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Damage Identification in Concrete Structures using Physics-informed Neural Networks (PINNs)

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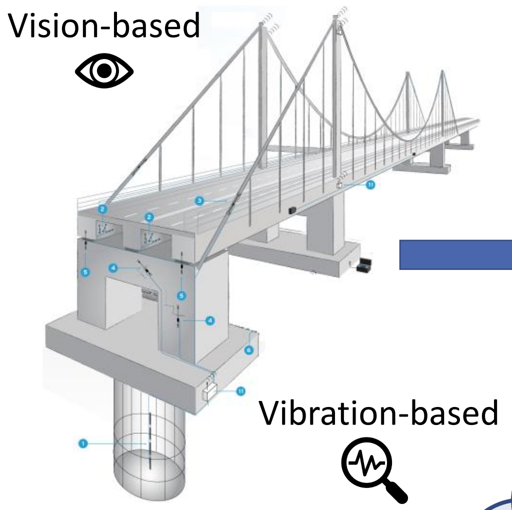
Structural damage identification aims to estimate the states of structural systems and the associated model parameters based on measurement data.



INPUT

Sensor Data

(Limited and noisy)

Structural damage identification approaches

OUTPUT

Structural condition assessment

METHODOLOGY

Physical model-based

(e.g., Finite element method)

Limitation: computationally intensive

Non-physical model-based

(e.g., Machine learning)

Limitation: no physics

Physics-informed neural network (PINN)

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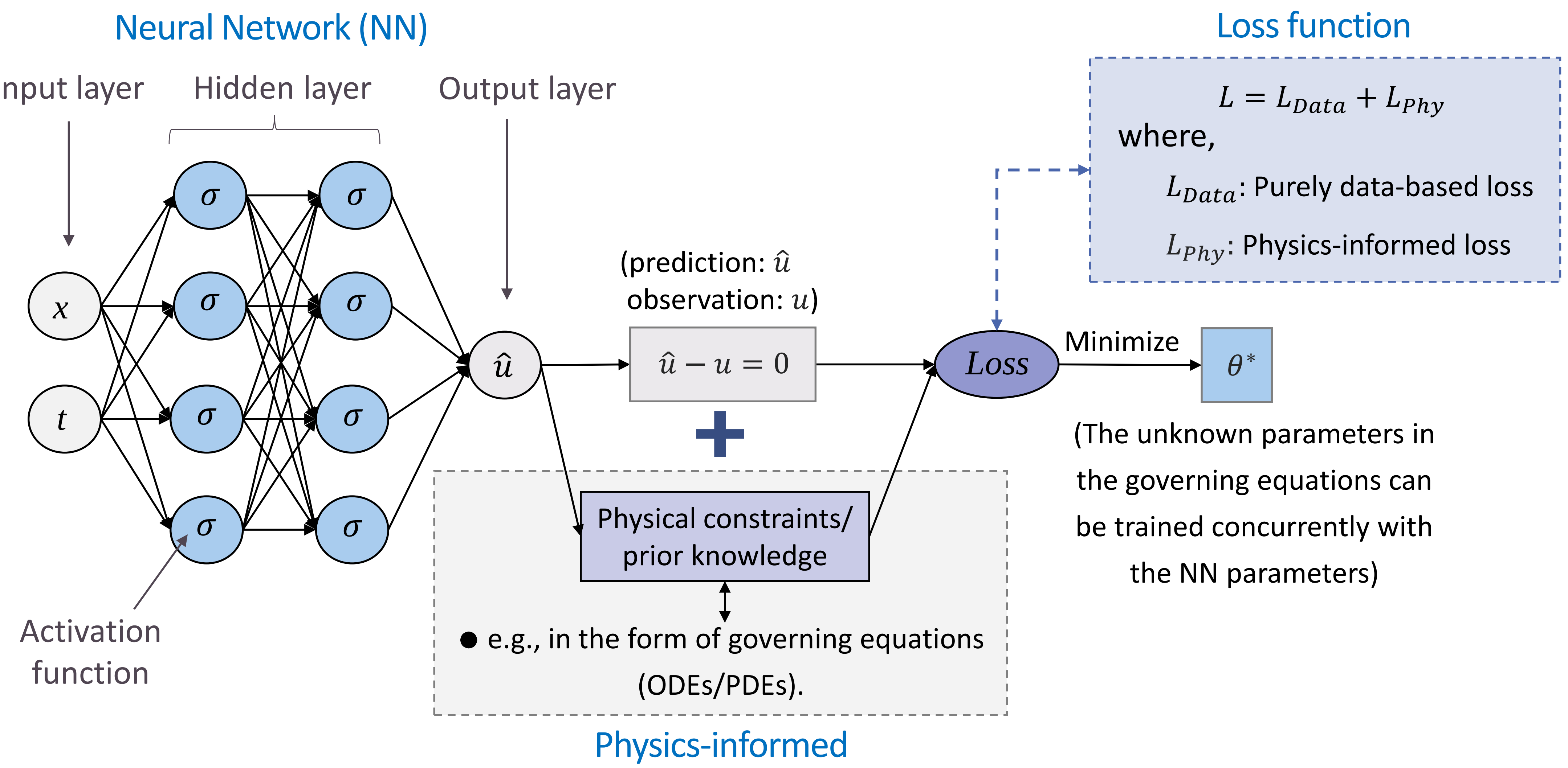

- Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 388, 686-707.

