

Neural Schrödinger Bridge for Minimum Effort Self-assembly

Iman Nodoozi

inodozi@ucsc.edu

Department of Electrical and Computer Engineering
University of California, Santa Cruz

Joint work with



Jared O'Leary (UC Berkeley)



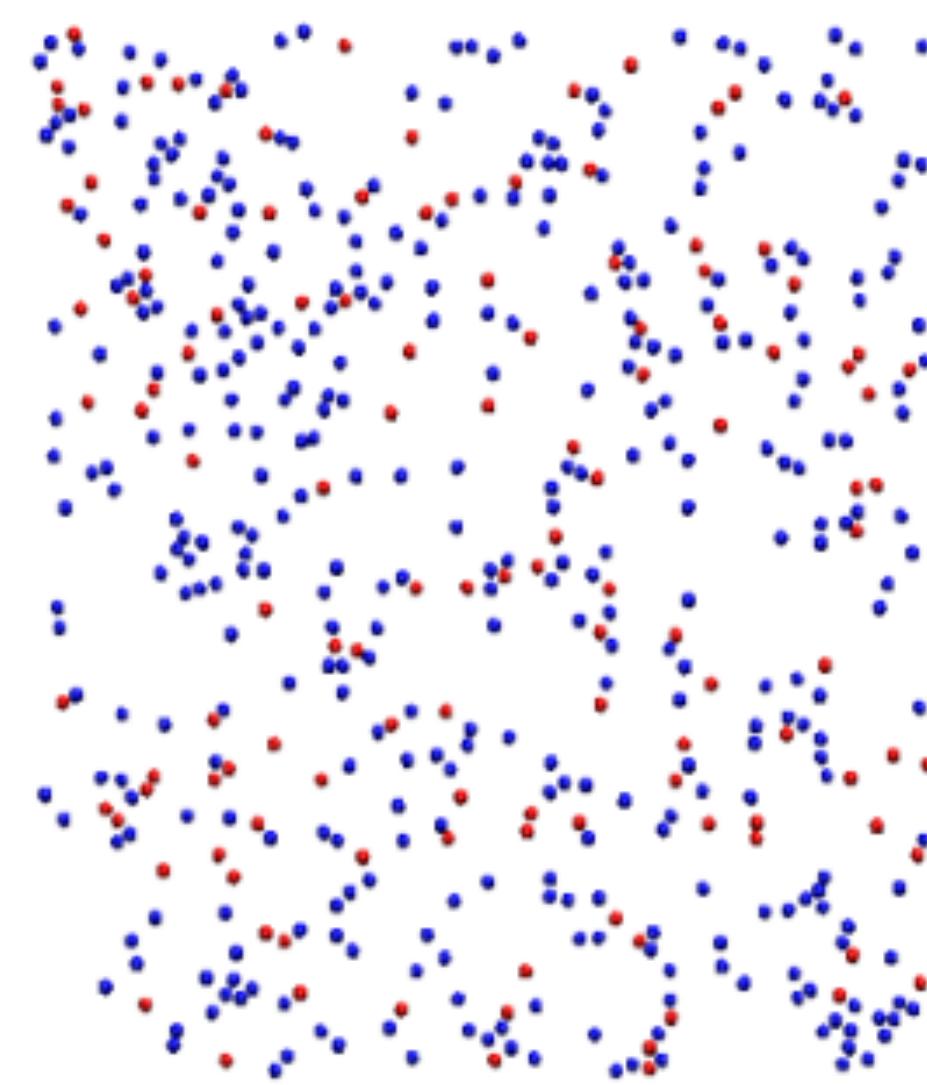
Abhishek Halder (UC Santa Cruz)



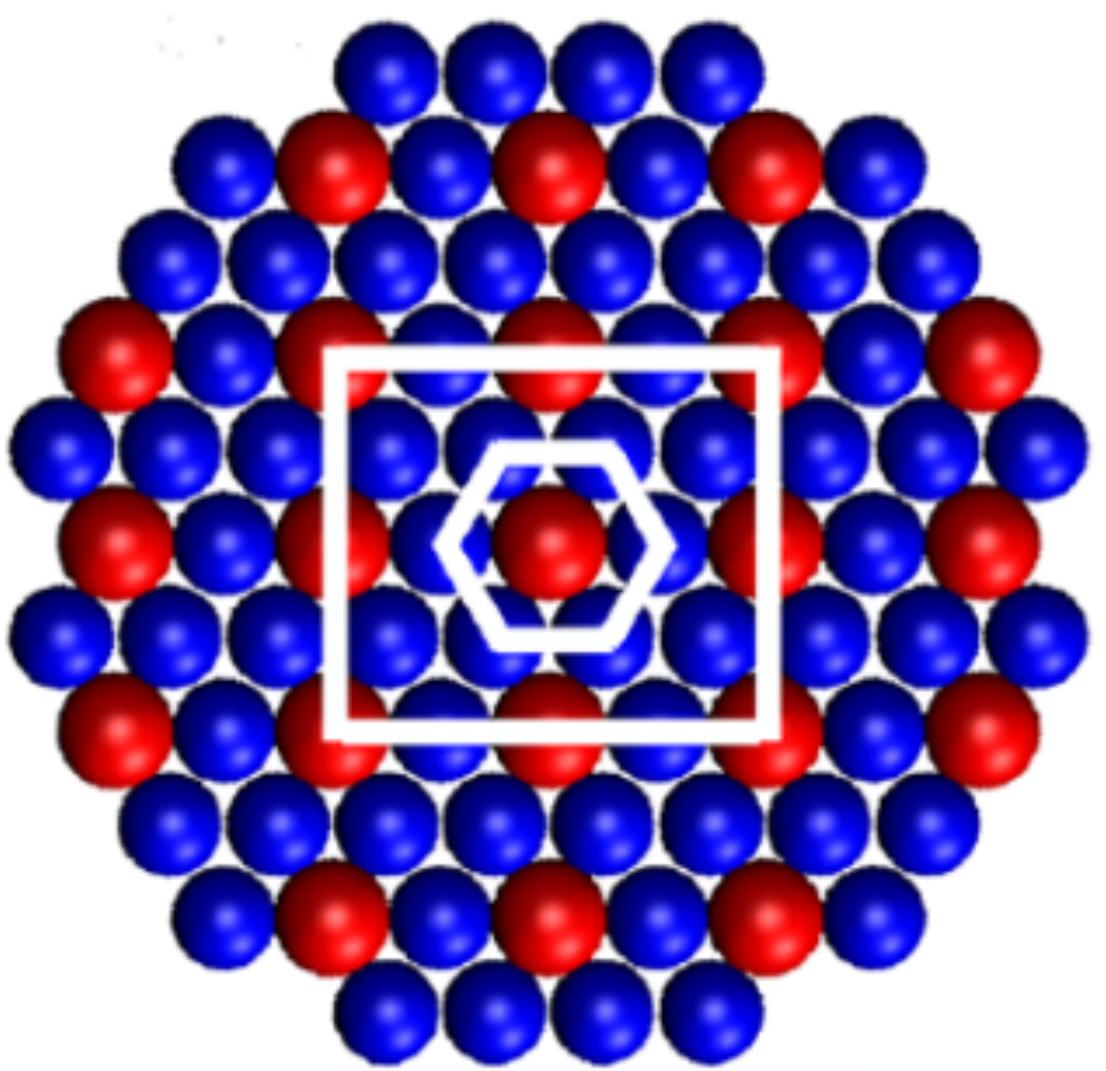
Ali Mesbah (UC Berkeley)

