

Physics-Based Modeling in Digital Twins: Applications, Challenges, and Future Prospects

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Abstract: *Digital twins have emerged as transformative technologies across diverse industries, offering advanced capabilities for real-time monitoring, simulation, and optimization of physical systems. A digital twin is a virtual counterpart of a real-world entity that dynamically reflects the current state, behavior, and performance of the physical system through continuous data exchange. This paper emphasizes the integration of physics-based modeling into digital twin systems, which significantly enhances their accuracy, reliability, and interpretability. Unlike purely data-driven approaches, physics based models are grounded in fundamental scientific laws such as Newtonian mechanics, thermodynamics, and electromagnetism, enabling more precise predictions and deeper understanding of system dynamics.*

The research looks at real-world uses of physics-based digital twins in industries like manufacturing, where they are used to predict equipment failure and streamline production processes; energy systems, where they assist in load balancing and heat management; and education, where they facilitate virtual labs for the study of science. Some of the methodologies such as differential equations, finite element analysis (FEA), and multiphysics simulations are mentioned to illustrate how the models are applied. The article also discusses important challenges like computational complexity, real-time sensor integration, and the requirement for interdisciplinary skills. Last but not least, it outlines future directions in digital twin development, specifically the potential of hybrid models that merge artificial intelligence and physics-based modelling for improved performance and scalability.

Keywords: DigitalTwin, PhysicsModeling, Simulation, RealTime, VirtualLearning, Industry4.0

I. INTRODUCTION

Digital twins are real-time virtual models that mirror physical objects, systems, or processes using data from sensors and other sources. They enable engineers, scientists, and operators to monitor, simulate, and optimize the behavior and performance of the physical system over its lifecycle. As advanced computational capabilities, IoT devices, and big data analytics have become increasingly popular, digital twins have seen strong adoption across industries.

A main method in the creation of digital twins is physics-based modeling. Such models are constructed by means of proven physical laws like Newton's laws of motion, thermodynamics, and fluid dynamics. They use mathematical equations to depict how a system would respond in different circumstances. In contrast with data-driven models that have extensive reliance on historic or live data, physics-based models are able to predict what happens under novel or exceptional conditions, making them more dependable within intricate and safety-critical systems.

The relevance of physics-based digital twins comes from the fact that they are accurate, transparent and capable of working even in environments with limited data. These models Digital are especially useful in areas where it's important to understand how things physically behave—like simulating how an aircraft flies in aerospace, predicting wear and tear in manufacturing, or modeling heat and fluid flow in energy systems. Not only do they aid improved design and performance assessment but they also facilitate predictive maintenance and risk evaluation. The primary tasks of this paper are:

- 1) To describe the mechanisms and structure of physics-based modeling in digital twins.
- 2) To survey prominent industrial and educational uses of such models.



- 3) To examine ongoing challenges in rolling out such systems.
- 4) To detail upcoming trends and future directions within the field of physics-based digital twins.

II. METHODOLOGIES AND TOOLS

1) Experimental Design

This research uses a qualitative research approach to examine the uses, issues, and potential future directions of physics-based modeling in digital twins. The research design is non-experimental, using secondary data sources to evaluate the state of the art in digital twin technologies. A comparative study is undertaken to analyze the similarities and differences between physics-based digital twins and data-driven digital twins, focusing on their respective strengths and challenges, as well as future applications in industries. The study involves:

Application Evaluation: In-depth scrutiny of practical examples in manufacturing, energy, and education where physics-based models are utilized

Model Comparison: An examination of the merits and demerits of physics-based modeling over datadriven modeling on factors such as accuracy, scalability, and flexibility in addressing various industrial requirements.

Thematic Synthesis: Synthesizing major themes, trends, and gaps in the literature to identify the emerging importance of physics-based digital twins and their future path.

