# MODELLING FOR ENGINEERING **& HUMAN BEHAVIOUR** 2021 JULY 14-16

 $im^2$ 

## Edited by

Juan Ramón Torregrosa

Juan Carlos Cortés

Antonio Hervás

Antoni Vidal

Elena López-Navarro







## Modelling for Engineering & Human Behaviour 2021

València, July 14th-16th, 2021

This book includes the extended abstracts of papers presented at XXIII Edition of the Mathematical Modelling Conference Series at the Institute for Multidisciplinary Mathematics *Mathematical Modelling in Engineering & Human Behaviour.*  I.S.B.N.: 978-84-09-36287-5

November 30<sup>th</sup>, 2021 Report any problems with this document to imm@imm.upv.es.

**Edited by:** I.U. de Matemàtica Multidisciplinar, Universitat Politècnica de València. J.R. Torregrosa, J-C. Cortés, J. A. Hervás, A. Vidal-Ferràndiz and E. López-Navarro



Instituto Universitario de Matemática Multidisciplinar

## Contents

	Density-based uncertainty quantification in a generalized Logistic-type model 1
	Combined and updated <i>H</i> -matrices7
tr	Solving random fractional second-order linear equations via the mean square Laplace ransform
	Conformable fractional iterative methods for solving nonlinear problems 19
	Construction of totally nonpositive matrices associated with a triple negatively realizable24
	Modeling excess weight in Spain by using deterministic and random differential equations31
ty	A new family for solving nonlinear systems based on weight functions Kalitkin-Ermankov vpe
	Solving random free boundary problems of Stefan type
Ì	Modeling one species population growth with delay
I	On a Ermakov–Kalitkin scheme based family of fourth order
ci	A new mathematical structure with applications to computational linguistics and spe- alized text translation
m	Accurate approximation of the Hyperbolic matrix cosine using Bernoulli matrix polyno- nials
de	Full probabilistic analysis of random first-order linear differential equations with Dirac elta impulses appearing in control
Ľ	Some advances in Relativistic Positioning Systems
I	A Graph–Based Algorithm for the Inference of Boolean Networks
m	Stability comparison of self-accelerating parameter approximation on one-step iterative nethods
m	Mathematical modelling of kidney disease stages in patients diagnosed with diabetes nellitus II
I	The effect of the memory on the spread of a disease through the environtment 101
ti	Improved pairwise comparison transitivity using strategically selected reduced informa- on
I	Contingency plan selection under interdependent risks
	Some techniques for solving the random Burgers' equation
de	Probabilistic analysis of a class of impulsive linear random differential equations via ensity functions

Probabilistic evolution of the bladder cancer growth considering transurethral resection 127	
Study of a symmetric family of anomalies to approach the elliptical two body problem with special emphasis in the semifocal case	
Advances in the physical approach to personality dynamics 136	
A Laplacian approach to the Greedy Rank-One Algorithm for a class of linear systems 143	
Using STRESS to compute the agreement between computed image quality measures and observer scores: advantanges and open issues	
Probabilistic analysis of the random logistic differential equation with stochastic jumps156	
Introducing a new parametric family for solving nonlinear systems of equations 162	
Optimization of the cognitive processes involved in the learning of university students in a virtual classroom	
Parametric family of root-finding iterative methods 175	
Subdirect sums of matrices. Definitions, methodology and known results 180	
On the dynamics of a predator-prey metapopulation on two patches	
Prognostic Model of Cost / Effectiveness in the therapeutic Pharmacy Treatment of Lung Cancer in a University Hospital of Spain: Discriminant Analysis and Logit	
Stability, bifurcations, and recovery from perturbations in a mean-field semiarid vegeta- tion model with delay	
The random variable transformation method to solve some randomized first-order linear control difference equations	
Acoustic modelling of large aftertreatment devices with multimodal incident sound fields 208	
Solving non homogeneous linear second order difference equations with random initial values: Theory and simulations	
A realistic proposal to considerably improve the energy footprint and energy efficiency of a standard house of social interest in Chile	
Multiobjective Optimization of Impulsive Orbital Trajectories	
Mathematical Modeling about Emigration/Immigration in Spain: Causes, magnitude, consequences	
New scheme with memory for solving nonlinear problems	
$SP_N$ Neutron Noise Calculations	
Analysis of a reinterpretation of grey models applied to measuring laboratory equipment uncertainties	
An Optimal Eighth Order Derivative-Free Scheme for Multiple Roots of Non-linear Equa- tions	
A population-based study of COVID-19 patient's survival prediction and the potential biases in machine learning	
A procedure for detection of border communities using convolution techniques267	