4th NorCal Control Workshop , June 03, 2022

Controlled Self-assembly



Dispersed particles

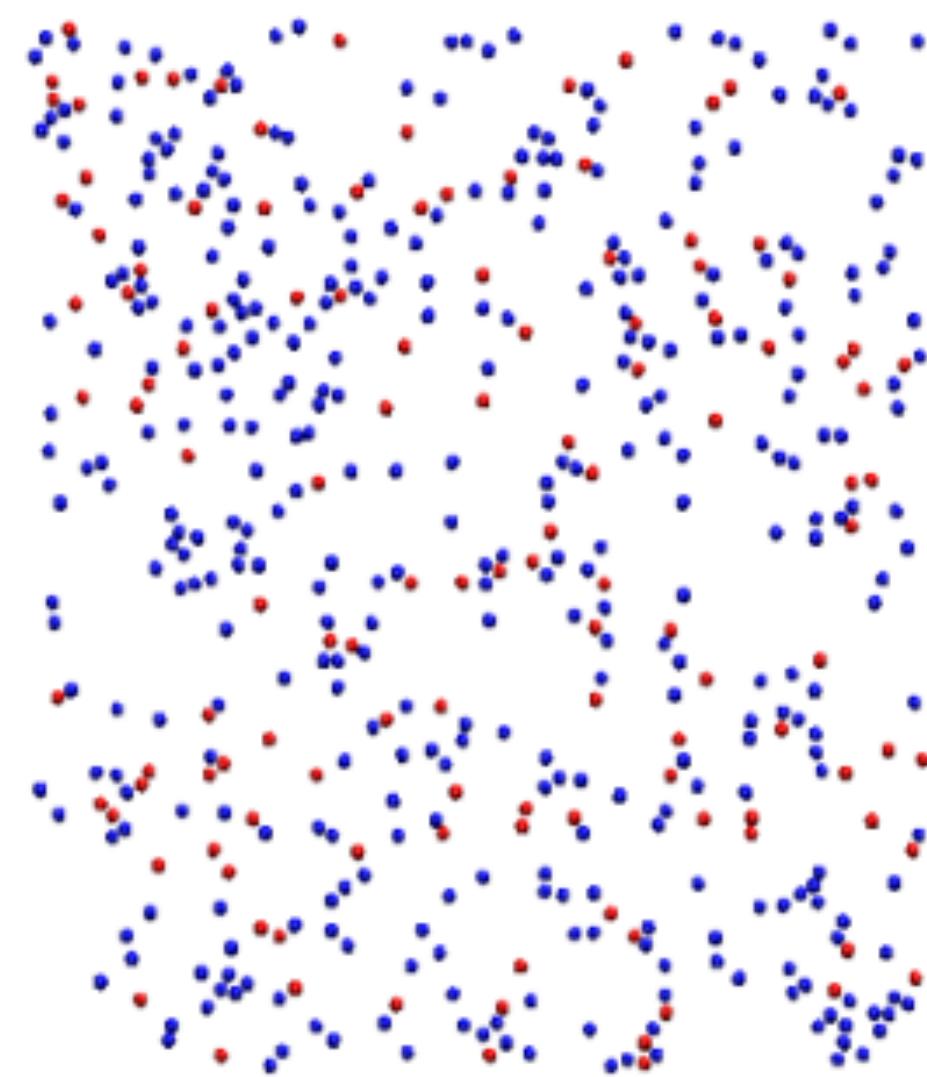


Ordered structure

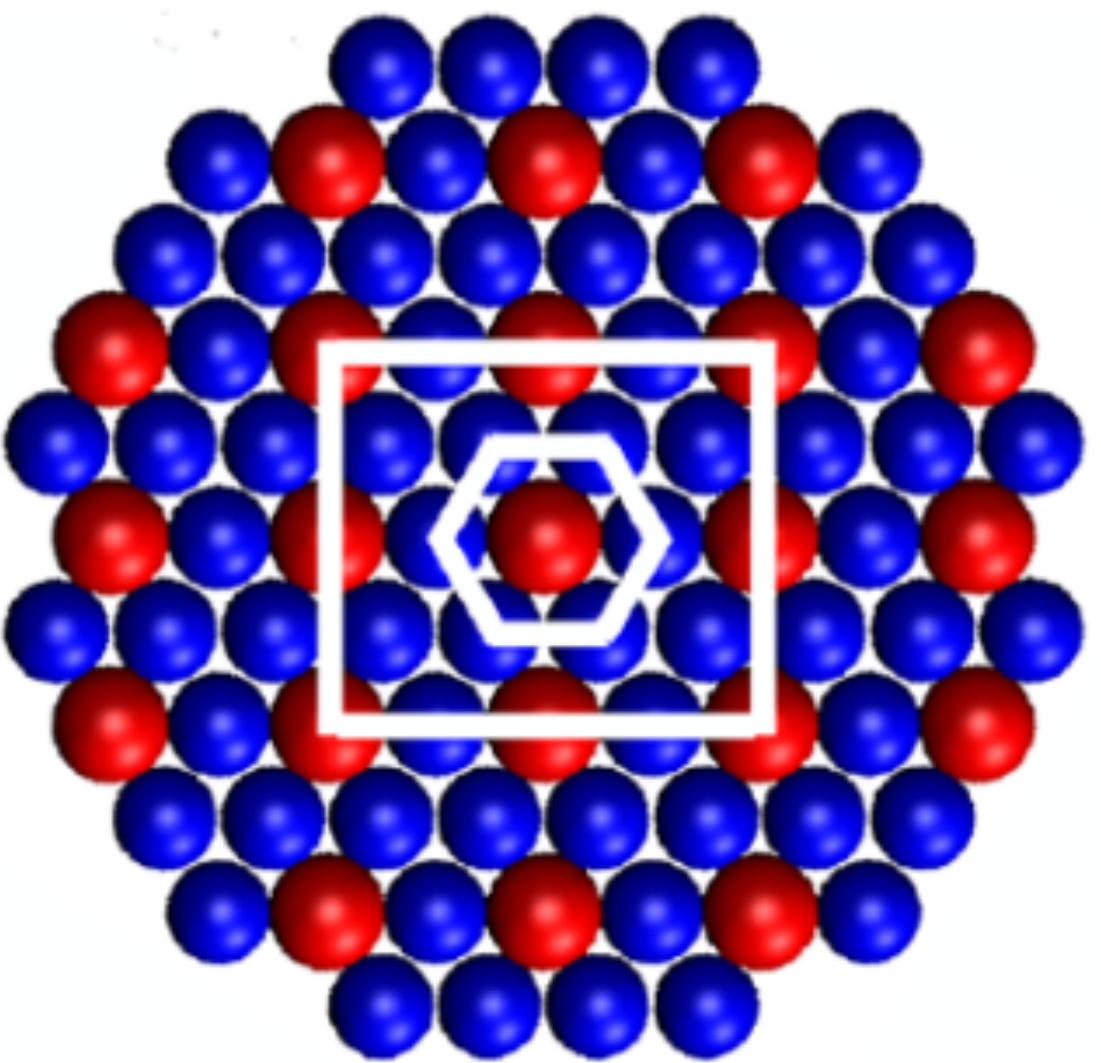
Applications:

Precision (e.g., sub nm scale) manufacturing of materials with advanced electrical, magnetic or optical properties

Controlled Self-assembly



Dispersed particles



Ordered structure

Typical state variable: $\langle C_6 \rangle \in (0,6)$

Average number of hexagonally close packed neighboring particles in 2D assembly ↪ measure of crystallinity order

Typical control variable: u

Electric field voltage

Technical challenge:

Nonlinear + noisy molecular dynamics



$\langle C_6 \rangle$ is a controlled stochastic process

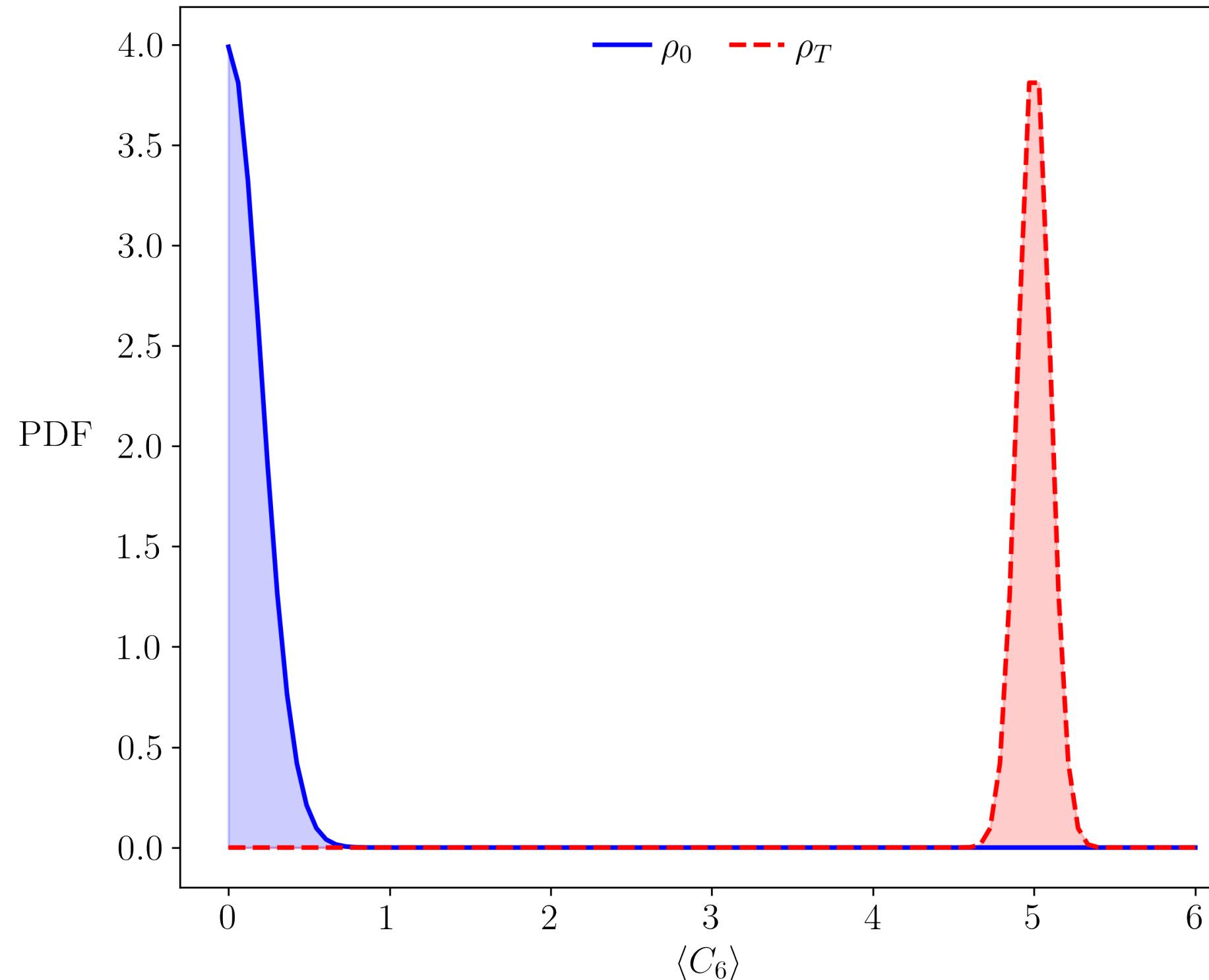
Controlled Self-assembly as PDF Steering

Intuition: $\langle C_6 \rangle \approx 0 \Leftrightarrow$ Crystalline disorder

$\langle C_6 \rangle \approx 5 \Leftrightarrow$ Crystalline order



Steer the PDF of the stochastic state $\langle C_6 \rangle$ from disordered at $t_0 = 0$ to ordered at $T = 200$ s



Typical prescribed finite horizon for controlled self-assembly

Endpoint PDF constraints: $\langle C_6 \rangle(t = t_0) \sim \rho_0$ (given)

$\langle C_6 \rangle(t = T) \sim \rho_T$ (given)

**Control policy to accomplish
the PDF steering:**

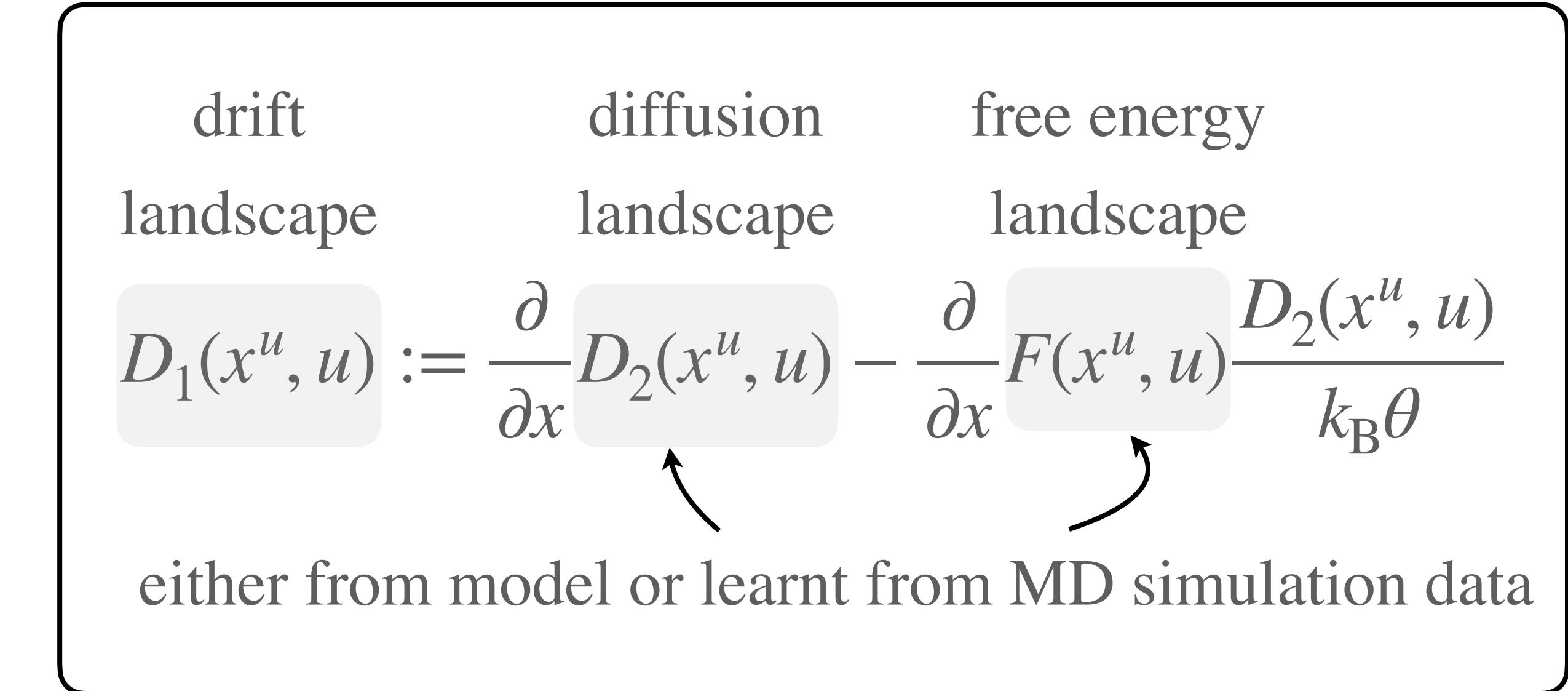
$$u = \pi(C_6, t)$$

Underdetermined

Minimum Effort Self-assembly

Proposed formulation:

$$\inf_{u \in \mathcal{U}} \mathbb{E}_{\mu^u} \left[\int_0^T \frac{1}{2} u^2 dt \right], \quad \mu^u \ll dx^u$$



