

DIGITAL TWIN CONSTRUCTION AND REAL-TIME SYNCHRONOUS KINEMATIC MAPPING FOR HYDRAULIC EXCAVATORS

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Abstract - The demand for real-time digital twins in heavy industry, particularly for hydraulic excavators, has grown substantially, driven by the pressing need to enhance operational safety and efficiency. Nevertheless, achieving high-fidelity physical-virtual synchronization in real time remains challenging due to pronounced transmission latency, sensor noise, and the excessive computational burden of multiphysics simulations. To tackle these issues, we present a physics-informed digital twin framework dedicated to real-time synchronous mapping. The proposed architecture synergistically integrates a multiphysics reduced-order model (ROM) that captures the coupled hydraulic-mechanical dynamics, an Extended Kalman Filter (EKF) that suppresses high-frequency noise and estimates unmeasurable states, and a State-Predictive Delay Compensation (SPDC) algorithm that effectively counteracts system latency. The framework was experimentally validated on a 1.5-ton hydraulic excavator test rig, interfaced with a Unity 3D virtual environment through an EtherCAT (a real-time industrial Ethernet protocol) and TCP/IP (standard network communication) network. Experimental results corroborate that the integrated system reduces the Mean Absolute Error (MAE) of kinematic tracking by 90.9% and curtails the synchronization delay to 4.8 ms. By bridging the gap between high-fidelity simulation and real-time execution, this work furnishes a robust, low-latency synchronization solution, with profound implications for cyber-physical systems, virtual commissioning, and teleoperation of heavy machinery.

Keywords: Digital twin; Hydraulic excavator; Reduced-order model; Delay compensation; State estimation.

1. Introduction

1.1 Background of Digital Twins in Construction Machinery

The evolution of digital twin technology has profoundly transformed the landscape of heavy industry, driving a transition from static virtual representations toward dynamic, bidirectional cyber-physical systems. In construction machinery, digital twins are instrumental in bolstering operational safety, enabling predictive maintenance, and optimizing cycle efficiency. By establishing a real-time virtual counterpart, operators and engineers can simulate complex tasks and predict failures before they occur in the physical environment. This technology is particularly advantageous for hydraulic excavators, which operate in dynamic and often hazardous environments. Recent studies have leveraged digital twins to model and optimize operator performance

via advanced simulation platforms [1], while complementary efforts have integrated extended reality environments with game engines such as Unity to enable real-time interactive virtual control of excavator systems [2].

1.2 Challenges in Real-Time Synchronization and Latency

Despite their evident advantages, achieving real-time synchronization remains a substantial hurdle owing to cumulative latencies. These delays arise from multiple sources, including sensor signal filtering, communication protocol overhead, and the intrinsic response time of hydraulic control valves. When compounded by high-frequency sensor noise, these delays substantially undermine the fidelity of physical-to-virtual mapping, manifesting as visual lag and spatial misalignment. Traditional digital twin

frameworks often concentrate on retrospective analyses, e.g., assessing the circular-economic impacts of hydraulic innovations [3], or are strictly confined to structural condition monitoring without addressing real-time motion synchronization [4]. Moreover, existing pure kinematic mapping methods inadequately accommodate dynamic latencies, which induces notable trajectory deviations and renders them ill-suited for high-precision real-time applications.

1.3 Objectives of the Study

To overcome these synchronization bottlenecks, this study aims to develop a low-latency, high-fidelity digital twin mapping system for hydraulic excavators. The objective is achieved by integrating a multiphysics reduced-order model (ROM), an Extended Kalman Filter (EKF), and a state-predictive delay compensation (SPDC) algorithm into a unified real-time framework. Unlike traditional virtual-real mapping approaches that rely on heavy computational models, this framework leverages a simplified yet highly accurate dynamic representation. This approach is conceptually motivated by digital twin frameworks developed for large hydraulic machinery, e.g., free forging presses, which employ 3D visualization engines to sustain real-time alignment between virtual and physical states [5]. By synthesizing these methodologies, the proposed system minimizes latency while preserving high tracking accuracy under dynamic operating conditions.