### Solving non homogeneous linear second order difference equations with random initial values: Theory and simulations

J.-C. Cortés<sup>b</sup>,<sup>1</sup> A. Navarro-Quiles<sup>‡</sup> and S.-M. Sferle<sup>b</sup>

(b) Instituto Universitario de Matemática Multidisciplinar, Universitat Politècnica de València Camí de Vera s/n, Valencia, Spain.
(b) Departamento de Estadística e Investigación Operativa, Universitat de València Dr.Moliner, 50, Burjassot, Spain.

#### 1 Introduction

38

Difference equations and differential equations are powerful equations for modeling the dynamics of real world phenomena. The former are suitable for modeling the evolution of species whose generations do not overlap and grow at regular intervals over fixed periods of time (e.g., annual) or for modeling the dynamics of economic quantities that are evaluated in discrete periods by connecting the present value with previous capitalized values (in a general sense). For its part, differential equations have been successfully applied to describe the dynamics of quantities from their instantaneous change. When both types of equations are applied to real problems, it is often necessary to take into account the inherent uncertainty of the phenomena under study or the sampled data errors required to determine the data specifying these models.

This simple approach leads to the need to examine this type of equations, both from a theoretical and applied point of view, taking into consideration the randomness in their formulation. There are different types of strategies to introduce randomness in the study of these problems, but in the present work we will consider noises defined through random variables or stochastic processes with regular sampling behavior.

This document is organized as follows. In Section 2, we will determine the first probability density function (1-p.d.f.). of the solution of the initial value problem (i.v.p.) bearing in mind the nature of the roots of the associated characteristic equation. In Section 3, we will illustrate the theoretical results developed through examples. The last section draws conclusions.

<sup>&</sup>lt;sup>1</sup>jccortes@mat.upv.es

#### 2 Computing the 1-p.d.f.

Let us consider the following initial value problem

$$Z_{n+2} + A_1 Z_{n+1} + A_2 Z_n = B, \quad n = 0, 1, 2, \dots,$$

$$Z_0 = \Gamma_0,$$

$$Z_1 = \Gamma_1.$$
(1)

In this problem, we will treat the parameters  $A_1, A_2$  and B as constant coefficients, and, without loss of generality, we will treat the initial conditions  $\Gamma_0 = \Gamma_0(\omega)$  and  $\Gamma_1 = \Gamma_1(\omega)$  as dependent continuous random variables (r.v.'s) defined on a common probability space  $(\Omega, \mathfrak{F}, \mathbb{P})$ , which have an arbitrary joint probability density function,  $f_{\Gamma_0,\Gamma_1}(\gamma_0, \gamma_1)$ . In the following, the domains of the input parameters  $\Gamma_0, \Gamma_1$  will be denoted as follows

$$D_{\Gamma_0} = \{ \gamma_0 = \Gamma_0(\omega), \omega \in \Omega : \gamma_{0,1} \le \gamma_0 \le \gamma_{0,2} \}, D_{\Gamma_1} = \{ \gamma_1 = \Gamma_1(\omega), \omega \in \Omega : \gamma_{1,1} \le \gamma_1 \le \gamma_{1,2} \},$$

where the endpoints of each interval can take any real value. For notation reasons, the sample dependence for r.v.'s denoted by the w-notation will be omitted.

Thus, since the problem is a non homogeneous linear second order difference equation with random initial conditions, its solution will be a stochastic process, say  $\{Z_n : n \ge 0\}$ . Therefore, our objective now is to determine the solution of the i.v.p. and, in addition, to calculate the first probability density function since from it we can determine statistical characteristics such as the mean  $\mathbb{E}[Z_n]$ , the variance  $\mathbb{V}[Z_n]$  or any other statistical moment

$$\mathbb{E}[(Z_n)^k] = \int_{-\infty}^{\infty} z^k f_{Z_n}(z) dz, \quad n, k = 0, 1, 2, \dots$$

Notice that this makes a considerable difference from the deterministic scenario.

In order to figure out the 1-p.d.f. of the solution of the i.v.p. we will use the Random Variable Transformation (R.V.T.) technique. Among the numerous versions of this technique, the one we are going to implement throughout this work is found in [2].

**Theorem 1.** Let  $\mathbf{V} = (V_1, ..., V_m)$  be a random vector of dimension m with joint p.d.f.  $f_{\mathbf{V}}(\mathbf{v})$ . Let  $\mathbf{r} : \mathbb{R}^m \to \mathbb{R}^m$  be a one-to-one deterministic map which is assumed to be continuous with respect to each one of its arguments, and with continuous partial derivatives. Then, the joint p.d.f.  $f_{\mathbf{W}}(\mathbf{w})$  of the random vector  $\mathbf{W} = \mathbf{r}(\mathbf{V})$  is given by

$$f_{\boldsymbol{W}}(\boldsymbol{w}) = f_{\boldsymbol{V}}(\boldsymbol{s}(\boldsymbol{w})) |J_m|, \qquad (2)$$

where s(w) is the inverse transformation of  $r(v) : v = r^{-1}(w) = s(w)$  and  $J_m$  is the Jacobian of the transformation, i.e

$$J_m = \det\left(\frac{\partial \boldsymbol{v}}{\partial \boldsymbol{w}}\right) = \det\left(\frac{\partial \boldsymbol{s}(\boldsymbol{w})}{\partial \boldsymbol{w}}\right) = \det\left(\frac{\frac{\partial \boldsymbol{s}_1(\boldsymbol{w})}{\partial w_1}}{\vdots & \ddots & \vdots} \\ \frac{\partial \boldsymbol{s}_1(\boldsymbol{w})}{\partial w_m} & \cdots & \frac{\partial \boldsymbol{s}_m(\boldsymbol{w})}{\partial w_m}\right),$$

which is assumed to be different from zero.

Based on the deterministic theory, it is known that the general solution  $Z_n$  of (1) is equal to the sum of the general solution of the associated homogeneous equation and a particular solution of the non-homogeneous equation

$$Z_n^c = Z_n^h + Z_n^p,$$

and depends on the character of the roots of the associated characteristic equation

$$r^2 + A_1r + A_2 = 0,$$

that is, on the values

$$r_1 = \frac{-A_1 + \sqrt{A_1^2 - 4A_2}}{2}, \qquad r_2 = \frac{-A_1 - \sqrt{A_1^2 - 4A_2}}{2}.$$
 (3)

The nature of the roots, which can be real or complex, depends on the discriminant

$$\Delta = A_1^2 - 4A_2.$$

So,

1. if the discriminant is positive,  $\Delta > 0$ , then there are two distinct real roots, i.e.

$$r_1, r_2 \in \mathbb{R}$$
 and  $r_1 \neq r_2$ .

2. if the discriminant is zero,  $\Delta = 0$ , then there is a real root of double multiplicity, i.e.

$$r_1 = r_2 = r \in \mathbb{R}.$$

3. if the discriminant is negative,  $\Delta < 0$ , then there are two distinct complex roots, i.e.

$$r_1 = a + ib, r_2 = a - ib \in \mathbb{C}$$
 and  $r_2 = \overline{r}_1$ 

Regarding the particular solution, which will be the same for the three cases, let us assume that it is a constant discrete function  $Z_n = k$ , with a constant k to be determined. Given this circumstance, the particular solution obtained is

$$Z_n^p = \frac{B}{1 + A_1 + A_2},\tag{4}$$

where  $1 + A_1 + A_2 \neq 0$ . We will now examine each of the three cases.

#### 2.1 Real and distinct roots

The solution of the (1) is

$$Z_n^c = \frac{r_1(r_2)^n - r_2(r_1)^n}{r_1 - r_2} \Gamma_0 + \frac{(r_1)^n - (r_2)^n}{r_1 - r_2} \Gamma_1 + \frac{B}{1 + A_1 + A_2} \left( \frac{r_2 - 1}{r_1 - r_2} (r_1)^n + \frac{1 - r_1}{r_1 - r_2} (r_2)^n + 1 \right),$$

where  $r_1$  and  $r_2$  are given by (3).

Now, we are going to calculate the 1-p.d.f. of the r.v.  $Z = Z_n$ . To do so, we set n and we apply the Theorem 1 using the following identification: m = 2 and

$$\mathbf{V} = (\Gamma_0, \Gamma_1), \qquad \qquad f_{\mathbf{V}}(\mathbf{v}) = f_{\Gamma_0, \Gamma_1}(\gamma_0, \gamma_1),$$
$$\mathbf{W} = (W_1, W_2) = \mathbf{r}(\Gamma_0, \Gamma_1).$$

The inverse mapping is given by

$$W_1 = r_1(\Gamma_0, \Gamma_1) = \frac{r_1(r_2)^n - r_2(r_1)^n}{r_1 - r_2} \Gamma_0 + \frac{(r_1)^n - (r_2)^n}{r_1 - r_2} \Gamma_1 + \frac{B}{1 + A_1 + A_2} \left(\frac{r_2 - 1}{r_1 - r_2} (r_1)^n + \frac{1 - r_1}{r_1 - r_2} (r_2)^n + 1\right)$$

$$\Rightarrow \Gamma_0 = s_1(W_1, W_2) = \left(W_1 - \frac{(r_1)^n - (r_2)^n}{r_1 - r_1}W_2 - \frac{B}{1 + A_1 + A_2}\left(\frac{r_2 - 1}{r_1 - r_2}(r_1)^n + \frac{1 - r_1}{r_1 - r_2}(r_2)^n + 1\right)\right) \frac{r_1 - r_2}{r_1(r_2)^n - r_2(r_1)^n},$$

$$W_2 = r_2(\Gamma_0, \Gamma_1) = \Gamma_1 \quad \Rightarrow \quad \Gamma_1 = s_2(W_1, W_2) = W_2.$$

The corresponding Jacobian is

$$J_2 = \frac{r_1 - r_2}{r_1(r_2)^n - r_2(r_1)^n} \neq 0.$$

Thus, we obtain the joint p.d.f. of the random vector  $\mathbf{W} = (W_1, W_2)$  by applying (2)

$$f_{\mathbf{W}}(\mathbf{w}) = f_{\Gamma_0,\Gamma_1} \left( \left( w_1 - \frac{(r_1)^n - (r_2)^n}{r_1 - r_2} w_2 - \frac{B}{1 + A_1 + A_2} \left( \frac{r_2 - 1}{r_1 - r_2} (r_1)^n + \frac{1 - r_1}{r_1 - r_2} (r_2)^n + 1 \right) \right) \cdot \frac{r_1 - r_2}{r_1 (r_2)^n - r_2 (r_1)^n}, w_2 \right) \cdot \left| \frac{r_1 - r_2}{r_1 (r_2)^n - r_2 (r_1)^n} \right|, \quad w_{i,1} \le w_i \le w_{i,2}, \quad 1 \le i \le 2.$$

Lastly, taking into account that  $Z = W_1$ , we obtain the 1-p.d.f. of the solution as follows

$$f_{Z_n}(z) = \int_{\gamma_{1,1}}^{\gamma_{1,2}} f_{\Gamma_0,\Gamma_1} \left( \left( z - \frac{(r_1)^n - (r_2)^n}{r_1 - r_2} \gamma_1 - \frac{B}{1 + A_1 + A_2} \left( \frac{r_2 - 1}{r_1 - r_2} (r_1)^n + \frac{1 - r_1}{r_1 - r_2} (r_2)^n + 1 \right) \right) \cdot \frac{r_1 - r_2}{r_1 (r_2)^n - r_2 (r_1)^n}, \gamma_1 \right) \cdot \left| \frac{r_1 - r_2}{r_1 (r_2)^n - r_2 (r_1)^n} \right| d\gamma_1.$$
(5)

To avoid cumbersome notation in this general context, we prefer to leave the explicit definition of the domains in the examples section.

#### 2.2 Real and equal roots

The solution of the (1) is

$$Z_n^c = (1-n)r^n \Gamma_0 + (nr^{n-1})\Gamma_1 + \frac{B}{1+A_1+A_2} \left(nr^n - nr^{n-1} - r^n + 1\right),$$

where  $r = r_1 = r_2$ .

Now, we are going to calculate the 1-p.d.f. of the r.v.  $Z = Z_n$ . To do so, we set n and we apply the Theorem 1 using the following identification: m = 2 and

$$\begin{aligned} \mathbf{V} &= (\Gamma_0, \Gamma_1), \qquad \qquad f_{\mathbf{V}}(\mathbf{v}) = f_{\Gamma_0, \Gamma_1}(\gamma_0, \gamma_1), \\ \mathbf{W} &= (W_1, W_2) = \mathbf{r}(\Gamma_0, \Gamma_1). \end{aligned}$$

The inverse mapping is given by

$$W_1 = r_1(\Gamma_0, \Gamma_1) = (1 - n)r^n \Gamma_0 + (nr^{n-1})\Gamma_1 + \frac{B}{1 + A_1 + A_2} \left(nr^n - nr^{n-1} - r^n + 1\right)$$
  
$$\Rightarrow \Gamma_0 = s_1(W_1, W_2) = \left(W_1 - (nr^{n-1})W_2 - \frac{B}{1 + A_1 + A_2} \left(nr^n - nr^{n-1} - r^n + 1\right)\right) \frac{1}{(1 - n)r^n},$$

$$W_2 = r_2(\Gamma_0, \Gamma_1) = \Gamma_1 \quad \Rightarrow \quad \Gamma_1 = s_2(W_1, W_2) = W_2.$$

The corresponding Jacobian is

$$J_2 = \frac{1}{(1-n)r^n} \neq 0.$$

Thus, we obtain the joint p.d.f. of the random vector  $\mathbf{W} = (W_1, W_2)$  by applying (2)

$$f_{\mathbf{W}}(\mathbf{w}) = f_{\Gamma_0,\Gamma_1} \left( \left( w_1 - (nr^{n-1})w_2 - \frac{B}{1+A_1+A_2} \left( nr^n - nr^{n-1} - r^n + 1 \right) \right) \cdot \frac{1}{(1-n)r^n}, w_2 \right) \cdot \left| \frac{1}{(1-n)r^n} \right|, \quad w_{i,1} \le w_i \le w_{i,2}, \quad 1 \le i \le 2.$$

Lastly, taking into account that  $Z = W_1$ , we obtain the 1-p.d.f. of the solution as follows

$$f_{Z_n}(z) = \int_{\gamma_{1,1}}^{\gamma_{1,2}} f_{\Gamma_0,\Gamma_1}\left(\left(z - (nr^{n-1})\gamma_1 - \frac{B}{1 + A_1 + A_2}\left(nr^n - nr^{n-1} - r^n + 1\right)\right) \cdot \frac{1}{(1-n)r^n}, \gamma_1\right) \cdot \left|\frac{1}{(1-n)r^n}\right| d\gamma_1.$$

To avoid cumbersome notation in this general context, we prefer to leave the explicit definition of the domains in the examples section.

#### 2.3 Complex roots

The solution of the (1) is

$$Z_n^c = \frac{R^n \sin(\theta(1-n))}{\sin(\theta)} \Gamma_0 + \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} \Gamma_1 + \frac{B}{1+A_1+A_2} \left( \frac{R^n \sin(\theta(n-1))}{\sin(\theta)} - \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} + 1 \right),$$

where  $R = |r_1| = |r_2| = \sqrt{a^2 + b^2}$  and  $\theta = \arctan(\frac{b}{a})$ . Now, we are going to calculate the 1-p.d.f. of the r.v.  $Z = Z_n$ . To do so, we set *n* and we apply the Theorem 1 using the following identification: m = 2 and

$$\mathbf{V} = (\Gamma_0, \Gamma_1), \qquad \qquad f_{\mathbf{V}}(\mathbf{v}) = f_{\Gamma_0, \Gamma_1}(\gamma_0, \gamma_1),$$
$$\mathbf{W} = (W_1, W_2) = \mathbf{r}(\Gamma_0, \Gamma_1).$$

The inverse mapping is given by

$$W_{1} = r_{1}(\Gamma_{0}, \Gamma_{1}) = \frac{R^{n} \sin(\theta(1-n))}{\sin(\theta)} \Gamma_{0} + \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} \Gamma_{1} + \frac{B}{1+A_{1}+A_{2}} \left( \frac{R^{n} \sin(\theta(n-1))}{\sin(\theta)} - \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} + 1 \right)$$
  
$$\Rightarrow \Gamma_{0} = s_{1}(W_{1}, W_{2}) = \left( W_{1} - \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} W_{2} - \frac{B}{1+A_{1}+A_{2}} \left( \frac{R^{n} \sin(\theta(n-1))}{\sin(\theta)} - \frac{R^{n-1} \sin(\theta n)}{\sin(\theta)} + 1 \right) \right) \frac{\sin(\theta)}{R^{n} \sin(\theta(1-n))} + W_{2} = r_{2}(\Gamma_{0}, \Gamma_{1}) = \Gamma_{1} \quad \Rightarrow \quad \Gamma_{1} = s_{2}(W_{1}, W_{2}) = W_{2}.$$

The corresponding Jacobian is

$$J_2 = \frac{\sin(\theta)}{R^n \sin(\theta(1-n))} \neq 0.$$

Thus, we obtain the joint p.d.f. of the random vector  $\mathbf{W} = (W_1, W_2)$  by applying (2)

$$f_{\mathbf{W}}(\mathbf{w}) = f_{\Gamma_0,\Gamma_1} \left( \left( w_1 - \frac{R^{n-1}\sin(\theta n)}{\sin(\theta)} w_2 - \frac{B}{1+A_1+A_2} \left( \frac{R^n \sin(\theta(n-1))}{\sin(\theta)} - \frac{R^{n-1}\sin(\theta n)}{\sin(\theta)} + 1 \right) \right) \cdot \frac{\sin(\theta)}{R^n \sin(\theta(1-n))}, w_2 \right) \cdot \left| \frac{\sin(\theta)}{R^n \sin(\theta(1-n))} \right|, \quad w_{i,1} \le w_i \le w_{i,2}, \quad 1 \le i \le 2.$$

Lastly, taking into account that  $Z = W_1$ , we obtain the 1-p.d.f. of the solution as follows

$$\begin{split} f_{Z_n}(z) &= \int_{\gamma_{1,1}}^{\gamma_{1,2}} f_{\Gamma_0,\Gamma_1} \left( \left( z - \frac{R^{n-1}\sin(\theta n)}{\sin(\theta)} \gamma_1 - \frac{B}{1+A_1+A_2} \left( \frac{R^n \sin(\theta(n-1))}{\sin(\theta)} - \frac{R^{n-1}\sin(\theta n)}{\sin(\theta)} + 1 \right) \right) \cdot \\ & \cdot \frac{\sin(\theta)}{R^n \sin(\theta(1-n))}, \gamma_1 \right) \cdot \left| \frac{\sin(\theta)}{R^n \sin(\theta(1-n))} \right| d\gamma_1. \end{split}$$

To avoid cumbersome notation in this general context, we prefer to leave the explicit definition of the domains in the examples section.

#### 3 Examples

In this section, we are going to illustrate the theoretical results through numerical examples. The aim is to plot the 1-p.d.f. of the solution of the i.v.p. (1) obtained in the three cases for some values of n.

In the first case we assume that the constant coefficients take the following values

$$A_1 = -4, \quad A_2 = -2 \quad B = 10$$

Furthermore, we consider that the random inputs follow a joint Gaussian distribution, i.e.

$$(\Gamma_0,\Gamma_1) \sim \mathcal{N}(\mu, \Sigma), \qquad \mu = (1, 10), \qquad \Sigma = \begin{pmatrix} 6 & 0.05 \\ 0.05 & 6 \end{pmatrix}.$$

Figure (1) shows the 1-p.d.f. at n = 0, 1, 2, 3. It seems to diverge monotonically as n increases. In the second case we assume that the constant coefficients take the following values

$$A_1 = -1, \quad A_2 = 1/4 \quad B = 1.$$

We also consider a joint Gaussian distribution, but now with the following mean and covariance matrix

$$\mu = (1, 1.5), \qquad \Sigma = \begin{pmatrix} 0.1 & 0.05\\ 0.05 & 0.1 \end{pmatrix}.$$

Figure (2) shows the 1-p.d.f. at n = 0, 1, 2, 3, 4, 5. It seems to converge monotonically as n increases.

Finally, the values that we assume in the last case are

$$A_1 = 1, \quad A_2 = 1/2 \quad B = 3, \quad \mu = (0.5, 1), \quad \Sigma = \begin{pmatrix} 0.2 & 0.01 \\ 0.01 & 0.3 \end{pmatrix}.$$

Figure (3) shows the 1-p.d.f. at n = 0, 1, 2, 3, 4. It seems to converge oscillating as n increases. Note that in all cases the z-domain of  $f_{Z_n}(z)$  is  $-\infty < z < \infty$ .



Figure 1: Plot of the 1-p.d.f.,  $f_{Z_n}(z)$ , of the solution,  $Z_n$ , in case I at different values of n = 0, 1, 2, 3.



Figure 2: Plot of the 1-p.d.f.,  $f_{Z_n}(z)$ , of the solution,  $Z_n$ , in case II at different values of n = 0, 1, 2, 3, 4, 5.



Figure 3: Plot of the 1-p.d.f.,  $f_{Z_n}(z)$ , of the solution,  $Z_n$ , in case III at different values of n = 0, 1, 2, 3, 4.

#### 4 Conclusions

In this work we have provided a general explicit formula for the 1-p.d.f. of the solution of a nonhomogeneous linear second order difference equation with random initial values, which depending on the character of the roots of the associated characteristic equation has one form or another, and where the random inputs involved are statistically dependent. The study has been based on the Random Variable Transformation technique. Moreover, we have shown with examples the theoretical development obtained, in which it can be observed that it is the deterministic counterpart.

#### Acknowledgements

This work has been supported by the grant PID2020-115270GB–I00 funded by MCIN/AEI/10.13039/501100011033 and the grant AICO/2021/302 (Generalitat Valenciana).

#### References

- [1] Casabán, M. C., Cortés, J. C., Romero, J. V. and Roselló, M. D. Probabilistic solution of random homogeneous linear second-order difference equations. *Applied Mathematics Letters*, 34:27-32, 2014.
- [2] Soong, T. T., Random Differential Equations in Science and Engineering. New York and London, Academic Press, 1973.