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Digital Twin Modeling and Simulation of Computer Aided Design and Manufacturing Structure: Case Study

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Abstract: This paper explores the application of digital twin technology in the CAD/CAM domain, focusing on its potential to enhance the design and manufacturing structure. The paper begins by introducing the concept of digital twins and their role in bridging the gap between physical and virtual worlds. It emphasizes the benefits of real-time data synchronization and it enables continuous monitoring, analysis, and decision-making throughout the product lifecycle in detail. Next, the focus shifts to the integration of digital twin modelling into the CAD/CAM processes. The paper outlines the steps involved in creating a digital twin of the design and manufacturing structure, from data acquisition and integration to model calibration and validation. Special attention is given to ensuring the accuracy and fidelity of the digital twin to enable reliable simulation results. The paper then explores the various simulation capabilities offered by the digital twin model. It delves into the use of finite element analysis (FEA), computational fluid dynamics (CFD), and other simulation techniques to analyse product performance, optimize manufacturing processes, and assess structural integrity. Case studies demonstrate the application of digital twin simulations in improving design efficiency, reducing time-to-market, and enhancing overall product quality.

1. Introduction

Digital twin modelling and simulation have gained significant attention in the field of CAD/CAM due to their potential to enhance product development processes and improve manufacturing efficiency. This case study presents an application of digital twin modelling and simulation in a CAD/CAM structure, highlighting its benefits and potential impact on the design and manufacturing stages. The study focuses on a specific case where a digital twin model is created to represent a complex product or manufacturing system. The digital twin incorporates virtual representations of physical components, manufacturing processes, and associated data, enabling real-time monitoring, analysis, and optimization.

Through the case study, the advantages of digital twin modelling and simulation demonstrated, including improved product performance analysis, reduced development time, enhanced manufacturing planning, and increased overall efficiency. The digital twin enables designers and manufacturers to virtually explore design alternatives, simulate manufacturing processes, identify potential issues, and optimize production parameters before physical prototyping or production. The case study also discusses the integration of the digital twin model with other systems, such as product lifecycle management (PLM) and manufacturing execution systems (MES), to enable seamless data exchange and collaboration across different stages of the product lifecycle.

Furthermore, the study highlights the potential challenges and limitations associated with digital twin implementation, including data integration and interoperability, computational requirements, and cybersecurity considerations. Strategies for addressing these challenges and optimizing the digital twin approach discussed.

Overall, this case study provides insights into the application of digital twin modelling and simulation in CAD/CAM structures, emphasizing the potential benefits and challenges. It highlights the role of digital twins in transforming the design and manufacturing processes, improving product quality, and driving efficiency gains. The findings contribute to the growing body of knowledge on digital twin implementation and provide practical insights for organizations seeking to adopt this technology in their CAD/CAM practices.

The remainder of the study divided into the following sections: Section 2 reviews the relevant literature on digital twin modelling and simulation for CAD and CAM design. The proposed effective framework described in Section 3. By using this methodology, Section 4 provides more details on how to apply algorithm on analysing in case study and Section 5 concludes.