1.4 Key Contributions of the Paper

The principal contributions of this work are fourfold:

- A real-time multiphysics reduced-order model (ROM) is developed to capture the complex hydraulic-mechanical coupling within 0.15 ms.
- An EKF-based sensor fusion algorithm is implemented to suppress high-frequency noise and to estimate unmeasured states.
- A physics-informed SPDC algorithm is proposed, which leverages ROM-derived acceleration to predict future kinematic states.
- The proposed framework is experimentally validated, achieving a 90.9% reduction in trajectory tracking error and a synchronization delay of merely 4.8 ms.

This framework advances the state-of-the-art in real-time monitoring and optimization of proprietary hydraulic systems [6] by successfully mitigating physical control delays and sensor noise without sacrificing computational efficiency.

1.5 Outline of the Paper

The remainder of this paper is structured as follows. Section 2 reviews the related work, focusing on digital twin applications in heavy industry and real-time control methodologies. Section 3 details the proposed methodology, describing the overall closed-loop system architecture, the development of the multiphysics reduced-order model, the EKF state estimation, and the formulation of the SPDC algorithm. Section 4 outlines the experimental setup, detailing the hardware-in-the-loop test rig and sensor configurations. Section 5 presents the experimental results and provides a comparative analysis of kinematic mapping accuracy and dynamic response. Section 6 discusses on the synchronization performance, the physical constraints of the predictor, and the limitations of the current system, and Section 7 concludes the paper.

2. Related Work

2.1 Digital Twin Applications in Heavy Industry

The concept of the digital twin has emerged as a cornerstone for the digitalization of heavy machinery, enabling real-time monitoring, virtual testing, and predictive maintenance. In hydraulic systems, digital twins have been widely deployed to monitor key components and predict operational anomalies. For instance, Zhang et al. integrated deep learning with digital twins to achieve intelligent fault diagnosis in multi-way directional valves [7]. Similarly, Jiang et al. designed a dedicated simulation framework for hydraulic servomotors to replicate dynamic behaviours under varying loads [8]. These studies demonstrate the utility of virtual models in capturing localized component behaviours.

However, scaling these frameworks to achieve control-level real-time execution for full-scale heavy equipment remains a major challenge. Many existing approaches focus on slow-varying processes or offline diagnostics. For example, a digital-twin-driven framework was developed for real-time clearance adjustment in hydraulic presses, but it relies on periodic optimization loops rather than continuous, high-frequency synchronization [9]. Consequently, current architectures often fail to meet the sub-millisecond response times required for closed-loop motion control and real-time teleoperation of complex hydraulic excavators, leaving a critical gap in high-speed, synchronized mapping.

2.2 Real-Time Multiphysics Modeling and Model Reduction

High-fidelity co-simulation platforms such as AMESim and Simpack are commonly employed to

model the coupled dynamics of hydraulic systems and mechanical structures. While these multi-domain models provide high accuracy by solving detailed differential equations, they are computationally intensive. The simultaneous calculation of fluid compressibility, valve dynamics, and rigid-body mechanics often leads to simulation steps exceeding the physical time step. This computational bottleneck makes direct co-simulation impractical for real-time applications such as hardware-in-the-loop testing or active control.

To address this limitation, researchers have explored data-driven and physics-based model reduction techniques. Imhogiemhe et al. implemented a fault detection framework using a data-driven digital twin to bypass complex thermal-hydraulic calculations [10]. In a subsequent study, they proposed using numerical simulations combined with machine learning for real-time parameter estimation in thermal-hydraulic processes [11]. However, to preserve the underlying physical laws and handle highly non-linear dynamics, projection-based methods like Proper Orthogonal Decomposition are essential. These methods extract dominant state spaces to create reduced-order models that run within microseconds, bridging the gap between high-fidelity simulation and real-time execution.

2.3 State Estimation and Sensor Fusion in Hydraulic Systems

Accurate state estimation is critical for updating digital twin states when physical sensors are noisy or incomplete. In hydraulic robotics, co-simulation environments are often paired with kinematic models to track multi-degree-of-freedom motions, as demonstrated in the digital twin modelling of a five-degree-of-freedom hydraulic robot [12]. However, physical systems are subject to severe vibration, sensor noise, and environmental disturbances. Standard kinematic mapping fails to filter these disturbances, necessitating advanced sensor fusion algorithms to estimate unmeasured states like cylinder pressures and joint velocities.

