the whole manufacturing system (Werner et al., 2018). There is a lack of a general method that can speed up the design, construction, and following up stages of the assembly line design.

As mentioned above, most changes and advancements in assembly systems are driven by markets and new technologies, these driven forces pay less attention to the term “resilience” which is proposed by Ayyub in 2014. It is defined as the ability of a system to return to stability after disruption on the engineering side. Based on resilient engineering, resilient operation, a term that emphasizes the ability to handle uncertainties of production and sourcing, the frangibility of humans, and various sources of failure is introduced. Modern assembly system design needs to value operation resilience seriously especially after the COVID-19 pandemic has exposed the lack of operation resilience in manufacturing systems.

In this paper, a digital twin-enhanced smart assembly system design process for resilient operation is proposed to address the above issues. The proposed process leverages digital twin features to enhance the current assembly line design in multiple stages. To present such a system, four technical challenges are identified. Firstly, identification of the design process of a digitalized assembly system. Secondly, how to integrate digital twins in the smart assembly line design process. Thirdly, identifying services enabled and enhanced by digital twins in the assembly line design process. Lastly, digital twin-enhanced resilient operation services can be provided by a smart assembly system; The paper is organized as follows. Section 2 summarizes related fields of study that inspire the work in the paper. Section 3 introduces and compares digitalized assembly system design process to the digital twin-enhanced smart assembly system design process. Section 4 presents the framework of a digital twin-enhanced smart assembly system by demonstrating the flows in the system. Section 5 discusses the findings, limitations, and future works of this paper. Section 6 concludes the paper.

2. Literature Review

2.1 Smart Assembly System

As one of the key enabling technologies in Industrial 4.0, digital twin results in a large amount of data processed in the system. Researchers have proposed various digital twin-based applications for the assembly system by acquiring and processing different kinds of real-time and non-real-time data. Rosen et al in 2015 implemented digital twins to build a cyber-physical production system. The proposed cyber-physical production system focused on autonomy in the production system which involves data synchronization, part flow tracking, and fault handling. Liu et al developed an easy-to-deploy framework to build digital twins of the manufacturing system. Fan et al proposed a digital-twin visualized architecture for manufacturing system in 2021. It was aimed at the full life cycle digitalization of a flexible manufacturing system to improve the efficiency of life-cycle planning, design, and debugging.

Despite the digitalization methodology, decision-making in digital twin modeling also attracts attention from researchers. Zhang et al proposed a method that defines and builds the right digital twin with reducing unnecessary complexity through the view of model engineering. It developed lists of metrics to define and evaluate digital twins. Continuous improvement of the production system driven by data and AI is another important application of digital twins. A prediction and reverse control system for thermal errors that utilizes digital twin and neural networks is proposed by Liu et al in 2023.

2.2 Assembly System Design

Assembly system design is a process that determines organizations, and equipment that are necessary for product assembly under different types of constraints (Mülle and Parunak, 1997). Line balancing and sequencing are primary decision-making problems that need to be solved since it determines the main benchmarks of the assembly system. Axiomatic design principles have been applied to assembly line balancing and sequencing through the mapping between domains, task decompositions, and design matrix analysis (Yilmaz et al., 2020). Jefferson et al presented an axiomatic assembly system framework for wing structure assembly. The framework utilized axiomatic design theory and design structure matrix for design decision-making and design project planning.

Other than assembly design based on traditional manufacturing system design axioms, assembly line design that is driven by advancement in robot, vision, and AI are proposed for some specific areas. Song et al introduced a vision-based design of a robotic mobile phone assembly system in 2020. Instead of using axiomatic design theory, the assembly line design is based on the feasibility of a vision-guided robot in the phone assembly process.

3. System Architecture of Digital Twin Enhanced Smart Assembly System Design

Adapted from axiomatic design theory proposed by Suh et al in 1998. The design process of a digital twin-enhanced smart assembly system design contains four domains as shown in Figure 1. With the vision of industrial 4.0, the assembly system follows the advancement of the manufacturing system which is required to have a higher digitalization level and higher flexibility. The general design process of the line is initialized by engineering requirements $[ERs]$ of the product such as product information, process information, sample parts, and capabilities. The engineering requirements domain is relatively constant with the assumption that the product specifications are fixed. Process design parameters $[PDPs]$ are variables described by the process design in physical space which is mapped from engineering requirements. Similar to the design parameters in axiomatic design theory, process design parameters are design concepts generated from detailed engineering requirements. In the mapping process, process design concepts are derived from the decomposition and resequencing of requirements in the assembly process. Furthermore, the number of workstations, assembly task sequences, and assembly line configuration are initially determined in this mapping process.

