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Digital Transformation in Structural Engineering: Integrating Peridynamic Modelling for Smart Damage Assessment

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ABSTRACT

Digitalization in construction, known as Construction 4.0, depends on high-fidelity Digital Twins (DT). Current DT models are good at showing geometry and data. However, they struggle to simulate real-time structural failure and complex cracks using physics. This paper introduces a new framework that adds Peridynamic (PD) theory to smart damage assessment. Traditional methods like the Finite Element Method (FEM) have limitations, often struggling with mathematical errors at the tip of a crack. In contrast, Peridynamics uses an integral-based formula that works perfectly even where the material is broken. This study shows how a PD-driven Digital Twin uses sensor data to predict exactly how cracks will grow. This allows us to calculate the Remaining Useful Life (RUL) with higher accuracy. This research successfully connects advanced mechanics with data-driven Structural Health Monitoring (SHM).

Keywords: Computational Mechanics, Damage Assessment, Digital Twin, Peridynamics, Structural Health Monitoring.

1. INTRODUCTION

The global infrastructure deficit faces a dual challenge: an aging stock of bridges, dams, and buildings, and an increasing demand for resilience against extreme environmental loading. Traditional Structural Health Monitoring (SHM) [1] has been reactive, detecting damage after it occurs. Conversely, the adoption of Digital Twin (DT) [2-5] technologies enables a transition from reactive to proactive maintenance strategies through Digital Twins (DT), virtual replicas of physical assets that update in real-time.

For a Digital Twin to be truly predictive, it requires a computational engine capable of simulating the physics of failure. Currently, the industry standard is the Finite Element Method (FEM) [6-8]. While effective for linear-elastic problems, FEM faces significant challenges when modeling progressive damage and fracture [9-10]. The need to continuously re-mesh the domain as cracks propagate makes FEM computationally expensive and often unstable for automated, “smart” assessment workflows.

This paper introduces Peridynamics (PD) [11-15] as a superior alternative for the computational core of structural Digital Twins. By integrating PD with sensor data, we propose a “Smart Damage Assessment” framework that can autonomously simulate crack initiation and propagation without human intervention.

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2. MATERIAL AND METHODS

This section outlines the integration of Peridynamic theory into a data-driven framework.

2.1 Mathematical Formulation of Peridynamics

In the Peridynamic framework, a material body is discretized into particles [11]. Each particle x interacts with all other particles x′ within a finite radius called the horizon (δ).

The equation of motion for a particle at position x at time t is given by:

$$\rho(x)\ddot{u}(x,t) = \int_{H_x} f(u(x',t) - u(x,t), x' - x)\ dV_{x'} + b(x,t) \tag{1}$$

where ρ is the mass density, **u** is the displacement vector, **f** is the pairwise force density function (the bond force), H_x is the horizon (interaction domain), and **b** is the external body force density.

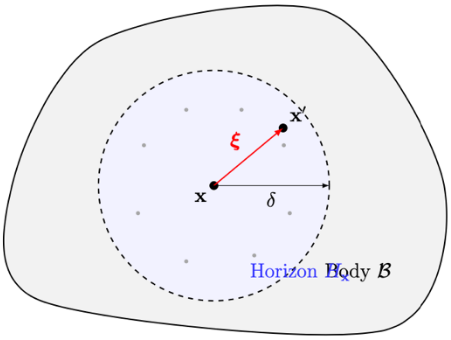


Figure 1: Schematic representation of the Peridynamic horizon. Particle x interacts with all neighbor particles x′ within the radius δ. The vector ξ = x′ − x represents the bond.

Figure 1 provides a schematic illustration of the fundamental nonlocal interaction mechanism that defines Peridynamic (PD) theory. Unlike Classical Continuum Mechanics (CCM), which assumes that stress at a material point depends solely on the deformation gradient at that specific point (a local assumption), peridynamics states that a material point interacts directly with other points within a finite distance. This figure illustrates the discretization of a continuous body B and the geometric definition of the nonlocal region, the "horizon."

