

# Homework 4

NE 795-001: Fall 2023

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## Problem 1 - UQ with gPCE

The Generalized Polynomial Chaos Expansion (gPCE) is a method used to represent uncertain parameters in a stochastic system. It allows us to express the uncertain parameters as a series of orthogonal polynomials with respect to the probability distribution of the underlying random variables. Let's denote  $\omega$  as the random variable with a known probability distribution, and  $\alpha(\omega)$  and  $\gamma(\omega)$  as the uncertain parameters in the Lotka-Volterra equations.

The Lotka-Volterra equations with stochastic parameters are:

$$\begin{aligned}\frac{dx}{dt} &= \alpha(\omega)x - \beta xy \\ \frac{dy}{dt} &= \delta xy - \gamma(\omega)y\end{aligned}$$

To apply the gPCE to these equations, we first need to expand the uncertain parameters  $\alpha(\omega)$  and  $\gamma(\omega)$  into a polynomial chaos series:

$$\begin{aligned}\alpha(\omega) &= \sum_{i=0}^P a_i \Psi_i(\omega) \\ \gamma(\omega) &= \sum_{i=0}^P g_i \Psi_i(\omega)\end{aligned}$$

where  $a_i$  and  $g_i$  are the deterministic coefficients of the expansion,  $\Psi_i(\omega)$  are the orthogonal polynomials with respect to the probability distribution of  $\omega$ , and  $P$  is the order of the expansion.

Next, we also expand the state variables  $x(t, \omega)$  and  $y(t, \omega)$  into gPCE series:

$$\begin{aligned}x(t, \omega) &= \sum_{i=0}^P x_i(t) \Psi_i(\omega) \\ y(t, \omega) &= \sum_{i=0}^P y_i(t) \Psi_i(\omega)\end{aligned}$$

Substituting these expansions into the Lotka-Volterra equations, we get:

$$\begin{aligned}\frac{d}{dt} \left( \sum_{i=0}^P x_i(t) \Psi_i(\omega) \right) &= \left( \sum_{i=0}^P a_i \Psi_i(\omega) \right) \left( \sum_{j=0}^P x_j(t) \Psi_j(\omega) \right) - \beta \left( \sum_{k=0}^P x_k(t) \Psi_k(\omega) \right) \left( \sum_{l=0}^P y_l(t) \Psi_l(\omega) \right) \\ \frac{d}{dt} \left( \sum_{i=0}^P y_i(t) \Psi_i(\omega) \right) &= \delta \left( \sum_{k=0}^P x_k(t) \Psi_k(\omega) \right) \left( \sum_{l=0}^P y_l(t) \Psi_l(\omega) \right) - \left( \sum_{i=0}^P g_i \Psi_i(\omega) \right) \left( \sum_{j=0}^P y_j(t) \Psi_j(\omega) \right)\end{aligned}$$

Now, we apply the Galerkin projection, which involves multiplying both sides of the equations by  $\Psi_m(\omega)$  and integrating over the probability space of  $\omega$ :

$$\begin{aligned}\int \Psi_m(\omega) \frac{d}{dt} \left( \sum_{i=0}^P x_i(t) \Psi_i(\omega) \right) d\mathbb{P}(\omega) &= \int \Psi_m(\omega) \left[ \left( \sum_{i=0}^P a_i \Psi_i(\omega) \right) \left( \sum_{j=0}^P x_j(t) \Psi_j(\omega) \right) - \beta \left( \sum_{k=0}^P x_k(t) \Psi_k(\omega) \right) \left( \sum_{l=0}^P y_l(t) \Psi_l(\omega) \right) \right] d\mathbb{P}(\omega) \\ \int \Psi_m(\omega) \frac{d}{dt} \left( \sum_{i=0}^P y_i(t) \Psi_i(\omega) \right) d\mathbb{P}(\omega) &= \int \Psi_m(\omega) \left[ \delta \left( \sum_{k=0}^P x_k(t) \Psi_k(\omega) \right) \left( \sum_{l=0}^P y_l(t) \Psi_l(\omega) \right) - \left( \sum_{i=0}^P g_i \Psi_i(\omega) \right) \left( \sum_{j=0}^P y_j(t) \Psi_j(\omega) \right) \right] d\mathbb{P}(\omega)\end{aligned}$$

Since the polynomials  $\Psi_i(\omega)$  are orthogonal with respect to the probability distribution of  $\omega$ , the integrals of the products of different polynomials are zero, and the integral of the square of a polynomial is not zero. This property simplifies the above equations significantly.

To simplify the equations obtained from the Galerkin projection, we will use the orthogonality property of the polynomial basis  $\Psi_i(\omega)$ . The orthogonality condition states that:

$$\int \Psi_i(\omega) \Psi_j(\omega) d\mathbb{P}(\omega) = \begin{cases} 0 & \text{if } i \neq j \\ \langle \Psi_i^2 \rangle & \text{if } i = j \end{cases}$$

where  $\langle \Psi_i^2 \rangle$  is the expected value of  $\Psi_i^2(\omega)$ , which is a constant.