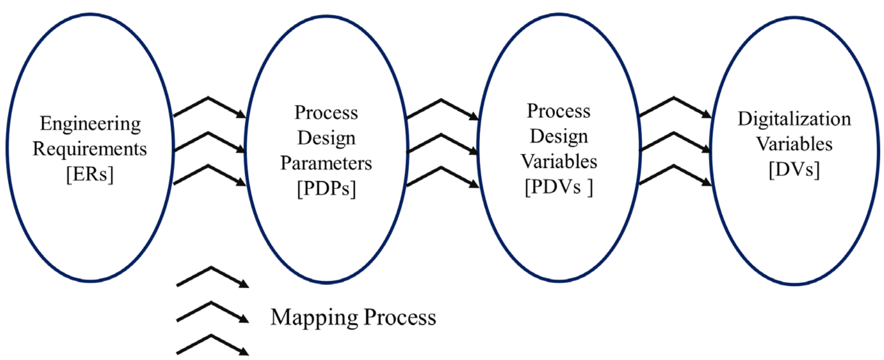

Figure 1. Four domains of DT enhanced smart assembly system design process

Process design variables are detailed design specifications of the assembly process which are mapped from the process design parameters domain. This mapping process is relatively complex due to the number of decision-making problems under different dimensions. In the domain of process design variables, equipment selections, mechanical design, electrical design, and software architecture design are finished, reviewed, and ready for the next stage. Digitalization variables domain $[DVs]$ is the last domain. This domain contains variables representing the digitalization of assembly line design in mechanical, electrical in process design variables. Furthermore, digitalization variables strongly depend on variables in the previous domain since digitalization requires support from both the software and hardware side.

3.1 Assembly System Design Process with Digitalization

Figure 2 demonstrates the design method of the assembly line with the following first three design domains in Figure 1. There are three stages in the design process. The initialization stage is the first stage initialized by the customer. Customers refer to stakeholders that require an assembly line design for their products. Therefore, product specifications and requirements are relatively clear which are the input of the design process. Designers and engineers gather important information and requirements and start analysis based on their experiences and existing solutions. The assembly process and requirements are redefined by designers and engineers in the mapping process and result in task sets in the design stage.

Task sets $\{T\}$ are mapped from the input in the initialization stage which contain individual assembly tasks t_i. Individual tasks t_i are furtherly decomposed to sub-tasks t_i^j where j is the index of sub-tasks. Individual tasks are unstructured in task sets $\{T\}$ since they are simply identified based on the assembly process of the product. After assembly tasks derivation and decomposition, design problems are formulated for further analysis. There are four key steps in the decision problem formulation. Firstly, task sets $\{T\}$ need to be structured by determining the relationship in the level of individual tasks and sub-tasks. Two types of relationships could be identified at the same level which are serial and parallel. Graph theory can be a useful tool for representing the relationship between tasks at the same level. Suppose a graph $G(V, E)$ represents task relations, if task i and task j are in a serial relationship, then a directed edge E_{ij} starts from V_i to V_j. If two tasks are parallel, then no edges exist between corresponding vertices. Figure 3 shows an example of using the graph to represent relationships between eight tasks. Graph clustering can be employed for dividing tasks into different groups. Depending on different use cases, unsupervised graph clustering methods like spectral graph portioning and graph cutting (Nacimento and De Carvalho, 2011). The selection of the graph clustering method should be able to balance the number of tasks in each cluster. Determining the sequence of task clusters is significant in identifying the number of necessary workstations and corresponding assembly tasks is identified.