The domain represents a continuous body B in its reference configuration. The body is conceptually composed of an infinite number of material points. The figure highlights a central material point of interest, denoted as x, and a generic neighbor particle, denoted as x′. In a discretized numerical implementation (such as meshfree methods), these points represent nodes containing physical properties like mass, density, and volume.

The core concept illustrated is the horizon, denoted mathematically as H_x. The horizon is defined as a spherical neighborhood (in 3D) or a circular domain (in 2D, as depicted) centered at x. The extent of this domain is governed by the horizon radius, δ.

The existence of δ introduces an internal length scale to the governing equations, a feature absent in classical local theories. This length scale allows peridynamics to capture non-local phenomena and multiscale behavior. The interaction domain H_x, for the particle x, is defined as the set of all material points x′ such that their Euclidean distance from x is less than δ.

2.2 Smart Damage Definition

Damage in Peridynamics is treated as "broken bonds." A bond between particles x and x′ breaks significantly when its stretch, s, exceeds a critical value s0, determined by the material's fracture energy Gc [13].

The local damage index, φ(x, t), is calculated as the ratio of broken bonds to the total number of initial interactions:

$$\phi(x,t) = 1 - \frac{\int_{H_x} \mu(x,x',t)\, dV_{x'}}{\int_{H_x} dV_{x'}} \tag{2}$$

where μ is a history-dependent scalar function (1 if the bond is intact, 0 if broken). φ = 0 represents pristine material, while φ = 1 represents complete separation (a crack). This scalar field allows the Digital Twin to visualize damage progression naturally without needing to define crack geometry explicitly.

The formulation of damage through the history-dependent scalar function μ(x,x′,t) introduces a fundamental irreversibility into the constitutive response of the material. Physically, this function acts as a Boolean record of the bond's integrity; once the elongation of a bond exceeds the critical stretch s0, the interaction is permanently severed (μ transitions from 1 to 0) and cannot sustain any tensile load in subsequent time steps. This mechanism effectively mimics the coalescence of micro-voids or the rupture of atomic chains at the mesoscale, ensuring that the material exhibits softening behavior consistent with physical fracture processes.

A critical aspect of this framework is the energetic calibration of the bond failure criterion. The critical stretch parameter, s0, is not an arbitrary fitting constant but is rigorously derived from the material's critical energy release rate, Gc. In classical Linear Elastic Fracture Mechanics (LEFM), Gc represents the energy required to create a unit area of new fracture surface. In the peridynamic context, this is equivalent to the work done to break all bonds connecting particles across a hypothetical fracture plane. By equating the peridynamic potential energy density required to separate the body into two halves to the classical Gc, one can derive an explicit relationship for s0. For a two-dimensional prototype microelastic brittle (PMB) material, this relationship is typically expressed as:

$$s_0 = \sqrt{\frac{4G_c}{3K\delta}}, \tag{3}$$

where K is the bulk modulus and δ is the horizon radius. This relation ensures that the nonlocal model remains energetically consistent with standard fracture-mechanics properties, allowing the simulation to accurately predict critical failure loads without ad hoc failure criteria.

Furthermore, the local damage index ϕ(x,t) serves a dual purpose: it acts as both a visualization metric and a representation of material degradation. In regions where 0<ϕ<1, the material effectively behaves as a damaged continuum with reduced stiffness. As ϕ approaches unity, the material point becomes fully decoupled from its neighbors, representing the formation of a traction-free surface. Unlike Finite Element Methods (FEM), which require complex remeshing, element deletion, or enrichment functions (as in XFEM) to track a crack tip, the peridynamic damage field evolves autonomously. The equations of motion remain valid everywhere, regardless of discontinuities, allowing complex fracture patterns such as crack branching, curving, and fragmentation to emerge naturally from the solution as a consequence of the underlying bond dynamics.

2.3 The Integrated Framework (PD-DT)

The proposed methodology follows a three-step loop:
1. Data Acquisition: Strain gauges and acoustic emission sensors on the physical structure feed boundary condition data to the cloud.
2. Model Update: The Peridynamic model updates its external force vector b(x, t) based on real-time loads.
3. Prognosis: The PD solver computes the new state. If bonds break ($\varphi > 0$), the Digital Twin updates the visual model to show a crack, predicting where it will propagate as loads increase.