Goal of this presentation:

to demonstrate a *Physics-informed neural networks (PIPNNs)* framework for *structural damage identification*

- Example 1: a three-span continuous beam with cracking
- Example 2: a concrete column system with creep strain

Goal of this presentation:

to develop and demonstrate a *Physics-informed neural networks (PIPNNs)* framework for *structural damage identification problems*

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Damage identification of a three-span continuous beam with cracking

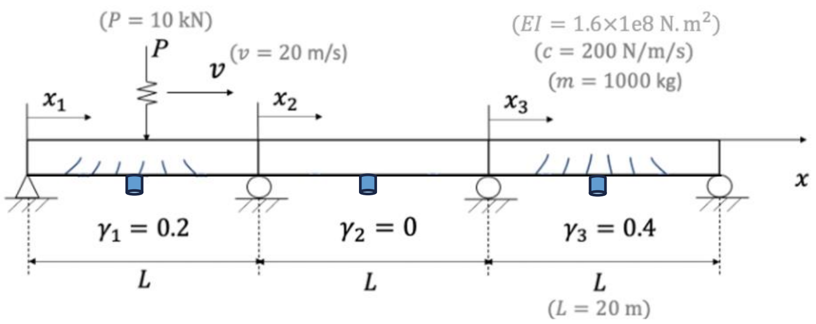


Fig. 1 A three-span continuous beam under a moving concentrated load

Damage parameter γ

- Represent the reduction of the flexural rigidity of each span of the beam due to damage.

$$EI_i = (1-\gamma_i)EI$$

- Undamaged: $\gamma = 0$
- Damaged: $0 < \gamma \leq \gamma_{cr}$
  - where γ_{cr} is a critical value (close or equal to 1) at finial failure.

Given:

1. **Sensor data** for accelerations: $\ddot{u}(t)$
   - simulated by superposing the reference acceleration responses* (ground truth) and the 5% Gaussian noise.
2. **Physics:**
   - Governing equation (PDE)

$$m\frac{\partial^2}{\partial t^2}u(x,t) + c\frac{\partial}{\partial t}u(x,t) + (1-\gamma_i)EI\frac{\partial^4}{\partial x^4}u(x,t) = P\delta(x-vt)$$

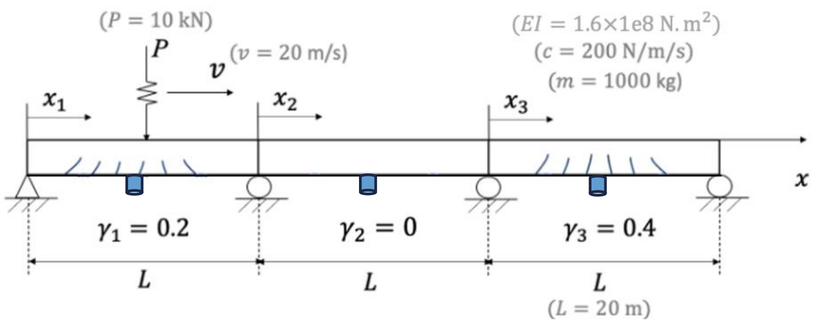
   - Boundary conditions

Determine:

- to identify γ_i for each span of the beam

* The reference responses (ground truth) are calculated by modal analysis considering the first 30 modes.