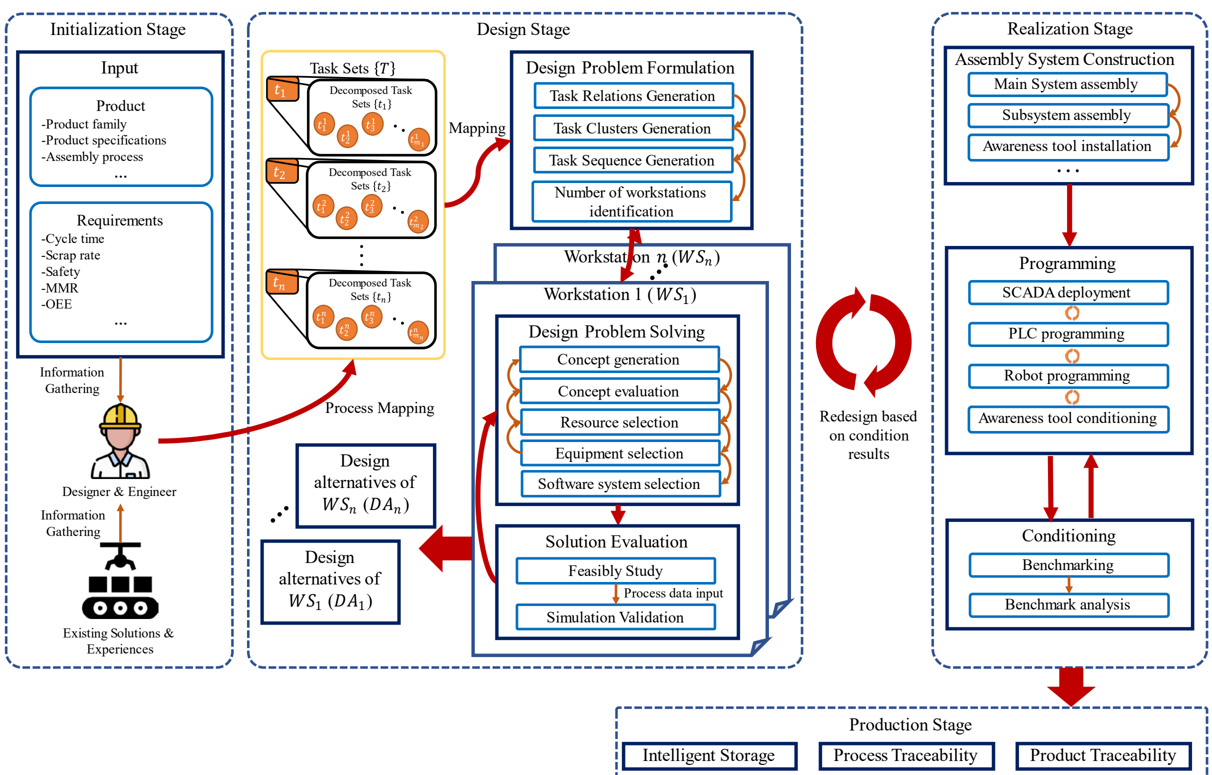

Figure 2. The design process of a digitalized assembly system

The design problem of the whole assembly line is decomposed. For the individual sub-design problem in each workstation, the design problem-solving process contains five steps which are concept generation, concept evaluation, resource selection, equipment selection, and software system selection. It should be noted that for any two sets of workstations $\{WS_i\}$ and $\{WS_j\}$, $\{WS_i\} \cap \{WS_j\} \neq \emptyset$. The shared components in design concepts, equipment, concept, and software systems reveal the modulization and standardization in assembly line design. Though the design problem is divided, workstations are never isolated physically and virtually. Solutions to each sub-design problem are evaluated through feasibility studies and simulations. Simulation validation can estimate the assembly line performance based on data obtained from feasibility studies. Design alternatives for each workstation are finished after the zigzag process of design problem-solving.

The realization stage is the last stage which consists of component purchase, component fabrication, assembly, programming, and testing. Assembly system construction happens in the physical world. Awareness tools are equipment such as sensors, fiber, and cameras. The awareness of assembly line status is obtained by data acquisition through those tools. Therefore, despite the software system selected for the assembly line, the selection of those awareness tools determines the digitalization level of the assembly line. Tasks in the programming sub-stage are processed parallelly. The deployment of SCADA systems, PLC programming, robot programming, and tool conditioning can't be processed solely. Conditioning is the last sub-stage that involves a relatively huge amount of labor. When the benchmark of the assembly system doesn't meet the exceptions of design or engineering requirements, different action items are listed based on the analysis of testing benchmarks. Similar to design problem-solving and solution evaluation in the design stage. Programming and conditioning need lots of rework. Nevertheless, if the assembly system can't meet the requirements through reworking programming. A redesign or modification to the current assembly system is necessary.

