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Digital Twin of Product Life Cycle Cost Management: Review and Theoretical Frame Work

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Abstract.

. The goal of this study is to investigate the theoretical underpinnings of smart manufacturing's use of digital twins, product life cycles, and cyber-physical systems. By integrating the flow of information as well as data throughout all phases of corporate operations, digitization is the foundation that enables swift reaction to constantly changing business environments. One of the 4th Fourth Revolution's technologies, known as a "digital twin," has emerged in reaction to the advancement of manufacturing techniques, goods, and services. Production goods and systems are no longer sophisticated systems that carry out their tasks and meet quality standards; they now also interact with other parts, goods, and services through the Internet of Things via cyber networks. According to this article, the concept of a digital twin hinges on controlling the full product life cycle through the integration of the physical and virtual worlds via cyber-physical systems through cyberspace. Additionally, it demonstrates how digital twin processes and analyzes data using machines learning, AI, IoT sensors, computing in the cloud, and virtual modeling to support development and decision-making. In order to boost industrial productivity, cut costs, forecast failures and unexpected stops, and perform predictive maintenance, it was required to create a convergence within the material universe and cyber domains.

Keywords: Internet of Things Technologies (IOTs), Product Life Cycle Management (PLCM), Product Lives Cycle Cost Administration (PLCCA), Digital Twins (DT), virtual physical systems (VPS), intelligent production (IP), Machine Learning (ML), and Deep Learning (DL).

1 Introduction

The current business climate is dynamic, ever-evolving, characterized by growing competition, rapid global development, and rising uncertainty.

The industry has undergone significant change as a result of the digital age, automation, and the advent of the so-called Fourth Industrial Revolution, that includes two key components: smart components, and networks. As a result, there is a pressing demand for a scientific method that makes it possible management to comprehend the nature of the challenges it faces and aids in their analysis and logical solution.

This is built on a set of artificial intelligence (AI) technologies that aid in the development of new solutions to create the life cycle of the product more effective, intelligent, adaptable, and capable of sensing, responding, predicting, and recreating) in a way that was previously difficult to envision. Therefore, industrial businesses must provide a variety of goods or customized solutions for each client, therefore emphasis must be placed on product quality, manufacturing costs, and the entire production cycle.

Many nations throughout the world have been eager to put the Fourth Industrial Revolution's concepts into practice in order to create high-quality products, an efficient production process, more flexible manufacturing, lower production costs, and smart factories.

The expense of the conventional product life cycle and the creation for novel operational characteristics of differ greatly from those of manufacturing systems are only two examples of the many changes brought about by modern manufacturing systems. The cost structure of production saw major modifications as a result of this. Manufacturing systems have recently seen a lot of technical advancements within cost management and planning, as well as in the domain of production processes.

Self-production processes adaptable manufacturing systems, ongoing technological progress, just-in-time production, including total quality management have been the most significant of these.

Industrial companies are dependent on the application of some or all of these advances, which are connected to one another with a variety of integration and harmony.

The most significant changes to the circumstances and backdrop of modern industry have been brought about by the use on modern technology mechanisms in planning, operation, and managerial processes, increased focus on production quality and planning, and the adoption fresh views and systems related to manufacturing management and planning. Recently, the majority of industrial businesses have concentrated their efforts on cutting costs through quality control, value engineering, and zero-defect production.

The fourth industrial revolution is centered on the transition from automatic manufacturing and smart production and production, comprising an advanced manufacturing environment built on a variety of technologies spanning the Internet of Things, big information machine learning, neural networks, with machine learning.

Facilities managers may improve critical operational areas like remote machine setup, preventive and emergency repairs, material supply, pricing for goods, information reporting, and more with the aid of these strategies. These improvements, which include more precise maintenance predictions, enhanced service agendas, and more precise and objective decisions, aid in optimizing product performance in comparison to services [1].

A number of enabling technologies, including life cycle management (PLM), enterprise-level resource planning (ERP), the internet of Things (IoT), and electronic physical systems (CPSs), which can interact with one another in real time, are necessary for the majority of SMEs to address industry problems pursuant to the 4th Industrial Revolution [2].

This advancement in technology, the ongoing advancement and information technology, especially the involvement of automation in the bulk of business activities have given rise to a brand-new idea known as the "digital twin," which connects the physical world with its digital twin in cyberspace. Due to the outcomes they contribute to, particularly their ability to predict and monitoring from the product throughout its lifespan and being able to take advantage of such information for enhancing and creating products, during which any changes to the physical object can be identified by sensors and transmitted to its digital version, digital twins have changed commercial and industrial activities.

This enables effective remote control, early breakdown detection, monitoring component wear, and proactive responses to such situations, as well as lowering the costs of unexpected disruptions and raising return on investment. It also gives a deeper glance at the processes that happen when the tangible thing is used, allowing one to anticipate events, enabling early breakdown detection, monitoring component wear, and responding to such situations in advance. For instance, by adopting a digital replica of the product, production costs associated with quality assurance procedures can be decreased because product quality can be checked during production [3, 4, 5, 6, 7].