Developed Physics-informed Parallel Neural Networks (PIPNNs) framework



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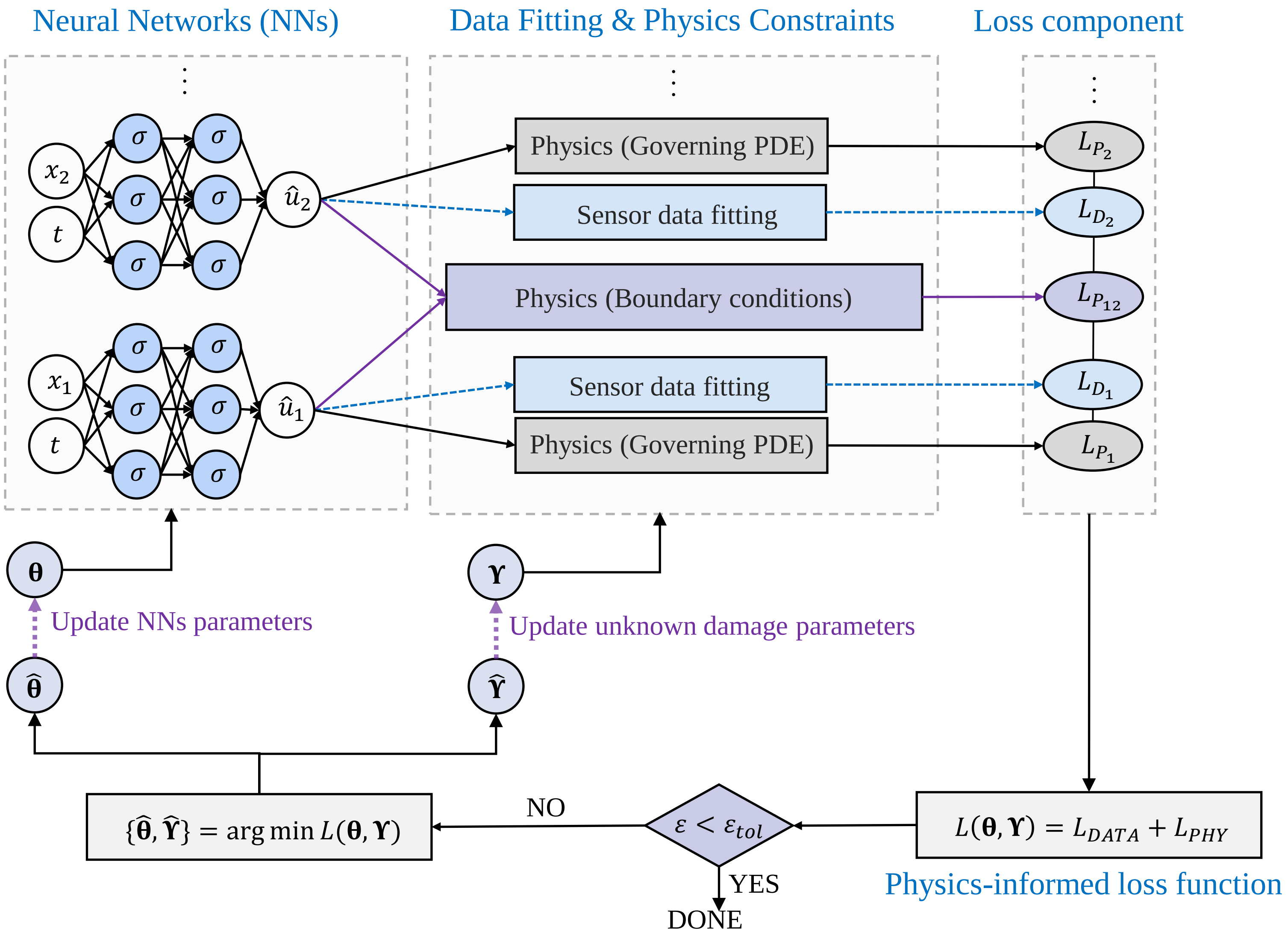
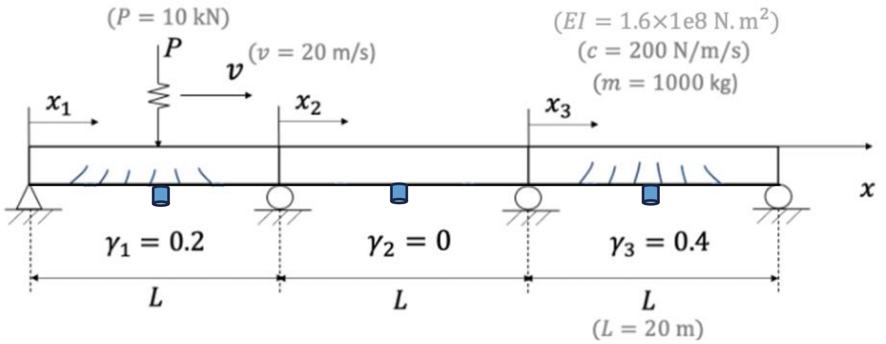