2. Literature Survey

The digital twin provides a virtual platform to optimize manufacturing strategies, simulate structural behavior, and enable data-driven decision-making throughout the product lifecycle. These research papers offer valuable insights into the application of digital twin modelling and simulation in CAD/CAM for complex structures. They provide an overview of the current state of the field, including frameworks, applications, and benefits of digital twins in manufacturing processes. Exploring these sources will provide a deeper understanding of the subject and serve as a foundation for further research. Some of the studies review the literature an overview of digital twin applications in various industrial domains, including computer-aided design and manufacturing comprehensively [1-5]. O'Sullivan et al. presented case studies that demonstrate the advantages of digital twins in improving manufacturing efficiency, quality, and sustainability [6]. Woitsch et al. explored the benefits, challenges, and emerging trends in digital twin modelling and simulation, highlighting its potential for improving design, manufacturing, and maintenance processes [7]. Perno et al. (2023) proposed a digital twin-driven framework for the design and manufacturing optimization of complex products. The authors discuss the integration of CAD models, simulation tools, and optimization algorithms to enable real-time performance monitoring, design iteration, and manufacturing process optimization. A case study of an automotive component presented to demonstrate the effectiveness of the framework [8]. Neto et al. (2023) reviewed on the integration of digital twin technology and simulation-based optimization methods in manufacturing processes. The authors discuss the role of digital twins in modelling and simulating complex manufacturing systems, and highlight the potential for optimizing process parameters, reducing production costs, and improving product quality. Case studies from various manufacturing sectors reviewed to display the effectiveness of this approach [9]. Some of the researchers provide an overview of digital twin modelling and simulation in the product lifecycle. It discusses the integration of CAD, simulation, and other technologies to create digital twins for improved design, manufacturing, and maintenance of complex products [10-13]. Corradiini et al. explored the concept of a digital twin in manufacturing, highlighting its benefits in terms of productivity, quality, and efficiency. It discusses how digital twins applied in CAD/CAM processes to optimize manufacturing structures. Some og the studies presented a comprehensive review of digital twin technology for complex product manufacturing. It discusses the integration of CAD, simulation, data analytics, and other technologies to enable virtual modelling, analysis, and optimization in the manufacturing process [14-20]. Liu et al. provided an overview of digital twin technologies, their enabling technologies, challenges, and open research areas. It discusses how digital twins applied in CAD/CAM processes to enhance design, manufacturing, and maintenance of complex structures [21]. Fan et al. reviewed an overview of digital twin modelling and simulation techniques for design and manufacturing optimization. It discusses the application of digital twins in CAD/CAM processes, including case studies on various industrial sectors [22]. Tang et al. presented a digital twin-based approach for virtual prototyping and optimization of manufacturing processes. It includes a case study on the optimization of a machining process, highlighting the benefits of digital twin simulation in reducing cycle times and improving process efficiency [23]. Assuad et al. reviewed an in-depth analysis of digital twin technology in design and manufacturing. It covers various aspects, including modelling, simulation, optimization, and case studies. The paper highlights the potential of digital twins in improving product quality, reducing costs, and enhancing decision-making [24]. Ruane et al. discussed the integration of CAD/CAM systems with digital twin models and the use of simulation for process optimization. The authors present case studies illustrating the benefits of digital twins in improving product quality and reducing lead times [25].

These selected studies provide a comprehensive understanding of the use of digital twin modelling and simulation in CAD/CAM for complex structures. They highlight the potential benefits, challenges, and various application areas of digital twin technology in optimizing manufacturing processes, improving product performance, and enabling predictive maintenance. Further research in this field continues to explore advanced techniques and methodologies for leveraging digital twins in CAD/CAM applications.

3. Digital Twin Concepts and Frameworks

Predictive analytics and machine learning algorithms often employed to analyse sensor data and historical performance data, enabling real-time monitoring and decision-making. Digital twin modelling and simulation in CAD/CAM can involve the use of integer programming techniques to optimize various aspects of the design and manufacturing process. Integer programming is a mathematical optimization method that deals with decision variables that must take on integer values.

Digital twin modelling and simulation in computer-aided design and manufacturing (CAD/CAM) can involve the use of integer programming techniques to optimize various aspects of the design and manufacturing process. Integer programming is a mathematical optimization method that deals with decision variables that must take on integer values.

3.1 Mathematical Model

The formulation of a mathematical model for digital twin modelling and simulation in CAD/CAM involves representing the relationships and constraints within the system using mathematical equations and variables. Here is a high-level overview of the formulation:

1) Decision Variables: Identify the variables that represent the design and operational decisions within the CAD/CAM system. These variables could include geometric parameters, material properties, scheduling variables, resource allocation variables, etc.

2) Objective Function: Define the objective function that represents the goal or objective of the simulation. This could be minimizing production time, maximizing resource utilization, minimizing

costs, optimizing product performance, or a combination of multiple objectives. The objective function typically expressed as a mathematical expression involving the decision variables.