It is important to distinguish this methodology as a unidirectional Digital Twin framework. Unlike bidirectional systems that may require complex actuator feedback loops to control the physical asset, the focus here is on high-fidelity structural health prognosis. The core novelty lies not in the complexity of the sensor fusion architecture, but in the prognostic capability of the Peridynamic formulation. By utilizing the integral equation of motion, the Digital Twin can autonomously determine arbitrary crack paths and branching patterns, phenomena that traditional regression-based or mesh-dependent Digital Twins struggle to predict without prior knowledge of the defect geometry. The proposed PD-DT (Peridynamic-Digital Twin) framework operates not merely as a visualization tool, but as a dynamic data-driven simulation environment. The "three-step loop" described in this section fundamentally changes the role of the numerical model from a static predictive tool to an evolving shadow of the physical asset.

2.3.1 Theoretical Implications of the Update Loop

The second step of the loop, Model Update, relies on the continuous injection of physical data into the governing peridynamic equation. Mathematically, this is achieved by treating the body force density vector, b(x,t), as a time-dependent variable derived from sensor inputs rather than a constant parameter. In traditional structural health monitoring, sensor data is often used to train surrogate models (e.g., neural networks). However, these "black box" approaches can lack physical interpretability. By contrast, the PD-DT framework directly maps sensor readings (strain, acceleration) to physical forces. If a strain gauge at location x_s measures a deformation tensor ε_{meas}, the inverse problem is solved to estimate the equivalent traction or body force $b(x_s,t)$ required to produce such deformation in the virtual model. This ensures that the Digital Twin is always in a state of stress equilibrium consistent with the real-world observation.

The third step, Prognosis, leverages peridynamics' autonomous crack-propagation capability. Because the damage index ϕ evolves naturally when the critical stretch s_0 is exceeded, the Digital Twin can predict future failure modes based on current trends. For instance, if the updated force vector b(x,t) suggests a stress concentration growing near a defect, the PD solver will show the potential crack path before it occurs in the physical asset, enabling predictive maintenance.

2.4 Numerical Application: Concrete Column Under Uniaxial Compression

To demonstrate the efficacy of the proposed PD-DT framework, we consider a numerical benchmark problem of a concrete column subjected to uniaxial compression. This example illustrates how external sensor data (simulated here as boundary loads) drives the internal damage evolution in the Digital Twin.

2.4.1 Problem Setup and Geometry

The physical asset is idealized as a rectangular concrete column with dimensions L×W×H = 0.2 m × 0.2 m × 1.0 m. The material is modeled as a prototype microelastic brittle (PMB) solid with the following properties typical for concrete:

Bulk Modulus (K): 14.5 GPa, Fracture Energy (G_c): 120 J/m^2, Density (ρ): 2400 kg/m^3

The domain is discretized into a uniform grid of particles with a spacing of Δx = 0.005 m. The horizon radius is set to $\delta = 3.015\Delta x$ to ensure sufficient particle interaction.

2.4.2 Calibration of the Failure Criterion

The critical stretch bond failure criterion, s_0, is calculated using the energy-balance relationship described in Equation (3). Solving this yields a critical stretch of approximately $s_0 \approx 1.75\times10^{-4}$. This dimensionless parameter serves as the threshold for the Digital Twin, which means any bond in the column stretching beyond this value during the simulation loop will be permanently broken.