Once the assembly line meets all engineering requirements and design expectations, it steps into the production stage which is the last stage in the design process. The reason for adding this post-design stage is that the types of services enabled by digitalization are determined during the early design stage. As shown in Figure 2, three types of services are intelligent storage, process traceability, and product traceability. The process is tracked through robots, cameras, sensors, RFIDs, and other awareness tools from workstation to workstation. Product traceability refers to the sub-assembly and product tracking. Product traceability is not as real-time as process traceability since it is tracked or updated when the entity is inspected or transferred to the next workstation.

As shown in the system, digitalization only assists in the conditioning and operation process. The design process still requires a large amount of labor when the redesign is necessary. Digitalization can't accelerate and assist the redesign or modification process which could even result in multiple times of redesigns and modifications.

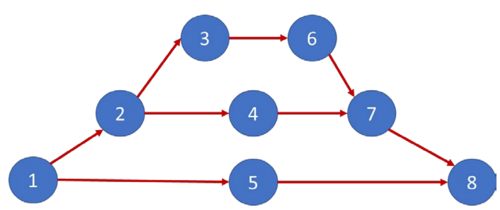

Figure 3. Task relationships represented by the graph

3.2 Evolving from Digitalization to Digital Twin Enhanced Smart Assembly System

An evolved design process is presented in this section addressing issues identified in section 3.1. As shown in Figure 4, the evolved design process has the same initialization stage where product information and requirements are input for the design initialization. Designers and engineers gather information from the new production requirements existing in this stage and then determine the task sets $\{T\}$ from the mapping process. The design problem formulation, decision problem solving, and solution evaluation also follow the same procedures as Figure 2. After generating design alternatives, an additional step is required before stepping into the realization stage.

This additional step is another mapping process between designing alternatives in the physical domain and the cyber domain. The mapping process is the first step where all elements in the design alternative need to have a method of building a digital model. The method can be direct or indirect. For example, the digital model of Siemens PLC can be directly built using Siemens PLM software (Siemens, 2017) and the digital model of a conveyor belt could be built indirectly by real-time data monitoring of the motor that drives the belt. The decision-making process in digitalization design contains four steps after the mapping process. Service identification is aimed to determine the types of service enabled by the digitalization of design alternatives. This is a vital step since unnecessary services could lead to unnecessary complexity in the digital twin construction of the assembly line. By analyzing the use case of the smart assembly system and identifying key services, only digital models that enable the key services should be built. Digital models of some other elements can be ignored. Digital model clustering is the third step that tries to find similarities in the building method. Digital models that utilize the same software platform will be in the same system for development and digital models. The digital model decision-making step is the process of planning the digital model construction of corresponding design alternatives. The last step is digital twin configuration construction which links and integrates selected digital models. Similar to workstation sets, any two sets of digital models $\{DM_i\}$ and $\{DM_j\}$, $\{DM_i\} \cap \{DM_j\} \neq \emptyset$. This relationship is derived from $\{WS_i\} \cap \{WS_j\} \neq \emptyset$ since digital model sets are created through mapping from the design alternative sets.