3) Constraints: Specify the constraints that govern the behaviour of the CAD/CAM system. These constraints can be related to design requirements, manufacturing capabilities, resource limitations, scheduling constraints, material constraints, etc. Formulate these constraints as mathematical equations or inequalities involving the decision variables.

4) Mathematical Models: Incorporate mathematical models that capture the behaviour of the CAD/CAM system into the formulation. This can include geometric models, material models, process models, simulation models, and any other relevant mathematical representations. These models can be expressed as equations that relate the decision variables to the system behaviour.

5) Optimization: Use mathematical optimization techniques to solve the formulated mathematical model. The goal is to find values for the decision variables that optimize the objective function while satisfying the specified constraints. The specific optimization technique will depend on the nature of the problem, such as linear programming, nonlinear programming, integer programming, or other optimization methods.

6) Simulation and Analysis: Once the mathematical model solved, use the obtained values for the decision variables to perform simulations and analyse the behaviour of the CAD/CAM system. This involves running simulations based on the model's equations and evaluating the system's performance under different scenarios and conditions.

It's important to note that the formulation of the mathematical model will depend on the specific objectives, constraints, and variables relevant to the CAD/CAM system being modelled. The level of detail and complexity in the formulation can vary depending on the specific application and requirements. The formulation process may require collaboration between domain experts, mathematicians, and software developers to ensure an accurate and effective representation of the system and its behaviour.

In a digital twin (CAD mathematical model, there can be a wide range of variables and constraints depending on the specific system or object modelled. Here are some common variables and constraints that may be included:

Variables:

1) Geometric Variables: These represent the shape, size, and dimensions of the object or system modelled. They can include parameters such as length, width, height, angles, and curves.

2) Material Properties: Variables that describe the physical properties of the materials used in the system, such as elasticity, density, thermal conductivity, and coefficient of friction.

3) Environmental Variables: Parameters that capture the environmental conditions influencing the system, such as temperature, humidity, pressure, and external forces or loads.

4) Operational Variables: These variables represent the operating conditions or inputs to the system, such as velocity, acceleration, flow rates, or control signals.

5) Performance Variables: Variables that measure the performance or output of the system, such as stress, strain, displacement, temperature distribution, fluid pressure, or energy consumption.

Constraints:

1) Geometric Constraints: These constraints ensure that the geometric relationships and interactions between components or parts of the system maintained. Examples include assembly constraints, clearance requirements, or tolerance limits.

2) Material Constraints: Constraints related to the physical properties of materials, such as maximum allowable stress, strain limits, temperature limits, or fatigue life requirements.

3) Functional Constraints: Constraints that enforce specific functional requirements or specifications of the system. These could include performance targets, efficiency goals, safety regulations, or design standards.

4) Resource Constraints: Constraints related to available resources, such as cost limitations, manufacturing constraints, or time constraints for fabrication or assembly.

5) Compatibility Constraints: These constraints ensure compatibility and consistency between different parts or subsystems of the system. They can include compatibility of interfaces, electrical or mechanical connections, or system compatibility with existing infrastructure or equipment.

These variables and constraints integrated into the mathematical model, which allows for the simulation and analysis of the digital twin. Through the manipulation of these variables and the enforcement of constraints, designers and engineers can explore different scenarios, optimize designs, evaluate performance, and make informed decisions before implementing the physical system.

The equations used in a digital twin CAD mathematical model can vary depending on the specific system modelled and the level of complexity desired. However, here are some general equations that commonly used in digital twin CAD models:

1) Geometric Equations:

* Equation of a line: $y = mx + c$

* Equation of a circle: $(x - a)^2 + (y - b)^2 = r^2$

* Equation of a curve: $f(x, y) = 0$ (where f is a function representing the curve)

2) Material Property Equations:

* Hooke's Law for linear elasticity: $\sigma = E\varepsilon$ (where σ is stress, E is Young's modulus, and ε is strain)

* Heat conduction equation: $q = -k\nabla T$ (where q is heat flux, k is thermal conductivity, and ∇T is temperature gradient)

