

# The Randomized Non-Autonomous Scaled Logistic Differential Equation: Theory and Applications

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## 1 Introduction

In this contribution we study the randomization of the classical logistic differential equation

$$X'(t) = K(t)(1 - X(t))X(t), \quad t > t_0 \in \mathbb{R}, \quad X(t_0) = X_0. \quad (1)$$

We will assume that the initial condition  $X_0$  is an absolutely continuous real random variable (r.v.) and the diffusion coefficient,  $K(t)$  is a stochastic process (s.p.) defined on a common complete probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . For the sake of convenience, it is assumed the equation is normalized, that is,

$$\mathbb{P}[\{\omega \in \Omega : 0 < X_0(\omega) < 1\}] = 1.$$

We compute approximations of the first probability density function (1-p.d.f.),  $f_1(x, t)$ , of the solution s.p.  $X(t)$  to the random non-linear differential with initial condition (1). The computation of the 1-p.d.f. of the solution s.p.

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is advantageous since it permits to compute all one-dimensional statistical moments of the solution s.p.

$$\mathbb{E} [(X(t))^k] = \int_{-\infty}^{+\infty} (x(t))^k f_1(x, t) dx, \quad k = 0, 1, 2, \dots$$

As a consequence, the mean  $\mu_X(t) = \mathbb{E}[X(t)]$  and the variance,  $\sigma_X^2(t) = \mathbb{V}[X(t)] = \mathbb{E} [(X(t))^2] - (\mu_X(t))^2$ , are easily derived as particular cases. Furthermore,  $f_1(x, t)$  allows us to compute the probability that the solution lies in specific sets of interest,

$$\mathbb{P} [\{\omega \in \Omega : a \leq X(t)(\omega) \leq b\}], \quad -\infty \leq a < b \leq +\infty.$$

To conduct our study, we will apply to different techniques. First, the so-called Karhunen-Loève expansion (KLE) and, secondly, the Random Variable Transformation (RVT).

The KLE allows us to represent the second-order s.p.  $K(t)$ , i.e.,  $\mathbb{E}[K^2(t)] < +\infty$  for all  $t$ , as a function of a denumerable set of r.v.'s, say  $\{\eta_i : i \geq 1\}$  having zero-mean, unit variance and uncorrelated,  $\mathbb{E}[\eta_i] = 0$ ,  $\mathbb{V}[\eta_i] = 1$  and  $\mathbb{E}[\eta_i \eta_j] = 0$  for every  $i, j \geq 1, i \neq j$ . KLE constitutes a generalized Fourier-type spectral representation for s.p.'s.

**Theorem 1 (KLE expansion)** [3, p.202]. *Let us consider the second-order s.p.  $\{X(t) : t \in \mathcal{T}\}$  being  $\mathcal{T} \subset \mathbb{R}$  and assume that  $X$  is a second-order r.v., i.e.,  $\mathbb{E}[X^2] < +\infty$ . Then,*

$$X(t, \omega) = \mu(t) + \sum_{j \geq 1} \sqrt{v_j} \phi_j(t) \eta_j(\omega), \quad \omega \in \Omega, \tag{2}$$

where this sum is mean square convergent and

$$\eta_j(\omega) := \frac{1}{\sqrt{v_j}} \mathbb{E} [(X(t) - \mu(t)) \phi_j(t)],$$

being  $\{(v_j, \phi_j(t)) : j \geq 1\}$  the eigenpairs of the covariance  $\Gamma_X(t, s)$  operator satisfying the integral equation

$$\lambda_i \phi_n(t) = \int_{\mathcal{T}} \Gamma_X(t, s) \phi_j(s) ds,$$

In its multi-dimensional version, this result can be stated as follows

**Theorem 2 (Multidimensional RVT method)** [1, p.25]. *Let us consider  $\mathbf{X} = (X_1, \dots, X_n)^\top$  and  $\mathbf{Z} = (Z_1, \dots, Z_n)^\top$  two  $n$ -dimensional absolutely continuous random vectors defined on a probability space  $(\Omega, \mathfrak{F}, \mathbb{P})$ . Let  $\mathbf{r} : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be a one-to-one deterministic transformation of  $\mathbf{X}$  into  $\mathbf{Z}$ , i.e.,  $\mathbf{Z} = \mathbf{r}(\mathbf{X})$ . Assume that  $\mathbf{r}$  is continuous in  $\mathbf{X}$  and has continuous partial derivatives with respect to each  $X_i$ ,  $1 \leq i \leq n$ . Then, if  $f_{\mathbf{X}}(\mathbf{x})$  denotes the joint probability density function of random vector  $\mathbf{X}$ , and  $\mathbf{s} = \mathbf{r}^{-1} = (s_1(z_1, \dots, z_n), \dots, s_n(z_1, \dots, z_n))^\top$  represents the inverse mapping of  $\mathbf{r} = (r_1(x_1, \dots, x_n), \dots, r_n(x_1, \dots, x_n))^\top$ , the joint probability density function of random vector  $\mathbf{Z}$  is given by*