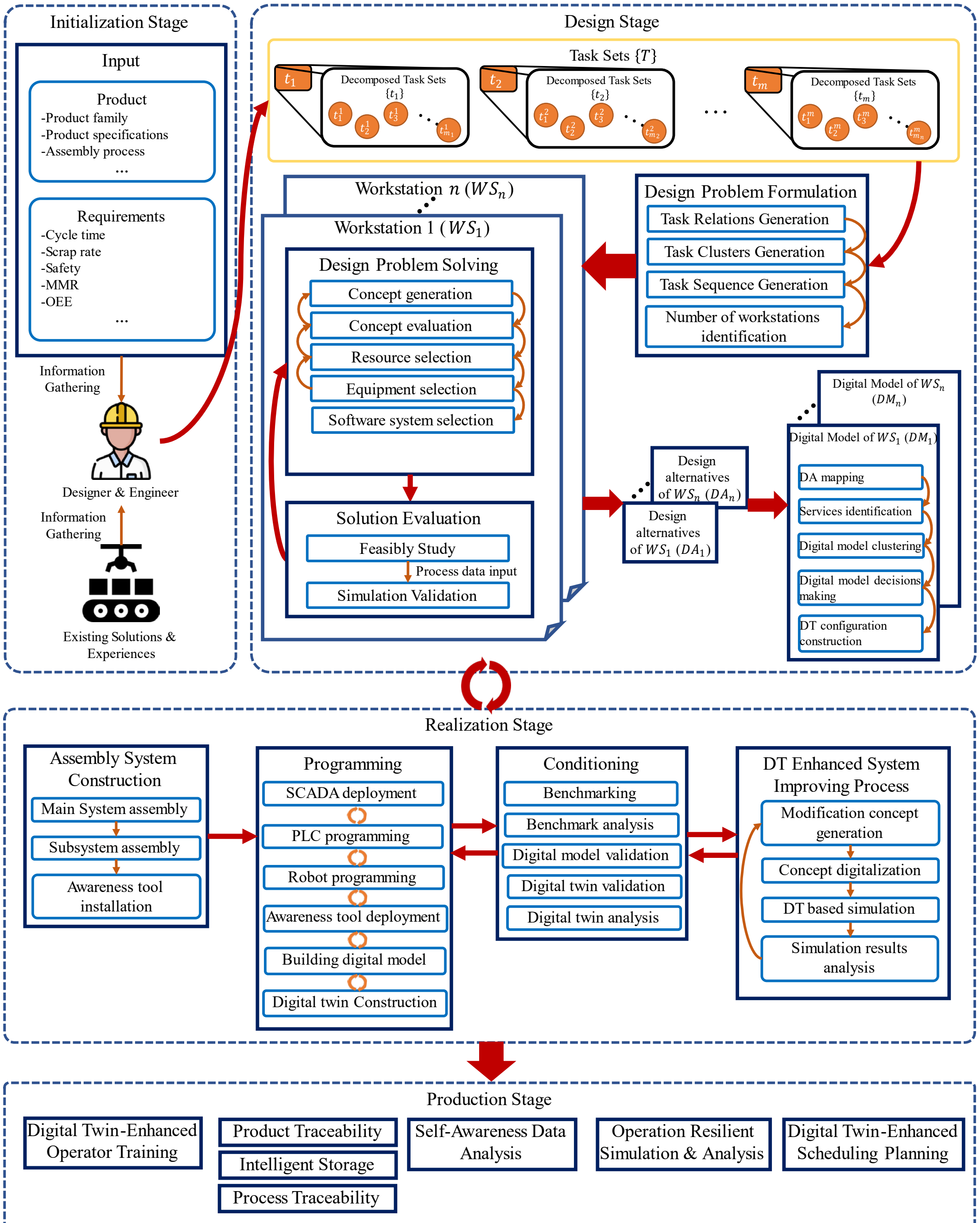

Figure 4. The evolved design process of the digital twin-enhanced smart assembly system

Different from the process introduced in section 3.1, the realization stage can start before finishing the design stage since assembly system construction can be started once design alternatives are finished. In the programming sub-stage, building a digital model and digital twin construction are two extra steps that are parallel to other. During conditioning, besides benchmark testing and benchmark analysis, digital model validation, digital twin validation, and digital twin analysis are necessary for validating the deployment of digital twins. Digital twin analysis is coupled with benchmark analysis. A fully validated digital twin should have the identical simulated performance to the actual assembly line. Digital twin enhanced system improvement process supports rapid validation of redesign or modification when the smart assembly line can't meet the requirements due to hardware design. The improvement process is initiated by generating new concepts for the current design. Digital models are created or modified based on existing digital models in the concept digitalization step. The effect of modification can be obtained from digital twin-based simulation and simulation results analysis. Once the condition stage is finished, the process steps into the production stage. In the production stage, four additional services digital twin-enhanced operator training, self-awareness data analysis, operation resilient simulation, and digital twin-enhanced scheduling & planning are enabled by digital twin.

In this enhanced design process, digital twins are constructed based on digital models of physical components. Digital twin not only enhances the design process but also provides additional services at the end stage of the assembly line design process. Compared to the design process in section 3.1, the digital twin-enhanced design process is more intelligent and resilient.