subject to $dx^u = D_1(x^u, u) dt + \sqrt{2D_2(x^u, u)} dw$,

$\curvearrowleft \langle C_6 \rangle$
 \curvearrowleft standard Wiener process

$$x^u(t=0) \sim d\mu_0 = \rho_0 dx^u, \quad x^u(t=T) \sim d\mu_T = \rho_T dx^u$$

Minimum Effort Self-assembly

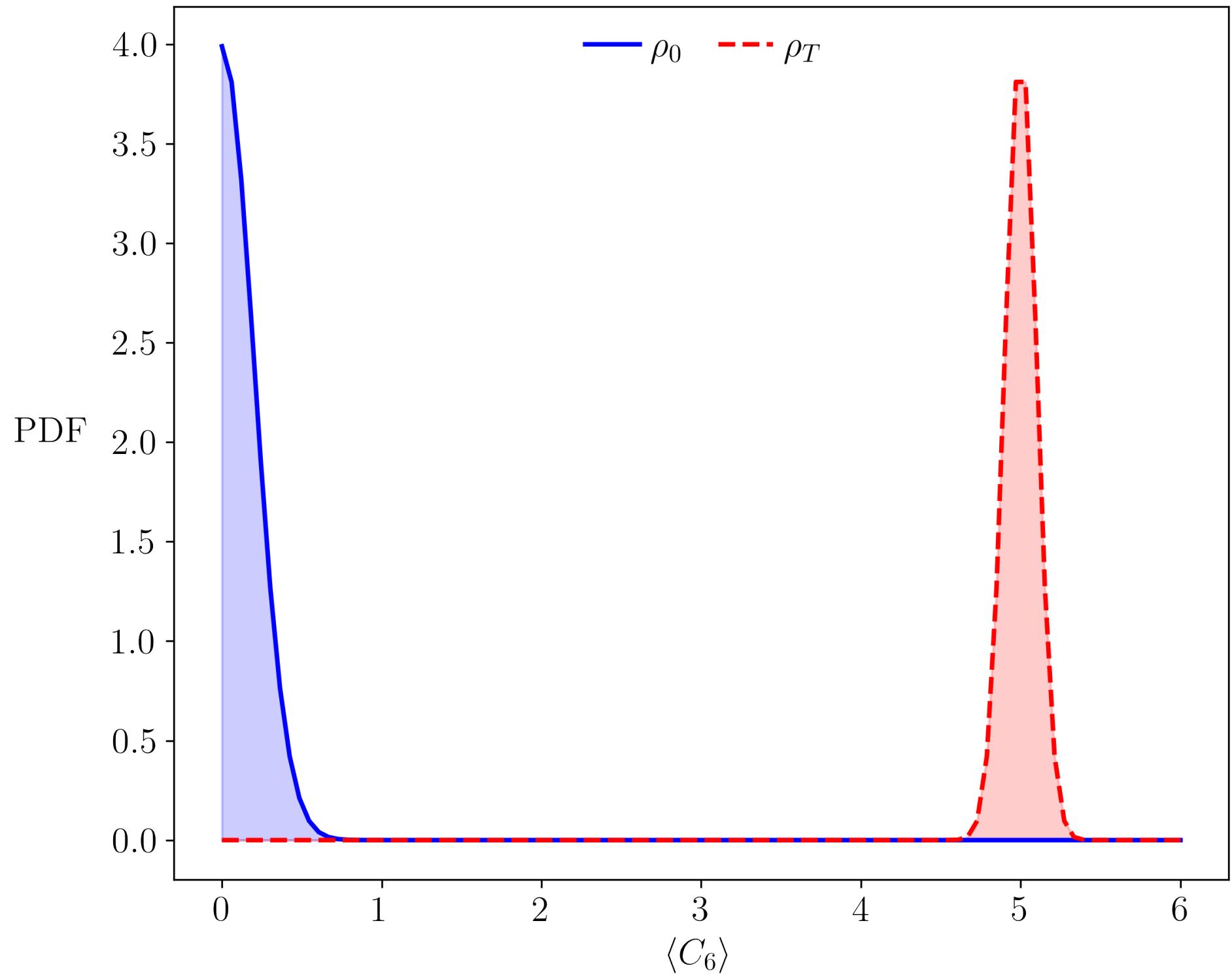
Equivalent formulation:

$$\inf_{(\rho^u, u)} \int_0^T \int_{\mathbb{R}} \frac{1}{2} u^2(x^u, t) \rho^u(x^u, t) dx^u dt$$

subject to $\frac{\partial \rho^u}{\partial t} = - \frac{\partial}{\partial x^u} (D_1 \rho^u) + \frac{\partial^2}{\partial x^{u2}} (D_2 \rho^u)$

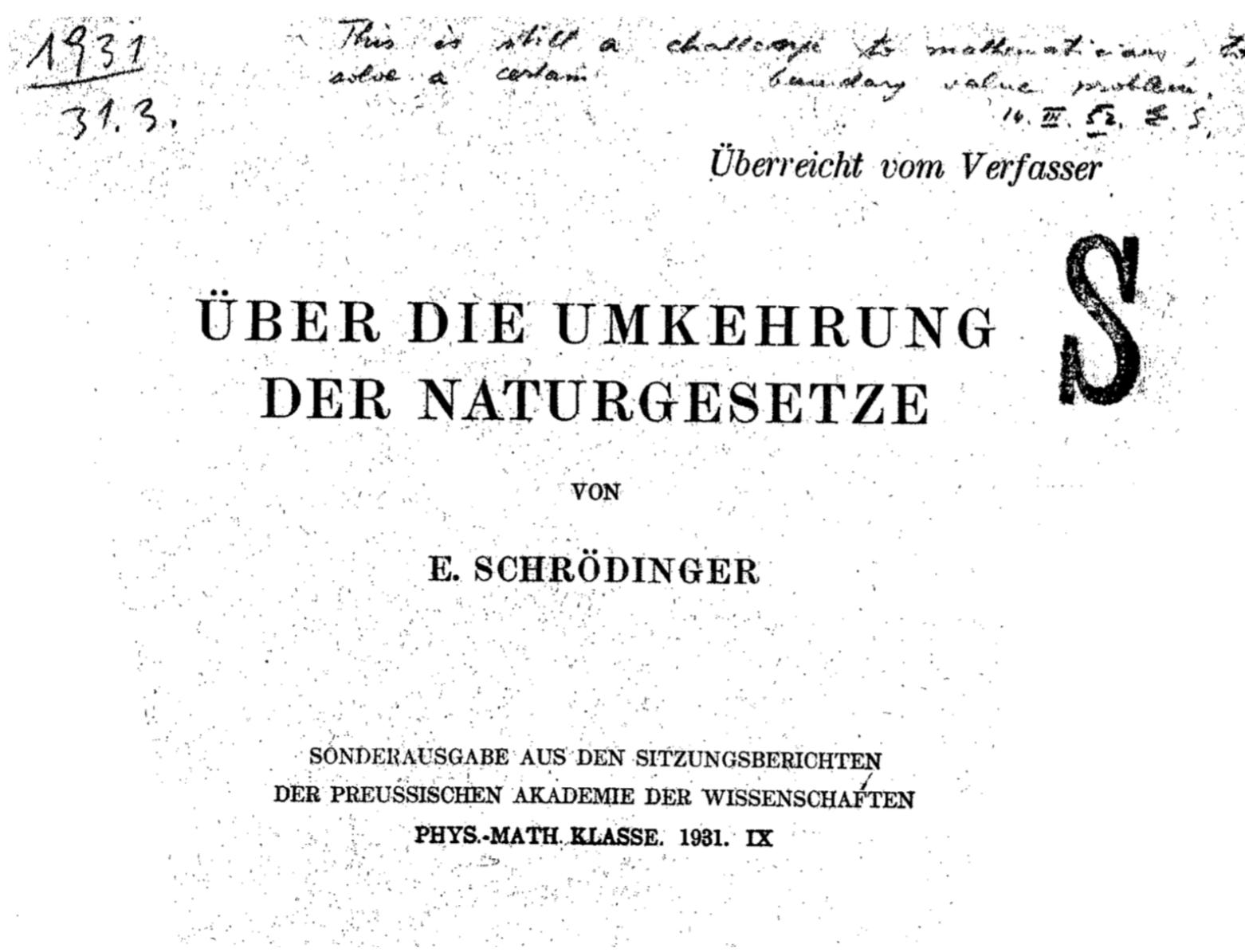
$$\rho(x^u, t = 0) = \rho_0, \quad \rho(x^u, t = T) = \rho_T$$