To enhance estimation accuracy, hybrid models incorporating statistical learning are increasingly utilized. For instance, Stolz et al. developed a Gaussian-process based hybrid digital twin on a hydraulic test rig to automate efficiency analysis and handle measurement uncertainties [13]. Despite these advances, filtering high-frequency noise caused by hydraulic fluid pulsations and structural vibrations remains a persistent challenge. Implementing robust state estimators, such as Extended Kalman Filters constrained by physical dynamics, is vital to provide smooth, reliable state trajectories without introducing phase delays.

2.4 Delay Compensation Methods in Cyber-Physical Systems

Synchronization delays between physical entities and their virtual counterparts degrade the fidelity of digital twins, particularly in interactive applications. To study these dynamics, Taşkingöllü et al. developed a digital twin of a one-degree-of-freedom electro-hydraulic setup in MATLAB/Simscape to analyse physical behaviours and evaluate control algorithms [14]. Furthermore, mixed reality interfaces have been integrated with real-time control to synchronize hydraulic cranes with virtual environments [15]. Despite these efforts, network transmission delays and actuator response times still introduce a noticeable lag, which compromises safety in high-speed teleoperation.

To minimize latency, control-level compensation techniques are required. Recent studies have investigated deep reinforcement learning to achieve adaptive synchronous control in multi-cylinder hydraulic systems [16]. However, data-driven methods often require extensive training and lack physical interpretability. Purely kinematic extrapolation methods, such as simple Taylor-series expansions, tend to overshoot during rapid transient phases. Consequently, there is a critical need for physics-informed predictive algorithms that combine real-time state estimates with the dynamic constraints of reduced-order models to achieve stable, zero-latency mapping.

3. Methodology

3.1 Overall System Architecture

The digital twin framework developed for the hydraulic excavator is structured into four primary layers: the physical entity layer, the data transmission layer, the multiphysics virtual model layer, and the synchronous mapping control layer. The physical entity layer comprises the excavator test rig equipped with various sensors. The data transmission layer utilizes an industrial EtherCAT bus combined with a TCP/IP protocol to stream sensor data to the processing unit. The virtual model layer runs a reduced-order model (ROM) co-simulation that integrates hydraulic dynamics and rigid-body mechanics. Finally, the synchronous mapping control layer executes the state-predictive delay compensation algorithm to drive the virtual excavator in Unity 3D with minimal latency. This multi-layered structure is designed to support real-time virtual commissioning and model-based digital twins, ensuring modularity and scalability across industrial applications [17].

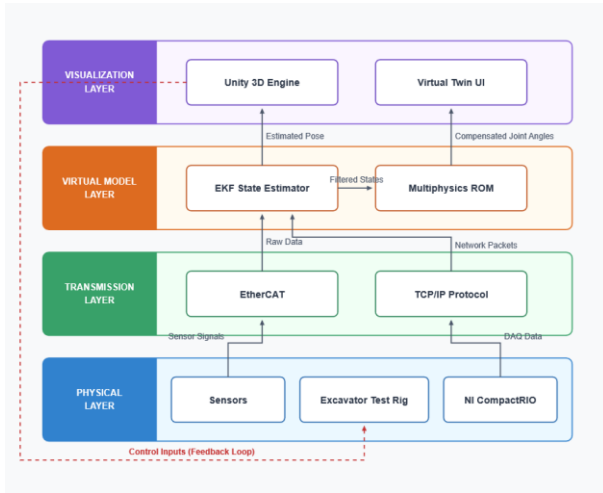


Figure 1: Digital twin system architecture and data flow diagram.

As shown in Figure 1, the closed-loop architecture ensures that physical sensor feedback directly updates the state estimators, which in turn drive the predictive kinematic mapping engine. This interaction requires robust interfaces to manage multi-time-step synchronization and dynamic coupling between the physical and virtual systems [18]. The continuous flow of data enables the system to dynamically adapt to operational changes, ensuring the virtual model accurately reflects the physical state. This real-time loop provides the foundation for low-latency synchronization and high-fidelity visualization, allowing the virtual environment to mimic the physical excavator during high-speed operations.