4. Framework of Digital Twin-Enhanced Smart Assembly System

Figure 5 shows the framework of the smart assembly system developed based on the design process introduced in section 3.2. It presents the assembly system from the view of service enabled by digital twins. The physical layer is the bottom layer which is fundamental to all other layers. As mentioned in Section 3, the design and equipment selection in the physical world determine the upper limit of the digitalization level. In the physical layer, PLCs, material handling systems, industrial PC, robots, sensors, and cameras are components of workstations in the smart assembly line. Operators, parts, sub-assemblies, and tools, are not fixed on workstations. Therefore, no data can be collected from them directly within short time intervals.

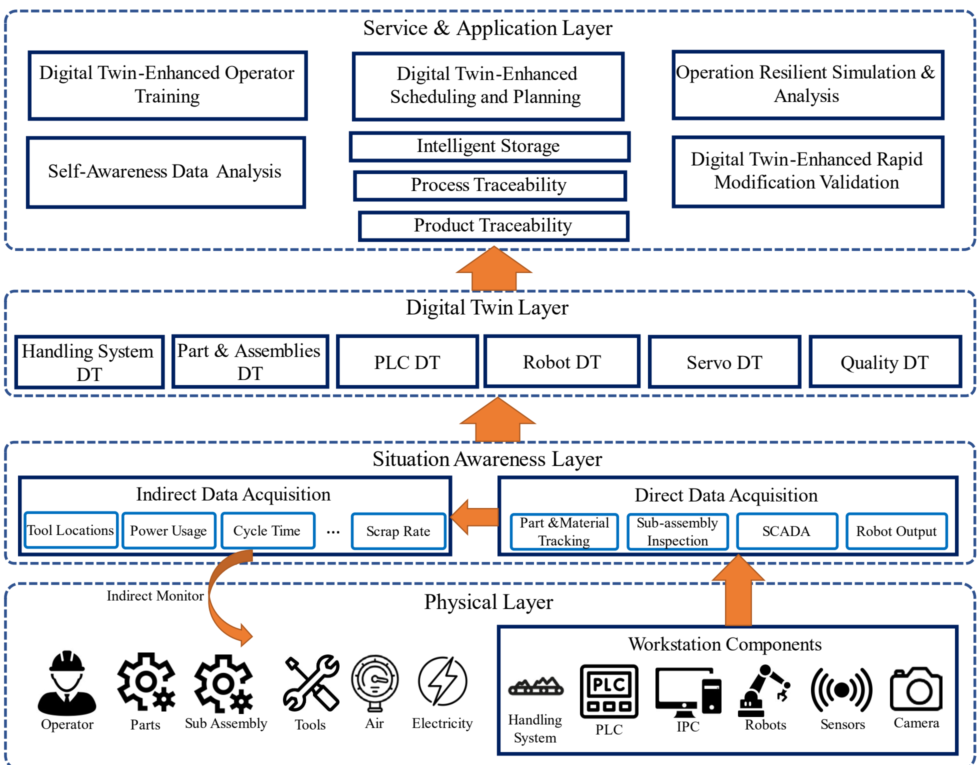

Figure 5. The framework of twin enhanced smart assembly system

The situation awareness layer is the second layer in the framework. Real-time data is directly collected from workstation components in the physical layer. By processing the direct data, the status of entities that are outside the workstation can be monitored. This monitoring process is called indirect data acquisition. Indirectly acquired data can reflect the performance of the smart assembly line. In the situation awareness layer, digitalization and information technologies bring intelligence to the smart assembly line. In the digital twin layer, six kinds of digital twin models are summarized as the digital twin of the handling system, the digital twin of parts and assemblies, the digital twin of PLC, the digital twin of robots, the digital twin of servos and motors, and digital twin of assembly quality. Services and applications are the final layer in the framework which provides additional services to the manufacturer. The digital twin layer and service & application layer leverage the intelligence of the smart assembly system which become the main characteristics of the digital twin-enhanced assembly system. Services and applications are introduced in the following sub-sections.

4.1 Digital Twin-Enhanced Operator Training

Digital twin-enhanced operator training is one of the main services in the service and application layer. It is aimed to provide remote training to operators before the smart assembly line is transferred to customers. By using AR and VR technologies, trainees can understand the workflow of a line before seeing the actual line.