Guaranteed existence-uniqueness
for compactly supported ρ_0, ρ_T



Generalized Schrödinger Bridge

Schrödinger bridge problem: $D_1 \equiv 0$ and $D_2 \equiv$ Identity



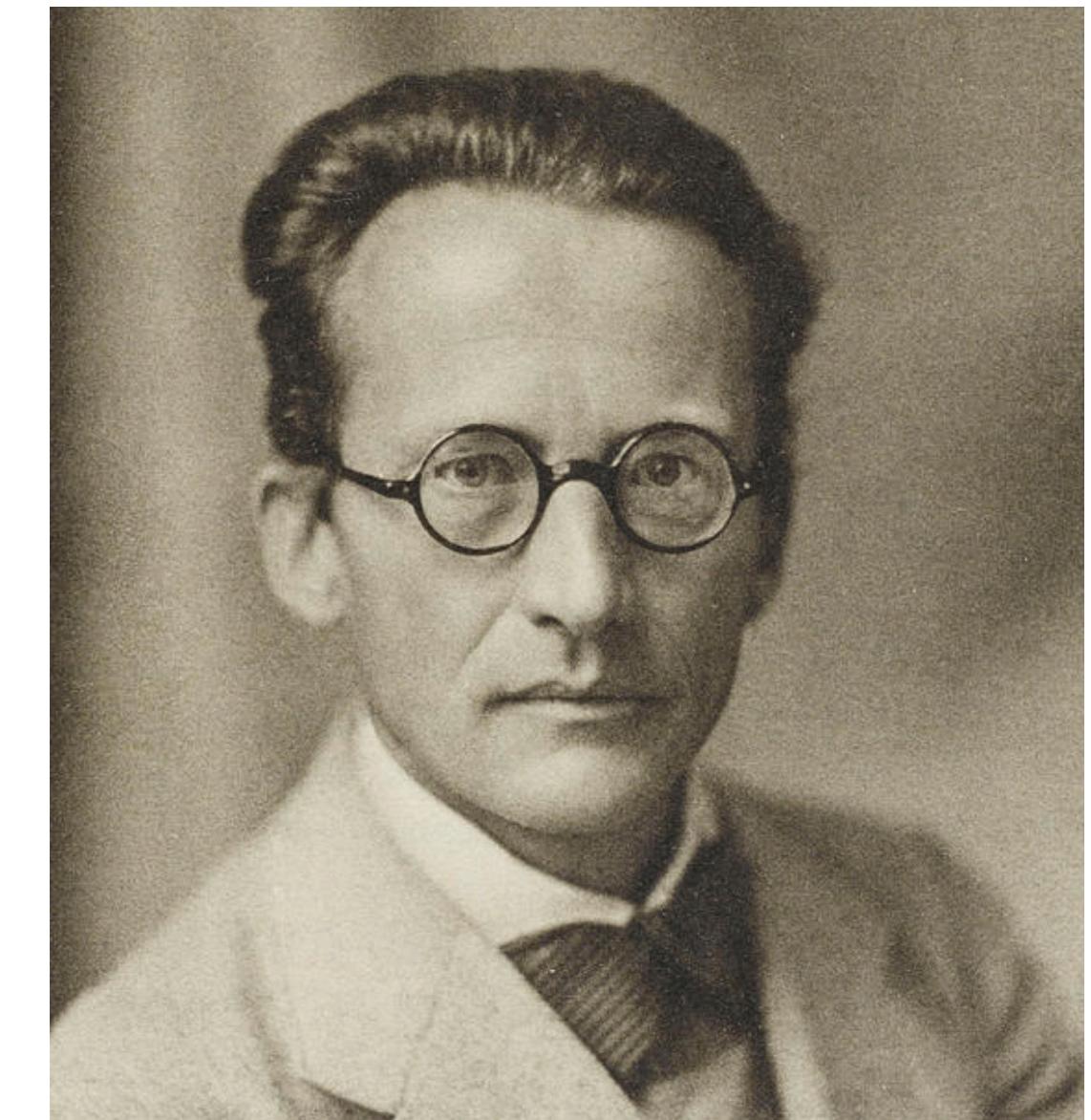
Sur la théorie relativiste de l'électron
et l'interprétation de la mécanique quantique

PAR

E. SCHRÖDINGER

I. — Introduction

J'ai l'intention d'exposer dans ces conférences diverses idées concernant la mécanique quantique et l'interprétation qu'on en donne généralement à l'heure actuelle ; je parlerai principalement de la théorie quantique relativiste du mouvement de l'électron. Autant que nous pouvons nous en rendre compte aujourd'hui, il semble à peu près sûr que la mécanique quantique de l'électron, sous sa forme idéale, *que nous ne possédons pas encore*, doit former un jour la base de toute la physique. A cet intérêt tout à fait général, s'ajoute, ici à Paris, un intérêt particulier : vous savez tous que les bases de la théorie moderne de l'électron ont été posées à Paris par votre célèbre compatriote Louis de BROGLIE.



In our setting: both D_1 and D_2 are nonlinear + control non-affine

Conditions for Optimality

$$\frac{\partial \psi}{\partial t} = \frac{1}{2} (\pi^{\text{opt}})^2 - \frac{\partial \psi}{\partial x} D_1 - \frac{\partial^2 \psi}{\partial x^{u2}} D_2$$

HJB PDE

$$\frac{\partial \rho^u}{\partial t} = - \frac{\partial}{\partial x^u} (D_1 \rho^u) + \frac{\partial^2}{\partial x^{u2}} (D_2 \rho^u)$$

Controlled FPK PDE

$$\pi^{\text{opt}}(x^u, t) = \frac{\partial \psi}{\partial x^u} \frac{\partial D_1}{\partial u} + \frac{\partial^2 \psi}{\partial x^{u2}} \frac{\partial D_2}{\partial u}$$

Optimal policy

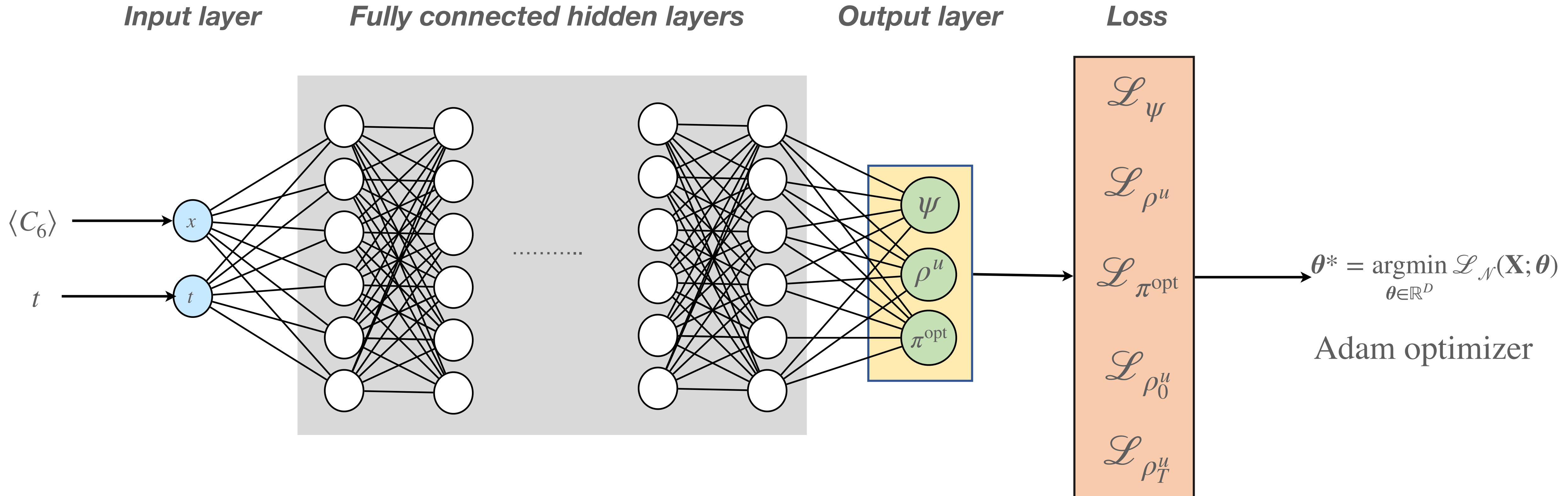
$$\rho(x^u, t=0) = \rho_0, \quad \rho(x^u, t=T) = \rho_T$$

Boundary conditions

value function	optimally controlled PDF	optimal policy
-------------------	-----------------------------	-------------------

to be solved for the triple: $\psi(x^u, t), \rho^u(x^u, t), \pi^{\text{opt}}(x^u, t)$

Solve via PINN



$$\mathcal{L}_{\mathcal{N}} = \mathcal{L}_\psi + \mathcal{L}_{\rho^u} + \mathcal{L}_{\pi^{\text{opt}}} + \mathcal{L}_{\rho_0^u} + \mathcal{L}_{\rho_T^u}$$

[Lu Lu et al, 2021] [Niaki et al, 2021]