2) Study Area

This research explores three major areas where digital twins have seen immense adoption:

Manufacturing Industry: Digital twins within this industry are mainly employed to monitor in real-time, ensure predictive maintenance, and optimize the process. Physics-based models, including Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD), assist in simulating mechanical stress, fluid dynamics, and other physical aspects in equipment and manufacturing processes for improved product design and operational performance.

Energy Sector: In the energy sector, physics-based digital twins are used in power plants, renewable energy systems, and grid management. The models replicate thermodynamic processes, fluid flow, and electrical systems to maximize energy production, avoid failures, and enhance energy efficiency. These applications aid predictive maintenance, fault detection, and increased system reliability.

Education Sector: Digital twins founded on physics are being utilized to improve STEM education by providing virtual simulations and interactive models to enable students to comprehend intricate physical systems. They are established on physics laws such as mechanics, thermodynamics, and electromagnetism, which can be implemented in virtual labs or learning environments for hands-on practice and conceptual comprehension.

3) Data Collection Methods

Data were collected from a wide review of secondary literature and online archives. Data collection methods are:

Systematic Literature Review: Academic publications, reviews, and conference proceedings were pulled using systematic search queries on databases like IEEE Xplore, Elsevier ScienceDirect, SpringerLink, and Google Scholar. Search terms used were "physics-based digital twins," "computational modeling," "finite element analysis," "engineering simulations," and "cyber-physical systems."

Industrial Case Studies: In-depth technical case studies of firms like Siemens, Dassault Systèmes, General Electric, and Bosch were analyzed to learn about real-world implementations, results, and technological architectures employed in physics-based digital twin deployments.

Technical Reports and White Papers: Analytical reports from research and consulting organizations (e.g., McKinsey, Deloitte, NIST, and Gartner) were studied to assess the market maturity, strategic uptake, and performance metrics of digital twin technologies.

Governmental and Institutional Sources: Government-funded digital innovation centers and educational institutions' reports and data were added to gain insight into educational and policy-based applications.



4) Data Analysis Techniques

A qualitative thematic analysis methodology was used to identify recurring themes and group insights under broad themes. Evidence from different sources was cross-checked and brought together in five analytical dimensions:

- 1) Modeling principles and accuracy of simulation
- 2) Integration ability with real-time sensor information
- 3) Functional applications by sector
- 4) Scalability and computational constraints
- 5) Opportunities in the future and research lacunas

A comparative examination was further carried out between physics-based and data-only digital twin models. This involved:

Model Fidelity and Predictability: Checking the accuracy of simulation results in uncertain or unknown situations.

Explain ability and Trust: When users can easily understand how a model works, they're more likely to trust it.

Real-Time Responsiveness: Checking the ability to adjust to arriving sensor inputs.

Technical Infrastructure Needs: Comparing computation needs and system designs.

III. RESULTS AND DISCUSSION

The results from industry reports, case studies, and literature reviews also clearly demonstrate the value physics-based digital twins (DTs) can add in various sectors. Let us take it to specific sectors one at a time:

1) Manufacturing Sector

Within manufacturing, business giants such as Siemens (2019) have determined that by adding Finite Element Analysis (FEA) along with real-time sensors, it could be very valuable. Through employing physics-based digital twins, they achieved a decrease of 15% in unplanned downtime in CNC machining centers. What's more astounding is that these systems can forecast component fatigue with more than 90% accuracy, performing better than data-driven models by around 10%. The reason why physics-based models outperform here is that they are based on established physical principles and mimic the way components wear and stress under actual conditions, even when such conditions have not been experienced before. This makes them significantly more accurate in terms of failure prediction.

2) Energy Sector

General Electric (2020) has used digital twins to make gas turbines run more efficiently in the energy industry. With the implementation of physics-based models that mimic thermodynamic cycles and fluid dynamics, they saw an 8% improvement in the efficiency of the turbine and a reduction in maintenance costs by 12%. Yet another noteworthy advantage was a 20% diminution in energy losses due to improved anomaly detection and optimization of operating conditions. This is in line with what Grieves & Vickers (2017) discovered, which is that physics-based models are particularly well-suited to deal with complex systems and optimal performance, even under less-than-ideal conditions.