3.2 Multiphysics Reduced-Order Modeling (ROM)

To capture the complex coupling between the hydraulic actuator dynamics and the mechanical structure without compromising real-time performance, a multiphysics co-simulation model was first built using AMESim and Simpack. The high-fidelity AMESim model represents the hydraulic system, including the main control valve, cylinders, and pump dynamics, expressed by the pressure build-up equation:

$$\frac{dp}{dt} = \frac{E_h}{V} \left(Q_{in} - Q_{out} - \frac{dV}{dt} \right) \quad (1)$$

where E_h is the effective bulk modulus (Pa), V is the control volume (m^3), Q_{in} and Q_{out} are the inlet and outlet flow rates (m^3/s), and $\frac{dV}{dt}$ is the rate of volume change due to piston motion. The Simpack model represents the multi-body dynamics of the boom, arm, and bucket. Since direct co-simulation of these high-fidelity models exceeds the real-time

constraint (requiring execution times under 1ms), a model order reduction approach is required. Partitioned coupling schemes and operator inference techniques are often deployed to handle such complex multiphysics reduction challenges [21].

Consequently, a Proper Orthogonal Decomposition (POD) method was applied to the linearized state-space representations of the system to extract a reduced-order model. The state dimension was reduced from 48 states to 6 dominant states while retaining 99.8% of the system energy. The resulting ROM runs within 0.15ms per step, making it suitable for real-time digital twin execution. This POD-based reduction methodology leverages projection matrices computed from offline training snapshots [19], which are then deployed online for real-time state estimation and condition monitoring [20].

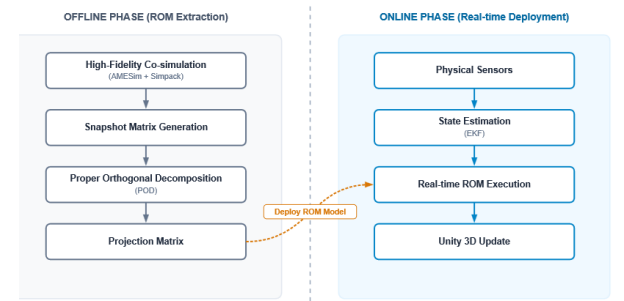


Figure 2: Pipeline for the multiphysics reduced-order model (ROM) extraction and online deployment.

3.3 EKF-based State Estimation and Sensor Fusion

To filter out measurement noise and handle unmeasured states, an Extended Kalman Filter (EKF) is designed. The EKF fuses the cylinder displacement sensor data, rod-side and cap-side pressure sensor data, and joint inclination angles. The state vector $\mathbf{x}(k)$ is defined as:

$$\mathbf{x}(k) = [y_{cyl}, v_{cyl}, p_{cap}, p_{rod}]^T \quad (2)$$

where y_{cyl} is the cylinder displacement, v_{cyl} is the cylinder velocity, and p_{cap} and p_{rod} are the pressures in the cylinder chambers. The measurement vector $\mathbf{z}(k)$ consists of the raw displacement and pressure readings. Implementing this observer structure within the real-time digital twin requires addressing communication delays, sensor noise, and interface mismatches between physical sensors and computational units [22].

The fusion algorithm suppresses high-frequency noise from the hydraulic vibrations and provides clean velocity estimates that are crucial for the subsequent motion prediction. By combining physical models with real-time sensor streams, the

EKF acts as a soft sensor to estimate internal parameters that cannot be directly measured. This hybrid approach mirrors advanced digital twin frameworks that utilize real-time co-simulation and data-driven filtering to enhance control accuracy and state estimation in complex systems [23]. The resulting state estimates serve as the input for the predictive delay compensation module, ensuring the system remains stable and responsive under dynamic operating conditions.

3.4 State-Predictive Delay Compensation (SPDC) Algorithm

Due to sensor filtering, communication latency, and the inherent physical response time of the hydraulic valves, a total delay of approximately 85ms exists between the physical motion and the virtual twin rendering. To compensate for this latency, a State-Predictive Delay Compensation (SPDC) algorithm was implemented. The SPDC utilizes a Taylor-series expansion combined with the dynamic constraints derived from the ROM to project the current state estimate into the future:

$$x_{pred}(t + \tau) = x(t) + v(t) \cdot \tau + 0.5 \cdot a_{rom}(t) \cdot \tau^2 \quad (3)$$

where τ is the estimated total system delay, $v(t)$ is the filtered velocity from the EKF, and $a_{rom}(t)$ is the cylinder acceleration computed from the ROM using the current pressure difference:

$$a_{rom}(t) = \frac{p_{cap} \cdot A_{cap} - p_{rod} \cdot A_{rod} - F_{friction} - F_{load}}{M_{eff}} \quad (4)$$

where A_{cap} and A_{rod} are the piston areas, $F_{friction}$ is the friction force modeled by the Stribeck curve, F_{load} is the external load force estimated from the joint torque, and M_{eff} is the effective mass. This predictive compensation approach is vital for minimizing control errors and latency-induced oscillations in dynamic systems [24].