Product Lifecycle Management, more commonly known as PLM, grows into a comprehensive system covering the entire product lifecycle and the company, from requirements management including IoT data processing, as these technologies advance. Document management solutions have been heavily utilized in the conventional product life cycle tracking (PLM) methodology. Contrarily, the modern application of the PLM (product life cycle management) concept encourages the sharing and exchange of data rather than documents, with the data in documents being examined and saved in a database as metadata or stored in specialized microforms.

Making sure that what's stored is the only means if truth for the item over its entire life cycle is crucial. Additionally, as data management advances in the cloud-based internet world, a different viewpoint is being established. Whereas product metadata is connected to the term "digital twin" because it is described as the dual of the brand's digital information [8, 9, 10].

The six sections of the paper are as the following: Section 2 introduces the theoretical underpinnings of the goods life cycle or the digital counterpart. Cyber-physical systems are discussed in Section 3 along with how they relate to digital twins. Smart Manufacturing and Strategy Cost Management are presented in Section 4. Application of the use of digital twins to autonomous cars is covered in Section 5. A review and summary are provided in Section 6 of the paper.

2 Theoretical Background of the Product Life Cycle and the Digital Twin

2.1 Product Life Cycle Management

One way to describe a product life cycle leadership approach is as an organization of shared information about an item and business, which includes establishing, overseeing, and organizing all steps necessary to generate and thoroughly manage all data, papers, and resources throughout every stage of a product's life cycle [11].

The industry has long used the term Product Lifecycle Management Plan (PLM), which provides a thorough understanding of all phases of industrial production. PLM is the most efficient way to manage the parts, products, and systems created throughout their life cycles, from the conception of the product to its final disposal.

Product Lifecycle Management, more commonly known as PLM, establishes a continuous information flow so that all stakeholders involved in the development, production, and use of a product have access to both current product information and historical development and operating circumstances as needed [10].

As illustrated in Figure (1) [2], there are numerous user and stakeholder groups participating in information creation and exchange during the planning, manufacturing, design, as well as service phases in traditional PLM methods to product development.

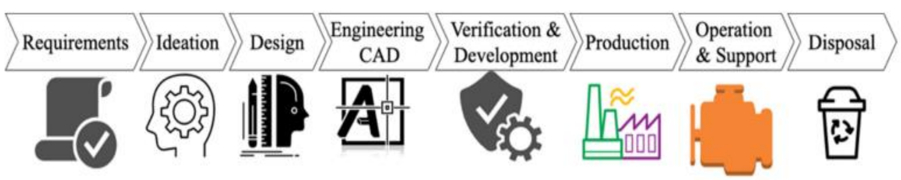

Fig. 1. The Traditional Product Life Cycle Management Process [2].

The management of the product's life cycle (PLM) enhances product quality by making processes transparent, which also saves money and time over the course of the full life cycle. Considered being an interface strategy, the management of the product life cycle (PLM) should take into account production processes scattered throughout the full product life span [12].

In order to improve the product's qualities, feedback from the last process phases, such as product use, recycling, and disposal, ends the whole lifespan of the product. As a result, a control loop is created that enables businesses to respond to client needs more quickly and incorporate product application expertise into the creation of fresh, cutting-edge goods [12, 13].

The data in life cycles of products are isolated, fragmented, and inefficient, and they offer little value in enhancing production control when there doesn't exist any convergence in the physical and digital worlds [14].

To manage all stages during the life cycle of a good, from ideation through engineering, testing, confirmation, manufacturing, procedures, maintenance, and finally disposal, better processes must be developed with the use of the technologies during the Fourth Industrial Revolution [15, 16]. Product lifecycle management, however, developed into a comprehensive system the fact that reflected the entire product life cycle from the management of requirements to IoT data processing throughout the cyber physical space as the technologies of the fourth industrial age advanced. As a result of the establishment of each of these cyber systems, a product's life cycle was divided into three stages, which are what is known as the biggening of the life cycle (BoL), the middle part of the life cycle (MoL), and the end of the life cycle (EoL). [17] shown in Figure (2).