$$f_{\mathbf{Z}}(\mathbf{s}) = f_{\mathbf{X}}(\mathbf{h}(\mathbf{z})) |J|, \quad (3)$$

where  $|J|$ , which is assumed to be different from zero, is the absolute value of the Jacobian defined by the determinant

$$J = \det \left( \frac{\partial \mathbf{s}^\top}{\partial \mathbf{z}} \right) = \det \begin{pmatrix} \frac{\partial s_1(z_1, \dots, z_n)}{\partial z_1} & \dots & \frac{\partial s_n(z_1, \dots, z_n)}{\partial z_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1(z_1, \dots, z_n)}{\partial z_n} & \dots & \frac{\partial s_n(z_1, \dots, z_n)}{\partial z_n} \end{pmatrix}. \quad (4)$$

## 2 General case

In a first step, we consider a general s.p. for the coefficient  $K(t)$  and then it is represented via the KLE

We first consider the well-known representation

$$X(t) = Y_0 S_1(t; A) + Y_1 S_2(t; A), \quad (5)$$

$$S_1(t; A) = \sum_{n \geq 0} C_n(A) (t - t_0)^n, \quad S_2(t; A) = \sum_{n \geq 0} D_n(A) (t - t_0)^n, \quad (6)$$

of the solution s.p. of IVP (1)–(??) being  $S_1(t; A)$  and  $S_2(t; A)$  two linearly independent solutions. Then, we take its truncation

$$X_N(t) = Y_0 S_1^N(t; A) + Y_1 S_2^N(t; A), \quad (7)$$

$$S_1^N(t; A) = \sum_{n=0}^N C_n(A) (t - t_0)^n, \quad S_2^N(t; A) = \sum_{n=0}^N D_n(A) (t - t_0)^n, \quad (8)$$

being  $N$  a positive integer previously fixed, to construct the following approximation

$$f_1^N(x, t) = \iint_{\mathcal{D}_{A, Y_1}} f_{A, Y_0, Y_1} \left( z_1, \frac{x - y_1 S_2^N(t; a)}{S_1^N(t; a)}, y_1 \right) \times \left| \frac{1}{S_1^N(t; a)} \right| dy_1 da, \quad (9)$$

to the 1-p.d.f. of the truncated s.p.  $X_N(t)$  to IVP (1)–(??).

Finally, we will introduce suitable hypotheses to legitimate that

$$\lim_{N \rightarrow +\infty} f_1^N(x, t) = f_1(x, t), \quad \text{for each } (x, t) \in \mathbb{R} \times [t_0, +\infty[ \text{ fixed}, \quad (10)$$

being

$$f_1(x, t) = \iint_{\mathcal{D}_{A, Y_1}} f_{A, Y_0, Y_1} \left( z_1, \frac{x - y_1 S_2(t; a)}{S_1(t; a)}, y_1 \right) \times \left| \frac{1}{S_1(t; a)} \right| dy_1 da, \quad (11)$$

where  $S_1(t, a)$  and  $S_2(t, a)$  are defined in (6).

### 3 An illustrative example

In this example we will display the behaviour of second-order random differential equation

$$X''(t) - AtX(t) = 0, \quad (12)$$

with initial conditions

$$X(0) = Y_0, \quad X'(0) = Y_1. \quad (13)$$

We will consider that  $A$ ,  $Y_0$  and  $Y_1$  are mutually independent r.v.'s. In a first step, by simplicity it is assumed that each one is uniformly distributed on the interval  $]0, 1[$ , i.e.  $A, Y_0, Y_1 \sim U(]0, 1[)$ . Then, we obtain the 1-p.d.f. of  $X_N(t)$ ,  $f_1^N(x, t)$ . Figure 1 shows  $f_1^N(x, t)$  on the time instant  $t = 3$  for different values of  $N$  (truncation order). On the left, for  $N = 1, \dots, 3$ , on the right for  $N = 4, \dots, 8$ . We can observe that when the truncation increase  $f_1^N(x, 3)$  converges to the exact 1-p.d.f,  $f_1(x, 3)$ , of the solution s.p. of the IVP (12)–(13).

Figure 1: Plot of  $f_1^N(x, 3)$  given by (9) for different values of  $N$ :  $N = 1, \dots, 3$  (left),  $N = 4, \dots, 8$  (right).

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