Identifying the damage parameters using the PIPNNs framework



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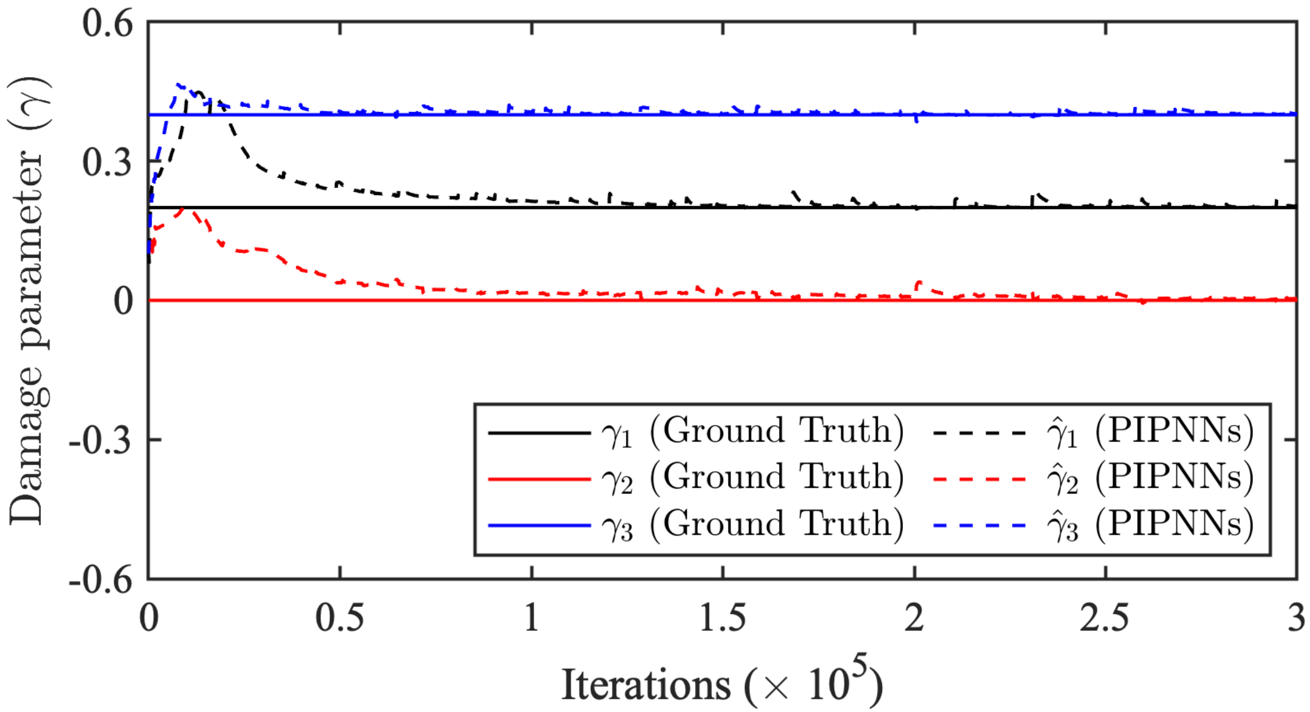


Fig. 2 Comparison of the identified damage parameters and the true values.

Goal of this presentation:

to develop and demonstrate a *Physics-informed neural networks (PIPNNs)* framework for *structural damage identification problems*

- Example 1: a three-span continuous beam with cracking
- Example 2: a concrete column system with creep strain

Damage identification of a concrete column system with creep

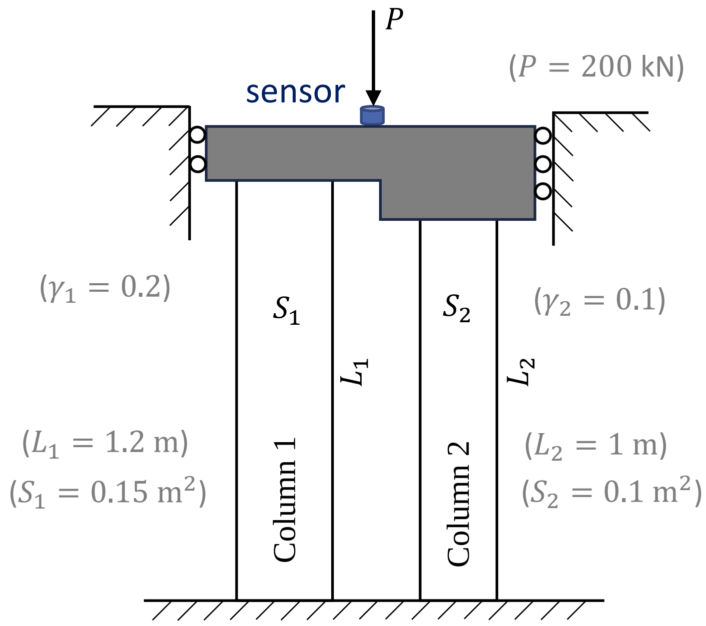


Fig. 1 A two-column system

Table. 1 Material properties for concrete

Property	Value
relative humidity	h = 90%
cylinder compression strength	f_c = 27.6 MPa
volume to surface ratio	v/s = 0.75
cement content (Type I cement)	c = 220 kg/m^3
water-cement ratio	w/c = 0.60
water content of concrete	w = 132 kg/m^3
aggregate-cement ratio	a/c = 7.0

Damage parameter γ

- Represent the reduction of the effective cross-sectional area of each column due to damage: $(\gamma_1 = 0.2; \gamma_2 = 0.1)$.

Given:

1. **Sensor data** for deflection: $u(t)$ with 5% Gaussian noise
2. **Physics:**
   1. Equilibrium of force:
   $$\sigma_1 S_1(1-\gamma_1) + \sigma_2 S_2(1-\gamma_2) = P$$
   2. Compatibility of displacement:
   $$\varepsilon_{T1} L_1 = \varepsilon_{T2} L_2 = u$$

Determine:

1. Damage parameters: γ_1 and γ_2
2. Responses: (a) stress: $\sigma_i(t)$; (b) Strain: $\varepsilon_{T_i}(t)$; $\varepsilon_{E_i}(t)$; $\varepsilon_{cr_i}(t)$.