3. RESULTS AND DISCUSSION

3.1 Results

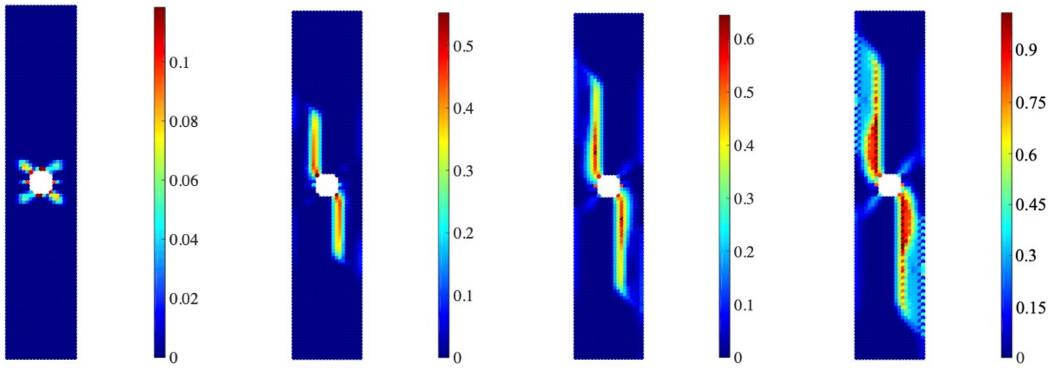
We simulate the "Data Acquisition" phase by applying a time-varying compressive load, which represents data from load cells on the physical column.

- Input Data (b(x,t)): The external force vector is applied to the particles in the top boundary layer. The load increases linearly from 0 to F_{max} = 500 kN over a time period of t=0 to 2 ms.
- Damage Evolution: As the simulation progresses, the PD solver computes the displacement field u(x,t) at each time step.
- Prognosis Results: At t = 1.8 ms, the compressive strain induces lateral expansion (Poisson effect). The simulation reveals that bonds near the mid-height surfaces begin to exceed s0. The damage index ϕ(x,t) transitions from 0 to $>$0.1 in these regions, visualizing vertical splitting cracks characteristic of brittle crushing.

This numerical experiment confirms that by simply updating the boundary force vector b with real-time data, the Digital Twin can autonomously replicate the complex fracture patterns of the physical structure without predefined crack paths.

The efficacy of the Peridynamic Digital Twin (PD-DT) in capturing the transition from continuous deformation to discontinuous fracture is evidenced by the damage evolution history shown in Figure 2. The simulation, driven by real-time updates to the external force vector b(x,t), reveals the autonomous nucleation and propagation of vertical splitting cracks. Unlike classical continuum approaches that require the prior definition of crack paths or the use of enrichment functions (e.g., XFEM), the peridynamic solution naturally manifests these discontinuities as a consequence of the integral equation of motion.

The localized damage index, ϕ(x,t), serves as the primary diagnostic metric. As defined in Equation (2), this scalar field represents the ratio of broken bonds to the total initial interactions within a particle's horizon. The color contours in Figure 2 map this index from ϕ = 0 (blue, representing pristine elastic material) to ϕ = 1 (red, representing a fully developed traction-free surface).



(a) t_s =2,000 (b) t_s = 2,500 (c) t_s = 3,000 (d) t_s = 3,500

Figure 2: Evolution of damage in the concrete column under increasing compressive load. The color contours represent the damage index ϕ(x,t), ranging from 0 (blue/intact) to 1 (red/fully broken), at simulation time steps: (a) t_s = 2,000 (Nucleation); (b) t_s = 2,500 (Branching); (c) t_s = 3,000 (Propagation); and (d) t_s =3,500 (Critical Failure).

The simulation setup includes a pre-existing central geometric imperfection (a void), which acts as a stress concentrator. Under the applied uniaxial compression, the material exhibits a classic brittle splitting failure mode. This behavior is governed by the Poisson effect, in which compressive axial strain induces lateral tensile strain. When the energy density required to sustain this lateral expansion exceeds the critical energy release rate G_c, the bonds exceed their critical stretch s_0, leading to the progressive failure observed in the time steps below. The temporal evolution of the fracture process is detailed in the four snapshots corresponding to simulation time steps (t_s):