4.2 Self-Awareness Data Analysis for Fault Prediction

Self-awareness data analysis contains faults prediction and analysis. The neural network is one of the possible methods for fault predictions. RNNs, unlike many other neural networks, incorporate feedback connections in their neural architecture (Ondruska, and Posner, 2016). This loop in the neural structure enables the continuous flow of information, empowering the network to effectively process long-term information. In contrast to the conventional Convolutional Neural Network (CNN), RNNs are better equipped to learn and capture long-term dependencies within data. A specific variant of RNNs known as Long Short-Term Memory Networks (LSTM) excels in addressing sequence classification problems. As shown in Figure 6, two types of input are encoded and fed into the LSTM model. The first type of input data is discrete which is updated at a time interval. The second type of input data is continuous. The training dataset of the model is prepared through fault case identification.

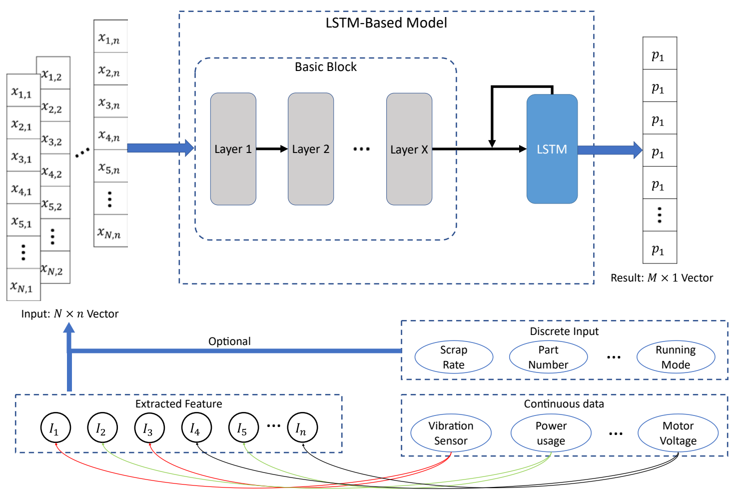

Figure 6. LSTM-based fault prediction model

4.3 Digital Twin-Enhanced Scheduling and Planning

The scope of digital twin-enhanced scheduling and planning is inside the assembly system which is focused on shift scheduling and production planning. For shift scheduling, digital twins can simulate the production status of the assembly system according to the schedule. The schedule-making process is a process of solving vehicle routing problems that doesn't require any input from digital twins directly. For production planning, simulation conducted through digital twins can predict the performance of the production plan.

4.5 Operation Resilience Simulation & Analysis

Operation resilience refers to the ability to handle unexpected failures. The unexpected failures come from two sources. The first source is from machine to operator. Using the digital twin, the operational resilience of the smart assembly system can be validated through simulation. For example, a robot digital twin can simulate the effect of extreme motions when force sensors are out of control. If the robot has risks of harming the operator from the simulation results, the safety cover of the workstation needs improvement. The other source is the lack of human operators' overwatch. Similarly, the digital twin can simulate the case for resilience analysis. For example, it can simulate the case when a motor continues running as a result of the malfunction of a sensor, the line can detect the fault status and stop automatically using SCADA, PLC digital twin, and servo motor digital twin, it can be found.

5. Discussion and Limitations

For a digital twin-enhanced assembly system, the digital twin technology is not the only keystone. Furthermore, the leverage of intelligence in the smart assembly system driven by the integration of digital twin technology is more important. Digital twin-enabled services and applications are the main characteristics of a DT-enhanced smart assembly system. Suitable digital twin design based on the services and applications in the system can implement proper use of the collected data which transfers the unstructured data to important information for system design decision-making, system maintenance, and system analysis. There are three major limitations of this work. Firstly, a general design method is not proposed. Secondly, the lack of technical methodology for some services and applications in the system framework. Thirdly, the lack of case studies for validating the proposed design process and new system design.

6. Conclusion

This paper proposed an original concept of the digital twin-enhanced smart assembly system for resilient operation. By presenting a general design process of the proposed system, the advancements enabled by digital twin technologies are clear. The advancements are not only in accelerating the design process but also in the post-design stage. Furthermore, the term resilient operation is also defined by the scope of the assembly system. Four unique services and applications based on digital twin technology are identified which are DT-enhanced operator training, DT-enhanced self-awareness data analysis, DT-enhanced scheduling & planning, and DT-enhanced rapid modification validation. The future work of this paper has three aspects. The first aspect is to apply the proposed design process to an actual smart assembly line design case. The second aspect is to develop a general design method for the smart assembly system. The third aspect is to continue working on some methodologies of services and applications demonstrated in the framework of smart assembly systems.

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