Total strain of concrete under load

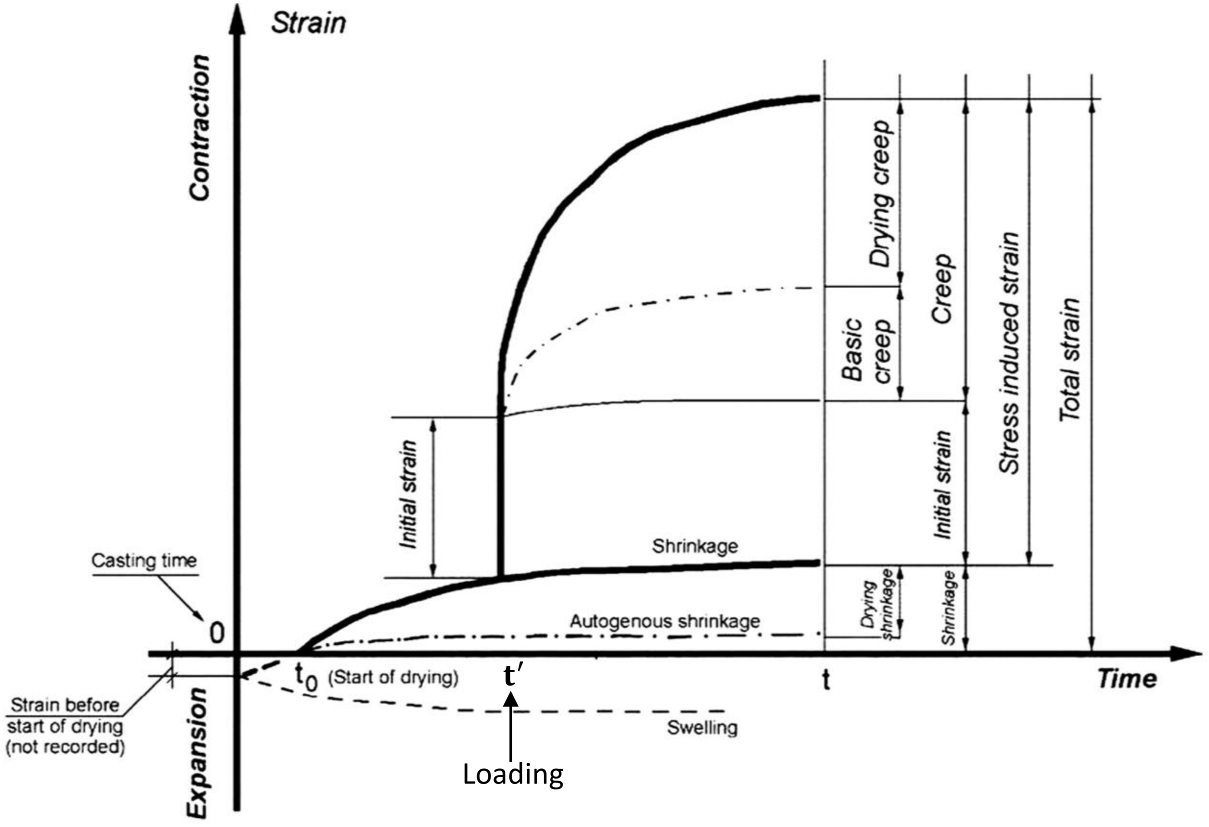


Fig.1 Strain components of concrete under loading.

Total strain*: $\varepsilon_{\text{Total}} = \varepsilon_{sh} + J(t, t')\sigma$

1. Shrinkage: ε_{sh}

2. Stress induced strain: $J(t, t')\sigma$

   - where J is the compliance function:

$$J(t, t') = q_1 + C_0(t, t') + C_d(t, t', t_0)$$

(a). instantaneous strain due to unit stress: q_1

(b). basics creep: C_0

$$\dot{C}_0\,(t, t') = f(t) = \frac{n(q_2 t^{-m} + q_3)}{(t - t') + (t - t')^{1-n}} + \frac{q_4}{t}, \qquad m = 0.5, n = 0.1$$

(c). drying creep: C_d

$$C_d(t, t', t_0) = g(t) = q_5\left[e^{-8H(t)} - e^{-8H(t_0')}\right]^{1/2}, \qquad t_0' = \max(t', t_0)$$

* Bazant, Zdenek P., and W. P. Murphy. "Creep and shrinkage prediction model for analysis and design of concrete structures-model B3." *Matériaux et constructions* 28.180 (1995): 357-365.

