

# Learning in Modal Space: Solving Time-Dependent Stochastic PDEs Using Physics-Informed Neural Networks

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## 1 Problem Setup

We consider the following time-dependent SPDE:

$$\frac{\partial u}{\partial t} = \mathcal{N}_x[u(x, t; \omega)], \quad x \in D, t \in [0, T], \omega \in \Omega \quad (1)$$

with initial and boundary conditons

$$u(x, t_0; \omega) = u_0(x; \omega) \quad (2)$$

$$\mathcal{B}_x[u(x, t; \omega)] = h(x, t; \omega) \quad (3)$$

## 2 An overview of the Dynamically Orthogonal decomposition methods

For a random field  $u(x, t; \omega)$  that evolves in time, the generalized KL expansion at a given time  $t$  is

$$u(x, t; \omega) = \bar{u}(x, t) + \sum_{i=0}^{\infty} \sqrt{\lambda_i} \phi_i(x, t) \xi_i(t; \omega)$$

$$\int_D C_{u(x_1, t)u(x_2, t)} \phi_i(x_2, t) dx_2 = \lambda_i \phi_i(x_1, t)$$

$$C_{u(x_1, t)u(x_2, t)} = \mathbf{E}[(u(x_1, t; \omega) - \bar{u}(x_1, t))(u(x_2, t; \omega) - \bar{u}(x_2, t))]$$

Next, we consider a generalized expansion

$$u(x, t; \omega) = \bar{u}(x, t) + \sum_{i=1}^{\infty} u_i(x, t) Y_i(t; \omega), \quad \omega \in \Omega$$

$$\bar{u}(x, t) = \mathbf{E}[u(x, t; \omega)] = \int_{\Omega} u(x, t; \omega) dP(\omega)$$

$$\langle u_i, u_j \rangle = 0 \quad i \neq j$$

$$E[Y_i] = 0$$

We define the linear subspace  $V_S = \text{span}\{u_i(x, t)\}_{i=1}^N$ .

### 2.1 Dynamically orthogonal representation

A natural constraint to overcome redundancy is that the evolution of bases be orthogonal to the space  $V_S$ , this can be expressed through the following DO condition:

$$\frac{dV_S}{dt} \perp V_S \iff \left\langle \frac{\partial u_i(x, t)}{\partial t}, u_j(x, t) \right\rangle = 0 \quad i, j = 1, \dots, N$$

here  $\langle u(x, t), v(x, t) \rangle = \int_D u(x, t) v(x, t) dx$ . The DO condition preserves the orthonormality and the length of the bases  $\{u_i(x, t)\}_{i=1}^N$  since

$$\frac{\partial}{\partial t} \langle u_i(\cdot, t), u_j(\cdot, t) \rangle = \left\langle \frac{\partial u_i(\cdot, t)}{\partial t}, u_j(\cdot, t) \right\rangle + \left\langle u_i(\cdot, t), \frac{\partial u_j(\cdot, t)}{\partial t} \right\rangle = 0 \quad i, j = 1, \dots, N$$

**Theorem 2.1.**

$$\frac{\bar{u}(x, t)}{\partial t} = \mathbf{E}[\mathcal{N}_x[u(\cdot, t; \omega)]]$$

$$\frac{dY_i(t; \omega)}{dt} = \langle \mathcal{N}_x[u(\cdot, t; \omega)] - \mathbf{E}[\mathcal{N}_x[u(\cdot, t; \omega)]] , u_i(\cdot, t) \rangle$$

$$\sum_{i=1}^N C_{Y_i(t)Y_j(t)} \frac{\partial u_i(x, t)}{\partial t} = \Pi_{V_s^\perp} \mathbf{E}[\mathcal{N}_x[u(\cdot, t; \omega)]Y_j]$$

The projection in the orthogonal complement of the linear subspace  $V_S$  is defined as:

$$\Pi_{V_s^\perp} F(x) = F(x) - \Pi_{V_s} F(x) = F(x) - \sum_{k=1}^N \langle F(\cdot), u_k(\cdot, t) \rangle u_k(\cdot, t)$$

The boundary conditions are :

$$\begin{aligned} \mathcal{B}_x[\bar{u}(x, t; \omega)] &= \mathbf{E}[h(x, t; \omega)] \\ \mathcal{B}_x[u_i(x, t)] &= \mathbf{E}[Y_j(t; \omega)h(x, t; \omega)]C_{Y_i(t)Y_j(t)}^{-1} \end{aligned}$$

The initial condition:

$$\begin{aligned} \bar{u}(x, t_0) &= \mathbf{E}[u_0(x; \omega)] \\ Y_i(t_0; \omega) &= \langle u_0(\cdot, \omega) - \bar{u}(x, t_0), v_i(\cdot) \rangle \\ u_i(x, t_0) &= v_i(x) \end{aligned}$$

where  $v_i(x)$  is the eigenfield of the standard KL expansion of  $u_0(x; \omega)$ .

$$\int_D C_{u(\cdot, t_0)u(\cdot, t_0)}(x, y) v_i(x) dx = \lambda^2 v_i(x)$$