



Stochastic Partial Differential Equations and Random Dynamical Systems

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Motivation of SPDE

Flow in a porous medium

Flow in a random porous medium

From random PDE to stochastic PDE

SOC and SPDE

Random Dynamics

Dynamics of distributions

Random Dynamical Systems (RDS)

(Random) Attractors

Main obstacles



Gas Flow in a porous medium

Flow of an ideal gas in a homogeneous porous medium. ρ density, p pressure, v velocity

- Mass conservation:

$$\varepsilon \partial_t \rho + \nabla \cdot (\rho v) = 0,$$

- Darcy's law:

$$\mu v = -k \nabla p,$$

- State equation:

$$p = p_0 \rho^\gamma,$$

where γ polytropic exponent, ε porosity of the medium, k permeability of the medium, p_0 reference pressure. We get:

$$\partial_t \rho = c \Delta(\rho^m).$$



Porous Medium Equation

General form:

$$\partial_t u = \Delta \Phi(u), \quad (PME).$$

Applications:

- Nonlinear heat transfer (thermal conductivity depends on temperature).
- Phase transition (Stefan problem).
- Groundwater infiltration.
- Heat radiation in plasmas.
- Population dynamics (crowd avoiding).



PME and random environment

- Stochastic fluctuation of the permeability of the medium.
Darcy's law: $\mu v = -k(\xi_t)\nabla p$.
- Model of the noise:
 - No further information on the correlations: ξ_{t_1}, ξ_{t_2} independent.
 - ξ_t identically distributed.
 - Central limit theorem: ξ_t normally distributed.
 - $\mathbb{E}[\xi_t \xi_s] = \delta(t - s)$.

I.e. ξ is white noise.

- End up with

$$\partial_t \rho = c(\xi_t) \Delta(\rho^m), \quad (RPME).$$



PME and random environment

- **Aim:** Derive stochastic properties of u from those of c .
- ξ -wise approach: Fix a realization of the noise ξ and solve (RPME) as a deterministic equation. Then derive information about distributions etc. from ξ -wise statements.



PME and SPDE

- **Aim:** Use probabilistic methods to study random PDE, e.g. consider corresponding Kolmogorov/Fokker-Planck equations.
- Much is known for SDE of the form

$$dX_t = b(X_t)dt + \sigma(X_t)dW_t.$$

- (So far) our equation has the form:

$$\frac{d}{dt}X_t = c(\xi_t)\Delta\Phi(X_t) = A(X_t, \xi_t).$$



PME and SPDE

- Expansion of first order in the noise:

$$\frac{d}{dt}X_t = A(X_t, 0) + D_\xi A(X_t, 0)\xi_t$$

- White noise is the “derivative” of Brownian motion:

$$\xi_t dt = \dot{W}(t)dt = dW_t.$$

- We get: (SPDE with multiplicative noise)

$$dX_t = A(X_t)dt + B(X_t)dW_t.$$

Note that this is an equation with infinitely many variables, i.e. on some infinite dimensional state space H . Usually H is some space of functions like $H = L^2(\mathcal{O})$.



Reduction to additive noise

- Fix the noise: $B \equiv B(Y_t)$ then study

$$dZ_t = A(Z_t)dt + B(Y_t)dW_t,$$

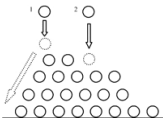
which is an SPDE with additive random noise.

- Denote by $\Gamma(Y) = Z$ the solution given the noise Y . Then recover the original solution X as a fixed point of Γ .



Self-organized criticality and SPDE

Bak-Tang-Wiesenfeld sandpile:



- Sand grains are dropped on a table at a random position.
- If the gradient of the density exceeds threshold an avalanche occurs, i.e. rapid diffusion of mass.
- Model:

$$dX_t = \text{div}(\delta_{X_t=X_c} \nabla X_t) dt + dW_t = \Delta H(X_t \geq X_c) dt + dW_t.$$

- used to study chaotic phenomena (e.g. earthquakes, traffic jams).



Long-time behavior of SPDE

- Interested in invariant states.
- Reduction of complexity (due to ergodicity or energy dissipation).