Applying Physics-informed Neural Network (PINN) framework on the concrete column system

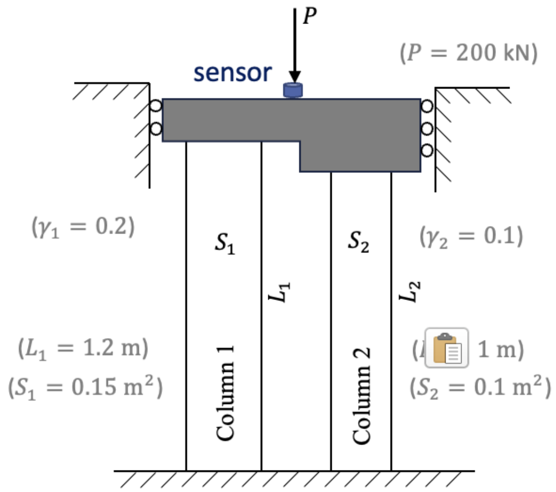
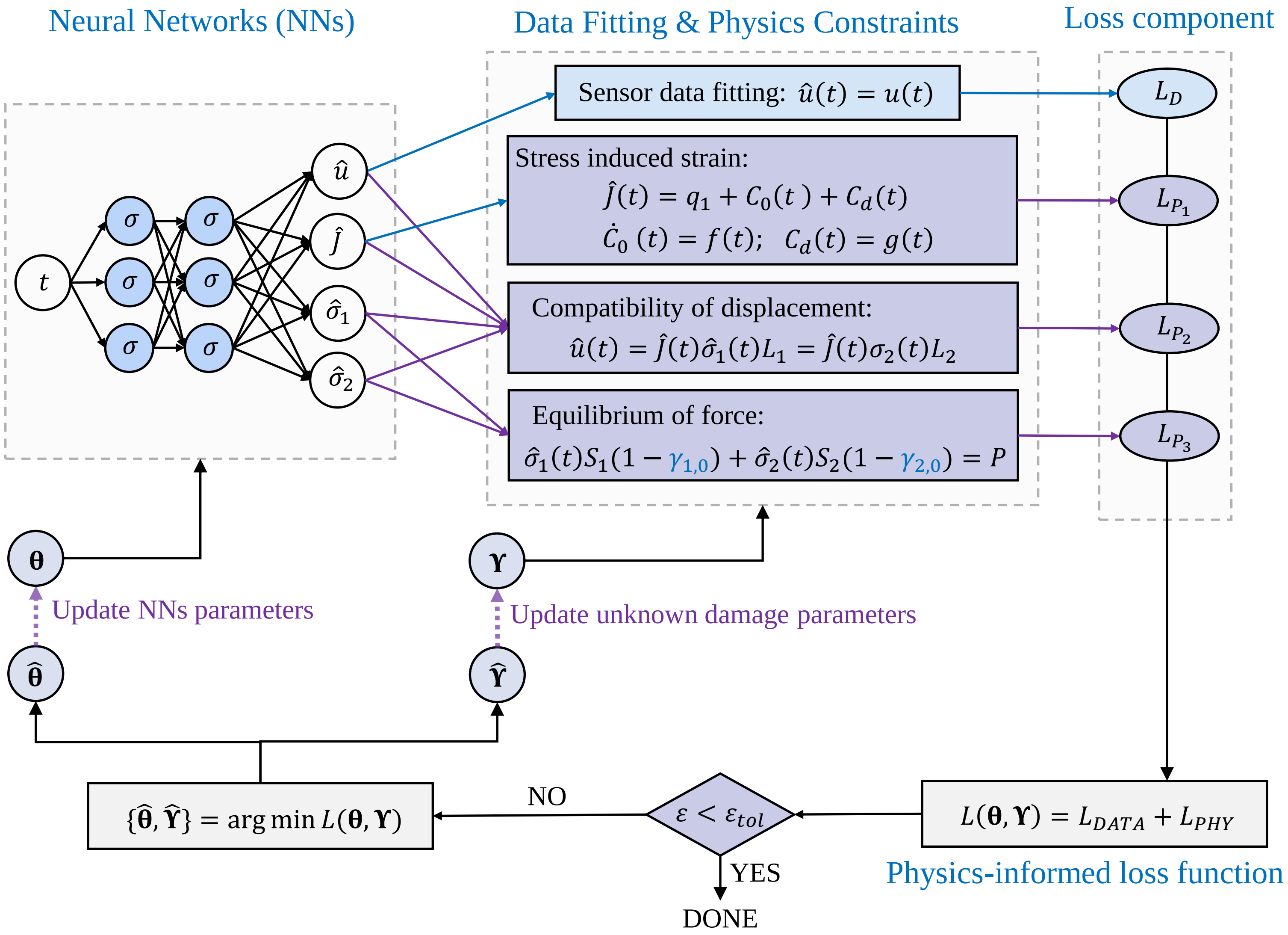
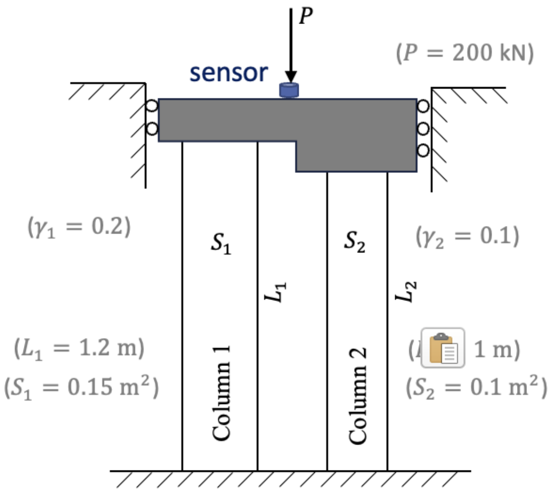


