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Digital Twin and Co-Simulation Techniques for Cyber-Physical Control Systems: A Review

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Abstract: *Cyber-physical control systems integrate computational intelligence, communication networks, sensing technologies, actuators, and physical processes to achieve real-time monitoring and automated control. The increasing complexity of these systems has created a strong need for advanced modelling, simulation, testing, prediction, and control techniques. Digital Twin (DT) technology provides a dynamic virtual representation of a physical system that can exchange information with its physical counterpart, while co-simulation enables multiple heterogeneous models, simulators, and computational environments to operate together.*

The combination of Digital Twin and co-simulation techniques provides a promising framework for designing, validating, monitoring, optimizing, and controlling complex cyber-physical systems. Existing research demonstrates that digital twins can support real-time visualization, predictive analysis, fault detection, condition monitoring, adaptive control, and testing of cyber-physical systems.

Keywords: Digital Twin, Co-Simulation, Hardware-in-the-Loop, Functional Mock-up Interface, Predictive Control.

I. INTRODUCTION

Cyber-physical systems have emerged as an important technological paradigm in which computational processes interact continuously with physical environments through sensing, communication, computation, and actuation. Cyber-physical control systems extend this concept by placing control algorithms and decision-making mechanisms at the centre of the interaction between digital and physical components. Such systems are increasingly used in smart manufacturing, robotics, autonomous vehicles, energy systems, smart grids, transportation, aerospace, healthcare equipment, and industrial automation.

The integration of multiple domains makes these systems difficult to design and validate because their behaviour depends not only on physical dynamics but also on software execution, communication delays, network conditions, controller performance, sensor uncertainty, and cyber events. Digital Twins have emerged as an important mechanism for addressing these challenges because they provide a dynamic digital representation connected to a physical system. Tao et al. described Digital Twins as an important element of smart manufacturing and emphasized their relationship with cyber-physical integration, real-time interaction, and intelligent decision-making.

A major challenge in developing a Digital Twin for a complex control system is that no single modelling environment can efficiently represent every subsystem. For example, a mechanical component may require a multi-body dynamics simulator, an electrical subsystem may require circuit simulation, the controller may be implemented in MATLAB/Simulink or another control environment, while the communication network may require a discrete-event simulator. Co-simulation provides a solution by allowing heterogeneous models to communicate during execution. Instead of replacing all models with one monolithic model, co-simulation coordinates specialized models through defined interfaces and synchronization mechanisms. The resulting environment can therefore represent physical dynamics, control algorithms, communication networks, embedded software, and external disturbances simultaneously.

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II. DIGITAL TWIN IN CYBER-PHYSICAL CONTROL SYSTEMS

A Digital Twin can be understood as a continuously connected digital representation of a physical object, process, or system. Unlike a conventional simulation model, a Digital Twin is generally associated with continuous data exchange between the physical and digital domains. In a cyber-physical control system, sensors collect information from the physical process and transfer it to the digital environment. The Digital Twin processes the information, estimates the current state, performs simulation or prediction, and can provide information back to the control system. This bidirectional relationship creates a feedback loop between the physical and cyber domains. Research comparing CPS and Digital Twins highlights that both technologies depend on intensive cyber-physical connectivity and real-time interaction, while the Digital Twin particularly emphasizes the virtual representation and mapping of a physical entity.

The Digital Twin architecture normally consists of a physical layer, data acquisition layer, communication layer, digital model layer, analytics and simulation layer, and application or control layer. The physical layer contains sensors, actuators, machines, processes, and environmental elements. The data acquisition layer collects measurements such as temperature, pressure, speed, vibration, position, current, voltage, and operational status. The communication layer transports data between the physical and virtual environments. The digital model represents system behaviour using mathematical, physical, data-driven, or hybrid models. Analytics and simulation mechanisms use these models for diagnosis, prediction, optimization, and control. Finally, the application layer uses the resulting information to support decision-making and automated control.

Digital Twins can also be differentiated according to their level of coupling. A conventional digital model may exist independently of the physical system. A digital shadow receives information from the physical system but does not necessarily send control information back. A full Digital Twin establishes a more interactive relationship in which information can flow in both directions. This distinction is particularly important for control applications because closed-loop interaction requires synchronization, causality, timing, and validation of information exchanged between the physical and digital components.

III. CO-SIMULATION TECHNIQUES

Co-simulation is a simulation methodology in which two or more simulation models execute together while exchanging variables during the simulation process. Each subsystem can use an appropriate modelling formalism and solver. For cyber-physical control systems, co-simulation can combine continuous-time physical models, discrete-event communication models, controller models, software components, and hardware interfaces.

The main advantage of co-simulation is modularity. A complex system can be decomposed into manageable subsystems, with each subsystem represented by an appropriate simulator. This reduces the requirement to develop a single comprehensive simulation model. It also enables existing validated models to be reused. Another important advantage is the ability to investigate interactions among heterogeneous domains. For example, an electric vehicle Digital Twin can combine vehicle dynamics, battery models, power electronics, motor control, charging infrastructure, and communication models within a single coordinated simulation environment.