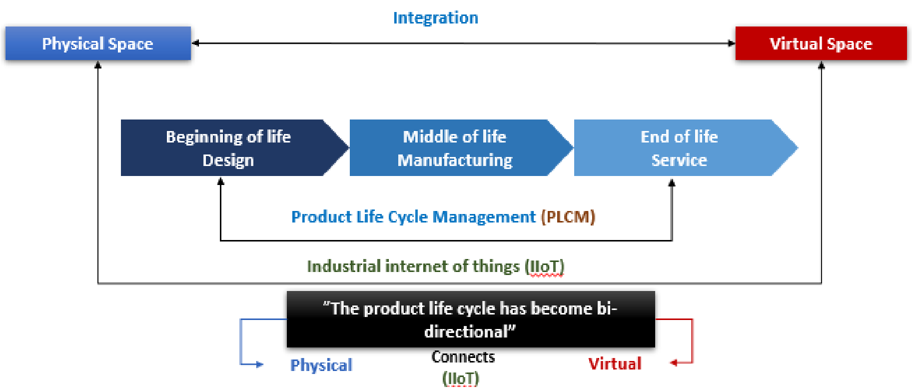

Fig. 2. The Phases of the Bi- directional Product Life Cycle

2.2Concept of Digital Twin

In order to cover the complete product life cycle, Michael Grieves created the digital twin concept. A digital duplicate is a virtual version of a physical thing or process that may collect data from the real world and validate and mimic the physical twin's behavior in the present and the future. It is a crucial enabler for object lifecycle management, complex systems evaluation, product validation, and simulation [18]. As a model made up of three key parts: the real-world physical product, the cyber-digital virtual product, and the cyber-physical space's connectivity between tangible and intangible things thanks to Industrial Internet the Things (IIoT) technologies [19].

In addition to a set of physical world sensors, edge processing power, data security, intelligent systems, the Internet of Things, deep computing, machine learning, big data, as well as information mining, digital twins also rely on the availability of data transfer interfaces like the Internet, wireless LAN, Bluetooth, and satellites. In light of this vast industrial expansion, this technology is regarded as the core of digital transformation, and several significant businesses, including Tesla and Siemens, have successfully done so [20]. By simulating the course of manufacturing, any potential sources of mistake or malfunction can be found and eliminated before actual production can begin, which has improved production.

When data is gathered from several sources, Digital Twin (DT) aids in data integration by analyzing hidden patterns that would have been impossible to find from just one source of information, and the incorporation for artificial intelligence (AI) techniques in Digital Twin (DT) aids in improving thinking and problem-solving. So, by combining manufacturing processes and boosting production scheduling in manufacturing implementation, digital twin has the potential to increase performance by providing exceptional goods at the lowest logical cost [6, 17]. Grieves created this brand-new idea as a way to build products that match design standards and combine it with the idea of a product's lifespan cycle. The illustration below provides an example of how digital twins are being used in the business world [21].

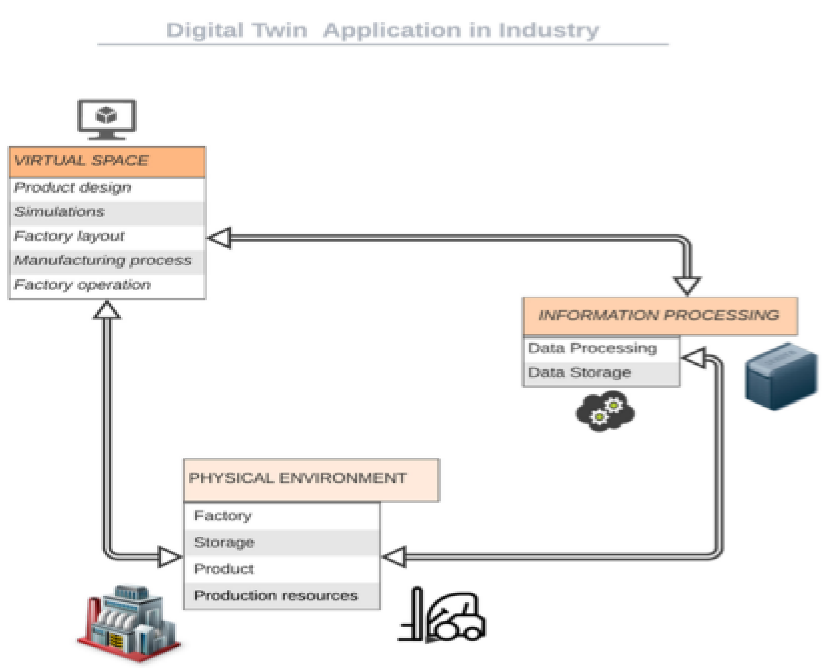

Fig. 3. The Application of Digital Twin in the industry [2].

As a more sophisticated kind of process model simulation, the industry employs digital twins (DT) to establish standards for predictive study of asset performance. Operators can use the real-time data that digital twins give for planning, production, and sourcing in a variety of ways. In terms of smart approach savvy operations, smart controls, and smart management, they promote effective production strategies [1, 14, 17, 22].

According to the research firm Grand View Research, Inc., the worldwide marketplace to earn digital twin is anticipated to reach $26.07 billion from 2025, at an average yearly increase of 38.2%. By utilizing the benefits provided by the digital twin, inadequate manufacturing companies have improved automation and adaptability towards shifts in consumer requirements, greater effectiveness in production planning, and improved manufacturing execution. To achieve smart manufacturing, it is necessary for sensors that are networks, and sources of finances in general as well as price information in particular to interact cooperatively and independently across production lines which data is gathered from physical infrastructure, used to extract proposed implementation mechanisms, and provided predictions in this area. The expense of R&D will also be crucial because it aims to develop new approaches to smart manufacturing by delivering skilled labor and modern technology [17, 23, 24, 25].