Fig. 1 A two-column system



Comparison of the estimation from PINN and Ground truth



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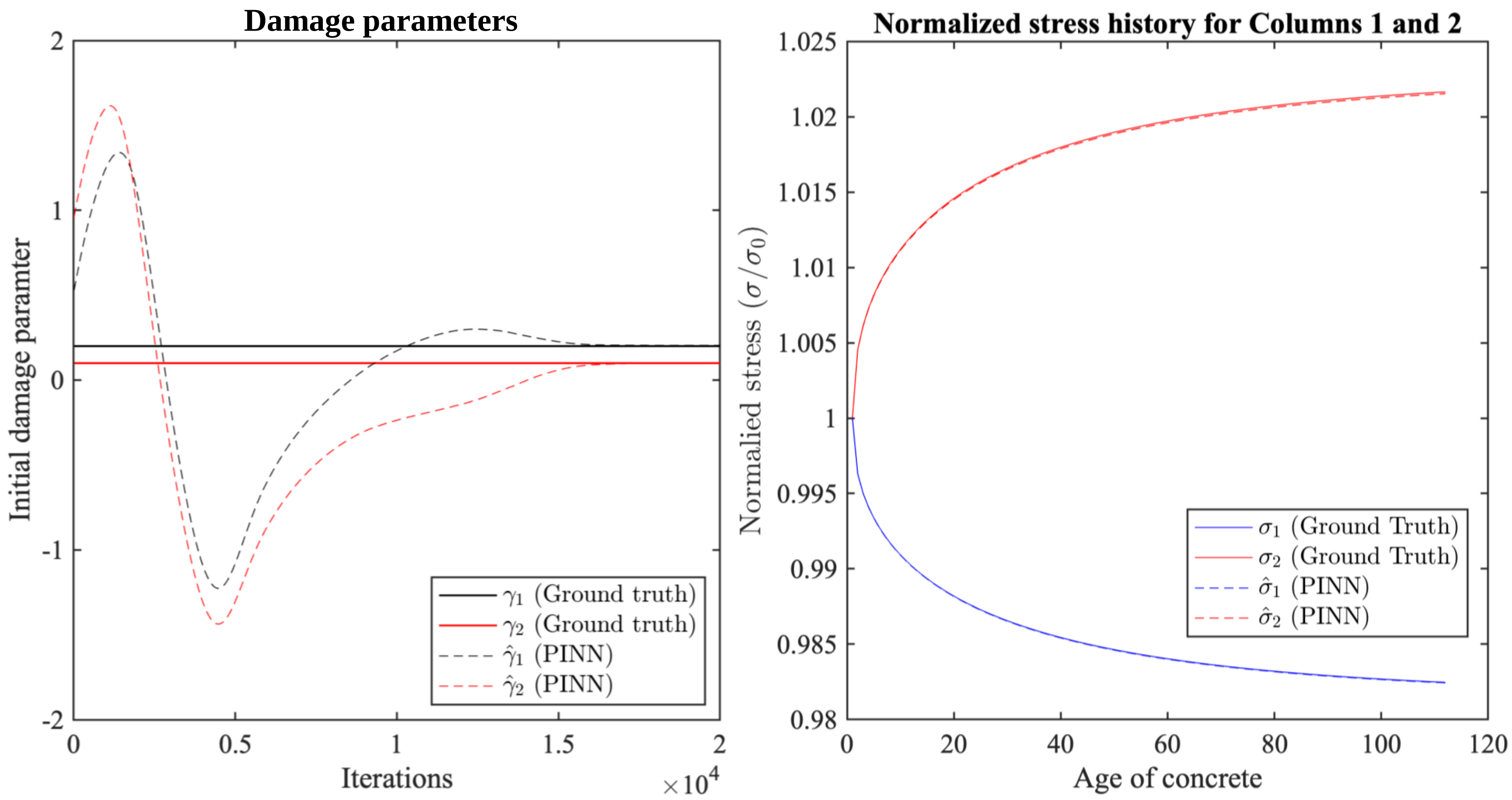
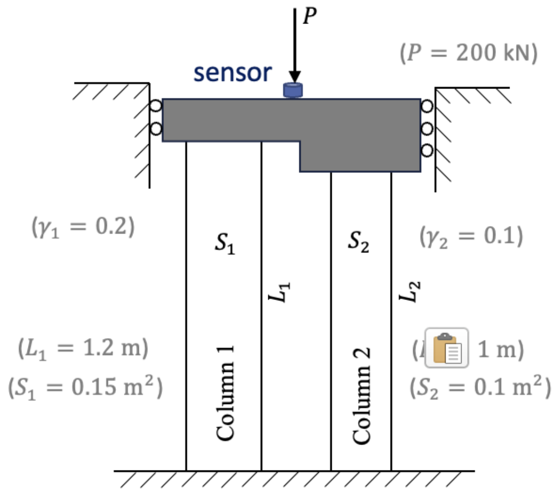


(a) (b)

Fig. 2 Comparison of estimated (a) damage parameters and (b) normalized stress history for two columns and ground truth.