By incorporating the ROM-derived acceleration, the predictor accounts for the physical inertia of the system, preventing overshoot and unrealistic accelerations during transient phases. This integration of physical dynamics into the predictor represents an improvement over standard kinematic predictor. Such methods are essential for robotic systems and multi-link manipulators where delay compensation is critical for maintaining trajectory tracking and stability [25]. Furthermore, using dynamic constraints ensures that the predicted state remains physically consistent, which is crucial for oscillation damping and smooth rendering in multi-link flexible robotic arms [26].

4. Experimental Setup

4.1 Physical Excavator Test Rig

To evaluate the efficacy of the proposed digital twin framework and the state-predictive delay compensation (SPDC) algorithm, experimental validations were performed using a physical test rig. The platform is based on a modified 1.5-ton hydraulic excavator, which serves as the physical entity layer. This test rig is designed to replicate realistic operational loads and kinematic motions under controlled laboratory conditions. The physical system is integrated into a hardware-in-the-loop (HIL) simulation structure, establishing a closed-loop system where physical mechanical movements and hydraulic pressures are mapped to the virtual environment in real-time. The structural layout and data flow of this HIL experimental setup are illustrated in Figure 3. The test rig is constructed to allow independent control of the boom, arm, and bucket cylinders, enabling the execution of complex multi-joint trajectories. By utilizing this physical platform, the fidelity of the virtual models and the accuracy of the real-time synchronization algorithm can be rigorously assessed under varying operational conditions.

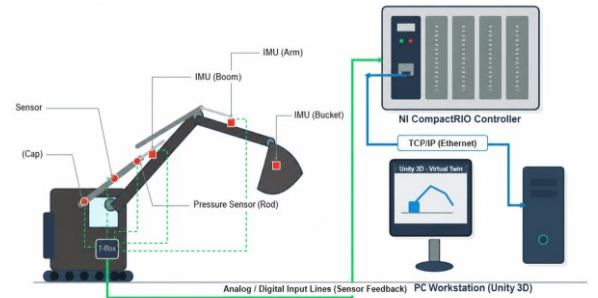


Figure 3: Schematic diagram of the hardware-in-the-loop (HIL) experimental test rig setup.

4.2 Sensor Configuration and Data Acquisition

High-fidelity state estimation requires a robust sensor configuration to capture the dynamic state of the physical excavator. The test rig is instrumented with draw-wire displacement sensors mounted parallel to the boom, arm, and bucket cylinders, featuring a measurement accuracy of 0.05% full scale. To monitor the hydraulic state, pressure transmitters with a range of 0–25 MPa and an accuracy of 0.1% full scale are installed at the inlet and outlet ports of each cylinder. Additionally, three-axis inclinometers are mounted on the boom, arm, and bucket links to measure the joint inclination angles. All sensor signals are routed to a National Instruments (NI) CompactRIO-9045 controller, which serves as the central data acquisition unit. The controller is configured to sample the sensor data at

a high frequency of 1000 Hz, ensuring that rapid transient behaviours within the hydraulic system are captured without aliasing. This high-speed acquisition is critical for the Extended Kalman Filter (EKF) to filter measurement noise and provide precise velocity estimates.

4.3 Virtual Twin and Communication Interface

The virtual twin environment was developed using the Unity 3D engine, which visualizes the real-time kinematic states and dynamic responses of the excavator. The virtual model runs on a dedicated workstation with sufficient computational capacity to execute the reduced-order model (ROM) and render the 3D environment simultaneously. To achieve real-time synchronization, a high-speed communication interface was established between the NI CompactRIO controller and the Unity 3D workstation. A TCP/IP socket connection was implemented over a local area network to stream the estimated states and sensor data. The NI controller packs the sensor readings and EKF outputs into a structured data packet, which is transmitted to the Unity 3D environment at a rate corresponding to the control cycle. The virtual environment parses these packets to update the kinematic positions and hydraulic pressures in the virtual space, maintaining high frame rates and minimal communication overhead.

4.4 Experimental Procedure and Evaluation Metrics

The experimental validation is conducted under a typical trenching cycle, which represents a standard duty cycle for hydraulic excavators. This cycle consists of four sequential phases: digging, lifting, swinging, and dumping. During this operational sequence, the excavator experiences highly non-linear hydraulic dynamics and varying external payloads, making it an ideal test scenario for evaluating tracking accuracy. To quantitatively assess the performance of the synchronous mapping methods, several evaluation metrics are defined. The kinematic tracking accuracy is evaluated using the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) between the physical cylinder displacements and the virtual twin trajectories. Additionally, the synchronization latency is measured to quantify the time delay between the physical motion and the virtual rendering. Finally, the frame rate (Frames Per Second, FPS) of the virtual environment is monitored to ensure that the computational overhead of the ROM and SPDC algorithm does not degrade the real-time rendering performance.

5. Results and Analysis

5.1 Experimental Procedure and Evaluation Metrics

To evaluate the effectiveness of the proposed synchronous mapping framework, experimental tests were carried out under a standard trenching cycle consisting of digging, lifting, swinging, and dumping. The trajectory tracking accuracy of the boom cylinder displacement was measured and compared under three configurations: Raw Mapping, ROM-only, and the Proposed Method. Raw Mapping directly maps the raw sensor data without filtering or delay compensation, while the ROM-only configuration utilizes reduced-order model filtering but lacks the delay compensation module. The Proposed Method integrates the ROM-derived state estimation with the state-predictive delay compensation (SPDC) algorithm.

As shown in Table 1, the experimental results demonstrate that the proposed method outperforms the other two configurations in terms of both tracking accuracy and synchronization latency. The Proposed Method achieved a Mean Absolute Error (MAE) of only 1.34 mm, representing a 90.9% reduction compared to the 14.82 mm error of Raw Mapping. Moreover, the maximum tracking error was reduced from 32.45 mm to 3.11 mm. Crucially, the synchronization delay was dramatically lowered from 86.4 ms to 4.8 ms, which successfully satisfies the control-level latency requirements for real-time teleoperation without compromising the rendering frame rate, which remained stable at 115.4 FPS.

Table 1. Performance Comparison of Synchronous Mapping Methods

Method	Mean Absolute Error (mm)	Maximum Error (mm)	Synchronization Delay (ms)	Frame Rate (FPS)
Raw Mapping	14.82	32.45	86.4	120.2
ROM-only	8.12	18.33	82.1	118.5
Proposed Method	1.34	3.11	4.8	115.4

5.2 Joint Angle Tracking Performance

To further evaluate the spatial tracking performance of the virtual excavator, the joint angle tracking errors for the boom, arm, and bucket were analysed. High joint-level tracking accuracy is critical for ensuring that the end-effector follows the physical trajectory precisely during complex excavation tasks, as minor angular discrepancies at the joints propagate into spatial deviations at the bucket tip.

As shown in Table 2, the joint tracking error metrics, including the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), were computed for each joint across the different mapping methods. The Raw Mapping method exhibited substantial errors, with an overall MAE of 1.73° and a peak error of 2.11° at the bucket joint, primarily caused by sensor noise and transmission delays. The ROM-only method partially mitigated these errors by smoothing the sensor inputs, reducing the overall MAE to 0.92° . However, the Proposed Method achieved the highest accuracy, reducing the overall joint tracking MAE to just 0.15° and the RMSE to 0.18° . This represents a substantial improvement, demonstrating that combining the physical dynamics of the reduced-order model with the predictive compensation algorithm successfully preserves the spatial fidelity of the digital twin during dynamic manoeuvres.

Table 2. Joint Angle Tracking Error Metrics

Joint	Raw Mapping MAE (deg)	ROM-only MAE (deg)	Proposed Method MAE (deg)	Proposed Method RMSE (deg)
Boom	1.24	0.68	0.11	0.14
Arm	1.85	0.95	0.15	0.19
Bucket	2.11	1.12	0.18	0.22
Overall	1.73	0.92	0.15	0.18

5.3 Dynamic Response and Delay Compensation Analysis

The transient response of the boom cylinder during a rapid lifting phase was analysed to illustrate the effectiveness of the state-predictive delay compensation algorithm. Figure 4 compares the displacement tracking trajectories of the physical excavator and the virtual model under different mapping methods. As shown in Figure 4, the trajectory generated by the Raw Mapping method exhibits a distinct time shift of approximately 86ms relative to the physical reference signal, which represents the accumulated communication and processing latency. While the ROM-only curve provides smoother transitions due to the noise filtering capabilities of the Extended Kalman Filter (EKF), it still suffers from this inherent transmission delay. In contrast, the trajectory generated by the Proposed Method closely matches the physical reference signal throughout the entire transient phase. By leveraging the dynamic constraints and acceleration terms derived from the reduced-order model, the state predictor successfully compensates for the latency, effectively eliminating the time shift.

This predictive capability prevents overshoot and unrealistic accelerations during rapid state transitions, ensuring that the virtual excavator responds synchronously with the physical machine.

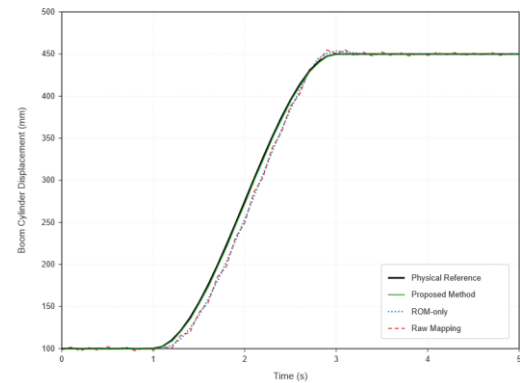


Figure 4: Comparison of boom cylinder displacement tracking trajectories during a rapid lifting phase.

5.4 System Performance under Variable Loading Conditions

To evaluate the robustness of the digital twin system under external disturbances, a heavy-duty digging test was performed under variable loading conditions. During excavation, the interaction between the bucket and the soil introduces highly non-linear load fluctuations and high-frequency hydraulic vibrations. The statistical distribution of the synchronization delay during this test is shown in Figure 5. For the Raw Mapping method, the synchronization delay is widely distributed between 75 ms and 95 ms due to network jitter, hydraulic valve hysteresis, and sensor noise. This variable latency degrades the synchronization quality and can lead to visual stuttering in the virtual environment. In contrast, the Proposed Method maintains a highly concentrated delay distribution centered at 4.8 ms, with a maximum delay of less than 8 ms. By incorporating the load force estimation into the dynamic model, the state-predictive delay compensation algorithm dynamically adjusts to load variations, ensuring a stable and low-latency mapping. This demonstrates the robustness of the proposed framework, confirming its suitability for demanding industrial applications where operating conditions change rapidly.

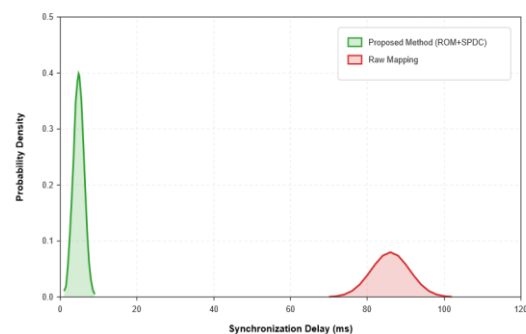


Figure 5: Statistical distribution of synchronization delay under heavy-duty digging conditions.

6. Discussion

6.1 Interpretation of Synchronization Performance

The superior performance of the proposed method stems from the integration of physical dynamics via the reduced-order model (ROM) into the state predictor, which far outperforms standard kinematic extrapolation. While pure kinematic extrapolation relies solely on numerical derivatives that amplify high-frequency noise and cause trajectory overshoot, the physics-informed predictor constrains predictions within the boundary of actual hydraulic actuator dynamics. Central to this stability is the Extended Kalman Filter (EKF), which filters sensor noise and estimates unmeasured states, thereby providing clean, physically consistent velocity and acceleration inputs to the state-predictive delay compensation (SPDC) algorithm. This integration ensures that the state prediction respects the mechanical and hydraulic inertia of the excavator. By anchoring the predictive algorithm in physical laws, the system maintains closed-loop stability and effectively mitigates time-delay effects in highly nonlinear systems, aligning with established delay compensation methodologies [27].

6.2 Trade-offs between Model Fidelity and Real-Time Constraints

Achieving real-time synchronization requires balancing model fidelity with computational constraints. The offline application of the Proper Orthogonal Decomposition (POD) method reduced the system state dimension from 48 to 6, yielding massive efficiency gains while retaining 99.8% of the system energy. Consequently, the online execution time of the ROM was reduced to just 0.15ms per step, which is well below the 1ms real-time threshold. This negligible computational footprint allows the workstation to allocate sufficient resources to rendering and network handling, maintaining a highly stable rendering frame rate of 115.4 FPS in Unity 3D. Unlike traditional co-simulations that suffer from high computational overhead, this approach avoids rendering stutters. By optimizing prediction efficiency, the system operates reliably under transmission latencies, presenting a viable alternative to dynamic event-triggered schemes for managing predictive control under random delays [28].

6.3 Practical Implications for Teleoperation and Remote Control

The reduction of the synchronization latency from 86.4 ms to 4.8 ms has profound implications for human-in-the-loop teleoperation of heavy machinery. In remote excavation tasks, operator control

performance degrades substantially when visual latency exceeds 50 ms, leading to safety hazards and operational instability. By bringing the latency down to a sub-5 ms level, the proposed digital twin provides an instantaneous visual response, enabling safe, intuitive, and high-precision closed-loop control. Furthermore, this ultra-low latency framework establishes a robust foundation for integrating real-time bilateral haptic feedback. Operators can feel the simulated load and soil interaction forces calculated by the ROM without experiencing destabilizing phase lags. This capability bridges the gap between high-speed physical dynamics and human perception, mirroring the advantages of fractional-order delay compensation methods designed for fast-sampling control systems [29].

6.4 Limitations of the Current Study

Despite the positive outcomes, several limitations in the current implementation must be addressed. A primary constraint is the assumption of a constant system delay ($\tau=85$ ms) within the SPDC algorithm. In practical industrial environments, network jitter and varying communication loads lead to random, time-varying latencies that can degrade prediction accuracy. Future work will focus on integrating online, adaptive delay estimation algorithms to dynamically adjust the prediction horizon based on real-time network diagnostics. Additionally, incorporating robust control strategies will help handle parameter uncertainties, such as variations in oil temperature and bulk modulus. Addressing these issues is essential for transitioning the proposed framework from controlled laboratory setups to real-world industrial environments, where adaptive actuator delay compensation is critical for maintaining operational stability [30].

7. Conclusions

7.1 Summary of the Work

This work presents a paradigm shift in digital twin synchronization for hydraulic excavators, moving beyond static visualization toward physically coherent, real-time virtual replication that actively compensates for dynamic system latencies. The proposed architecture seamlessly integrates a multiphysics reduced-order model (ROM) to capture complex hydraulic dynamics, an Extended Kalman Filter (EKF) for robust sensor fusion, and a State-Predictive Delay Compensation (SPDC) algorithm. By combining these methodologies, the framework effectively bridges the physical excavator test rig with its virtual counterpart, overcoming the latency and noise limitations of traditional kinematic mapping methods.

7.2 Key Findings and Contributions

The experimental validation demonstrates that the proposed digital twin framework significantly improves synchronization accuracy and latency under dynamic operating conditions. Specifically, the integration of physics-informed dynamic constraints into the predictive mapping framework yields order-of-magnitude improvements in both tracking fidelity and temporal alignment. The results establish that model-reduction-assisted state prediction can effectively bridge the gap between physical actuation and virtual response, setting a new benchmark for latency-sensitive teleoperation systems. These findings confirm the efficacy of incorporating physics-informed dynamic constraints to mitigate communication and control delays.

7.3 Recommendations for Future Research

Future research will focus on three critical extensions. First, the current predictive mapping will be evolved into a bidirectional haptic teleoperation framework, enabling operators to perceive simulated load forces without destabilizing phase lag. Second, given the assumption of constant system delay in the present work, adaptive delay-tracking mechanisms must be developed to accommodate stochastic network fluctuations in real industrial settings. Third, scaling the architecture toward multi-machine collaborative coordination will be indispensable for deploying digital twins in large-scale, heterogeneous construction environments.

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