The conventional strategy is mostly based on subject-matter expertise or depends on one-time neural network outputs, whereas the twin's method for increasing production control is based on continuous data. The digital twin method, on the other hand, creates an ongoing collaboration between a real physical factory and a digital replica of that factory. The virtual technological factory will continuously gather current information compared to the physical production line as part of the digital twin's framework, use historical as well as real-time information to train the model, then validate the model, informed the model, and finally give feedback on to the real factory to feed production and cost control objectives [14].

2.2.1 The digital twin in the manufacturing process consists of three levels "the Digital Master, the Digital Shadow, and the Digital Twin"

1. Based on the outcomes of the development, the digital master is produced concurrently with product development. Virtual prototypes containing simulation models, habits, and many product configurations and variations are included.

2. The digital shadow occurs when a single real instance on the product goes online, such as when someone places an order or production is initiated. These physical objects throw an electronic shadow over the virtual world. Both simple data like identifiers and more complicated data like status, production, maintenance, or consumption data can be displayed.
3. The digital twin is created when the fundamental data from the digital master and the digital shadowed data are merged.

This architecture consists of a data-driven practice loop, a virtual digital model, as a continuous real-time data interchange between them for continual cost, production, and data improvement [14]. The structure of the digital twin is depicted as follows in Figure 4:

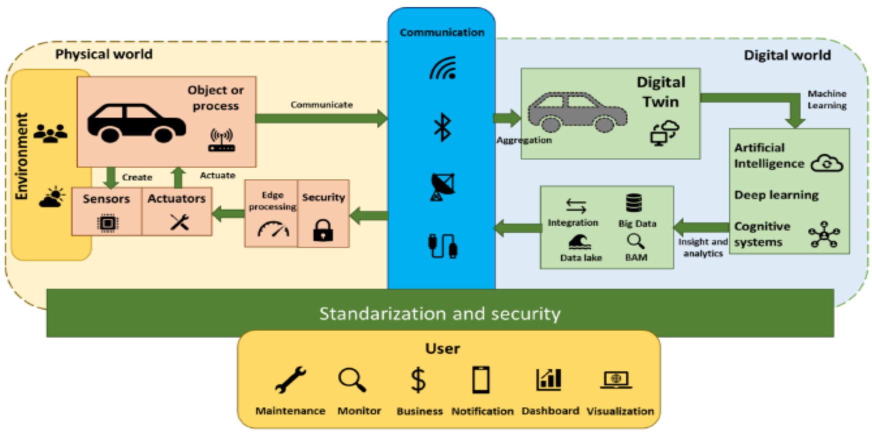

Fig. 4. Digital twin architecture [26]

2.2.2 Digital twins have many uses, the most important of which are the following

1. **Engineering:** improving the efficiency of engineering processes. Connect virtual models to actual physical items to enable the development of new products based on lessons from the behavior of current products into the real world. By conducting what-if scenarios, the digital twin enables product faults to be caught in the earlier manufacturing and development stages, lowering engineering costs and enabling quicker design cycles. This has an impact on product development and cost, for instance, because the digital twin reflects customer usage. over the course of the product's lifecycle, by setting up a feedback loop. Through status observing, whether it is analytical or predictive, the digital twin can provide information about the production

processes, and this knowledge can be utilized, for instance, to enhance plant maintenance.

2. **Operation and Service:** Through optimal communication across all operative and service processes, the digital twin enables an understanding of how a factory shop floor is operated more effectively and efficiently. The evaluation of performance assessments to lower production costs and optimize all supply chain components is one of the major capabilities provided by the digital twin. By anticipating faults and fixing them before they occur, the analytical capabilities of digital twins increase production efficiency. In order to maximize benefit and save cost, new manufacturing strategies are reproduced by changing parameters throughout an assembly line in a digital replication. Digital twins assist in detecting the consequences of a quality trend earlier and preserving its parameters throughout actual production.
3. **Marketing and sales:** Use digital twins to make consumer engagement processes more effective. When a product was first introduced to the market, product development essentially came to an end. But that's not the case now. Comprehensive data management is made possible by feedback and product remarks that go beyond the delivery of the product to include after-sales services. modifying the method for consumer validation and pursuing perfection in digital marketing.
4. **Asset management:** A digital twin can help strengthen the operational efficiency of physical possessions through efficient preventative and predictive upkeep processes, thereby lowering overall maintenance and shutdown costs. A digital twin is the cyber-twin of an actual object and encounters the ability to view real-time information about physical objects alongside relevant historical data. It can also be used as a predictive analytic technique to foretell how a material thing or related process will behave. A digital firm can improve its whole process, production system, or product by expanding this example. Improved production scheduling, the detection of possible bottlenecks, the evaluation of asset use, and the reduction of production lead times are potential advantages [22].
5. A variety from tools and methodologies are used, including tools for data administration and interaction, items for displaying data and keeping, tools for machine learning, and analytical methods, to reduce costs, boost profitability, effectiveness, and competitiveness in new sectors. Artificial intelligence (AI) and data analysis techniques must be utilized to deal with data and transform it into knowledge [17].