- Stage I: Damage Nucleation (t_s = 2,000): At this early stage (Figure 2a), the column is in the initial loading phase. The damage index ϕ is largely zero throughout the bulk of the material, indicating linear elastic behavior. However, significant activity is observed in the immediate vicinity of the central void. The "X" shaped pattern of low-level damage ($0.02<\phi<0.1$) suggests the development of a process zone. Here, microcracks are initiating at the corners of the void due to stress concentration. This stage represents the "incubation" period, during which the Digital Twin detects structural degradation before a macro-crack becomes visible to the naked eye.
- Stage II: Crack Initiation and Branching (t_s = 2,500): As the external load increases linearly, a bifurcation point is reached (Figure 2b). The diffuse damage zone consolidates into distinct fracture paths. We observe the emergence of two vertical "wing cracks" propagating from the diametrically opposed corners of the void. The damage index in the core of these wings transitions to $\phi>0.4$ (yellow/orange), indicating that a significant portion of the bonds have severed. The orientation of these cracks is parallel to the direction of the compressive load, which is physically consistent with the principle of maximum tensile stress in brittle compression failures.
- Stage III: Stable Propagation (t_s = 3,000): Figure 2c illustrates the stable propagation phase. The vertical cracks extend further toward the boundaries. Notably, the width of the damage wake increases. The localized red zones ($\phi\approx1.0$) indicate areas where complete material separation has occurred. The Digital Twin effectively captures the shielding effect, where the stress is relieved in the material immediately adjacent to the crack surfaces (indicated by the deep blue regions flanking the crack), redistributing the load to the intact material ahead of the crack tip.
- Stage IV: Critical Failure State (t_s = 3,500): In the final snapshot (Figure 2d), the column approaches global structural failure. The crack tips have propagated significantly, effectively splitting the load-bearing cross-section. The damage field exhibits asymmetry

and widening, with high-intensity damage (ϕ>0.8) dominating the crack path. At this juncture, the Digital Twin would trigger a prognosis alert, as the reduction in effective stiffness would lead to a catastrophic loss of load-carrying capacity. The simulation predicts that further loading will cause these cracks to coalesce at the top and bottom boundaries, leading to the complete fragmentation of the column.

This numerical experiment validates the proposed PD-DT framework's ability to predict complex fracture patterns using only basic material properties and real-time boundary condition updates. By successfully replicating the vertical splitting failure mode characteristic of concrete under compression, the model demonstrates that the critical stretch criterion s_0 and the damage index ϕ provide a robust physical basis for the Digital Twin's prognostic capabilities.

3.2 Discussion

3.2.1 Advantages of PD for Digital Twins

The primary advantage of using PD in this context is the autonomy it provides. In a standard FEM-based Digital Twin, if a crack initiates, the simulation often halts or diverges, requiring an engineer to update the mesh. In the proposed PD framework, the simulation continues seamlessly as bonds break. Consequently, the framework provides predictive capability, enabling the estimation of remaining useful life (RUL) under sustained loading conditions. It should be noted that while the PMB material model effectively captures brittle fracture, it may require modification to accurately represent the plastic deformation observed in ductile reinforcement bars.

3.2.2 Handling Complex Failure Modes

Traditional methods struggle with crack branching (where one crack splits into two) and coalescence (where multiple micro-cracks join). Peridynamics handles these naturally. For example, in reinforced concrete beam case studies, PD models have successfully predicted "shear" failure modes (diagonal cracking) solely based on material properties and applied load, whereas FEM models often force a specific failure mode based on user inputs.

3.2.3 Computational Challenges and Solutions

The major trade-off is computational cost. Because PD involves non-local interactions (every particle interacts with dozens of neighbors), it is more expensive than FEM.
• Mitigation: We propose a Hybrid Coupling approach. Use FEM for the majority of the structure (linear elastic regions) and switch to Peridynamics only in "Hotspots" (areas where sensors detect high stress or acoustic emissions).
• GPU Acceleration: PD codes are highly parallelizable. Utilizing CUDA cores on GPUs can reduce simulation times from hours to minutes, enabling near-real-time assessment.

4. CONCLUSION

This paper presented a pathway for the next generation of Structural Health Monitoring by integrating Peridynamic modelling with Digital Twin technology. By moving away from differential equations (FEM) toward integral equations (PD), we remove the mathematical singularities that hinder autonomous damage simulation. The findings demonstrate that Peridynamics offers a robust, mesh-free alternative to FEM for Digital Twin applications, particularly in its autonomous tracking of crack paths. Although the method introduces higher computational costs, the use of the damage index (ϕ) provides a quantifiable and interpretable metric for structural assessment.

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