3) Physical Behaviour Equations:

* Newton's second law of motion: $F = ma$ (where F is force, m is mass, and a is acceleration)

* Euler-Bernoulli beam equation: $EI(d^4y/dx^4) = q(x)$ (where E is Young's modulus, I is moment of inertia, y is displacement, x is position, and q(x) is distributed load)

4) Environmental Equations:

* Convective heat transfer equation: $q = hA(T - T\infty)$ (where q is heat transfer rate, h is convective heat transfer coefficient, A is surface area, T is temperature, and $T\infty$ is ambient temperature)

* Fluid flow equations (e.g., Navier-Stokes equations) for modelling fluid behaviour in the system

5) Sensor Equations:

* Sensor measurement equations: These equations can vary depending on the type of sensor and the physical quantity measured. Examples include voltage-to-temperature conversion equations, strain gauge equations, or displacement sensor equations.

6) Constraint Equations:

* Geometric constraint equations: These equations enforce geometric relationships, such as distance constraints or angle constraints between components.

* Assembly constraint equations: Equations that ensure proper assembly and mating conditions between components.

* Physical constraint equations: Equations that enforce physical limitations, such as stress constraints or temperature constraints.

* Design constraint equations: Equations that capture design requirements or specifications, such as weight constraints or cost constraints.

It's important to note that the specific equations used in a digital twin CAD model will depend on the system being modelled, the complexity of the model, and the mathematical representations chosen to describe the system's behaviour. The equations listed above serve as general examples and may need to be adapted or expanded for specific applications.

The equations used in a digital twin CAD mathematical model will depend on the specific system modelled and the physical phenomena involved. Here are some examples of equations commonly used in digital twin CAD models for different domains:

Structural Analysis:

- Stress-Strain Relationship: $\sigma = E\varepsilon$, where σ is the stress, E is the elastic modulus, and ε is the strain.
- Finite Element Method Equations: These equations represent the behaviour of the structure under applied loads, boundary conditions, and material properties. They involve solving systems of equations derived from the discretization of the structure into finite elements.

Fluid Dynamics:

- Navier-Stokes Equations: These equations describe the motion of fluid under various conditions and include the conservation of mass, momentum, and energy equations.
- Reynolds-Averaged Navier-Stokes (RANS) Equations: These equations commonly used for turbulent flow simulations and involve additional terms for modelling turbulence.
- Boundary Conditions: Equations that define the velocity, pressure, temperature, or other properties at the boundaries of the fluid domain.

Heat Transfer:

- Fourier's Law of Heat Conduction: $q = -k\nabla T$, where q is the heat flux, k is the thermal conductivity, and ∇T is the temperature gradient.
- Convection Equations: Equations that describe heat transfer due to fluid flow and convective heat transfer coefficients.
- Radiation Equations: Equations that represent heat transfer through radiation, considering factors like emissivity, temperature, and surface properties.

Control Systems:

- Control System Equations: These equations represent the behaviour of the control system components, such as sensors, actuators, feedback loops, and control algorithms. They can include differential equations, transfer functions, or state-space representations.

Electromagnetics:

- Maxwell's Equations: These equations describe the behaviour of electric and magnetic fields, including the laws of electromagnetism such as Gauss's Law, Faraday's Law, and Ampere's Law.
- Electromagnetic Wave Equations: Equations that describe the propagation of electromagnetic waves, such as the wave equation or the Helmholtz equation.

Here are some general equations commonly used in digital twin CAD models:

1) Geometry Equations: These equations describe the geometric properties of the object or system modelled. They can include equations for curves, surfaces, or solid models that define the shape and dimensions. Examples include parametric equations, B-spline equations, or equations for geometric transformations.

2) Material Equations: These equations describe the material properties and behaviour of the system. They can include constitutive equations that relate stress to strain for different materials, such as Hooke's law for linear elasticity or more complex material models like plasticity or viscoelasticity equations.

3) Physics Equations: These equations represent the physical behaviour and interactions within the system. They can include equations for motion, deformation, heat transfer, fluid flow, electromagnetic fields, or other relevant physical phenomena. Examples include Newton's laws of motion, conservation of mass and energy equations, or fluid flow equations like the Navier-Stokes

equations.

4) Constraint Equations: These equations enforce the constraints imposed on the system. They can include equations that ensure geometric relationships, assembly constraints, or physical limitations are satisfied. Examples include equations for maintaining distances, angles, clearances, or equations that enforce compatibility between different parts of the system.

5) Boundary Conditions: These equations specify the conditions at the boundaries or interfaces of the system. They can include equations that prescribe the applied forces, displacements, or other boundary conditions based on the system's interaction with its environment or other systems.

It's important to note that the specific equations will vary significantly depending on the complexity and nature of the system being modelled. The equations used in a digital twin CAD model based on first principles, empirical data, or a combination of both. Additionally, numerical methods and simulation techniques employed to solve the equations and simulate the behaviour of the system over time. The development of the mathematical model and the associated equations requires expertise in the specific domain and an understanding of the physical phenomena and interactions involved in the system being modelled.

4. Case Study

A schema for digital twin CAD typically involves the organization and structure of data and information related to the digital twin. It defines the entities, attributes, and relationships that represent the physical product or system and its digital counterpart. While the specific schema can vary depending on the CAD software or platform used, some common elements found in a digital twin CAD schema in below:

1) Product Representation:

Geometry: This includes the representation of the product's shape, dimensions, and spatial relationships. It may involve geometric primitives, parametric models, or more complex representations like point clouds or meshes.

Material Properties: Attributes that describe the physical behaviour of materials used in the product, such as elasticity, stiffness, thermal conductivity, and density.

Kinematics: Attributes related to the product's movement, including joint angles, displacements, velocities, and constraints.

2) Manufacturing Information:

- Bill of Materials (BOM): A hierarchical list of components, sub-assemblies, and materials required to manufacture the product.

- Process Information: Data related to the manufacturing processes involved in producing the product, such as machining operations, assembly steps, and quality control checkpoints.

3) Simulation and Analysis Data:

- Simulation Models: Information related to the mathematical models used for simulating the product's behaviour, including structural analysis, fluid dynamics, heat transfer, or other physical phenomena.

- Simulation Results: Data generated from simulations, such as stress distributions, temperature profiles, or fluid flow characteristics.

4) Control and Optimization Data:

- Control Algorithms: Information about the control algorithms or strategies used to regulate and optimize the product's performance.

- Optimization Parameters: Attributes representing the design or operational parameters that are optimized to achieve specific performance objectives, such as efficiency, strength, or cost.

5) Sensor and Data Integration:

- Sensor Data: Information captured from sensors.

To conduct a comprehensive literature survey, it would be advisable to search academic databases, conference proceedings, and relevant journals in the fields of CAD/CAM, digital twin technology, and manufacturing engineering. This will provide you with up-to-date research articles, papers, and studies on the topic.

First, a map of what needs to be done for a new model vehicle on which improvement is desired to be made on the design phase and production structure has been drawn. The design structure was clarified, and then the production of this design structure with the existing system was discussed and process improvement was discussed over 2 different scenarios. In the design, it foreseen to improve the material, production methodology, fixture, apparatus and/or all parts to be used together with the study.

In this study, the chassis and engine selections of a factory that can produce 4 models with 2 different chassis types and 2 different engine options were determined randomly. After the necessary additions made with a combination depending on the relevant engine type and chassis option, it was transferred to the relevant production line determined with the help of sensors and people in the first stage, and then the assembly situation was discussed for the necessary add-on sequence. In this position, it has been observed that the points clearly determined on the static report evaluation and graphics have improved. Line structures that create waiting and blocking in other cases that are complex and unnecessary have been removed and a single line structure is considered where all resources can effectively interfere with all models. Increasing the stock area and re-evaluating its outputs on indicators were discussed. Product-based setup times, error rates, and pre- and post-editing thesis were also handled as a simulation model. In this study, different case scenarios, improvements, and contributions to the proposed model were shown in Figure 1.

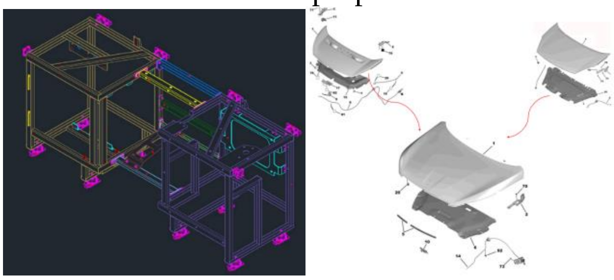

Figure 1: Improvement in Design with Collaboration

Along with the design improvement, product accompanyment is provided in models consisting of structures of different shapes, thereby reducing production times, cost, equipment used, etc. gains from many aspects. In addition, material selections have been made to facilitate use. By simulating the strength of the part, it is checked that it meets the sufficient values, then at the point where it seems insufficient, the alloy is changed and simulated again. Welding combinations in the parts rearranged depending on the type of metals used and the simulation is continued with this information. At points where body strength is not required, weight savings achieved and improvements were made by using AL alloys. It is +5/-5 mm in 3 axes (x, y, z) for different welding responses in different material types. In addition, for situations that fall within the relevant tolerances but will differ from product to product, mounting provided by using a spacer plate (shim). Additionally, out-of-tolerance values evaluated with simulation outputs for conditional Acceptance. It is the same in structure, only the source methodology has been changed in accordance with a1. Post-weld dimensions tolerance values filled and reduced by placing a shim between the parts visible in pink and the carcass. This improvement has been made with the Digital twin. We used the ATI V5 R6 drawing program. There is no dimensional change. The dimensions of the product are 1815x724x570 mm. The related part table weight is 82 kg steel. It comes with 27.5 kg aluminum.

5. Conclusion

Digital twin modelling and simulation of CAD/CAM structures has emerged as a powerful approach in the field of engineering and manufacturing. In this conclusion, we summarize the key findings and implications of the research.

Enhanced Design and Manufacturing Efficiency: The adoption of digital twin technology in CAD/CAM structures allows for real-time monitoring, analysis, and optimization of the entire product lifecycle.

Predictive Maintenance and Fault Detection: Digital twin simulations enable engineers to predict potential failures and faults in the early stages of the product lifecycle. This capability allows for proactive maintenance, reducing downtime and minimizing operational costs.

Virtual Prototyping and Testing: The ability to create virtual prototypes and conduct simulations before physical production has significant cost-saving benefits. Digital twin technology facilitates rapid iterations and design improvements, thereby accelerating the development process.

Resource Optimization: With real-time data and simulations, manufacturers can optimize resource allocation, including materials, energy, and equipment usage. This optimization leads to a more sustainable and cost-effective manufacturing process.

Collaboration and Communication: Digital twin technology promotes collaboration and communication between various teams involved in the product lifecycle, such as design, manufacturing, and maintenance. It enhances cross-functional understanding and facilitates data sharing, leading to better decision-making.

Integration with Industry 4.0: Digital twins are a crucial component of Industry 4.0 initiatives. They integrate with other advanced technologies like IoT sensors, AI, and big data analytics, further enhancing the capabilities and insights derived from the digital twin models.

Challenges and Future Directions: While the potential benefits of digital twin modelling and simulation are significant, there are challenges that need to addressed. These include data security and privacy concerns, integration with legacy systems, and the need for skilled personnel to manage and interpret the vast amounts of data generated.

In conclusion, the adoption of digital twin modelling and simulation in CAD/CAM structures offers immense potential to transform the engineering and manufacturing industries. By harnessing the power of real-time data and predictive capabilities, businesses can achieve increased efficiency, reduced costs, and improved product performance. However, successful implementation requires a strategic approach that addresses challenges and maximizes the benefits of this transformative technology. As the field continues to evolve, digital twin technology expected to play a pivotal role in shaping the future of engineering and manufacturing.

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