2.2.3How to build a digital twin

The four phases that make up the digital twin's structure are as follows:

1. The Initiation phase.
2. The modeling.
3. Enrichment and Utilization.
4. Reuse.

1. Namely Initiation phase:

In this stage, the digital twin's scope is defined, and the foundational needs are derived. Creating a digital twin over predictive auto maintenance, for instance. In this example, the band is the digital twin of the automobile product that monitors several characteristics to aid in preventative maintenance. The first step is to establish the digital twin scope. To better schedule the service is the business strategy. The goal of the economic structure is to lower the cost of maintenance and repair.

The following step is to establish the fundamental criteria for creating a virtual counterpart based on the precise parameters of the company's operational model and finance model. Examples include specifications for data collection from a car engine, guidelines for analyzing the information, and more.

2. Modeling phase:

To generate a digital twin, a virtual replica of the physical thing is made, and the digital twin is then linked to historical and current data to provide a complete depiction of the thing in its surroundings. In the manufacturing environment, sensors that are put on equipment at various stages of production allow for this. The data must be enhanced and utilized to further the digital twin model's objective once it is complete and connected.

3. Enrichment & Utilization phase:

It's crucial to establish an affiliation between the physical thing and the digital counterpart in order to collect data from the tangible thing.

Hence, take into account:

- Protocols and standards for communication.
- Safety.
- The middleware.
- Data archiving.
- Data science that is essential for applications.

4. Phase of Reuse:

Based on the historical data held in the database that which is mined using sophisticated data mining techniques, and then examined with artificial intelligence systems, this information can be used to improve the product or the entire process. Machine learning technique is used in teaching the digital model to not only arrive at the optimal solution at the prospect of actual testing, but also to predict the future outcomes.

2.2.4 Digital twins have many advantages, the most important of which are

1. Significantly more openness is the key benefit. The product or system may be better monitored and the information is displayed in such a way that the user can understand the current status directly and clearly thanks to the numerous models, which continuously contain up-to-date information. The present situations could potentially be seen in three dimensions.
2. You can also save money and effort on maintenance. Future issues can be predicted by continuously gathering and evaluating data and applying simulations [27].
3. Simulations are usually based on the whole data history, maintenance can be planned in advance by predicting the life of individual components, and through predictive maintenance, these components can be replaced before failures or faults occur [28].
4. Shortening the time, it takes to launch a product since simulations may be used to foresee how a system or product will operate before it is fully developed, allowing for the easy elimination of any potential flaws or sources of mistake.
5. Where technological and commodity data are transferred in real time and present performance can be examined, product or system operation may always be kept at its best.
6. The digital twin can be employed at various stages of the lifespan of the product and specific characteristics are automatically modified if environmental or operational conditions change, ensuring that the system or item in question always acts as intended. [29, 30].
7. Digital simulation can take the place of prototype testing, saving costs and time for the production process.
8. Changes in environmental circumstances or settings can be evaluated on a digital twin, and data from virtual sensors can be used to generate fresh insights into areas that physical sensors on the object wouldn't typically be able to access.
9. Predictability from raw material demand via digital twining based on algorithms, optimizing both internal and outside logistics, optimizing

inventory, identifying correlations between various process points, anticipating output composition while product ratios, optimum the production process distribution, forecasting energy use and optimizing water consumption, electricity and other governmental assets, estimating the way people act, forecasting leaps for human safety, giving risk warnings, assessing environmental performance, predicting threats to human safety, and lowering costs.

3 Cyber-physical systems and their relationship to digital twin

Cyber-physical systems (CPSs), which include sensor operating capabilities and also control, are frequently network-connected systems with distributed work and wireless connectivity between smart physical components. Real-time action is a significant problem because the physical world needs to be constantly monitored and under management. They are intricate, adaptable, and adaptive networks, and the individuals who build them up exhibit greater independence and intellect. Cybersecurity strategies must also be part of an integrated solution to attack detection, durability, and concerns regarding privacy [20, 22].

CPSs are located at the nexus of the material and digital realms. The biggest difficulty they have is integrating physical processes with computers because the cyber component constantly monitors the state of the real system and applies judgments and actions to govern it. Additionally, CPSs provide a broad range of use cases in numerous businesses, such as manufacturing, and energy, healthcare, service delivery, and critical facility monitoring [22].

Industrial engineers frequently use operational simulations and other graphical representations of CPSs today. The development of IoT and AI technologies allows for complex interactions of these virtual representations over the course of an entire system instance under the framework of a digital twin (DT), and that presents a number of difficulties for how it seamlessly fits into the real world [20].

The Industrial Internet of Things (IIoT) provides the framework for circuits of physical objects for sensing, interpersonal interaction, and interaction, making it an enabling technology for CPSs. The market for the Internet of Things is predicted to contribute $14.2 trillion in the global economy by 2030. The Internet of Something has caused an explosion among data and information. The three biggest markets for IoT are manufacturing, connected arrangements, transportation, energy, and utilities. As these markets become more digital, new chances for businesses to gain understanding through this data arise [31].