Comparison of the estimation from PINN and Ground truth (continued)



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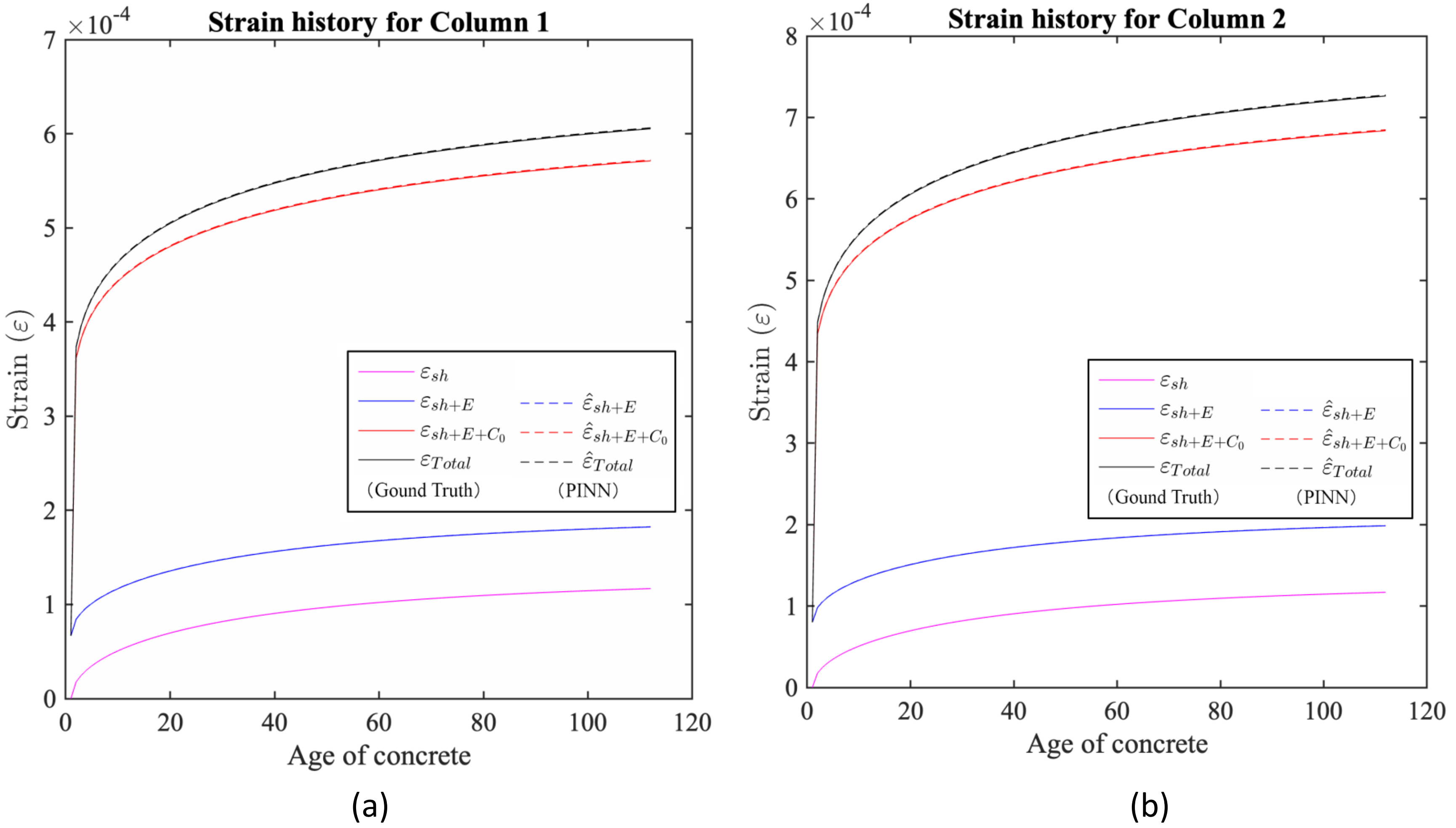

Fig. 2 Comparison of estimated strain history for (a) Column 1 and (b) Column 2 vs ground truth.

Summary of Work

- A Physics-informed Neural Network (PINN) framework for structural damage identification has been developed:
  - both physics and data are integrated into the loss function of the neural network;
  - by minimizing this physics-informed loss function, the PINN can estimate the unknown parameters.
- Through numerical examples, it is demonstrated that the PINN framework can estimate unknown damage parameters (e.g., cracking) and responses (e.g., creep strain history) with high accuracy from noisy data.

Thank you!