Dynamics of distributions

- Let $dX_t = b(X_t)dt + \sigma(X_t)dW_t$ on $H = \mathbb{R}^n$ “state space”. Denote X_t^ν solution with initial distribution $X_0 \sim \nu$.
- Let $P_t\nu := (X_t^\nu)_*\mathbb{P}$ be the distribution of X_t^ν at time t , i.e.

$$P_t\nu(A) = \mathbb{P}[X_t^\nu \in A].$$

- Let $\mathcal{P} = Pr(H)$ be the set of all probability distributions over H . Then $P_t : \mathcal{P} \rightarrow \mathcal{P}$ is a (deterministic) dynamical system, i.e.

$$\begin{aligned}P_{t+s}\nu &= P_t(P_s\nu), \\ P_t\nu &\rightarrow \nu, \quad \text{for } t \rightarrow 0.\end{aligned}$$



Dynamics of distributions

- P_t satisfies the Fokker-Planck equation:

$$\partial_t P_t \nu = \sum_{i,j=1}^n (\sigma(x)^t \sigma(x))_{i,j} \partial_i \partial_j P_t \nu + b(x) \cdot \nabla P_t \nu.$$

- Long-time behavior:

$$P_t \nu \rightarrow \mu, \text{ for } t \rightarrow \infty$$

$$P_t \nu \rightarrow \mathcal{A} \subseteq \mathcal{P}, \text{ where } \mathcal{A} \text{ is some "small", invariant set.}$$



Dynamics on the state space (RDS)

- $X_t : \Omega \rightarrow H = \mathbb{R}^n$. $t \mapsto X_t(\omega)$ is a random path in H .
- Problem: noise yields inhomogeneity in time

$$"dX_t = b(X_t)dt + \dot{W}(t)dt"$$

Get an inhomogeneous semigroup.



Dynamics on the state space (RDS)

- Solution: Homogenization

Let $\Omega = C_0(\mathbb{R}; \mathbb{R}^n)$ and

$$\begin{aligned}\theta_t : \Omega &\rightarrow \Omega \\ \omega &\mapsto \omega(t + \cdot) - \omega(t),\end{aligned}$$

be the Wiener shift (ergodic dynamical system).

- Then

$$\begin{aligned}\Pi_t : \Omega \times X &\rightarrow \Omega \times X \\ (\omega, x) &\mapsto (\theta_t \omega, X_t^x(\omega)).\end{aligned}$$

is a dynamical system.

- The flow property for X becomes

$$X_{t+s}^x(\omega) = X_t^{X_s^x(\omega)}(\theta_t \omega)$$

which is called cocycle property and X a random dynamical system (RDS).



Attraction

Reduction of complexity of the dynamics due to long-time evolution. For P_t on \mathcal{P} (Π_t on $\Omega \times H$) we try to find a subset $A \subseteq \mathcal{P}$ ($A \subseteq \Omega \times H$ resp.) such that

- A invariant.
- A captures the complete dynamics for large times, i.e. each trajectory can be approximated arbitrarily well by one lying in A .
- A is minimal.

Then A is said to be an attractor for P_t (Π_t resp.).



Comparison of approaches

Assertions for RDS (Π_t) are usually stronger. E.g. attractor for RDS (Π_t) implies attractor for distributional dynamics (P_t) .



Main obstacles

- Hard to show that a solution X_t to an SPDE gives an RDS i.e. that

$$X_{t+s}^x(\omega) = X_t^{X_s^x(\omega)}(\theta_t \omega),$$

because for SPDE X_t is usually only well-defined and unique \mathbb{P} -a.s.

- Only existing technique: Transform SPDE into RPDE

$$dX_t = A(X_t)dt + BdW_t, \quad (\text{SPDE}).$$

Let $Y_t = X_t - BW_t$, then

$$dY_t = A(Y_t + BW_t)dt, \quad (\text{RPDE}).$$



Main obstacles

- Prove dissipation: X_t^x lies in a bounded set of the state space independent of the initial condition x after large enough times t .
- Prove regularization: e.g. for $x \in L^2(\mathcal{O})$ the solution has more differentiability $X_t^x \in H_0^1(\mathcal{O})$.