3.1Key characteristics and requirements for the integration of Digital Twin Technology (DT) and Cyber Physical Systems (CPSs)

1. **Everywhere connectivity plus smart things:** Manufacturing equipment needs to include intelligent sensors that can monitor in real time and communicate with other network nodes to exchange data. A safe, dependable, and fast platform are also necessary for these permanent data transfers [32].
2. **Advanced Analytics:** Without the need for a lot of manual feature engineering or preparation of the data, the entire analysis, acquiring knowledge, and execution process must be automated. Manufacturing systems now have the ability to self-configure, self-adapt, and self-learn, boosting productivity, quickness, versatility, and efficiency [33].
3. **Collaborative Decision-Making:** For the best global solution, data from many resources and real-time restrictions must be taken into account. Feasibility studies, operational effectiveness, and implementation strategies for all of the orders are assessed during this procedure [34].
4. **Establishing an independent, quick model and its updates:** Data synchronization and advanced model mapping within physical and virtual platforms guarantee that there is little difference across digital elements and the physical ones, which is necessary for real-time control, improvement, forecasting, etc. [35].
5. **Handling self-disturbances and managing flexibility:** To avoid disastrous operational disruptions, manufacturing systems must react to failure independently and flexibly [35].

4 Smart Manufacturing and Strategic Cost Management

4.1 The Idea of Smart Manufacturing

A collaborative, integrated manufacturing ecosystem known as "smart manufacturing" reacts in real time to shifting conditions and demands in the factory, with the supply the internet, and in the constantly shifting needs of the consumer [36]. "Digital or Smart Manufacturing" refers to the information and communication technology that enables all users in the chain of custody and enterprise levels of the value chain of products to digitally connect and perform data-driven analytics, resulting in intelligent integration of supply and demand matching, a quicker time reaching consumers, mass customization, benefits from cost reduction, and machine maintenance. For instance, General Electric (GE) said that use of a sensor connected Predix, also software suite at one of its plants led to the discovery of gas leaks, and preventing them saved $350,000 yearly [37].

4.2 Strategic Cost Management in a Smart Manufacturing Environment

One of the crucial phases in cost control is the stage of product manufacture. If at this point the design is created and executed into a finished product and resources are depleted in the process, expenses must be properly managed to guarantee that the resources are utilized for the intended reasons. Additionally, it helps in identifying and keeping value-adding activities while attempting to exclude and get rid of non-value-adding ones. This is accomplished through raising the efficiency of various tasks, which promotes leadership and lowers costs. Digital businesses that employ production methods consistent with the fifth industrial revolution are necessary.

Smart factories (SF) connected to international manufacturing networks serve as a representation of them. The combination of Robotics, Sensor, and Automation Networks, as well as their integration within Cloud Networks, and the use of advanced and developed technologies like Big Data Computing and Process Virtualization have resulted in these product lines, which are digital. The creation and subsequent implementation of fresh technologies and production techniques are necessary for this type of digital production as well as process virtualization. Smart sensors that can exchange data with other network elements and monitor manufacturing assets in real time are a requirement. A safe, dependable, and fast platform is also necessary for these ongoing data transfers [35, 38].

Realizing a vision of physical goods or processes that support virtual relationships how develop throughout their entire lifecycle is driven by the increased availability when pervasiveness of real-time operational data as well as improved AI application capabilities in learning and inference. The important technology for comprehensively describing components, products, and systems with data from all phases of the life cycle is the digital twin [10, 22].

Machine learning and the use of digital twins can help manufacturers control output accurately and quickly in reaction to changes in market demand. These technologies also aid in lowering the cost of inefficient production, enhancing economic benefits, and improving SMEs' capacity for sustainable development. When manufacturers use the Digital Twin framework, they can react fast to changes and maintain optimal output [17].

In addition to being employed in the design and manufacture of products, digital twins are an effective approach to virtualize and enhance the actual production equipment and procedures. This involves the movement of employees or robots in factories, the use of finances and administrative tasks, plus the virtual execution of machinery. Using this adaptable and effective method, manufacturers make customized, high-quality items more quickly.AI has enormous potential to increase production's effectiveness, adaptability, and dependability [39].

Deep learning (DL) is a member of a larger family of methods for machine learning (ML) that may produce the necessary representations for a variety of applications, including regression, classification, clustering, and recognition of patterns using just raw data. Deep learning (DL) has many uses in the manufacturing industry since it is extremely effective at identifying complicated structures in data with high dimensions. Several fields, including data identification, image processing, managing stocks, and error identification and diagnostics, have proven its outstanding performance [35]. Digital twin and deep learning DT & DL are used to achieve self-maintainability, self-configuration, and predictive services. Deep learning (DL) has been employed to give independent functionality with reliable success replication and lessen dependency on human decision-making. The operational network as a whole is made more transparent through the usage of the Digital Twin DT. Predictions regarding the remaining useful lives of multiple parts are transmitted to the computational layer in this design, where current as well as past information from hardware, inventory, vendors, clientele, and maintenance employees are combined into DT predicts for simulating and improving predictive maintenance techniques. The physical system receives the optimized plan and other visual data for execution. All models cooperate and work independently to build a closed-loop preventative care platform throughout this iterative, near-real-time process [14, 35, 36].

The manufacturing industry's growing reliance on digital physical systems (CPS), the Internet of Things, ranging Big Data Analytics, and Cloud Computing has paved the way for cost savings and the methodical implementation of digital twins (DT), which have a significant impact on (a) product design and development, (b) keep the health of devices and machinery, and (c) supplementary goods and services. Transparency, communication, versatility, production speed, scalability, and manufacturing efficiency will all enhance with an effective introduction of the digital twin [20, 35].

4.3Phases of the development of the manufacturing process under the integration of the physical and virtual cyber space [40]

Prior to the development of information technology, production in its initial phase was limited to the physical world. Specifically, either people or machines carry out all manufacturing-related tasks. However, there was a lack in data, which reduced manufacturing productivity and efficiency.

The cyber-physical space emerged in the second phase, and numerous intelligent manufacturing-related programs were created, put into use, and used in production. The advantages and possibilities of the cyber-physical sphere have not yet been completely realized due to technological restrictions.

The third phase is when the physical world and the digital world start to interact. The handling of the production cycle has been improved thanks to the internet, which has improved information flow, capital movement, and logistics. But at this point, manufacturing's physical and digital realms are not coordinated.

But at this point, the fourth stage of the development process for smart manufacturing is real-time interaction and greater integration between the physical and virtual spaces of manufacturing due to the ongoing advancements in new information technology. The best way to achieve a smart manufacturing environment and guarantee the implementation if the smart factory is to integrate digital twin and cyber-physical networks, as demonstrated in the following figure:

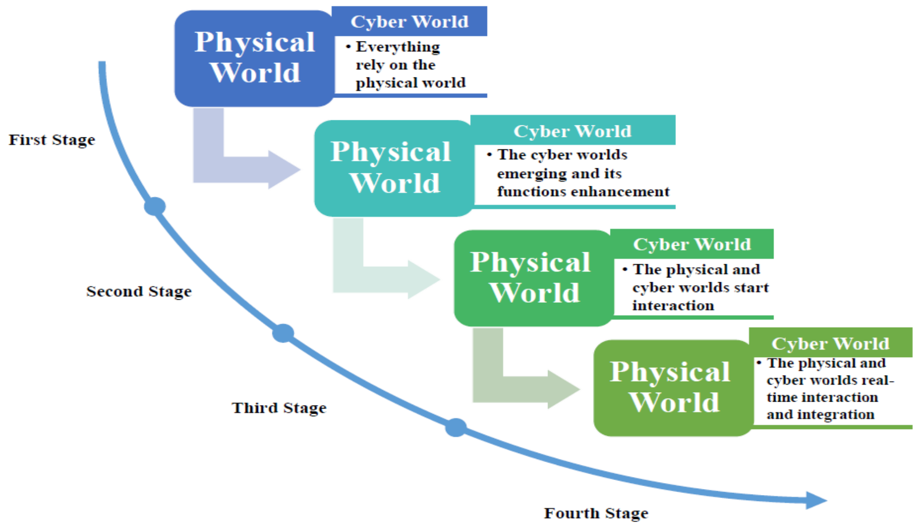

Fig.5. The development of the manufacturing process

5 Application of digital twin technology to autonomous vehicles: a practical example

As software companies often release new programs and upgrades, the automotive sector is currently undergoing significant changes. As a result, the industry must constantly keep up with these changes. The application of artificial intelligence technology in the automotive manufacturing industry has significantly increased, from design and innovation through the end user and after-sales services. To create autonomous vehicles, this has led to the necessity for smart manufacturing techniques to process enormous volumes of data.

Since AI is currently being incorporated into so many items, including cutting-edge IoT gadgets and smartphones, autonomous vehicles may be where it has the most of an influence. Machine learning (ML) algorithms found in the custom AI chips put on the intricate electronic systems within the car are capable of identifying objects on the road and taking the right actions. Additionally, designers need to be able to develop synthetic scenarios and train algorithms. Autonomous vehicles shall be able to share knowledge and continuously improve their algorithms in response to input from other vehicles dealing with various situations. Designers can assess the optimal fit based on the outcomes of AI-based algorithms by modifying the design settings and running the algorithms [39]. A digital twin system, as seen in figure 4, is used to describe the efforts undertaken to design and implement the procedures required to improve the privacy, security, and security in autonomous cars [41].

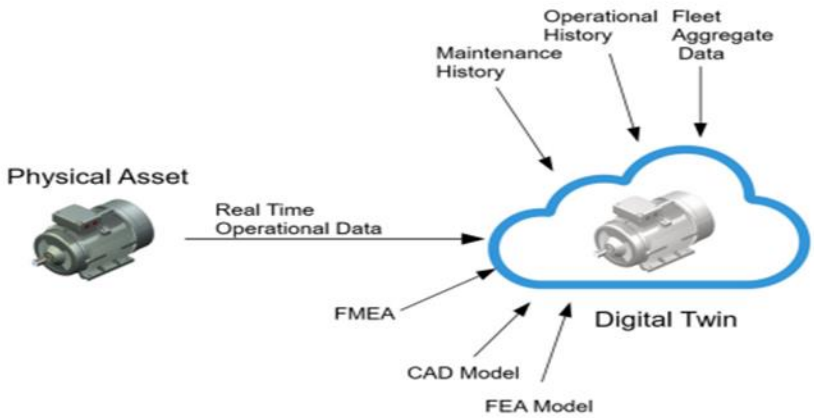

Fig.6. The Digital Twin System [42] Failure modes and effects analysis (FMEA)

The biggest issue for automakers and developers is unexpected, unforeseen shutdowns. The digital twin can do predictive maintenance using data powered by AI.

Machine learning may assess "learner" behavior against simulation models, assisting in numerous ways, such as:

- Establish dependency between parameters.
- Digital twin model calibration.
- Define the simulation models' internal problems.
- Quicken the process of design space exploration and validation for applications involving mechanical, electrical, technological and multi-domain systems.

However, well-trained AI models can take the place of simulation models that calculate performance and memory footprint, like virtual sensors on controls [43].

5.1Example of Siemens Autonomous Vehicle based on Digital Twin Technology

Siemens has developed a "Comprehensive Digital Twin," a virtual representation of a physical product, machine, or process that includes all aspects of its manufacture (mechanical, electrical, and software) throughout its lifecycle, and makes the necessary improvements to reduce the need for prototyping, improve product quality, and minimize production costs. This "Comprehensive Digital Twin" will help to build the future of autonomous mobility.

In order for an autonomous car to move effectively and securely, a complicated system that uses digital twin technology and artificial intelligence technologies is developed. When moving to smart cities, the new computer model in these cities will deal with a vast volume of big data that needs to be processed. This sophisticated digital model Figure (7) is employed in application of smart manufacturing systems.

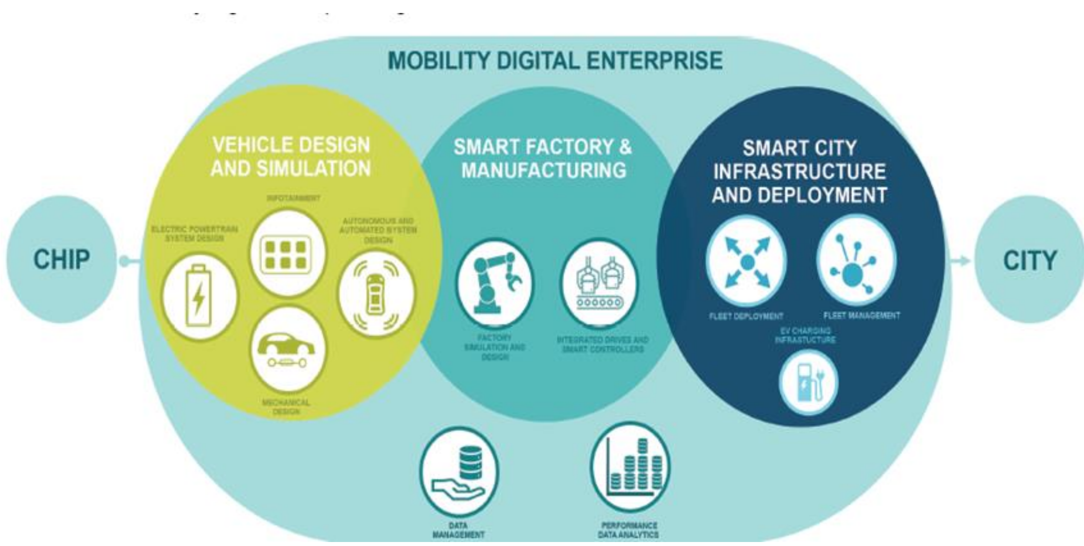

Fig.7. Digital Twin and Autonomous Vehicle (https://profiles.siemens.com)

Discussion and Conclusion

In order to respond to the question: How might digitally twin technology be used to manage the lifecycle of goods cost in an environmentally smart manufacturing environment? this article analyzes studies on the topic. Knowing whether this technology can save production costs, enhance product development, offer early problem detection, and enable predictive maintenance is also important. A review of papers addressing the theoretical underpinnings of managing the product life cycle and digital twin technology was done.

It has been shown that the virtual replica in smart manufacturing operations consists of three levels. Additionally, the five applications of the digital twin technology as well as the creation process and key benefits of these models were highlighted. Additionally, it covered the fundamental qualities and prerequisites for their integration, as well as cyber-physical systems' connections to digital twin technology. As a final illustration of the practical usage of digital twin technology, the phases of development of automated production were discussed using the example: Siemens autonomous vehicles.

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