Co-simulation generally requires three important mechanisms: model interfaces, data exchange, and synchronization. Model interfaces determine which variables are exchanged among simulators. Data exchange determines the direction, frequency, and format of communication. Synchronization determines how individual simulators advance their simulation clocks. Errors in synchronization can lead to inaccurate or unstable results, especially when the system contains fast control loops or strong feedback interactions.

Recent work on efficient simulation tools for Digital Twins identifies multi-domain modelling, real-time synchronization, large differential-algebraic equation systems, event-based dynamics, and efficient simulation-code generation as important challenges for future Digital Twin development.

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IV. DIGITAL TWIN–CO-SIMULATION ARCHITECTURE

The integration of Digital Twin and co-simulation creates a layered environment in which the physical system operates in parallel with a collection of interacting virtual models. The physical system provides sensor information to the Digital Twin. The Digital Twin distributes the information to different simulation components, including physical-process models, controller models, communication models, and AI-based analytical models. The co-simulation framework coordinates these components and produces predictions or control recommendations. Where appropriate, control outputs are transmitted to the physical system through actuators.

A simplified architecture can be represented as:

Physical System → Sensors → Data Acquisition → Digital Twin → Co-Simulation Models → Analysis/Prediction → Controller → Actuators → Physical System

The architecture may also include cloud and edge computing. Edge-based Digital Twins are useful when control decisions must be made with low latency, whereas cloud-based environments can provide large-scale computation, historical analysis, optimization, and model training. Hybrid edge-cloud architectures can therefore distribute computational tasks according to timing and resource requirements.

V. MAJOR TECHNIQUES USED IN DIGITAL TWIN AND CO-SIMULATION

Several techniques have become important for implementing Digital Twin-based cyber-physical control systems. Model-based simulation uses mathematical and physical equations to reproduce system behaviour. Data-driven modelling uses operational data and machine-learning methods to approximate system behaviour. Hybrid modelling combines physical knowledge with data-driven models and is increasingly attractive because it can provide better adaptability while maintaining physical consistency.

Functional Mock-up Interface (FMI) is another important technology for model exchange and co-simulation. FMI allows simulation models to be packaged as Functional Mock-up Units and exchanged between compatible simulation environments. This supports interoperability and helps integrate models created using different software tools. Hardware-in-the-loop (HIL) simulation extends co-simulation by replacing one or more simulated components with real hardware. This approach is particularly useful for testing controllers before deployment because the controller can interact with a simulated plant under controlled and repeatable conditions.

Software-in-the-loop (SIL) simulation similarly enables control software to be tested against simulated plant models. Processor-in-the-loop and controller-in-the-loop approaches provide intermediate levels of realism. These techniques allow progressively more realistic validation while reducing the cost and risk associated with testing directly on physical equipment.

VI. APPLICATIONS IN CYBER-PHYSICAL CONTROL SYSTEMS

Digital Twin and co-simulation techniques have broad applications. In smart manufacturing, they can model production equipment, robotic systems, material flows, and controllers. Digital Twins can predict machine behaviour, identify abnormal conditions, and support production optimization. In energy systems, Digital Twins can represent power converters, batteries, turbines, microgrids, and renewable-energy systems. Co-simulation can combine electrical-network models with communication and control models to examine system stability and control performance.

In autonomous vehicles and robotics, Digital Twins can be used to test navigation, motion control, perception, and decision-making algorithms under different environmental conditions. The digital environment enables repeated experiments without exposing physical equipment to unnecessary risk. Digital-twin-based testing research has identified manufacturing, pumps, engines, batteries, power converters, turbines, drones, and 3D printers among the cyber-physical applications investigated in the literature.

Digital Twins are also useful for predictive maintenance. Sensor data can be continuously compared with simulated behaviour to identify deviations that may indicate degradation or faults. This capability enables maintenance decisions to be based on predicted system condition rather than only on fixed maintenance schedules. Recent research further

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highlights the use of Digital Twins for simulation, predictive maintenance, real-time optimization, and adaptive intelligent systems.

VII. COMPARATIVE ANALYSIS OF MAJOR TECHNIQUES

Technique	Main Purpose	Major Strength	Major Limitation	Typical CPS Application
Digital Twin	Dynamic virtual representation of physical system	Real-time monitoring and prediction	Requires accurate models and reliable data	Manufacturing, energy, robotics
Co-Simulation	Integration of heterogeneous simulation models	Supports multi-domain modelling	Synchronization complexity	Integrated control systems
FMI	Model exchange and interoperability	Enables model reuse across tools	Interface and compatibility issues	Industrial simulation
Software-in-the-Loop	Test control software using simulation	Low-cost and repeatable testing	Does not fully reproduce hardware effects	Embedded control
Hardware-in-the-Loop	Test real hardware with simulated plant	High realism without full physical system	Expensive and technically demanding	Automotive, aerospace, power electronics
Model-Based Simulation	Simulate physical and control dynamics	Strong physical interpretability	Computational complexity	Control design
Data-Driven Modelling	Learn system behaviour from data	Adaptable to complex systems	Requires high-quality datasets	Fault detection and prediction
Hybrid Modelling	Combine physical and data-driven models	Balances interpretability and adaptability	Model-development complexity	Predictive control
Real-Time Simulation	Execute simulation within operational time constraints	Supports online control/testing	High computational requirements	Industrial control
Cloud-Based Simulation	Large-scale computation and analytics	Scalable computational resources	Network latency and security concerns	Smart factories
Edge-Based Digital Twin	Local real-time monitoring/control	Low latency	Limited local resources	Robotics and IoT
HIL Co-Simulation	Combine real hardware with multiple simulated subsystems	High-fidelity validation	Integration and synchronization challenges	Autonomous and embedded systems

VIII. ADVANTAGES OF DIGITAL TWIN AND CO-SIMULATION

The combined approach provides several important benefits. First, it improves system development by allowing engineers to evaluate designs before physical deployment. Second, it supports continuous monitoring and predictive analysis during system operation. Third, co-simulation allows heterogeneous models to remain modular and reusable. Fourth, Digital Twin environments can support fault diagnosis by comparing measured and simulated behaviour. Fifth, HIL and SIL approaches enable systematic testing of controllers under different operating conditions.

Another important advantage is risk reduction. Safety-critical systems can be exposed to abnormal conditions within the virtual environment without physically damaging equipment. Digital-twin-based testing has been identified as a growing

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area because Digital Twins can provide dynamic representations against which cyber-physical behaviour can be evaluated. However, systematic research also indicates that many existing applications remain focused on passive or conformance-oriented testing, suggesting a need for more active and predictive testing approaches.

IX. CHALLENGES AND RESEARCH GAPS

Despite their potential, Digital Twin and co-simulation systems face several challenges. The first is model fidelity. A Digital Twin must be sufficiently accurate to provide useful predictions, but highly detailed models can require substantial computational resources. The second challenge is synchronization. When multiple simulators operate at different time steps, incorrect synchronization may introduce numerical errors or unstable control behaviour.

Interoperability is another major challenge. Different simulation environments may use different modelling languages, data structures, solvers, and communication protocols. Standards such as FMI help address this problem, but complete interoperability remains difficult. Data quality is also important because sensor errors, missing values, communication delays, and measurement noise can affect the Digital Twin.

Cybersecurity is particularly important because the Digital Twin creates additional communication and computational interfaces. Attackers could attempt to manipulate sensor data, compromise simulation models, inject false information, or interfere with control commands. Consequently, future Digital Twin architectures need secure communication, authentication, access control, anomaly detection, and trustworthy data management.

Validation and verification also remain important research gaps. A Digital Twin cannot automatically be assumed to be a correct representation of its physical counterpart. The literature has emphasized that Digital Twin-based testing may rely on the assumption that the twin itself is sufficiently accurate, creating a need for stronger validation procedures and uncertainty analysis.

X. FUTURE RESEARCH DIRECTIONS

Future research should focus on developing standardized architectures for Digital Twin and co-simulation-based control systems. Greater attention is required for real-time synchronization, automated model calibration, uncertainty quantification, and adaptive model updating. Artificial intelligence and machine learning can be integrated with physics-based Digital Twins to create hybrid models capable of learning from operational data while preserving physical constraints. Recent reviews identify hybrid Digital Twins, scalable verification and validation, uncertainty management, interoperability, and real-time reliability as important emerging research areas.

Another important direction is the development of scalable co-simulation environments for large systems of systems. Future frameworks should be capable of coordinating thousands of interconnected components while maintaining acceptable latency and numerical accuracy. Edge-cloud collaboration can further improve scalability by placing latency-sensitive control functions near the physical system while assigning computationally intensive analytics to cloud infrastructure. Research is also needed on automated generation of simulation code, real-time reduced-order modelling, secure Digital Twin communication, and autonomous controller adaptation.

XI. CONCLUSION

Digital Twin and co-simulation techniques represent complementary approaches for addressing the complexity of modern cyber-physical control systems. Digital Twins provide dynamic virtual representations that can support monitoring, diagnosis, prediction, optimization, and control, while co-simulation provides the mechanism for integrating heterogeneous models and simulation environments. Their combination enables engineers to reproduce complex interactions among physical processes, controllers, communication networks, software, and intelligent decision-making mechanisms. The literature indicates significant potential in manufacturing, robotics, energy, transportation, autonomous systems, and other safety-critical applications. At the same time, challenges related to synchronization, interoperability, computational efficiency, model fidelity, cybersecurity, uncertainty, and verification remain unresolved. Current research is moving toward hybrid, intelligent, scalable, and real-time Digital Twin environments. Therefore, future cyber-physical control systems are likely to depend increasingly on integrated Digital Twin and co-simulation platforms capable of continuous model updating, secure data exchange, predictive analysis, and adaptive control.

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