Losses for Training

Loss term for HJB PDE

$$\mathcal{L}_\psi = \frac{1}{n} \sum_{i=1}^n \left(\frac{\partial \psi}{\partial t} \Bigg|_{x_i} - \frac{1}{2} (\pi^{\text{opt}})^2 \Bigg|_{x_i^u} + \frac{\partial \psi}{\partial x^u} D_1 \Bigg|_{x_i^u} + \frac{\partial^2 \psi}{\partial x^{u2}} D_2 \Bigg|_{x_i^u} \right)^2$$

Loss term for FPK PDE

$$\mathcal{L}_{\rho^u} = \frac{1}{n} \sum_{i=1}^n \left(\frac{\partial \rho^u}{\partial t} \Bigg|_{x_i^u} + \frac{\partial}{\partial x^u} (D_1 \rho^u) \Bigg|_{x_i^u} - \frac{\partial^2}{\partial x^{u2}} (D_2 \rho^u) \Bigg|_{x_i^u} \right)^2$$

Loss term for policy equation

$$\mathcal{L}_{\pi^{\text{opt}}} = \frac{1}{n} \sum_{i=1}^n \left(\pi^{\text{opt}} \Big|_{x_i^u} - \frac{\partial \psi}{\partial x^u} \frac{\partial D_1}{\partial u} \Big|_{x_i^u} - \frac{\partial^2 \psi}{\partial x^{u2}} \frac{\partial D_2}{\partial u} \Big|_{x_i^u} \right)^2$$

Loss term for initial condition

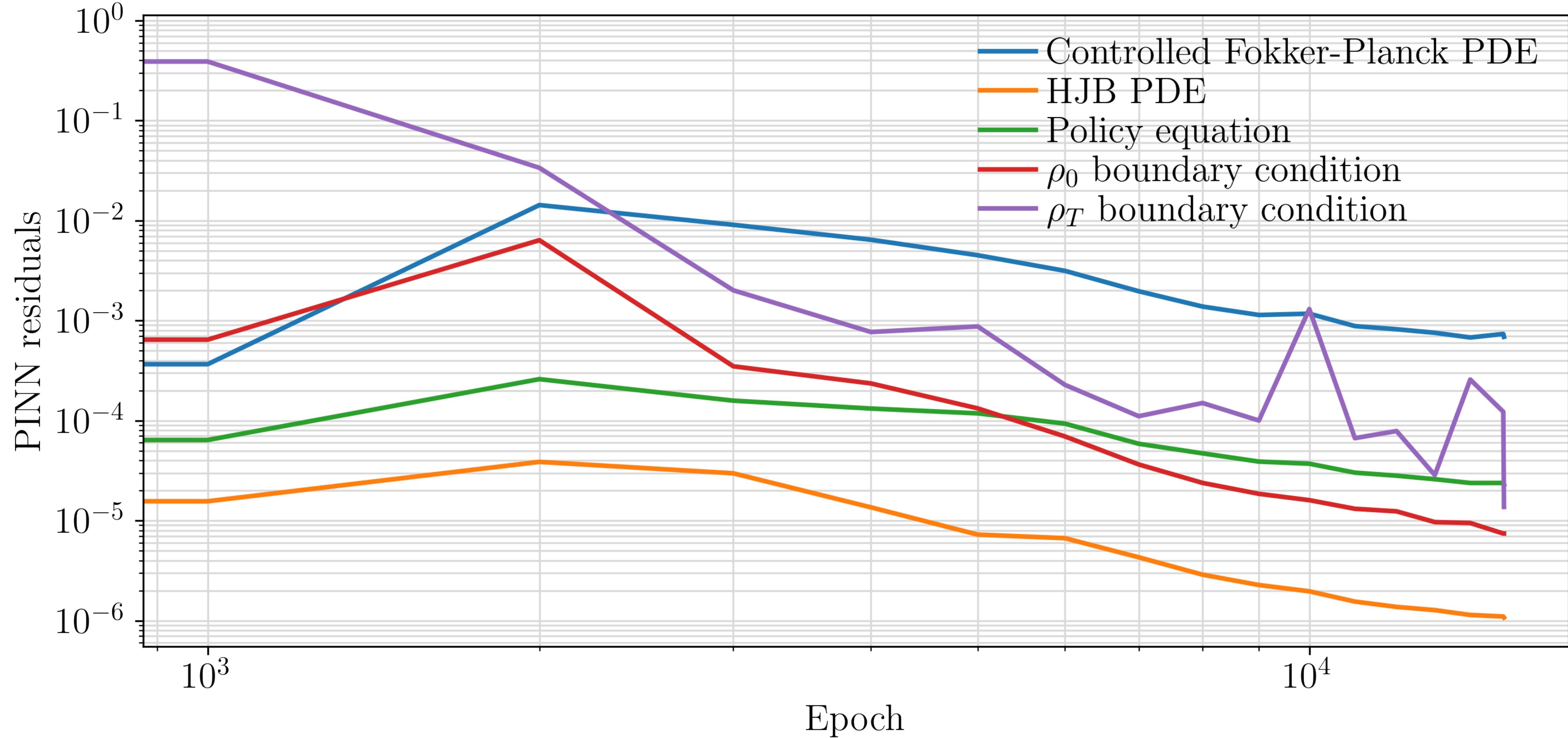
$$\mathcal{L}_{\rho_0^u} = \frac{1}{n} \sum_{i=1}^n \left(\rho^u \Big|_{t=0} - \rho_0^u(x) \right)^2$$

Loss term for terminal condition

$$\mathcal{L}_{\rho_T^u} = \frac{1}{n} \sum_{i=1}^n \left(\rho^u \Big|_{t=T} - \rho_T^u(x) \right)^2$$

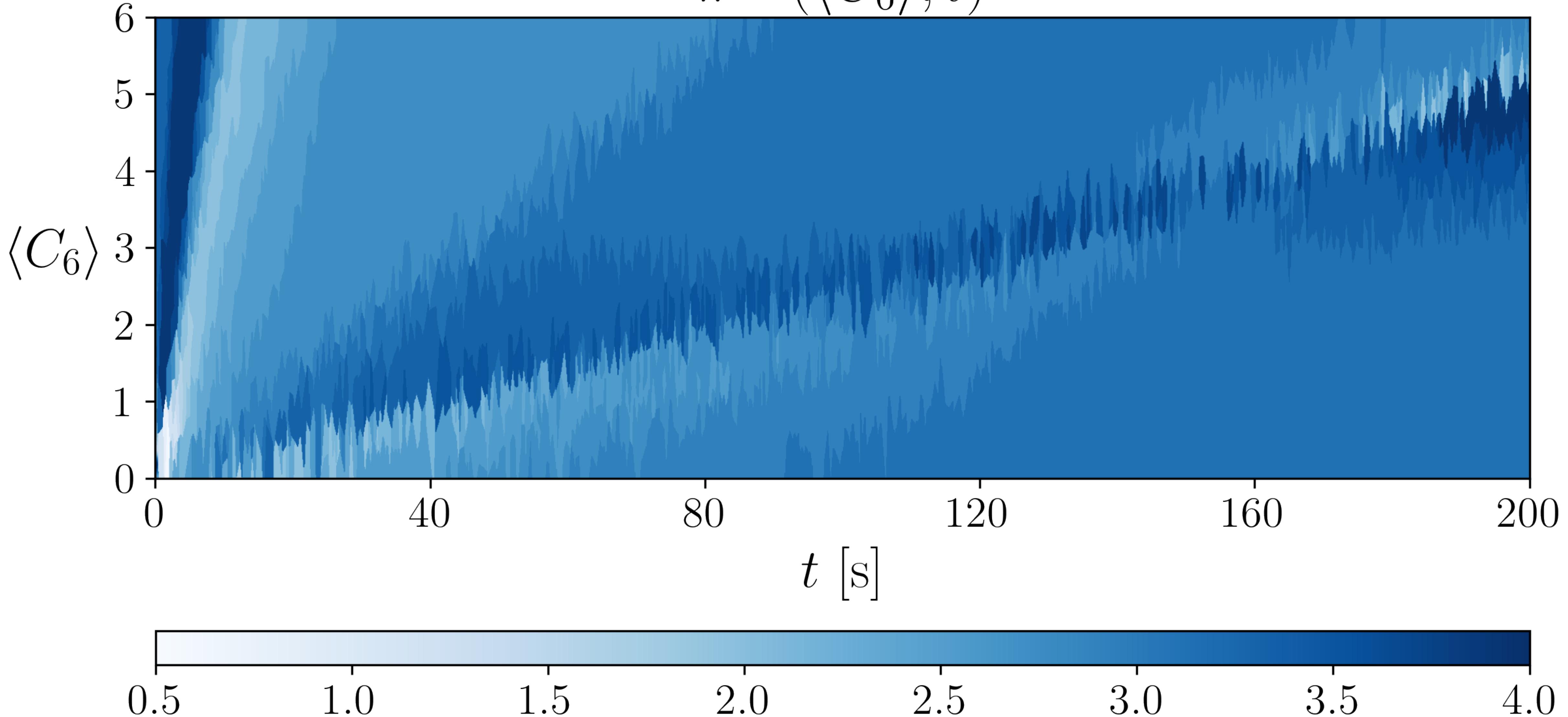
Training of the PINN

Benchmark controlled self-assembly system: [Y Xue, et al, *IEEE Trans. Control Sys. Technology*, 2014]



