

Artificial Intelligence–Enabled Cyber-Physical Systems for the Engineering of Large-Scale Structures

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ABSTRACT

The engineering of large-scale structures such as bridges, high-rise buildings, dams, offshore platforms, and major industrial facilities increasingly confronts limitations of traditional deterministic design, construction, and monitoring approaches. These limitations arise from the growing complexity of structural systems, the variability of environmental and operational conditions, and the need for continuous performance assessment throughout the lifecycle of infrastructure assets. Cyber-physical systems (CPS), which integrate physical processes with computational intelligence through sensing, communication, and actuation, have emerged as a foundational paradigm for addressing such challenges. More recently, the incorporation of Artificial Intelligence (AI) into CPS has significantly expanded their capabilities, enabling learning, adaptation, and predictive decision-making. This article examines the use of AI-enabled cyber-physical systems in the engineering of large structures, focusing on their role in design support, construction control, structural health monitoring, and lifecycle optimization. By integrating data-driven intelligence with physics-based models, AI-enabled CPS allow large structures to be treated as dynamic systems rather than static artifacts. The article argues that this integration represents a paradigm shift in structural engineering, enabling improved safety, resilience, and efficiency, while also introducing new technical, epistemological, and professional challenges.

Keywords: cyber-physical systems; artificial intelligence; large-scale structures; structural engineering; digital twins.

Domain	Implications of AI-enabled CPS for large structures
Structural Design	Integration of data-driven intelligence with physics-based models for multi-objective optimization and uncertainty management.
Construction Engineering	Real-time monitoring and adaptive control of construction processes, reducing deviations and rework.
Structural Health Monitoring	Continuous, intelligent assessment of structural condition and early detection of damage.
Asset Management	Predictive maintenance and lifecycle optimization based on real operational data.
Infrastructure Resilience	Enhanced ability to anticipate degradation, extreme events, and system-level vulnerabilities.

INTRODUCTION

The engineering of large-scale structures has historically relied on deterministic models, conservative safety margins, and periodic verification procedures to ensure structural integrity and serviceability. While these approaches have proven effective for decades, they are increasingly strained by the growing complexity of modern infrastructure systems. Large bridges, high-rise buildings, dams, offshore platforms, and industrial megastructures operate under highly variable environmental conditions, are exposed to evolving usage patterns, and must satisfy demanding performance, sustainability, and resilience requirements. In this context, traditional static models and discrete inspection-based practices reveal intrinsic limitations in capturing the dynamic nature of structural behavior over time.

Simultaneously, advances in sensing technologies, communication networks, and embedded computing have enabled the continuous observation of physical systems at unprecedented spatial and temporal resolutions. These developments have laid the foundation for cyber-physical systems (CPS), which tightly integrate physical processes with computational intelligence. In structural engineering, CPS enable real-time acquisition of structural response data, facilitating monitoring, diagnosis, and control functions that extend beyond conventional engineering workflows. However, early CPS implementations were largely limited to data acquisition and rule-based processing, offering limited adaptability to unforeseen conditions or evolving system dynamics.

The incorporation of Artificial Intelligence into CPS represents a qualitative shift in how large structures can be conceived, managed, and understood. AI techniques, particularly those based on machine learning and data-driven modeling, provide the ability to extract latent patterns from large volumes of heterogeneous data, learn from experience, and support predictive decision-making under uncertainty. When embedded within CPS architectures, AI transforms structural systems from passive entities into adaptive, learning systems capable of responding to changes in loading, environmental conditions, and structural state. This transition challenges the traditional view of structures as static artifacts verified at the design stage and instead positions them as evolving systems whose behavior can be continuously assessed and optimized.

Despite the growing interest in AI and CPS across engineering disciplines, the literature remains fragmented with respect to their application to large-scale structural systems. Research in AI-driven structural engineering often focuses on isolated tasks, such as damage detection, load

prediction, or optimization, without fully addressing the systemic integration of AI within cyber-physical frameworks. Conversely, studies on CPS frequently emphasize control theory and embedded systems, offering limited insight into how learning-based intelligence can be coherently integrated with physics-based structural models. As a result, there is a lack of comprehensive frameworks that articulate how AI-enabled CPS can support the full lifecycle of large structures, from design and construction to operation and long-term management.

This gap is particularly significant given the increasing demands placed on large infrastructure systems. Climate variability, aging assets, urban densification, and the expectation of uninterrupted service impose conditions that are difficult to accommodate using static design assumptions alone. Engineers are increasingly required to make decisions in environments characterized by incomplete information, nonlinear system behavior, and interacting uncertainties. In such contexts, predictive capabilities that rely solely on historical data or simplified analytical models may fail to anticipate critical system states or emergent failure mechanisms. AI-enabled CPS offer a promising pathway to address these challenges by combining real-time data, learning algorithms, and domain-specific knowledge within an integrated decision-support environment.

The objective of this article is to examine the use of Artificial Intelligence within cyber-physical systems aimed at the engineering of large structures, with a focus on their conceptual foundations, functional architecture, and implications for engineering practice. Specifically, the article seeks to (i) situate AI-enabled CPS within the broader evolution of structural engineering methodologies; (ii) analyze the theoretical underpinnings that support the integration of AI, CPS, and large-scale structural systems; and (iii) discuss how such systems contribute to enhanced safety, resilience, and lifecycle performance. Rather than presenting a purely technical review of algorithms, the article adopts a systems-oriented perspective, emphasizing the interaction between data-driven intelligence and physical modeling.

From a methodological standpoint, the article is based on a qualitative and conceptual analysis of the relevant literature in cyber-physical systems, artificial intelligence, structural engineering, and systems theory. Foundational and contemporary studies are synthesized to develop an integrated understanding of how AI-enabled CPS can be applied to large structures. This approach is particularly appropriate given the interdisciplinary nature of the topic and the need to bridge traditionally separated domains of knowledge. By focusing on conceptual integration rather than algorithmic detail, the article aims to provide a framework that can inform both research and practice.

The expected contribution of this work lies in clarifying the role of AI-enabled CPS as a unifying paradigm for large-scale structural engineering. By framing large structures as dynamic, data-informed systems rather than static designs, the article highlights a shift toward continuous assessment and adaptive management. This perspective has important theoretical implications, as it challenges conventional notions of structural safety and performance, and practical implications, as it influences how engineers design, monitor, and intervene in complex infrastructure systems. The introduction thus establishes the foundation for a deeper examination of the theoretical and conceptual elements that underpin AI-enabled cyber-physical systems, which are developed in the subsequent sections of the article.

INTEGRATED THEORETICAL FOUNDATIONS: CYBER-PHYSICAL SYSTEMS, ARTIFICIAL INTELLIGENCE, AND LARGE-SCALE STRUCTURAL ENGINEERING

The theoretical foundations of Artificial Intelligence–enabled cyber-physical systems applied to large-scale structural engineering are rooted in the convergence of three traditionally distinct domains: physical modeling of structures, computational intelligence, and systems integration. Understanding how these domains interact is essential to clarify the role of AI-enabled CPS not merely as technological tools, but as a new engineering paradigm capable of addressing the inherent complexity, uncertainty, and scale of modern infrastructure systems.

At the core of structural engineering lies the physics-based representation of material behavior, load transfer mechanisms, and global system response. Classical theories of elasticity, plasticity, structural dynamics, and soil–structure interaction provide the mathematical and conceptual basis for predicting structural performance. These models, however, are necessarily idealized representations of reality. Assumptions regarding boundary conditions, material homogeneity, and loading scenarios are introduced to make problems tractable, often at the cost of reduced fidelity when structures operate under real-world conditions. For large-scale structures, such discrepancies are amplified by spatial variability, construction tolerances, environmental influences, and long-term degradation processes.

Cyber-physical systems emerge as a response to these limitations by embedding sensing, computation, and communication directly into physical structures. In a CPS, the physical system continuously exchanges information with its digital counterpart, enabling observation and analysis of structural behavior as it unfolds. From a theoretical perspective, CPS represent

an evolution from model-centric engineering toward data-informed system understanding. Rather than relying solely on a priori assumptions, CPS allow models to be continuously confronted with empirical evidence. However, without advanced intelligence, this confrontation remains largely descriptive, providing information without necessarily yielding insight or actionable foresight.

Artificial Intelligence provides the missing layer that enables CPS to move from observation to interpretation and prediction. Machine learning algorithms are particularly effective at identifying patterns in high-dimensional data spaces, capturing nonlinear relationships that are difficult to model explicitly using traditional analytical approaches. In the context of large structures, AI can learn correlations between measured responses—such as vibrations, strains, or displacements—and underlying structural states that are not directly observable. This capacity is critical for systems in which damage, degradation, or anomalous behavior emerges gradually and may not trigger simple threshold-based alarms.

From a theoretical standpoint, the integration of AI into CPS challenges the traditional separation between model-based and data-driven approaches. Structural engineering has historically privileged physics-based models as the primary source of truth, while data were used mainly for validation or calibration. AI-enabled CPS invert this hierarchy by allowing data to actively inform and reshape models in real time. This does not imply the abandonment of physical theory, but rather its augmentation through adaptive, learning-based mechanisms. The resulting framework is hybrid in nature, combining deductive reasoning grounded in mechanics with inductive inference derived from observed behavior.

Systems theory provides an essential lens for understanding this hybridization. Large structures are not isolated artifacts but components of broader socio-technical systems that include users, operators, environmental conditions, and regulatory constraints. These systems exhibit characteristics of complexity, such as nonlinearity, emergence, and sensitivity to initial conditions. In such environments, local changes can produce global effects that are difficult to anticipate using linear reasoning. AI-enabled CPS align naturally with this perspective by treating structures as evolving systems whose behavior must be interpreted holistically rather than through isolated variables.

The notion of feedback is central to both CPS and systems theory. In traditional structural engineering, feedback is often implicit and delayed, occurring through inspections, maintenance reports, or post-event analyses. CPS introduce continuous feedback loops, in

which sensor data informs computational models, and model outputs influence decision-making or control actions. When AI is integrated into these loops, feedback becomes adaptive: the system learns not only from current conditions but also from past responses to similar situations. This adaptive feedback is particularly relevant for large structures subjected to variable loading regimes, such as wind, traffic, seismic activity, or thermal effects.

Another theoretical dimension concerns uncertainty management. Large-scale structures operate under multiple sources of uncertainty, including material properties, loading conditions, environmental variability, and modeling assumptions. Traditional engineering approaches address uncertainty through safety factors and probabilistic methods, which, while robust, are often conservative and static. AI-enabled CPS introduce the possibility of dynamic uncertainty reduction by continuously updating predictions based on observed data. Bayesian learning frameworks, for example, allow prior assumptions to be revised as new evidence becomes available, leading to progressively refined assessments of structural performance.

The integration of AI and CPS also raises epistemological questions about knowledge generation in engineering. Physics-based models offer explanatory insight grounded in first principles, whereas AI models often function as black boxes, providing accurate predictions without transparent causal explanations. In safety-critical domains such as structural engineering, this tension is particularly pronounced. The theoretical challenge lies in developing CPS architectures that balance predictive accuracy with interpretability, ensuring that AI-driven insights can be understood, trusted, and justified within established engineering frameworks.

Digital twins represent a concrete manifestation of this theoretical integration. As continuously updated virtual representations of physical structures, digital twins embody the synthesis of physical modeling, data streams, and AI-based inference. Theoretically, they function as dynamic hypotheses about system behavior, constantly tested and refined through interaction with the physical structure. For large-scale engineering systems, digital twins enable scenario analysis, predictive maintenance, and resilience assessment in ways that static models cannot achieve.

Finally, the human dimension must be considered as an integral part of the theoretical foundation. Engineers remain responsible for interpreting results, making decisions, and assuming accountability for structural safety. AI-enabled CPS do not replace engineering judgment; rather, they reshape it by expanding the informational and analytical context in which

decisions are made. From a theoretical perspective, this implies a shift from engineer-as-calculator to engineer-as-system-integrator, capable of synthesizing physical understanding, data-driven insights, and contextual knowledge.

In summary, the theoretical foundations of AI-enabled cyber-physical systems for large-scale structural engineering rest on the integration of physical modeling, computational intelligence, and systems thinking. This integration enables a transition from static, assumption-driven approaches to adaptive, data-informed engineering practices. By reconciling physics-based understanding with learning-based intelligence, AI-enabled CPS provide a conceptual framework capable of addressing the complexity, uncertainty, and scale inherent in modern structural systems. These foundations set the stage for the subsequent discussion of how such systems are architected and operationalized in practice, which is developed in the following section.

CONCEPTUAL DEVELOPMENT: ARCHITECTURE AND OPERATION OF AI-ENABLED CYBER-PHYSICAL SYSTEMS FOR LARGE STRUCTURES

The conceptual development of Artificial Intelligence-enabled cyber-physical systems for large-scale structural engineering requires a clear understanding of how intelligence, physical processes, and decision mechanisms are coupled within a unified architecture. Unlike conventional monitoring or control systems, AI-enabled CPS are not designed merely to observe or regulate predefined variables. Their purpose is to establish a continuous, adaptive relationship between the physical structure and its digital counterpart, allowing the system to learn, interpret, and anticipate structural behavior across multiple operational conditions and time horizons.

At an architectural level, AI-enabled CPS for large structures can be understood as multi-layered systems in which physical sensing, data processing, modeling, and decision-support functions operate in a tightly integrated manner. The physical layer consists of the structure itself and the associated sensing infrastructure, including strain gauges, accelerometers, displacement sensors, temperature probes, and other instrumentation capable of capturing structural response and environmental conditions. These sensors generate high-frequency, high-dimensional data streams that reflect the evolving state of the structure under real operating conditions.

Above the physical layer lies the data and communication layer, responsible for acquiring, filtering, synchronizing, and transmitting sensor data. For large structures, this layer must handle significant data volumes, spatially distributed measurements, and varying data quality. The reliability of AI-enabled CPS depends critically on the robustness of this layer, as noise, latency, or data loss can compromise downstream inference and decision-making. Consequently, preprocessing, data validation, and redundancy mechanisms are integral components of the CPS architecture rather than auxiliary functions.

The intelligence layer represents the core differentiating element of AI-enabled CPS. This layer integrates machine learning models, statistical inference methods, and hybrid physics-informed algorithms that interpret sensor data in relation to structural behavior. In contrast to traditional model-based approaches, which rely on fixed equations calibrated at discrete stages, AI models continuously adapt as new data become available. For large structures, this adaptability enables the system to capture gradual changes in stiffness, damping, boundary conditions, or load patterns that may not be anticipated during design.

A key conceptual feature of this intelligence layer is the coexistence of data-driven and physics-based representations. Purely data-driven models may achieve high predictive accuracy but lack interpretability and generalization beyond observed conditions. Conversely, physics-based models offer explanatory power but may struggle to represent complex, real-world variability. AI-enabled CPS reconcile these approaches through hybrid modeling strategies, in which learning algorithms are constrained or informed by physical laws. This integration enhances both robustness and credibility, which are essential in safety-critical structural applications.

The operational logic of AI-enabled CPS is inherently dynamic. Rather than producing static assessments, the system operates through continuous feedback loops that connect observation, interpretation, and action. Sensor data are interpreted by AI models to infer the current structural state and identify deviations from expected behavior. These inferences are then used to update digital representations of the structure, such as reduced-order models or digital twins. Based on the updated state, the system can generate predictions about future behavior under anticipated loading scenarios or environmental conditions.

Decision-support functions constitute another critical component of the CPS architecture. In large structural systems, decisions may range from maintenance planning and load management to emergency response following extreme events. AI-enabled CPS do not replace human decision-makers but provide structured, evidence-based insights that support engineering

judgment. For example, predictive assessments of damage progression can inform maintenance prioritization, while scenario simulations can support risk evaluation under uncertain conditions. The conceptual emphasis is on augmenting human expertise rather than automating decisions that carry significant safety and ethical implications.

Construction-phase applications illustrate the operational advantages of AI-enabled CPS. During construction of large structures, deviations from design assumptions frequently arise due to material variability, environmental influences, or execution constraints. CPS equipped with AI can integrate real-time construction data with structural models to assess whether observed deviations remain within acceptable performance bounds. This capability allows engineers to intervene proactively, reducing the likelihood of latent defects that may compromise long-term structural integrity.

During the operational phase, AI-enabled CPS enable continuous structural health monitoring that extends beyond traditional inspection regimes. Rather than relying on periodic assessments, the system maintains an evolving understanding of structural behavior, identifying subtle changes that may indicate early-stage damage or degradation. Importantly, the CPS framework allows these observations to be interpreted in context, distinguishing between benign variations due to operational changes and critical anomalies that warrant intervention. This contextual interpretation is particularly important for large structures subjected to variable loads and environmental conditions.

Lifecycle management represents one of the most significant conceptual contributions of AI-enabled CPS. Large structures are long-lived assets, often expected to perform reliably for several decades. Over such time spans, uncertainties accumulate, and initial design assumptions become increasingly distant from operational reality. By continuously integrating observed data into predictive models, AI-enabled CPS support a shift from static lifecycle planning to adaptive lifecycle management. Maintenance strategies, retrofitting decisions, and resilience assessments can be updated dynamically, reflecting the actual condition and usage of the structure rather than idealized projections.

From a conceptual standpoint, AI-enabled CPS also redefine the notion of structural safety. Traditional safety assessments are typically based on worst-case scenarios and conservative assumptions applied at the design stage. While this approach ensures robustness, it may lead to inefficiencies or an incomplete understanding of evolving risk. AI-enabled CPS enable a complementary perspective in which safety is monitored and managed continuously, allowing

engineers to detect emerging vulnerabilities and respond before critical thresholds are reached. This does not eliminate the need for conservative design but enriches it with real-time intelligence.

The implementation of AI-enabled CPS for large structures also highlights organizational and professional implications. Engineers must interact with systems that produce probabilistic predictions, confidence intervals, and adaptive recommendations rather than deterministic outputs. This interaction requires new forms of expertise, combining structural mechanics, data interpretation, and systems thinking. Conceptually, the role of the engineer evolves from sole analyst to supervisor of intelligent systems, responsible for validating outputs, contextualizing insights, and making informed decisions.

In summary, the conceptual development of AI-enabled cyber-physical systems for large-scale structural engineering reveals a shift toward integrated, adaptive, and data-informed practice. By coupling physical structures with intelligent computational frameworks, these systems enable continuous assessment, predictive insight, and adaptive decision support across the entire structural lifecycle. This conceptual framework provides the basis for understanding the transformative potential of AI-enabled CPS, as well as the challenges associated with their implementation, which are addressed in the final section of this article.

DISCUSSION, CONTRIBUTIONS, LIMITATIONS, CONCLUSIONS, AND REFERENCES

The analysis developed throughout this article positions Artificial Intelligence-enabled cyber-physical systems as a transformative paradigm for the engineering of large-scale structures. By integrating physical sensing, computational intelligence, and adaptive decision-support mechanisms, AI-enabled CPS redefine how structures are conceived, managed, and assessed over their lifecycle. This final section discusses the main theoretical and practical contributions of this paradigm, acknowledges its limitations, and outlines its broader implications for structural engineering practice.

From a theoretical standpoint, a central contribution of AI-enabled CPS lies in reframing large structures as dynamic, evolving systems rather than static artifacts validated primarily at the design stage. Traditional structural engineering methods rely heavily on deterministic models and conservative assumptions that, while robust, often fail to capture the full complexity of real operational conditions. The integration of AI within CPS introduces a complementary logic in

which structural behavior is continuously interpreted and updated based on empirical evidence. This shift aligns structural engineering with contemporary systems thinking, emphasizing adaptation, feedback, and learning as core principles.

Another important theoretical contribution concerns the hybridization of physics-based and data-driven models. Rather than positioning AI as a replacement for established engineering theory, AI-enabled CPS demonstrate how learning algorithms can augment physical models by compensating for uncertainty, modeling gaps, and unanticipated behaviors. This hybrid approach offers a more nuanced representation of structural systems, combining explanatory power with predictive flexibility. In doing so, it addresses a long-standing tension in engineering between model fidelity and practical applicability, particularly relevant for large structures operating under variable and uncertain conditions.

At the practical level, AI-enabled CPS provide tangible benefits across all phases of the structural lifecycle. During design, data-driven insights can support more informed decision-making by exploring complex trade-offs between performance, cost, and resilience. During construction, real-time monitoring and intelligent interpretation reduce the risk of latent defects and improve quality control. In the operational phase, continuous structural health monitoring enables early detection of degradation, supporting predictive maintenance strategies that enhance safety while optimizing resource allocation. Over the long term, adaptive lifecycle management informed by real data allows infrastructure owners to move beyond static maintenance schedules toward condition-based decision-making.

The contribution of AI-enabled CPS to structural resilience is particularly significant. Large structures are increasingly exposed to extreme events, aging effects, and evolving usage patterns. Traditional safety assessments, based on fixed design scenarios, may not adequately capture these dynamics. AI-enabled CPS enable a continuous assessment of vulnerability and performance, allowing engineers to anticipate potential failure mechanisms and respond proactively. This capability does not negate the importance of conservative design principles but complements them with operational intelligence that reflects the actual state of the structure.

Despite these contributions, the implementation of AI-enabled CPS for large-scale structures faces important limitations. One major challenge concerns data availability and quality. AI models depend on reliable, representative datasets, yet sensor data may be affected by noise, drift, missing values, or measurement errors. For large structures, ensuring long-term data

integrity and sensor reliability remains a nontrivial task. Without careful data governance, the effectiveness of AI-driven inference may be compromised.

Another limitation relates to interpretability and trust. Structural engineering is a safety-critical discipline governed by strict regulatory frameworks and professional accountability. Black-box AI models, while powerful, may produce predictions that are difficult to explain or justify within traditional engineering reasoning. This limitation highlights the importance of developing interpretable AI models and hybrid approaches that maintain a clear link between data-driven insights and physical understanding. The acceptance of AI-enabled CPS in practice will depend not only on technical performance but also on transparency and alignment with established engineering norms.

Cybersecurity and system robustness also represent critical concerns. CPS are inherently exposed to digital vulnerabilities, and large structures constitute high-value, safety-critical assets. Protecting AI-enabled CPS from malicious attacks, data manipulation, or system failures is essential to ensure their safe deployment. Additionally, organizational and institutional barriers may limit adoption, as the integration of AI into engineering workflows requires new skills, interdisciplinary collaboration, and changes in professional culture.

From an epistemological perspective, AI-enabled CPS challenge traditional notions of engineering knowledge. The increasing reliance on adaptive, learning-based systems raises questions about validation, verification, and responsibility. Engineers must develop new frameworks for assessing the reliability of AI-driven insights and defining accountability in human-machine collaborative decision-making. These issues underscore the need for updated standards, guidelines, and educational programs that reflect the evolving nature of engineering practice.

In conclusion, the use of Artificial Intelligence within cyber-physical systems aimed at engineering large structures represents a significant evolution in the discipline. By enabling continuous observation, adaptive learning, and predictive decision support, AI-enabled CPS offer a powerful response to the complexity, uncertainty, and scale of modern infrastructure systems. While challenges related to data quality, interpretability, and cybersecurity remain, the integration of AI and CPS provides a robust framework for enhancing safety, resilience, and efficiency across the structural lifecycle.

As large-scale infrastructure continues to play a critical role in societal development, the ability to manage structural systems dynamically and intelligently will become increasingly important.

AI-enabled cyber-physical systems do not replace the foundational principles of structural engineering but extend them, embedding intelligence into the physical fabric of structures. Future research should focus on empirical validation, development of interpretable hybrid models, and the establishment of regulatory and professional frameworks that support the responsible adoption of this paradigm. In doing so, the engineering of large structures can transition from a predominantly static discipline to a dynamic, data-informed practice aligned with the realities of the twenty-first century.

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