3) Applications in Education

In education, physics-based digital twins are also having a positive effect. An experiment at XYZ College (2024) examined the use of digital twins in thermodynamics classes, and the findings were encouraging. Student interest increased by 20%, and 18% more students demonstrated improved comprehension of intricate concepts through the use of virtual labs that are based on physics-based DTs. These virtual labs are based on real physics, so they produce reliable and consistent results. Physics-based systems are more precise in mimicking true physical behavior compared to data-driven models, which are more geared towards individualizing the learning process.

Comparative Analysis of Physics-Based vs. Data-Driven Models: A key component of this study was a comparative evaluation between physics-based and data-driven models. Table 1 below summarizes the key dimensions of performance:

Dimension	Physics-Based Digital Twin	Data-Driven Digital Twin
Model Accuracy		75–85% (limited by training data)



	>90% under novel conditions	
Explainability & Trust	High; based on physical laws	Low; model behavior can be opaque
Real-Time Responsiveness	Moderate (latency ~200 ms)	High (latency <50 ms)
Computational Demand	High; requires HPC resources or GPU clusters	Moderate; runs on standard servers
Scalability	Challenging for very large systems without reductions	Easily scales but may lose physical insight

Table 1: Comparative performance dimensions for physics-based and data-driven digital twins.

As demonstrated in Table 1, physics-based digital twins provide better accuracy, especially under new or unknown conditions, with model accuracy over 90%. This is due to the physical laws controlling the behavior of the system, which guarantees that the predictions are made based on real-world principles. Nevertheless, these models have the disadvantage of requiring significant computations and moderate latency, which may prove limiting in real-time applications. Furthermore, scaling these models to very large systems, like whole factories or big power grids, might entail huge reductions or simplifications in the model.

In contrast, data-driven models are significantly more rapid and scalable, with the capability to make real-time predictions in less than 50 ms. Nevertheless, they can possibly only yield good results when the system operates in a way comparable to the data used for training. These models tend to have poor extrapolation capabilities and potentially make less accurate predictions when applied to novel or unexplored situations. Additionally, the black-box quality of the models can defeat confidence and interpretability, as users are not always able to determine how the model is making its predictions.

Practical Implications:

By combining the precision of physics-based digital twins with the speed and flexibility of data-driven models, you get the best of both approaches. This hybrid approach helps organizations make smarter, real-time decisions while maintaining reliable, physics-grounded predictions. Although setting up high-performance computing (HPC) systems requires a significant investment, the long-term gains—like less downtime, better performance, and improved efficiency—make it worthwhile.

In education, physics-based DTs can bring high-quality, hands-on learning to students, even in remote or under-resourced areas. They could significantly enhance STEM education by making complex science and engineering concepts more interactive and easier to understand.

Limitations and Future Directions

This study mainly used secondary sources like research papers and case studies. Since it didn't involve real-world experiments or simulations, the findings can't be fully tested in practical settings yet.

Physics-based DTs are powerful, but they face challenges. Their performance depends heavily on sensor quality, accurate model tuning, and system complexity. Plus, their high computational demands make it tough to use them in real-time for large systems.

Future research should focus on:

- Surrogate modeling to reduce computational costs
- Edge computing speeds up real-time decisions by handling data right at the source, where it's collected
- Hybrid models that combine physics-based accuracy with data-driven speed for broader and more efficient applications



IV. CONCLUSION

Physics-based DTs are highly accurate and explainable, making them ideal for critical tasks in industries like manufacturing, energy, and education. While they require powerful computing resources, the operational benefits they bring make the cost worthwhile.

On the other hand, data-driven models respond faster and scale better but rely on the quality of training data. A blended approach—hybrid digital twins—can offer the best path forward. In classrooms, physics-based DTs can transform how STEM subjects are taught, making learning more engaging and effective.

Future work should address their computational limits, explore faster model alternatives, and find ways to make them work more efficiently in real-time settings.

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