Let's simplify the first equation after applying the Galerkin projection:

$$\int \Psi_m(\omega) \frac{d}{dt} \left( \sum_{i=0}^P x_i(t) \Psi_i(\omega) \right) d\mathbb{P}(\omega) = \int \Psi_m(\omega) \left[ \left( \sum_{i=0}^P a_i \Psi_i(\omega) \right) \left( \sum_{j=0}^P x_j(t) \Psi_j(\omega) \right) - \beta \left( \sum_{k=0}^P x_k(t) \Psi_k(\omega) \right) \left( \sum_{l=0}^P y_l(t) \Psi_l(\omega) \right) \right] d\mathbb{P}(\omega)$$

We can take the time derivative outside of the integral and the summation because it does not depend on  $\omega$ :

$$\sum_{i=0}^P \frac{dx_i(t)}{dt} \int \Psi_m(\omega) \Psi_i(\omega) d\mathbb{P}(\omega) = \sum_{i=0}^P \sum_{j=0}^P a_i x_j(t) \int \Psi_m(\omega) \Psi_i(\omega) \Psi_j(\omega) d\mathbb{P}(\omega) - \beta \sum_{k=0}^P \sum_{l=0}^P x_k(t) y_l(t) \int \Psi_m(\omega) \Psi_k(\omega) \Psi_l(\omega) d\mathbb{P}(\omega)$$

Using the orthogonality condition, the integrals simplify to:

$$\frac{dx_m(t)}{dt} \langle \Psi_m^2 \rangle = \sum_{i=0}^P a_i x_i(t) \langle \Psi_m \Psi_i \rangle - \beta \sum_{k=0}^P x_k(t) y_k(t) \langle \Psi_m^2 \rangle$$

Since  $\langle \Psi_m \Psi_i \rangle$  is zero for  $i \neq m$  and  $\langle \Psi_m^2 \rangle$  for  $i = m$ , we can simplify further:

$$\frac{dx_m(t)}{dt} \langle \Psi_m^2 \rangle = a_m x_m(t) \langle \Psi_m^2 \rangle - \beta x_m(t) y_m(t) \langle \Psi_m^2 \rangle$$

Dividing both sides by  $\langle \Psi_m^2 \rangle$ :

$$\frac{dx_m(t)}{dt} = a_m x_m(t) - \beta x_m(t) y_m(t)$$

We can perform a similar simplification for the second equation:

$$\frac{dy_m(t)}{dt} = \delta x_m(t) y_m(t) - g_m y_m(t)$$

These are the simplified deterministic ODEs for the coefficients  $x_m(t)$  and  $y_m(t)$  in the gPCE expansion of the state variables  $x(t, \omega)$  and  $y(t, \omega)$ . The resulting system of ODEs can be solved to find the evolution of the moments of  $x(t, \omega)$  and  $y(t, \omega)$ .

After simplifying the equations using the orthogonality property of the polynomial basis  $\Psi_i(\omega)$ , we obtain a system of deterministic ordinary differential equations (ODEs) for the coefficients  $x_m(t)$  and  $y_m(t)$  in the gPCE expansion of the state variables  $x(t, \omega)$  and  $y(t, \omega)$ . The final form of these ODEs is:

For the prey population  $x(t, \omega)$ :

$$\frac{dx_m(t)}{dt} = a_m x_m(t) - \beta \sum_{k=0}^P \sum_{l=0}^P C_{mkl} x_k(t) y_l(t)$$

For the predator population  $y(t, \omega)$ :

$$\frac{dy_m(t)}{dt} = \delta \sum_{k=0}^P \sum_{l=0}^P C_{mkl} x_k(t) y_l(t) - g_m y_m(t)$$

where  $C_{mkl}$  are the triple product integrals of the polynomial basis:

$$C_{mkl} = \int \Psi_m(\omega) \Psi_k(\omega) \Psi_l(\omega) d\mathbb{P}(\omega)$$

These triple product integrals are typically nonzero only for certain combinations of indices  $m$ ,  $k$ , and  $l$ , depending on the specific polynomial basis used and the probability distribution of  $\omega$ . The coefficients  $a_m$  and  $g_m$  are the gPCE coefficients for the uncertain parameters  $\alpha(\omega)$  and  $\gamma(\omega)$ , respectively.

The system of ODEs can be solved numerically to obtain the time evolution of the coefficients  $x_m(t)$  and  $y_m(t)$ , which in turn provide the statistical moments of the prey and predator populations. This approach allows us to analyze the impact of uncertainty in the parameters  $\alpha(\omega)$  and  $\gamma(\omega)$  on the dynamics of the Lotka-Volterra system.