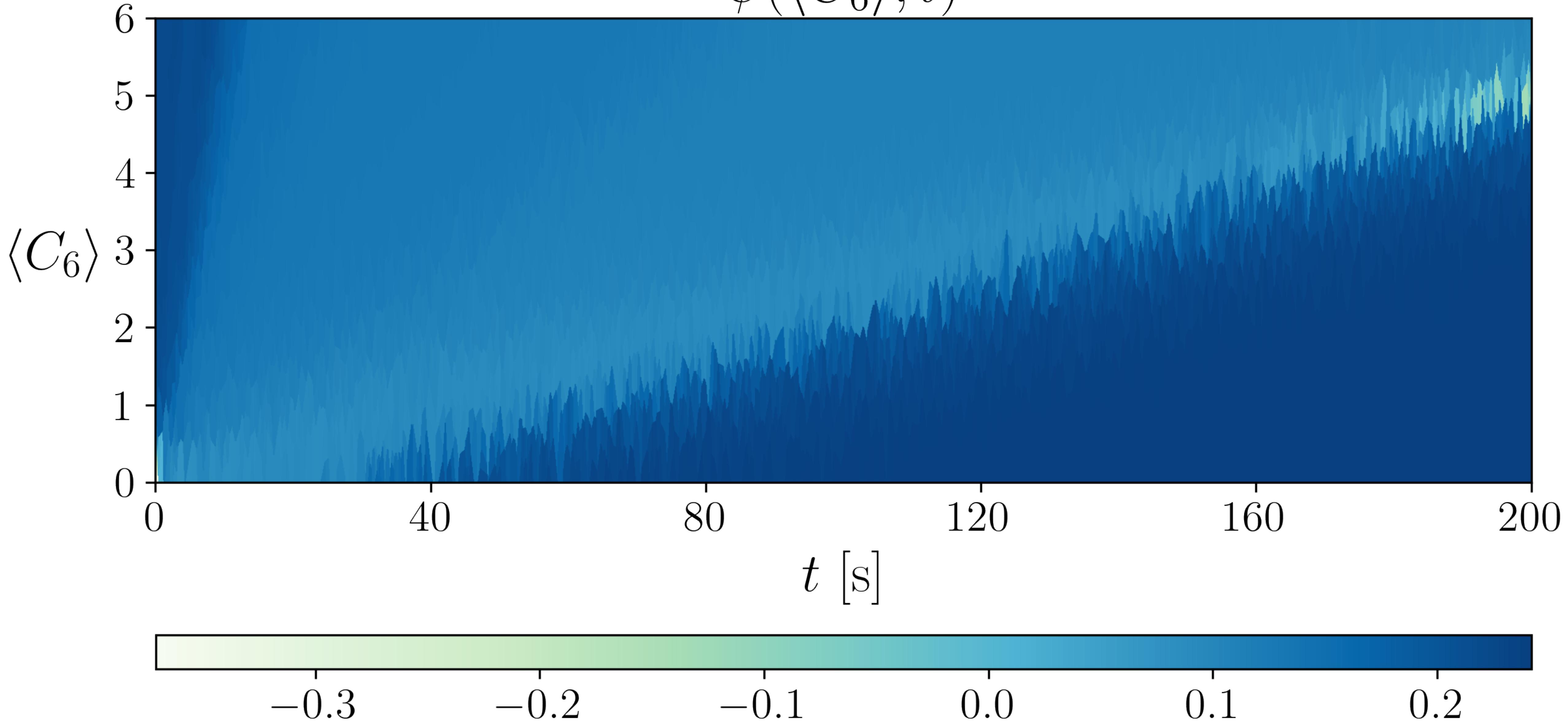
Optimal Policy

$$\pi^{\text{opt}}(\langle C_6 \rangle, t)$$

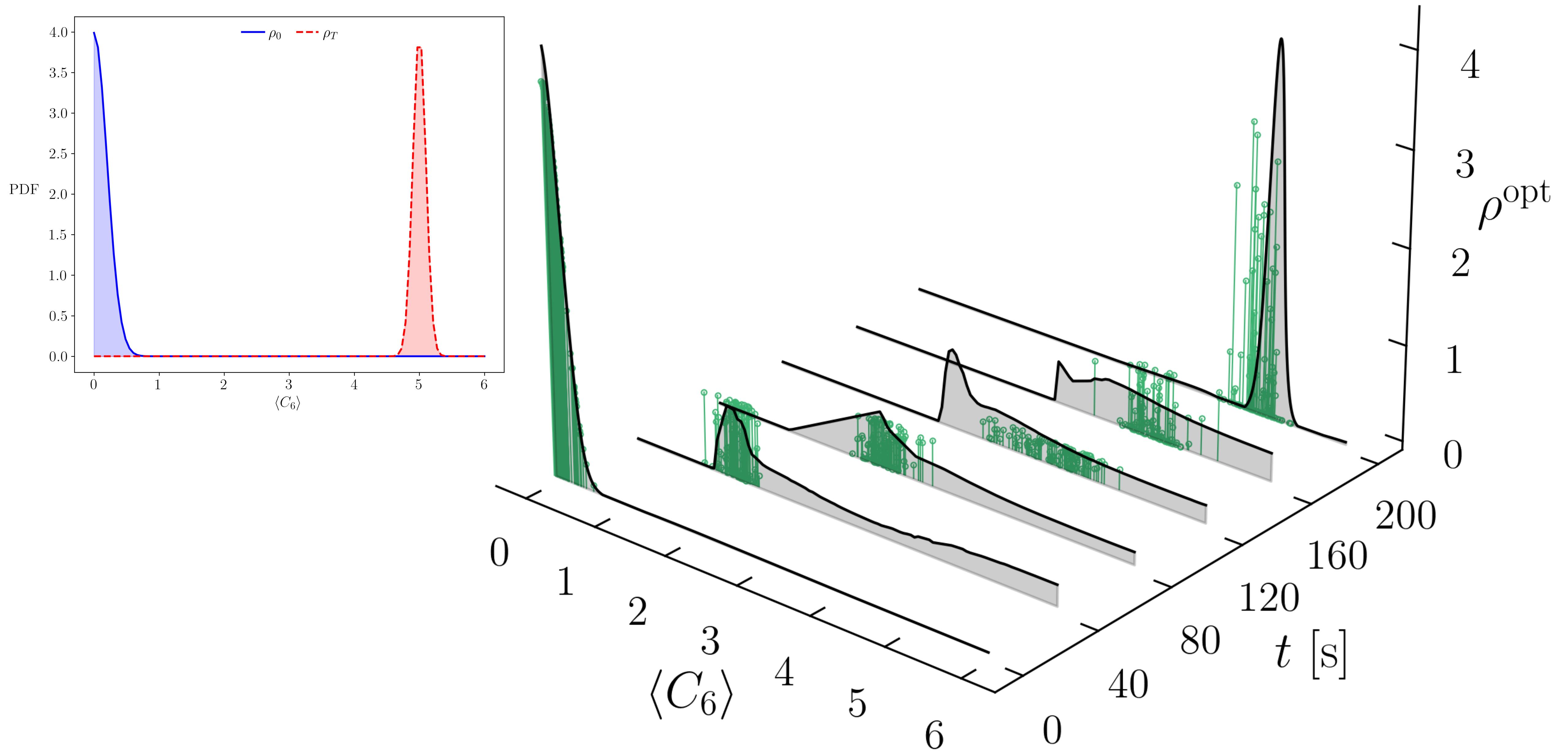


Value Function

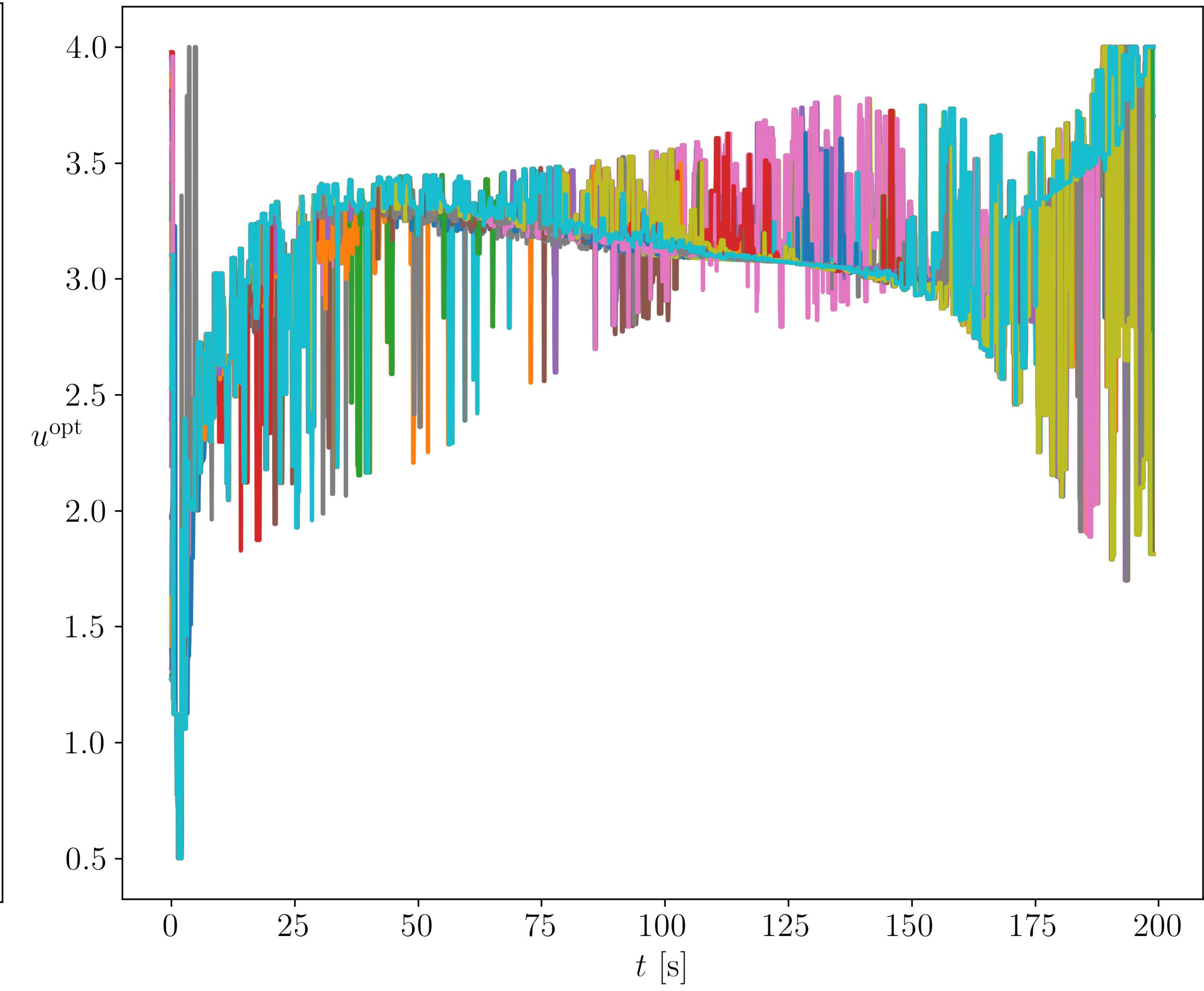
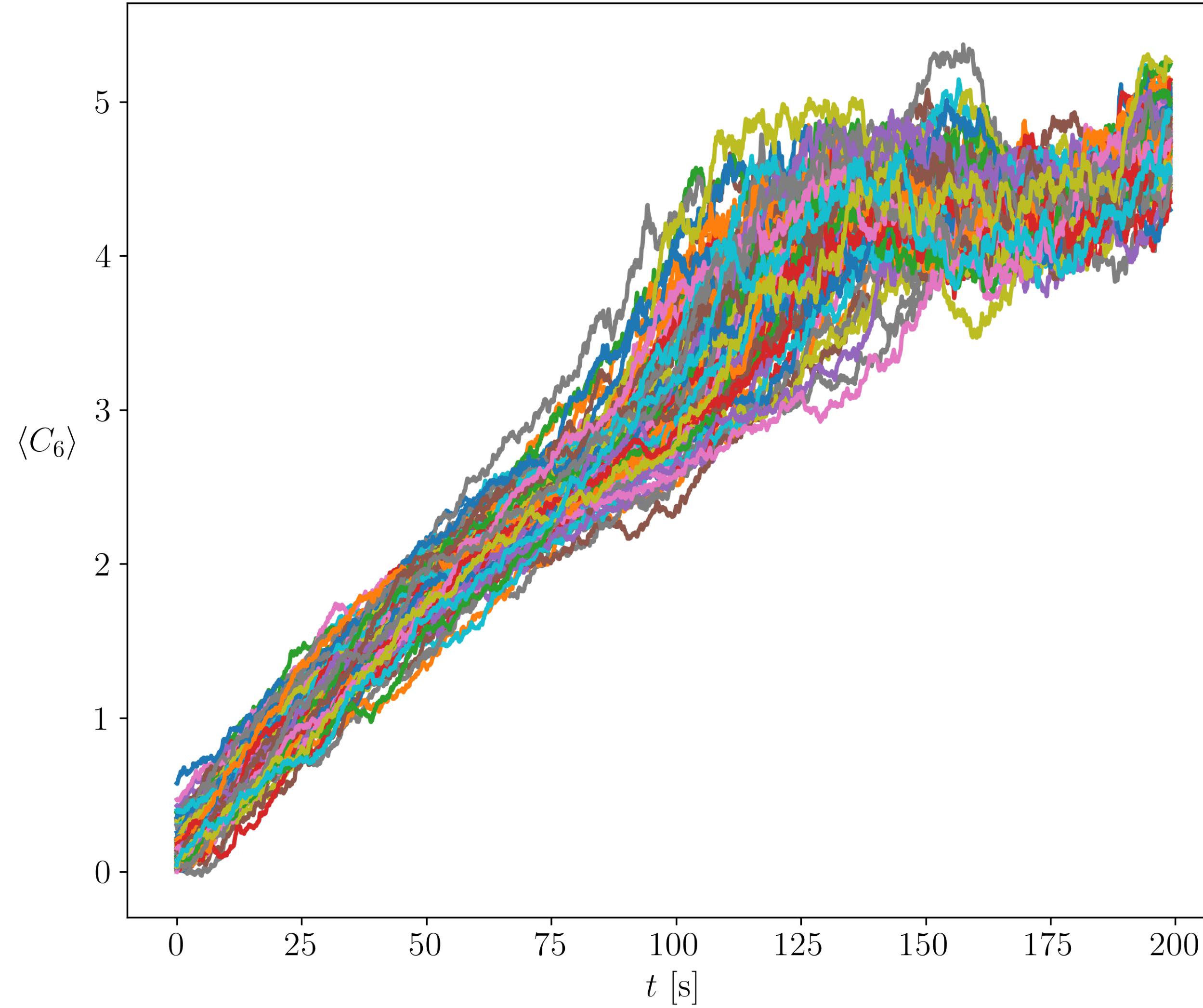
$$\psi(\langle C_6 \rangle, t)$$



Optimally Controlled State PDFs



Optimal State and Optimal Control Sample Paths



Ongoing Efforts

Learning from very high fidelity MD simulation data

Online learning and control

Robustness

Thank You

Acknowledgment:

