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Additional Information

Solving linear and quadratic random matrix differential equations using: A mean square approach. The non-autonomous case

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Abstract

This paper is aimed to extend, the non-autonomous case, the results recently given in the paper [1] for solving autonomous linear and quadratic random matrix differential equations. With this goal, important deterministic results like the Abel-Liouville-Jacobi's formula, are extended to the random scenario using the so-called L_p -random matrix calculus. In a first step, random time-dependent matrix linear differential equations are studied and, in a second step, random non-autonomous Riccati matrix differential equations are solved using the hamiltonian approach based on dealing with the extended underlying linear system. Illustrative numerical examples are also included.

Keywords: mean square random calculus, L_p -random matrix calculus, random non-autonomous Riccati matrix differential equation, analytic-numerical solution

1. Introduction

In the recent paper [1] linear and quadratic random autonomous differential equations were motivated and studied in the L_p -random sense. In that paper, all the coefficients were assumed to be random matrices rather than matrix stochastic processes, hence in [1] coefficients do not depend on time. Based on the well-known linear hamiltonian approach, (see [2] and [3] for excellent references about Riccati differential equations and the hamiltonian approach), the solution of the initial value problem for a general class of Riccati random quadratic matrix equations is obtained in terms of the blocks of the solution stochastic process of the underlying random linearized problem.

In this paper, we address the solution in the L_p -random sense of the non-autonomous Riccati matrix differential initial value problem (IVP)

$$W'(t) + W(t)A(t) + D(t)W(t) + W(t)B(t)W(t) - C(t) = 0, \quad W(0) = W_0, \quad (1)$$

where the variable coefficient matrices $A(t) \in L_p^{n \times n}(\Omega)$, $D(t) \in L_p^{m \times m}(\Omega)$, $B(t) \in L_p^{n \times m}(\Omega)$, $C(t) \in L_p^{m \times n}(\Omega)$, the initial condition $W_0 \in L_p^{m \times n}(\Omega)$ and the unknown $W(t) \in L_p^{m \times n}(\Omega)$ are matrix stochastic processes whose size are specified in the superindexes and defined in certain $L_p^{r \times s}(\Omega)$ spaces, that will be specified later. It is important to underline that in (1), the meaning of the derivative $W'(t)$ is understood in the p -th mean sense, that is, a kind of strong random convergence that it will be introduced in Section 2. It is convenient to highlight that using the $L_p^{r \times s}(\Omega)$ -random approach is not equivalent to deal with the averaged deterministic problem based on taking the expectations in every entry of the matrices that define the differential equation (1). Even more, from a practical point of view, it is more realistic to consider the random approach rather than the deterministic since when modelling input data of the Riccati equation (1) are usually fixed after measurements, hence having errors. We point out that the content of this paper may be regarded as a continuation of [1, 4, 5]. Finally, we highlight some recent and interesting contributions dealing with scalar random Riccati-type differential equations by means of $L_p(\Omega)$ -random calculus or alternative techniques [6, 7], for example.

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22 The organization of this paper is as follows. Section 2 is devoted to extend some stochastic results presented in
 23 section 2 of [1] and to introduce new ones as well. These new results are addressed to establish a random analogous
 24 of the Abel-Liouville-Jacobi's formula that will play a key role to deal with the non-autonomous random case. In
 25 Section 3 the random non-autonomous matrix linear problem is treated, including the bilateral case. In Section 4 the
 26 random non-autonomous Riccati matrix equation is solved based on the extended underlying linear problem, includ-
 27 ing a procedure for the numerical solution inspired in the results of [4] that were obtained for the non-autonomous
 28 deterministic counterpart. In Section 5 the theoretical results obtained throughout the paper are illustrated by means
 29 of several numerical examples. Finally, conclusions are drawn in Section 6.

30 2. New results on L_p -random matrix calculus

31 The aim of this section is to establish new results belonging the so called $L_p(\Omega)$ -random matrix calculus that
 32 will be required later for solving both non-autonomous linear systems (see Section 3) and non-autonomous nonlinear
 33 random Riccati-type matrix differential equations of the form (1) (see Section 4). This section can be viewed as
 34 continuation of the contents introduced in [1, Sec.2]. For the sake of consistency, hereinafter we will keep the same
 35 notation introduced in [1]. For ease of presentation, it is convenient to remember that given a complete probability
 36 space, $(\Omega, \mathcal{F}, \mathbb{P})$, $L_p^{m \times n}(\Omega)$ denotes the set of all real random matrices $X = (x_{i,j})_{m \times n}$ such as $x_{i,j} : \Omega \rightarrow \mathbb{R}$, $1 \leq i \leq m$,
 37 $1 \leq j \leq n$, are real random variables (r.v.'s) satisfying that

$$\|x_{i,j}\|_p = \left(\mathbb{E} [|x_{i,j}|^p] \right)^{1/p} < +\infty, \quad p \geq 1, \quad (2)$$

38 where $\mathbb{E}[\cdot]$ denotes the expectation operator. It can be proved that $(L_p^{m \times n}(\Omega), \|\cdot\|_p)$, where

$$\|X\|_p = \sum_{i=1}^m \sum_{j=1}^n \|x_{i,j}\|_p, \quad \mathbb{E} [|x_{i,j}|^p] < +\infty, \quad (3)$$

39 is a Banach space. Notice that no confusion is possible between the common notation used for the $\|\cdot\|_p$ in (2) and
 40 in (3) because they act on scalar r.v.'s (denoted by lower case letters) and random matrices (denoted by capital case
 41 letters), respectively. In the case that $m = n = 1$, both norms are the same and $(L_p^{1 \times 1}(\Omega) \equiv L_p(\Omega), \|\cdot\|_p)$ represents
 42 the Banach space of real r.v.'s with finite absolute moments of order p about the origin, being $p \geq 1$ fixed, [8]. In [9]
 43 a number of results corresponding to $p = 4$ (fourth random calculus) and its relationship with $p = 2$ (mean square
 44 calculus) are established and applied to solve scalar random differential equations. In [10] a scalar random Riccati
 45 differential equation whose nonlinear coefficient is assumed to be an analytic stochastic process is solved using the
 46 $L_p(\Omega)$ -random scalar calculus.

47 Given $\mathcal{T} \subset \mathbb{R}$, a family of t -indexed r.v.'s, say $\{x(t) : t \in \mathcal{T}\}$, is called a p -stochastic process (p -s.p.) if for each
 48 $t \in \mathcal{T}$, the r.v. $x(t) \in L_p(\Omega)$. This definition can be extended to matrix s.p.'s $X(t) = (x_{i,j}(t))_{m \times n}$ of $L_p^{m \times n}(\Omega)$, which are
 49 termed p -matrix s.p.'s, if $x_{i,j}(t) \in L_p(\Omega)$ for every $1 \leq i \leq m$ and $1 \leq j \leq n$.

50 The definitions of continuity, differentiability and integrability of p -matrix s.p.'s follow in a straightforwardly
 51 manner using the $\|\cdot\|_p$ -norm introduced in (3). As a simple but illustrative example that will be invoked later when
 52 showing more sophisticated examples in Section 5, below we show how to prove the p -differentiability of a matrix
 53 s.p. of $L_p^{n \times n}(\Omega)$.

54 **Example 1.** Let a be an absolutely continuous r.v. defined on the bounded interval (a_1, a_2) , i.e., $a_1 \leq a(\omega) \leq a_2$ for
 55 every $\omega \in \Omega$, and let us denote by $f_a(a)$ the probability density function (p.d.f.) of the r.v. a . Let us define the following
 56 matrix s.p.

$$H(t, a) = \begin{bmatrix} h_{1,1}(t, a) & h_{1,2}(t, a) \\ h_{2,1}(t, a) & h_{2,2}(t, a) \end{bmatrix} = \begin{bmatrix} \exp(at) & \cosh(at) \\ \sinh(at) & \exp(-at) \end{bmatrix}, \quad t \in [0, T].$$

57 On the one hand, by the definition of the random matrix p -norm (see (3)) one gets

$$\|H(t, a)\|_p = \sum_{i=1}^2 \sum_{j=1}^2 \|h_{i,j}(t, a)\|_p = \|\exp(at)\|_p + \|\cosh(at)\|_p + \|\sinh(at)\|_p + \|\exp(-at)\|_p.$$

58 On the other hand, if we denote

$$M_{t,p} := \max\{M_{t,p}^{i,j} : 1 \leq i, j \leq 2\}, \quad \text{where} \quad M_{t,p}^{i,j} := \max_{\omega \in \Omega} \{(h_{i,j}(t; a(\omega)))^p\} < +\infty.$$

59 It is clear that

$$\left(\|h_{i,j}(t; a)\|_p\right)^p = \mathbb{E} \left[(h_{i,j}(t; a))^p \right] = \int_{a_1}^{a_2} (h_{i,j}(t; a))^p f_a(a) da \leq M_{t,p}^{i,j} < +\infty, \quad \text{for every } t \in [0, T],$$

60 where in the last step we have used that the integral of $f_a(a)$ over $[a_1, a_2]$ is just 1 because it is a p.d.f. This proves
61 that $H(t; a) \in L_p^{2 \times 2}(\Omega)$ for every $p \geq 1$. Moreover the $H(t; a)$ is p -differentiable being its p -derivative

$$H'(t; a) = \begin{bmatrix} h'_{1,1}(t; a) & h'_{1,2}(t; a) \\ h'_{2,1}(t; a) & h'_{2,2}(t; a) \end{bmatrix} = \begin{bmatrix} a \exp(at) & a \sinh(at) \\ a \cosh(at) & -a \exp(-at) \end{bmatrix}, \quad t \in [0, T].$$

62 Indeed, observe that

$$\left\| \frac{H(t + \Delta t; a) - H(t; a)}{\Delta t} - H'(t; a) \right\|_p = \sum_{i=1}^2 \sum_{j=1}^2 \left\| \frac{h_{i,j}(t + \Delta t; a) - h_{i,j}(t; a)}{\Delta t} - h'_{i,j}(t; a) \right\|_p,$$

63 and, for example for $i = j = 1$,

$$\begin{aligned} \left(\left\| \frac{h_{1,1}(t + \Delta t; a) - h_{1,1}(t; a)}{\Delta t} - h'_{1,1}(t; a) \right\|_p \right)^p &= \mathbb{E} \left[\left(\frac{\exp(a(t + \Delta t)) - \exp(at)}{\Delta t} - a \exp(at) \right)^p \right] \\ &= \mathbb{E} \left[\left(\frac{\exp(a(t + \Delta t)) - \exp(at)(1 + a\Delta t)}{\Delta t} \right)^p \right] = O((\Delta t)^p) \xrightarrow{\Delta t \rightarrow 0} 0, \end{aligned}$$

64 and the same can be shown for the rest of the components $h'_{1,2}(t; a)$, $h'_{2,1}(t; a)$ and $h'_{2,2}(t; a)$.

65 The following two key inequalities for scalar r.v.'s will be used extensively throughout this paper (see [1])

$$\|x\|_r \leq \|x\|_s, \quad 1 \leq r \leq s, \quad x \in L_s(\Omega), \quad (4)$$

66 and

$$\|xy\|_p \leq \|x\|_{2p} \|y\|_{2p}, \quad x, y \in L_{2p}(\Omega). \quad (5)$$

67 As a consequence of inequality (4), the $L_p(\Omega)$ spaces are embedded according to the following relationship, that will
68 be play a key role throughout the this paper,

$$L_s(\Omega) \subset L_r(\Omega), \quad 1 \leq r \leq s. \quad (6)$$

69 The following result may be regarded as a matrix adaptation of the fundamental theorem of mean square calculus
70 but generalized to the p -norm defined in (3), [11, p.104]. We omit its proof since it follows the same argument shown
71 in [11, p.104] but working componentwise and using the p -norm defined in (2) instead of particularizing this norm
72 for $p = 2$.

73 **Proposition 1.** Let $Z(t) \in L_p^{m \times m}(\Omega)$ be a p -differentiable matrix s.p. and assume that $Z'(t)$ is p -integrable, then

$$Z(t) - Z(0) = \int_0^t Z'(s) ds.$$

74 **Definition 1.** Let $\{\ell_{i,j}(t) : t \in \mathcal{T} \subset \mathbb{R}, 1 \leq i, j \leq m\}$ be scalar s.p.'s. The trace, $\text{tr}(L(t))$, of the square matrix s.p.
75 $L(t) = (\ell_{i,j}(t))_{m \times m}$ is defined by the sum of its diagonal entries, that is,

$$\text{tr}(L(t)) = \sum_{i=1}^m \ell_{i,i}(t).$$

76 The following result generalizes inequality (5) to an arbitrary number of factors since it is obtained for the partic-
77 ular case $m = 2$. This inequality will be applied later.

78 **Lemma 1.** *Let us consider a set of scalar s.p.'s $\{x_i(t) : t \in \mathcal{T} \subset \mathbb{R}, 1 \leq i \leq m\}$ in $L_{2^{m-1}p}(\Omega)$. Then, for each $t \in \mathcal{T}$, it
79 is verified that*

$$\left\| \prod_{i=1}^m x_i(t) \right\|_p \leq \prod_{i=1}^m \|x_i(t)\|_{2^{m-1}p}, \quad (7)$$

80 and $\prod_{i=1}^m x_i(t)$ belongs to $L_p(\Omega)$.

81 **PROOF.** *It follows by induction over m . Let $t \in \mathcal{T} \subset \mathbb{R}$ be arbitrary but fixed. For $m = 1$ the proof is trivial since (7)
82 becomes an identity. Let us assume that (7) is satisfied for the $m - 1$ scalar s.p.'s $\{x_i(t) : 1 \leq i \leq m - 1\}$, that is to say,
83 the following inequality*

$$\left\| \prod_{i=1}^{m-1} x_i(t) \right\|_p \leq \prod_{i=1}^{m-1} \|x_i(t)\|_{2^{m-2}p}, \quad (8)$$

84 holds provided that $\|x_i(t)\|_{2^{m-2}p} < +\infty$, i.e., $x_i(t) \in L_{2^{m-2}p}(\Omega)$, $1 \leq i \leq m - 2$. Now assuming $m \geq 2$, we shall prove (7),

$$\begin{aligned} \left\| \prod_{i=1}^m x_i(t) \right\|_p &= \left\| \left(\prod_{i=1}^{m-1} x_i(t) \right) x_m(t) \right\|_p \\ &\stackrel{(I)}{\leq} \left\| \prod_{i=1}^{m-1} x_i(t) \right\|_{2p} \|x_m(t)\|_{2p} \\ &\stackrel{(II)}{\leq} \left(\prod_{i=1}^{m-1} \|x_i(t)\|_{2^{m-2}(2p)} \right) \|x_m(t)\|_{2p} \\ &= \left(\prod_{i=1}^{m-1} \|x_i(t)\|_{2^{m-1}p} \right) \|x_m(t)\|_{2p} \\ &\stackrel{(III)}{\leq} \left(\prod_{i=1}^{m-1} \|x_i(t)\|_{2^{m-1}p} \right) \|x_m(t)\|_{2^{m-1}p} \\ &\leq \prod_{i=1}^m \|x_i(t)\|_{2^{m-1}p} < +\infty. \end{aligned}$$

85 *In step (I) we have applied (5) for r.v.'s $x = \prod_{i=1}^{m-1} x_i(t)$, $y = x_m(t)$. Taking into account that by hypothesis $x_i(t) \in$
86 $L_{2^{m-1}p}(\Omega)$, $1 \leq i \leq m$, together with the proof itself, it is justified that $\prod_{i=1}^{m-1} x_i(t)$ and $x_m(t)$ are in $L_{2p}(\Omega)$, which is
87 required to legitimate the application of inequality (5). In step (II) we have applied the induction hypothesis (8) with
88 de identification $2p$ instead of p , and finally, in step (III) we have used the Lyapunov's inequality (4) with $r \equiv 2p$ and
89 $s \equiv 2^{m-1}p$, $m \geq 2$ since by hypothesis $x_m(t) \in L_{2^{m-1}p}(\Omega)$. \square*

90 **Remark 1.** Notice that if in Lemma 1 we consider $m - 1$ scalar s.p.'s $\{x_i(t) : t \in \mathcal{T} \subset \mathbb{R}, 1 \leq i \leq m - 1\}$ in $L_{2^{m-1}p}(\Omega)$,
91 then (7) is still true for $p \equiv 2p$ since $\|x_i(t)\|_{2^{m-2}(2p)} = \|x_i(t)\|_{2^{m-1}p} < +\infty$. As a consequence, $\prod_{i=1}^{m-1} x_i(t) \in L_{2p}(\Omega)$. This
92 result will be used in the proof of the following lemma.

93 **Lemma 2.** *Let us consider a set of scalar s.p.'s $\{x_i(t) : t \in \mathcal{T} \subset \mathbb{R}, 1 \leq i \leq m\}$ in $L_{2^{m-1}p}(\Omega)$ for every $t \in \mathcal{T}$ and
94 $(2^{m-1}p)$ -differentiable, then $\prod_{i=1}^m x_i(t)$ is p -differentiable and, for each $t \in \mathcal{T}$, its value is*

$$\left(\prod_{i=1}^m x_i(t) \right)' = \sum_{i=1}^m \left\{ \left(\prod_{\substack{j=1 \\ j \neq i}}^m x_j(t) \right) x_i'(t) \right\}. \quad (9)$$

95 **PROOF.** It follows by induction over m . Let $t \in \mathcal{T} \subset \mathbb{R}$ be arbitrary but fixed. For $m = 1$ the proof is trivial because
 96 both sides of (9) are the same. Let us assume that for $m \geq 2$

$$\left(\prod_{i=1}^{m-1} x_i(t) \right)' = \sum_{i=1}^{m-1} \left\{ \left(\prod_{\substack{j=1 \\ j \neq i}}^{m-1} x_j(t) \right) x_i'(t) \right\}, \quad (10)$$

97 holds. On the one hand, applying Remark 1 it is guaranteed that $\prod_{i=1}^{m-1} x_i(t) \in L_{2p}(\Omega)$. On the other hand, due to
 98 $x_m(t) \in L_{2^{m-1}p}(\Omega)$ and (6), it is known that $x_m(t) \in L_{2p}(\Omega)$. Then, according to Proposition 2 of [1] (in its scalar
 99 version) for the p -derivative of the product of two $2p$ -differentiable s.p.'s, one gets

$$\left(\prod_{i=1}^m x_i(t) \right)' = \left(\left(\prod_{i=1}^{m-1} x_i(t) \right) x_m(t) \right)' = \left(\prod_{i=1}^{m-1} x_i(t) \right)' x_m(t) + \left(\prod_{i=1}^{m-1} x_i(t) \right) x_m'(t). \quad (11)$$

100 Using the induction hypothesis (10) in (11), one obtains the result

$$\begin{aligned} \left(\prod_{i=1}^m x_i(t) \right)' &= \left(\sum_{i=1}^{m-1} \left(\prod_{\substack{j=1 \\ j \neq i}}^{m-1} x_j(t) \right) x_i'(t) \right) x_m(t) + \left(\prod_{i=1}^{m-1} x_i(t) \right) x_m'(t) \\ &= \sum_{i=1}^{m-1} \left\{ \left(\prod_{\substack{j=1 \\ j \neq i}}^m x_j(t) \right) x_i'(t) \right\} + \left(\prod_{i=1}^{m-1} x_i(t) \right) x_m'(t) \\ &= \sum_{i=1}^m \left(\prod_{\substack{j=1 \\ j \neq i}}^m x_j(t) \right) x_i'(t). \quad \square \end{aligned}$$

101 In [1], we defined the determinant of a square matrix s.p. $A(t) = (a_{i,j})_{n \times n}$ as

$$\det A(t) = \sum_{\sigma \in P_n} \text{sgn}(\sigma) a_{1,\sigma(1)}(t) \cdots a_{n,\sigma(n)}(t), \quad \text{for each } t \in \mathcal{T} \subset \mathbb{R},$$

102 being P_n the set of all permutations of the n elements $(1, 2, \dots, n)$, that is, the set of all permutations of the indexes
 103 defining the n columns of $A(t)$, and $\text{sgn}(\sigma)$ the signature of the permutation $\sigma = (\sigma(1), \dots, \sigma(n))$. Inasmuch as $A(t)$ is
 104 a matrix s.p. then $\det A(t)$ is a scalar s.p. Furthermore, under conditions given in Proposition 3 of [1], it is guaranteed
 105 that $\det A(t)$ is continuous in the p -norm defined by (2). The following result allows us to compute the p -derivative
 106 of the determinant of a family of s.p.'s. It can be regarded as an extension of the classical rule for differentiating the
 107 determinant whose entries are differentiable deterministic functions.

108 **Lemma 3.** *Let us consider a square matrix s.p. $A(t) = (a_{i,j}(t))_{n \times n}$, $t \in \mathcal{T} \subset \mathbb{R}$. Let us suppose that the scalar s.p.'s
 109 $a_{i,j}(t)$, $i, j = 1, \dots, n$, lie in $L_{2^{n-1}p}(\Omega)$ for every $t \in \mathcal{T}$ and are $(2^{n-1}p)$ -differentiable for every $t \in \mathcal{T}$. Then, the
 110 determinant s.p. of $A(t)$, $\det A(t)$, is p -differentiable and its p -derivative is given by*

$$(\det A(t))' = \det \begin{bmatrix} (a_{1,1}(t))' & \cdots & (a_{1,n}(t))' \\ a_{2,1}(t) & \cdots & a_{2,n}(t) \\ \vdots & & \vdots \\ a_{n,1}(t) & \cdots & a_{n,n}(t) \end{bmatrix} + \det \begin{bmatrix} a_{1,1}(t) & \cdots & a_{1,n}(t) \\ (a_{2,1}(t))' & \cdots & (a_{2,n}(t))' \\ \vdots & & \vdots \\ a_{n,1}(t) & \cdots & a_{n,n}(t) \end{bmatrix} + \cdots + \det \begin{bmatrix} a_{1,1}(t) & \cdots & a_{1,n}(t) \\ a_{2,1}(t) & \cdots & a_{2,n}(t) \\ \vdots & & \vdots \\ (a_{n,1}(t))' & \cdots & (a_{n,n}(t))' \end{bmatrix}. \quad (12)$$

111 **PROOF.** Since $a_{i,j}(t) \in L_{2^{n-1}p}(\Omega)$, then $E[|a_{i,j}(t)|^{2^{n-1}p}] < +\infty$, $\forall i, j : 1 \leq i, j \leq n$, $n \geq 1$, $t \in \mathcal{T}$, and accordingly to
 112 expression (15) of [1] it is guaranteed that $(\det A(t)) \in L_p(\Omega)$. Now, considering the definition of $\det A(t)$ one gets

$$(\det A(t))' = \left(\sum_{\sigma \in P_n} \text{sgn}(\sigma) \prod_{i=1}^n a_{i,\sigma(i)}(t) \right)' = \sum_{\sigma \in P_n} \text{sgn}(\sigma) \left(\prod_{i=1}^n a_{i,\sigma(i)}(t) \right)'. \quad (13)$$

113 Using that the n scalar s.p.'s $a_{i,\sigma(i)}(t)$, $i = 1, \dots, n$, are in $L_{2^{n-1}p}(\Omega)$ and they are $(2^{n-1}p)$ -differentiable, we can apply
 114 Lemma 2 to (13) (with the identification $m \equiv n$) for each $t \in \mathcal{T}$ and then obtaining

$$\begin{aligned} (\det A(t))' &= \sum_{\sigma \in P_n} \operatorname{sgn}(\sigma) \left\{ \sum_{i=1}^n \left(\prod_{\substack{j=1 \\ j \neq i}}^n a_{i,\sigma(j)}(t) \right) a'_{j,\sigma(j)}(t) \right\} = \sum_{i=1}^n \left\{ \sum_{\sigma \in P_n} \operatorname{sgn}(\sigma) \left(\prod_{\substack{j=1 \\ j \neq i}}^n a_{i,\sigma(j)}(t) \right) a'_{j,\sigma(j)}(t) \right\} \\ &= \sum_{i=1}^n \det \begin{bmatrix} a_{1,1}(t) & \cdots & a_{1,n}(t) \\ \vdots & & \vdots \\ (a_{i,1}(t))' & \cdots & (a_{i,n}(t))' \\ \vdots & & \vdots \\ a_{n,1}(t) & \cdots & a_{n,n}(t) \end{bmatrix}. \quad \square \end{aligned}$$

115 **Proposition 2 (Abel-Liouville-Jacobi's random formula).** Let $\Phi(t) = (\phi_i^j(t))_{n \times n}$, $t \in \mathcal{T} \subset \mathbb{R}$ be a matrix s.p. such
 116 that its entries, $\phi_i^j(t)$, are $(2^{n-1}p)$ -differentiable scalar s.p.'s. Let us assume that $\Phi(t)$ verifies the random matrix linear
 117 equation $\Phi'(t) = L(t)\Phi(t)$, where the elements $\ell_{i,j}(t)$ of the matrix s.p. $L(t) = (\ell_{i,j}(t))_{n \times n}$ lie in $L_{2^{n-1}p}(\Omega)$ and they
 118 are $(2^{n-1}p)$ -differentiable for each $t \in \mathcal{T}$. Then, the scalar s.p. $\det \Phi(t) \in L_p(\Omega)$ satisfies the random first-order
 119 homogeneous linear equation

$$(\det \Phi(t))' = \operatorname{tr}(L(t)) \det \Phi(t).$$

120 Furthermore, under the following conditions

121 (C1) $L(t) \in L_{2p}^{n \times n}(\Omega)$, for each $t \in \mathcal{T}$,

122 (C2) $\det \Phi(t_0) \in L_{2p}(\Omega)$, for $t_0 \in \mathcal{T}$,

123 (C3) There exist $r > 2p$ and $\delta > 0$, such that

$$\sup_{s, s^* \in [-\delta, \delta]} \mathbb{E} \left[\left(\exp \left(\int_{x+s}^{x+s^*} \operatorname{tr}(L(u)) du \right) \right)^r \right] = \sup_{s, s^* \in [-\delta, \delta]} \mathbb{E} \left[\prod_{i=1}^n \exp \left(r \int_{x+s}^{x+s^*} \ell_{i,i}(u) du \right) \right] < +\infty,$$

124 it is verified that $\det \Phi(t)$ satisfies the following identity for each t

$$\det \Phi(t) = \det \Phi(t_0) \exp \left(\int_{t_0}^t \operatorname{tr}(L(s)) ds \right), \quad t_0 \in \mathcal{T}. \quad (14)$$

125 **PROOF.** Let us fix $t \in \mathcal{T}$, and without loss of generality let us consider that the matrix s.p. $\Phi(t)$ takes the form

$$\Phi(t) = [\Phi^1(t) \cdots \Phi^n(t)] = \begin{bmatrix} \phi_1^1(t) & \cdots & \phi_1^n(t) \\ \vdots & & \vdots \\ \phi_i^1(t) & \cdots & \phi_i^n(t) \\ \vdots & & \vdots \\ \phi_n^1(t) & \cdots & \phi_n^n(t) \end{bmatrix},$$

126 where $\Phi^j(t)$, $j = 1, \dots, n$, denote the j -th column vector of the matrix s.p. $\Phi(t)$ and $\phi_i^j(t)$ the i -th component of the
 127 column vector $\Phi^j(t)$. Since the entries of the matrix s.p. $\Phi(t)$ are $(2^{n-1}p)$ -differentiable, then accordingly to Lemma 3
 128 the first p -derivative of the scalar s.p. $\det \Phi(t)$ exists, $(\det \Phi(t))'$, and by (12) it can be calculated as follows

$$(\det \Phi(t))' = \sum_{i=1}^n \det \begin{bmatrix} \phi_1^1(t) & \cdots & \phi_1^n(t) \\ \vdots & & \vdots \\ (\phi_i^1(t))' & \cdots & (\phi_i^n(t))' \\ \vdots & & \vdots \\ \phi_n^1(t) & \cdots & \phi_n^n(t) \end{bmatrix}. \quad (15)$$

129 Taking into account we are assuming that $\Phi(t)$ verifies the random matrix linear equation $\Phi'(t) = L(t)\Phi(t)$, then its
 130 column vectors $\Phi^j(t)$, $j = 1, \dots, n$, also hold this equation, that is,

$$(\Phi^j(t))' = L(t)\Phi^j(t), \quad \forall j = 1, \dots, n. \quad (16)$$

131 By (16), the i -th component, $\phi_i^j(t)$, $i = 1, \dots, n$, of each column vector s.p. $\Phi^j(t)$, $j = 1 \dots, n$, takes the form

$$(\phi_i^j(t))' = \sum_{k=1}^n \ell_{i,k}(t) \phi_k^j(t), \quad \forall i, j = 1, \dots, n. \quad (17)$$

132 Substituting (17) into (15), one gets

$$(\det \Phi(t))' = \sum_{i=1}^n \det \begin{bmatrix} \phi_1^1(t) & \cdots & \phi_1^n(t) \\ \vdots & & \vdots \\ \sum_{k=1}^n \ell_{i,k}(t) \phi_k^1(t) & \cdots & \sum_{k=1}^n \ell_{i,k}(t) \phi_k^n(t) \\ \vdots & & \vdots \\ \phi_n^1(t) & \cdots & \phi_n^n(t) \end{bmatrix}. \quad (18)$$

133 Note the i -th row, F_i , of the right-hand side of (18) is a linear combination of all remaining rows of (18). Then,
 134 making the elementary row operations

$$F_i - \sum_{\substack{k=1 \\ k \neq i}}^n \ell_{i,k}(t) F_k \longrightarrow F_i, \quad \forall i = 1, \dots, n,$$

135 and considering the standard determinant properties, one gets

$$(\det \Phi(t))' = \sum_{i=1}^n \det \begin{bmatrix} \phi_1^1(t) & \cdots & \phi_1^n(t) \\ \vdots & & \vdots \\ \ell_{i,i}(t) \phi_i^1(t) & \cdots & \ell_{i,i}(t) \phi_i^n(t) \\ \vdots & & \vdots \\ \phi_n^1(t) & \cdots & \phi_n^n(t) \end{bmatrix} = \left(\sum_{i=1}^n \ell_{i,i}(t) \right) \det \Phi(t) = \text{tr}(L(t)) \det \Phi(t). \quad (19)$$

136 Now, let us consider the following scalar random IVP

$$\left. \begin{aligned} y'(t) &= \text{tr}(L(t))y(t), \quad t \in \mathcal{T}, \\ y(t_0) &= \det \Phi(t_0), \end{aligned} \right\} \quad (20)$$

137 verifying the three conditions (C1)–(C3). Then, taking into account that $\det \Phi(t)$ verifies (19), that the $(2^{n-1}p)$ -
 138 differentiability of each $\ell_{i,j}(t)$ implies the $(2^{n-1}p)$ -continuity of the $\text{tr}(L(t))$ and, applying an analogous reasoning to
 139 the one shown in Theorem 8 of [12], we obtain that $\det \Phi(t)$ is a solution to random IVP (20) in $L_p(\Omega)$. Moreover, it
 140 is given by

$$\det \Phi(t) = \det \Phi(t_0) \exp \left(\int_{t_0}^t \text{tr}(L(s)) ds \right), \quad t_0 \in \mathcal{T}. \quad \square$$

141 3. Random non-autonomous linear systems

142 We begin this section with the solution of the random vector IVP

$$Y'(t) = L(t)Y(t), \quad Y(0) = Y_0, \quad t \in [0, T], \quad (21)$$

143 where $L(t) \in L_{2p}^{n \times n}(\Omega)$ is a matrix s.p. and $Y_0 \in L_{2p}^{n \times 1}(\Omega)$. Under the hypothesis, $L(t)$ is absolutely integrable in the
 144 $2p$ -norm defined by (3) (in short, $L(t)$ is $2p$ -absolutely integrable), that is,

$$\int_0^T \|L(t)\|_{2p} dt < +\infty, \quad (22)$$

145 it is guaranteed that, by submultiplicativity property (5), $F : [0, T] \times L_{2p}^{n \times 1}(\Omega) \rightarrow L_p^{n \times 1}(\Omega)$, defined by $F(t, Y) = L(t)Y$,
 146 satisfies

$$\|F(t, Y_1) - F(t, Y_2)\|_p = \|L(t)(Y_1 - Y_2)\|_p \leq \|L(t)\|_{2p} \|Y_1 - Y_2\|_{2p}.$$

147 Thus, function $F(t, Y)$ is p -Lipschitzian and by Theorem 10.6.1 of [13, p.292] which holds for abstract Banach spaces,
 148 the random vector IVP (21) admits a unique $L_p^{n \times 1}(\Omega)$ solution in $[0, T]$.

149 Let us denote by $\Phi_L(t; 0)$ the matrix s.p. in $L_p^{n \times n}(\Omega)$ whose i -th column is the unique solution of problem (21) with
 150 $Y_0 = [0, \dots, 0, 1, 0, \dots, 0]^\top$, where the i -th entry is 1 and 0 elsewhere, with probability one. Then, one satisfies

$$\Phi_L'(t; 0) = L(t) \Phi_L(t; 0), \quad \Phi_L(0; 0) = I_n, \quad (23)$$

151 being I_n the identity matrix of size n .

152 **Definition 2.** The matrix s.p. $\Phi_L(t; 0)$ satisfying (23) is referred to as the random fundamental matrix solution of the
 153 random linear system (21).

154 Note that if $L(t) = (\ell_{i,j}(t))$ satisfies the hypotheses of Proposition 2, then $\Phi_L(t; 0)$ is invertible in $L_p^{n \times n}(\Omega)$ in the sense
 155 introduced in the Definition 3 of [1] (see (14) and note that $\det \Phi(t_0) = I_n$ being I_n the identity matrix of size n).

156

157 For the sake of clarity in the presentation, below we introduce the following definition:

158 **Definition 3.** The linear system (21) is said to be random p -regular, $p \geq 1$, if the following conditions are satisfied:

- 159 • the matrix s.p. $L(t) \in L_{2p}^{n \times n}(\Omega)$ of (21) is $2p$ -absolutely integrable in $[0, T]$;
- 160 • the random fundamental matrix solution, $\Phi_L(t; 0)$, and its inverse, $\Phi_L^{-1}(t; 0)$, both lie in $L_p^{n \times n}(\Omega)$ and they are
 161 p -differentiable.

162 **Example 2.** Let $L = (\ell_{i,j})_{n \times n}$ be a random matrix for whose entries $\ell_{i,j} : \Omega \rightarrow \mathbb{R}$ there exist positive constants $m_{i,j}$
 163 and $h_{i,j}$ satisfying that

$$E \left[|\ell_{i,j}|^r \right] \leq m_{i,j} (h_{i,j})^r < +\infty, \quad \forall r \geq 0, \quad \forall i, j : 1 \leq i, j \leq n. \quad (24)$$

164 Then, by Section 3 of [1], the corresponding random autonomous linear system (23) with $L(t) = L$ is p -regular for any
 165 $p \geq 1$ with $\Phi_L(t; 0) = \exp(Lt)$ and $\Phi_L^{-1}(t; 0) = \exp(-Lt)$. Moreover, as indicated in Remark 3 into Section 3 of [1],
 166 any bounded or truncated r.v. satisfies condition (24). Therefore, important r.v.'s like binomial, uniform, beta satisfy
 167 condition (24). In addition, unbounded r.v.'s like exponential, gaussian, etc. can be truncated adequately in order for
 168 this property to be satisfied. As a consequence, the set of r.v.'s satisfying condition (24) is, in practice, quite broad.

169 **Example 3.** Let us consider the random IVP (21) where all entries, $\ell_{i,j}(t)$, of the matrix s.p. $L(t) = (\ell_{i,j}(t))_{n \times n}$ have
 170 s -degrees of randomness, [11, p.36],

$$\ell_{i,j}(t) = \ell_{i,j}(t; a_1, a_2, \dots, a_s).$$

171 Let us assume that $\ell_{i,j}(t; a_1, a_2, \dots, a_s) \in L_{2p}^{n \times n}(\Omega)$ is $2p$ -absolutely integrable, for each $i, j : 1 \leq i, j \leq n$, hence
 172 condition (22) is guaranteed. If $Y_0 = [y_{0,1}, \dots, y_{0,n}]$ is the random vector initial condition of the IVP (21), then it
 173 is easy to check, throughout the approximate successive method [13], that the random fundamental matrix solution
 174 $\Phi_L(t; 0)$ of (21) has $(s+n)$ -degrees of randomness determined by the r.v.'s $a_1, a_2, \dots, a_s, y_{0,1}, \dots, y_{0,n}$. By Proposition
 175 2, $\Phi_L(t; 0)$ is invertible, and assuming that $\Phi_L^{-1}(t; 0) \in L_p^{n \times n}(\Omega)$ and it is p -differentiable, then, the linear system (21)
 176 is p -regular.

177 Below, we show an example where the random fundamental matrix solution, $\Phi_L(t; 0)$, is available for the time-
 178 dependent case.

179 **Example 4.** Let us consider the random IVP (21) with $L(t) = f(t)L$, where $f(t)$ is a real continuous deterministic
 180 function, $f : [0, T] \rightarrow \mathbb{R}$, and $L = (\ell_{i,j})_{n \times n}$ is a random matrix whose entries satisfy the condition (24), hence
 181 $L \in \mathbf{L}_{2p}^{n \times n}(\Omega)$. Notice that $L(t)$ is $2p$ -absolutely integrable in $[0, T]$:

$$\int_0^T \|L(t)\|_{2p} dt = \int_0^T \|f(t)L\|_{2p} dt = \|L\|_{2p} \int_0^T |f(t)| dt < +\infty,$$

182 since $\|L\|_{2p} < +\infty$ (by assumption (24), see [1]) and $\int_0^T |f(t)| dt < +\infty$ (by continuity of $f(t)$). Also by hypothesis (24)
 183 and Section 3 of [1],

$$\psi_L(t; 0) = \exp\left(L \int_0^t f(s) ds\right), \quad (25)$$

184 and its inverse

$$\psi_L^{-1}(t; 0) = \exp\left(-L \int_0^t f(s) ds\right), \quad (26)$$

185 are well-defined in $\mathbf{L}_p^{n \times n}(\Omega)$ and it is also guaranteed that $\psi_L(t; 0)$ and $\psi_L^{-1}(t; 0)$, defined by (25) and (26), respectively,
 186 are p -differentiable. Therefore, the random IVP (21) with $L(t) = f(t)L$ is random p -regular and $\psi_L(t; 0)$ satisfies that

$$\psi_L'(t; 0) = L f(t) \exp\left(L \int_0^t f(s) ds\right) = f(t) L \psi_L(t; 0) = L(t) \psi_L(t; 0).$$

187 Thus, $\Phi_L(t; 0) = \psi_L(t; 0)$ is its random fundamental matrix solution.

188 The following result provides a closed form solution of p -regular random linear systems.

189 **Theorem 1.** Let us assume that the random linear system (21) is $2p$ -regular and let $L(t) = (\ell_{i,j}(t))_{n \times n}$ be a matrix s.p.
 190 such as its entries satisfy condition (24) for every t . Let us suppose that the random vector s.p. $B(t)$ lies in $\mathbf{L}_{2p}^{n \times 1}(\Omega)$
 191 and is $2p$ -integrable, and the initial condition $Y_0 \in \mathbf{L}_{2p}^{n \times 1}(\Omega)$. Then

$$X(t) = \Phi_L(t; 0) Y_0 + \Phi_L(t; 0) \int_0^t \Phi_L^{-1}(s; 0) B(s) ds, \quad (27)$$

192 satisfies the unhomogeneous problem

$$X'(t) = L(t) X(t) + B(t), \quad X(0) = Y_0,$$

193 where the derivative $X'(t)$ is understood in the $\mathbf{L}_p^{n \times 1}(\Omega)$ sense.

194 **PROOF.** On the one hand, observe that under hypothesis $L(t) = (\ell_{i,j}(t))_{n \times n}$ be a random matrix s.p. such as its entries
 195 satisfy condition (24) for every t fixed, it is guaranteed that $\Phi_L(t; 0) \in \mathbf{L}_{2p}^{n \times n}(\Omega)$ (see [1]). On the other hand, taking
 196 derivatives of the s.p. $X(t)$ defined by (27) and, applying Proposition 2 of [1], Proposition 1 and (23), one gets

$$\begin{aligned} X'(t) &= \Phi_L'(t; 0) Y_0 + \Phi_L'(t; 0) \int_0^t \Phi_L^{-1}(s; 0) B(s) ds + \Phi_L(t; 0) \Phi_L^{-1}(t; 0) B(t) \\ &= L(t) \Phi_L(t; 0) Y_0 + L(t) \Phi_L(t; 0) \int_0^t \Phi_L^{-1}(s; 0) B(s) ds + B(t) \\ &= L(t) \left[\Phi_L(t; 0) Y_0 + \Phi_L(t; 0) \int_0^t \Phi_L^{-1}(s; 0) B(s) ds \right] + B(t) \\ &= L(t) X(t) + B(t). \end{aligned}$$

197 In addition, by (23) one gets

$$X(0) = \Phi_L(0; 0) Y_0 = Y_0. \quad \square$$

198 The next result provides a random analogous of the deterministic case, solved by R. Bellman in [14], where the
 199 solution of a random matrix bilateral differential equation is constructed in terms of the solution of two auxiliary
 200 random linear systems of the form (21).

201 **Corollary 1.** Let $A(t)$ and $B(t)$ be matrix s.p.'s such that $A(t) \in L_{4p}^{n \times n}(\Omega)$, $B(t) \in L_{2p}^{n \times n}(\Omega)$. Let $X_0 \in L_{4p}^{n \times n}(\Omega)$ and let us
 202 suppose that the random linear system

$$Y'(t) = A(t)Y(t), \quad Y(0) = I_n, \quad 0 \leq t \leq T, \quad (28)$$

203 is $4p$ -regular, and

$$Z'(t) = (B(t))^T Z(t); \quad Z(0) = I_n, \quad 0 \leq t \leq T, \quad (29)$$

204 is $2p$ -regular. Then, the unique solution, $X : [0, T] \rightarrow L_p^{n \times n}(\Omega)$, of the random bilateral IVP

$$X'(t) = A(t)X(t) + X(t)B(t), \quad X(0) = X_0, \quad 0 \leq t \leq T,$$

205 is given by

$$X(t) = \Phi_A(t; 0) X_0 (\Phi_B(t; 0))^T, \quad 0 \leq t \leq T,$$

206 where $\Phi_A(t; 0)$ and $\Phi_B(t; 0)$ denote the random fundamental matrix solutions of random IVP's (28)–(29), respectively.

207 **PROOF.** Let $Y(t)$ and $Z(t)$ be the solution s.p.'s of the random IVP's (28) and (29) respectively, and consider the s.p.
 208 $X(t)$ defined by

$$X(t) = Y(t) X_0 (Z(t))^T, \quad 0 \leq t \leq T. \quad (30)$$

209 Considering the factorization $X(t) = (Y(t)X_0) (Z(t))^T$ of (30) and applying Proposition 2 of [1], one follows

$$\begin{aligned} X'(t) &= (Y(t)X_0)' (Z(t))^T + (Y(t)X_0) ((Z(t))^T)' \\ &= Y'(t)X_0 (Z(t))^T + Y(t)X_0 (Z'(t))^T \\ &= A(t)Y(t)X_0 (Z(t))^T + Y(t)X_0 (Z(t))^T B(t) \\ &= A(t)X(t) + X(t)B(t). \end{aligned}$$

210 Notice that in the last step, we have applied (28) and (29). Moreover for the initial condition, $X(0)$, from (30), (28)
 211 and (29), one gets

$$X(0) = Y(0)X_0 (Z(0))^T = I_n X_0 (I_n)^T = X_0.$$

212 Now, from Theorem 1 with $B(t)$ the null matrix of size $n \times n$, $B(t) = O_n$, we know that the solutions of random IVP's
 213 (28) and (29), are given by,

$$Y(t) = \Phi_A(t; 0) I_n = \Phi_A(t; 0), \quad Z(t) = \Phi_{B^T}(t; 0) I_n = (\Phi_B(t; 0))^T I_n = \Phi_{B^T}(t; 0), \quad (31)$$

214 respectively. Therefore, by (30), (31) and taking into account the p -Lipschitz property of $F(t, X) = A(t)X + X B(t)$
 215 that guarantees the uniqueness, one gets

$$X(t) = Y(t) X_0 (Z(t))^T = \Phi_A(t; 0) X_0 (\Phi_B(t; 0))^T. \quad \square$$

216 4. Random non-autonomous Riccati matrix equation

217 Once random linear vector systems have been treated in the previous section, we are in a good situation to apply
 218 a random version of the linearization method developed in [2] and [4] to construct local solutions of the random
 219 time-dependent Riccati IVP (1). This approach may be regarded as a continuation of paper [1], where the random
 220 autonomous Riccati problem has been recently treated.

221 Consider the matrix s.p. $L(t)$ in $L_{4p}^{(n+m) \times (n+m)}(\Omega)$ defined by

$$L(t) = \left[\begin{array}{c|c} A(t) & B(t) \\ \hline C(t) & -D(t) \end{array} \right], \quad (32)$$

222 and assume that the random matrix

$$Y_0 = \left[\frac{I_n}{W_0} \right], \quad (33)$$

223 lies in $L_{4p}^{(n+m) \times n}(\Omega)$ and that random linear matrix IVP

$$Y'(t) = L(t) Y(t), \quad Y_0 = \left[\frac{I_n}{W_0} \right], \quad (34)$$

224 is $2p$ -regular. Let us consider the block-partition of $Y(t)$ of the form

$$Y(t) = \left[\frac{U(t)}{V(t)} \right], \quad U(t) \in L_{2p}^{n \times n}(\Omega), \quad V(t) \in L_{2p}^{m \times n}(\Omega). \quad (35)$$

225 Note that $U(0) = I_n$ and that if $U(t)$ is invertible in an ordinary neighbourhood of $t = 0$, $\mathcal{N}_U(0)$, and $(U(t))^{-1} \in$
226 $L_{2p}^{n \times n}(\Omega)$, then the s.p.

$$W(t) = V(t) (U(t))^{-1}, \quad t \in \mathcal{N}_U(0), \quad (36)$$

227 is well-defined and it lies in $L_p^{m \times n}(\Omega)$. Assuming that $V(t)$ and $(U(t))^{-1}$ are $2p$ -differentiable, by (36), Proposition 2
228 and Corollary 1 of [1], one gets that $W(t)$ is p -differentiable in $\mathcal{N}_U(0)$ with

$$W'(t) = V'(t) (U(t))^{-1} + V(t) \left((U(t))^{-1} \right)' = V'(t) (U(t))^{-1} - V(t) (U(t))^{-1} U'(t) (U(t))^{-1}, \quad t \in \mathcal{N}_U(0). \quad (37)$$

229 Let us consider the block-partition of the random fundamental matrix solution $\Phi_L(t; 0)$ of the random linear IVP
230 (34), of the form

$$\Phi_L(t; 0) = \left[\begin{array}{c|c} \Phi_{1,1}(t; 0) & \Phi_{1,2}(t; 0) \\ \hline \Phi_{2,1}(t; 0) & \Phi_{2,2}(t; 0) \end{array} \right], \quad (38)$$

231 with

$$\Phi_{1,1}(t; 0) \in L_{4p}^{n \times n}(\Omega), \quad \Phi_{1,2}(t; 0) \in L_{4p}^{n \times m}(\Omega), \quad \Phi_{2,1}(t; 0) \in L_{4p}^{m \times n}(\Omega), \quad \Phi_{2,2}(t; 0) \in L_{4p}^{m \times m}(\Omega). \quad (39)$$

232 From the definition of $2p$ -regularity, (35) and (38) one gets

$$U(t) = \Phi_{1,1}(t; 0) + \Phi_{1,2}(t; 0)W_0; \quad V(t) = \Phi_{2,1}(t; 0) + \Phi_{2,2}(t; 0)W_0, \quad t \in \mathcal{N}_U(0). \quad (40)$$

233 Then, $W(t)$ defined by (36), can be written in the form

$$W(t) = (\Phi_{2,1}(t; 0) + \Phi_{2,2}(t; 0)W_0) (\Phi_{1,1}(t; 0) + \Phi_{1,2}(t; 0)W_0)^{-1}, \quad t \in \mathcal{N}_U(0). \quad (41)$$

234 From (32), (34), (35) and (37), it follows that

$$\begin{aligned} W'(t) &= V'(t) (U(t))^{-1} - V(t) (U(t))^{-1} U'(t) (U(t))^{-1} \\ &= \{C(t)U(t) - D(t)V(t)\} (U(t))^{-1} - V(t) (U(t))^{-1} U'(t) (U(t))^{-1} \\ &= C(t) - D(t)W(t) - W(t) \{A(t)U(t) + B(t)V(t)\} (U(t))^{-1} \\ &= C(t) - D(t)W(t) - W(t)A(t) - W(t)B(t)W(t), \end{aligned}$$

235 with $W(0) = V(0) (U(0))^{-1} = W_0$. As factors $V(t)$ and $(U(t))^{-1}$ of $W(t)$, both lie in $L_{2p}^{m \times n}(\Omega)$ and $L_{2p}^{n \times n}(\Omega)$ respectively,
236 then by Proposition 1 of [1] $W(t)$ lies in $L_p^{m \times n}(\Omega)$.

237

238 Summarizing, the following result has been established:

239 **Theorem 2.** Let us assume that matrix s.p. $L(t)$ defined by (32), lie in $L_{4p}^{(n+m) \times (n+m)}(\Omega)$, and that the random matrix
 240 Y_0 defined by (33), lie in $L_{4p}^{(n+m) \times n}(\Omega)$. Let us further assume that the random linear matrix IVP (34) is $2p$ -regular, and
 241 consider the block-entries $\Phi_{i,j}(t; 0)$ of the random fundamental matrix solution $\Phi(t; 0)$ defined by (38)–(39). Let $U(t)$
 242 and $V(t)$ be defined by (40) with $U(0) = I_n$ and $V_0 = W_0 \in L_{4p}^{m \times n}(\Omega)$. If $\mathcal{N}_U(0)$ is an ordinary neighbourhood of $t = 0$
 243 where $U(t) \in L_{2p}^{n \times n}(\Omega)$ is $2p$ -differentiable, invertible and $(U(t))^{-1} \in L_{2p}^{n \times n}(\Omega)$ is $2p$ -differentiable, then $W(t)$ defined by
 244 (41) is a solution of random Riccati IVP (1) in $L_p^{m \times n}(\Omega)$.

245 **Remark 2.** As it also occurs in the deterministic case, in dealing with non-autonomous IVP's, the fundamental matrix
 246 solution of a linear system is not available, in general. Thus, it is convenient to have the possibility of constructing
 247 reliable numerical approximations. Random linear multistep methods, for scalar problems, have been proposed in
 248 [15] and they can be extended to the random matrix framework in a similar way to the one developed in [4] in a
 249 non-trivial way. From the practical point of view, hereinafter we will consider the particular multistep matrix method
 250 (2.28) of [4]

$$Y_{k+1} - Y_k = \frac{h}{2} \{L(t_{k+1})Y_{k+1} - L(t_k)Y_k\}, \quad Y_0 = \begin{bmatrix} I_n \\ W_0 \end{bmatrix}, \quad (42)$$

251 for solving the random linear IVP (21), where $t_{k+1} = t_k + h$, $0 \leq k \leq N - 1$, $t_0 = 0$, $t_k \in [0, T]$, such that $Nh = T$.
 252 Solving (42), see (2.34) of [4] for small enough value of h , one gets the random approximations

$$\left. \begin{aligned} Y_0 &= \begin{bmatrix} I_n \\ W_0 \end{bmatrix}, \\ Y_k &= \prod_{j=0}^{k-1} \left\{ \left(I_{n+m} - \frac{h}{2} L(t_{k-j}) \right)^{-1} \left(I_{n+m} + \frac{h}{2} L(t_{k-j-1}) \right) \right\} Y_0, \quad 1 \leq k \leq N. \end{aligned} \right\} \quad (43)$$

253 Approximations (43) for the linear IVP (34) can be used to generate a sequence of approximations of the random
 254 non-autonomous Riccati IVP (1), see (2.40) of [4]. In fact, if $[I_n, O_{n \times m}]Y_k$ is invertible, being $O_{n \times m}$ the null matrix of
 255 size $n \times m$, and both $[O_{m \times n}, I_m]Y_k$ and $[I_n, O_{n \times m}]Y_k$ lie in $L_{2p}^{m \times n}(\Omega)$ and $L_{2p}^{n \times n}(\Omega)$, respectively, then

$$W_k = \{[O_{m \times n}, I_m]Y_k\} \{[I_n, O_{n \times m}]Y_k\}^{-1}, \quad k = 1, 2, \dots, N, \quad (44)$$

256 are random matrix approximations of the solution $W(t)$ of problem (1). This numerical procedure will be used in
 257 the subsequent section to compare the approximations of the mean and standard deviation of the solution s.p. to the
 258 random Riccati matrix IVP (1) constructed using the approach studied throughout this section.

259 5. Numerical examples

260 This section is devoted to illustrate the theoretical development previously exhibited by means of several examples
 261 where randomness is considered through a wide variety of probabilistic distributions. We emphasize that both scalar
 262 and random Riccati matrix differential equations are studied in the examples. Computations have been carried out
 263 using the software `Mathematica`.

264 **Example 5.** Let us consider the following random scalar IVP based on a non-autonomous Riccati differential equa-
 265 tion

$$w'(t) + a \exp(-t)(w(t))^2 - a \exp(-t) = 0, \quad 0 < t \leq T, \quad w(0) = w_0. \quad (45)$$

266 This IVP is a particular case of (1) taking $m = n = 1$ and

$$W(t) = w(t), \quad W(0) = w_0, \quad A(t) = a, \quad B(t) = a \exp(-t), \quad C(t) = a \exp(-t), \quad D(t) = -a. \quad (46)$$

267 We will assume that both input parameters, a and w_0 , in the random IVP (45), are independent, positive, and bounded
 268 or truncated r.v.'s defined in a common complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$. For the sake of clarity in the presentation,
 269 we split the construction of the approximations to the expectation and standard deviation of the solution s.p. to the
 270 random IVP (45) in several steps.

271 *Step 1. Construction of the auxiliary random linear vector IVP to (45).*

272 *According to (32)–(34) and (46), in this example, we have the following extended random linear system*

$$Y'(t) = L(t)Y(t), \quad Y_0 = \begin{bmatrix} 1 \\ w_0 \end{bmatrix}, \quad (47)$$

273 *where the matrix s.p. $L(t)$ is defined by*

$$L(t) = \left[\begin{array}{c|c} A(t) & B(t) \\ \hline C(t) & -D(t) \end{array} \right] = \left[\begin{array}{c|c} a & a \exp(-t) \\ \hline a \exp(-t) & a \end{array} \right]. \quad (48)$$

274 *As by hypothesis a and w_0 both are either bounded or truncated r.v.'s, then the random vector Y_0 , defined in*
 275 *(47), lies in $L_{4p}^{2 \times 1}(\Omega)$ and the matrix s.p. $L(t)$, defined in (48), is in $L_{4p}^{2 \times 2}(\Omega)$ for every $t \in T$.*

276 *Moreover, as the matrix s.p. $L(t)$, given by (48), commutes with its integral, that is,*

$$\begin{aligned} L(t) \left(\int_0^t L(s) ds \right) &= \begin{bmatrix} a^2 \exp(-2t) (-1 + \exp(t) + t \exp(2t)) & a^2 \exp(-t) (-1 + \exp(t) + t) \\ a^2 \exp(-t) (-1 + \exp(t) + t) & a^2 \exp(-2t) (-1 + \exp(t) + t \exp(2t)) \end{bmatrix} \\ &= \left(\int_0^t L(s) ds \right) L(t), \end{aligned}$$

277 *then, it is known its random fundamental matrix solution $\Phi_L(t; 0)$ is given by (see [16])*

$$\Phi_L(t; 0) = \exp \left(\int_0^t L(s) ds \right).$$

278 *Moreover, it can be seen that*

$$\begin{aligned} \Phi_L(t; 0) &= \left[\begin{array}{c|c} \Phi_{1,1}(t; 0) & \Phi_{1,2}(t; 0) \\ \hline \Phi_{2,1}(t; 0) & \Phi_{2,2}(t; 0) \end{array} \right] \\ &= \begin{bmatrix} \exp(at) \cosh [a(-1 + \exp(-t))] & \exp(at) \sinh [a(1 - \cosh(t) + \sinh(t))] \\ \exp(at) \sinh [a(1 - \cosh(t) + \sinh(t))] & \exp(at) \cosh (a(-1 + \exp(-t))) \end{bmatrix}. \quad (49) \end{aligned}$$

279 *Now, we are going to check that the random linear vector IVP (47) is $2p$ -regular.*

280 *• The matrix s.p. $L(t) = (\ell_{i,j}(t))_{2 \times 2}$, given by (48), only depends on the r.v. a , which is taken either bounded*
 281 *or truncated. Then, by Example 2 each entry $\ell_{i,j}(t)$ of $L(t)$ verifies condition (24) for every $t \in T$, and*
 282 *consequently, $L(t) \in L_{2p}^{2 \times 2}(\Omega)$, i.e., it is guaranteed that $L(t)$ is $2p$ -absolutely integrable in $[0, T]$:*

$$\int_0^T \|\ell_{i,j}(t)\|_{2p} dt = \int_0^T (\mathbb{E}[\|\ell_{i,j}(t)\|_{2p}^{2p}])^{1/(2p)} dt \leq \int_0^T (m_{i,j}(h_{i,j})^{2p})^{1/(2p)} dt = (m_{i,j})^{1/(2p)} h_{i,j} T < +\infty.$$

283 *• It can be checked that the inverse, $\Phi_L^{-1}(t; 0)$, of the random fundamental matrix solution $\Phi_L(t; 0)$ defined*
 284 *by (49), exists in an ordinary neighbourhood of $t = 0$ and it takes the following form*

$$\Phi_L^{-1}(t; 0) = \begin{bmatrix} \exp(-at) \cosh [a(1 - \cosh(t) + \sinh(t))] & -\exp(-at) \sinh [a(1 - \cosh(t) + \sinh(t))] \\ -\exp(-at) \sinh [a(1 - \cosh(t) + \sinh(t))] & \exp(-at) \cosh [a(1 - \cosh(t) + \sinh(t))] \end{bmatrix}. \quad (50)$$

285 *Notice that $\Phi_L^{-1}(0; 0) = I_2$. Moreover, based on the same argument previously shown about boundedness*
 286 *of the random input parameter a , it is easy to check that $\Phi_L(t; 0)$ and $\Phi_L^{-1}(t; 0)$ both lie in $L_p^{2 \times 2}(\Omega)$.*

287 *• Using an analogous argument to the one exhibited in the Example 1, it is straightforward to prove the*
 288 *p -differentiability of matrices s.p.'s $\Phi_L(t; 0)$ and $\Phi_L^{-1}(t; 0)$ defined by (49) and (50), respectively.*

289 *Step 2. Construction of the solution s.p. of the random scalar Riccati IVP (45).*

290 According to (36), (38), (40) and (49), the solution s.p. of the scalar random Riccati (45), $w(t)$, can be expressed
 291 in a closed form by terms of the random parameters a and w_0

$$\begin{aligned} w(t) &= V(t)(U(t))^{-1} = \frac{\Phi_{2,1}(t; 0) + \Phi_{2,2}(t; 0)w_0}{\Phi_{1,1}(t; 0) + \Phi_{1,2}(t; 0)w_0} \\ &= \frac{\exp(at) \{w_0 \cosh[a(-1 + \exp(-t))] + \sinh[a(1 - \cosh(t) + \sinh(t))]\}}{\exp(at) \cosh[a(-1 + \exp(-t))] + \exp(at)w_0 \sinh[a(1 - \cosh(t) + \sinh(t))]}, \quad t \in \mathcal{N}_U(0). \end{aligned}$$

292 Note that the parameter w_0 lies in $L_{4p}(\Omega)$ as well as the four block-entries $\Phi_{i,j}(t; 0)$, $1 \leq i, j \leq 2$, of the random
 293 fundamental matrix solution $\Phi_L(t; 0)$ given by (49).

294 Finally, taking into account the hypotheses of Theorem 2, it remains to check that $U(t) \in L_{2p}(\Omega)$ is $2p$ -
 295 differentiable and invertible and that its inverse $(U(t))^{-1} \in L_{2p}(\Omega)$ is also $2p$ -differentiable. These conditions
 296 can be checked following an analogous reasoning like the one showed in Example 1. We here omit because its
 297 checking is only cumbersome.

298 *Step 3. Computation of the expectation of solution s.p. of (45).*

299 Denote by $f_a(a)$ and $f_{w_0}(w_0)$ the probability density functions of r.v.'s a and w_0 , respectively. Compute the
 300 expectation of $w(t)$ as follows

$$E[w(t)] = \int_{\mathbb{R}^2} w(t) f_a(a) f_{w_0}(w_0) da dw_0.$$

301 *Step 4. Computation of the standard deviation of solution s.p. of (45).*

302 Determine the standard deviation by the expression

$$\sigma[w(t)] = +\sqrt{E[(w(t))^2] - (E[w(t)])^2},$$

303 computing, firstly, the following expectation

$$E[(w(t))^2] = \int_{\mathbb{R}^2} (w(t))^2 f_a(a) f_{w_0}(w_0) da dw_0.$$

304 In Figure 1 and Figure 2, the expectation, $E[w(t)]$, and the expectation plus/minus the standard deviation, $E[w(t)] \pm$
 305 $\sigma[w(t)]$, of the solution s.p. to the random scalar Riccati IVP (45) for different choices of the input r.v.'s a and w_0 have
 306 been plotted.

307 **Example 6.** Let us consider the random Riccati IVP (1) for the following election of the data

$$\left. \begin{aligned} W(t) &= \begin{bmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \end{bmatrix}, \quad W_0 = \begin{bmatrix} 1 \\ w_{2,0} \\ 0 \end{bmatrix}, \quad A(t) = \frac{t^2}{2} a, \quad B(t) = t^2 \begin{bmatrix} -\frac{1}{2} & 0 & \frac{b}{2} \end{bmatrix}, \\ C(t) &= t^2 \begin{bmatrix} 0 \\ -\frac{1}{2} \\ \frac{2}{0} \end{bmatrix}, \quad D(t) = \frac{t^2}{2} \begin{bmatrix} -1 & 0 & 0 \\ 0 & d & 0 \\ 1 & 0 & 1 \end{bmatrix}. \end{aligned} \right\}. \quad (51)$$

308 We will assume that the input parameters a , b , d and $w_{2,0}$ are r.v.'s. The parameter a has a beta distribution of
 309 parameters $\alpha = 3$ and $\beta = 2$, $a \sim Be(3; 2)$; b has an exponential distribution of parameter $\lambda = 1$ truncated at the
 310 interval $[1, 2]$, $b \sim Exp_{[1,2]}(1)$; d has a uniform distribution on the interval $[2, 4]$, $d \sim U(2, 4)$ and, finally, $w_{2,0}$ has a
 311 beta distribution of parameters $\alpha = 1$ and $\beta = 2$, $w_{2,0} \sim Be(1; 2)$. We will assume that all the input parameters are
 312 independent r.v.'s.

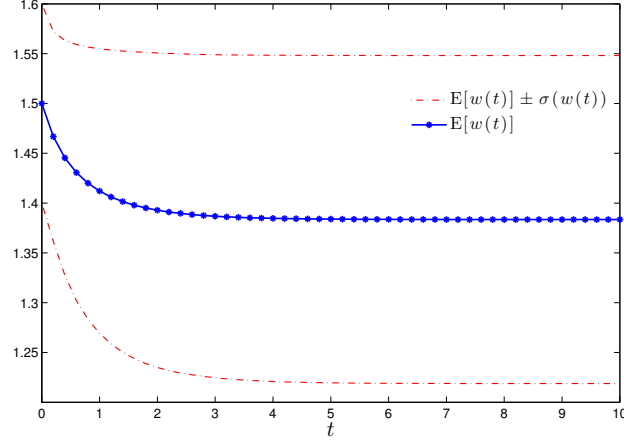


Figure 1: The expectation, $E[w(t)]$, and the expectation plus/minus the standard deviation, $E[w(t)] \pm \sigma[w(t)]$, of the solution s.p. to the random scalar Riccati IVP (45) for the following choice of the input r.v.'s: $a \sim \text{Be}(0.2; 1)$ (a has a beta distribution of parameters $(0.2; 1)$) and $w_0 \sim N_{[1,2]}(1.5; 0.1)$ (w_0 has a gaussian distribution of parameters $(1.5; 0.1)$ truncated on the interval $[1, 2]$). The expectation has been plotted on the time domain $t \in [0, 10]$ in the context of Example 5.

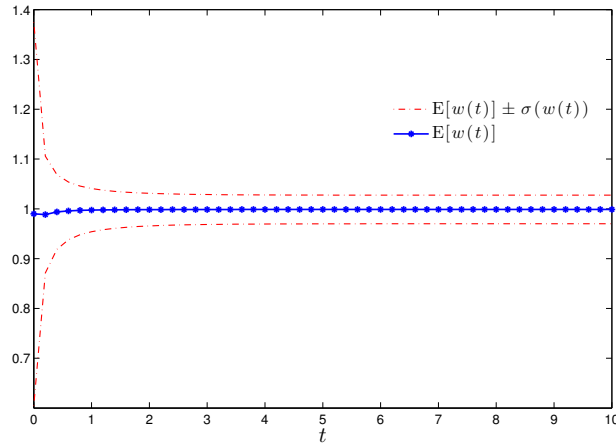


Figure 2: The expectation, $E[w(t)]$, and the expectation plus/minus the standard deviation, $E[w(t)] \pm \sigma[w(t)]$, of the solution s.p. to random scalar Riccati IVP (45) for the following choice of the input r.v.'s: $a \sim \text{Gamma}(2; 3)$ (a has a gamma distribution of parameters $(2; 3)$) and $w_0 \sim \text{Exp}_{[0.5,2]}(1.5)$ (w_0 has an exponential distribution of parameter $\lambda = 1.5$ truncated on the interval $[0.5, 2]$). The expectation has been plotted on the time domain $t \in [0, 10]$ in the context of Example 5.

313 *Step 1. Construction of the auxiliary random linear vector IVP of (1) with the data (51).*

314 *The extended random linear vector system (32)–(34), associated to (1) with data (51), takes the form*

$$Y'(t) = L(t)Y(t), \quad Y_0 = \begin{bmatrix} 1 \\ 1 \\ w_{2,0} \\ 0 \end{bmatrix}. \quad (52)$$

315 *Note that, it is verified that the random vector Y_0 , defined in (52), lies in $L_{4p}^{4 \times 1}(\Omega)$ because Y_0 satisfies condition*
 316 *(24) since $w_{2,0}$ is a bounded r.v.*

317 In Eq. (52) we have chosen the matrix s.p. $L(t)$ as the product of the real continuous deterministic function,
 318 $f(t) = t^2/2$, and the following random matrix L verifying condition (24)

$$L = \begin{bmatrix} a & -1 & 0 & b \\ 0 & 1 & 0 & 0 \\ -1 & 0 & -d & 0 \\ 0 & -1 & 0 & -1 \end{bmatrix},$$

319 because its entries a , b and d are bounded r.v.'s. Hence, the random coefficient matrix $L(t)$ takes the form

$$L(t) = f(t)L = \frac{t^2}{2}L, \quad L(t) \in \mathbb{L}_{4p}^{4 \times 4}(\Omega).$$

320 The block-partition of $L(t)$ is given by

$$L(t) = \left[\begin{array}{c|c} A(t) & B(t) \\ \hline C(t) & -D(t) \end{array} \right] = \left[\begin{array}{c|ccc} \frac{at^2}{2} & -\frac{t^2}{2} & 0 & \frac{bt^2}{2} \\ \hline 0 & \frac{t^2}{2} & 0 & 0 \\ -\frac{t^2}{2} & 0 & -\frac{dt^2}{2} & 0 \\ 0 & -\frac{t^2}{2} & 0 & -\frac{t^2}{2} \end{array} \right]. \quad (53)$$

321 As we shown in Example 4, the random linear vector IVP (52) with $L(t) = f(t)L$ is $2p$ -regular, and the random
 322 fundamental matrix solution, $\Phi_L(t; 0)$, is given by

$$\begin{aligned} \Phi_L(t; 0) &= \exp\left(L \int_0^t f(s) ds\right) = \exp\left(L \int_0^t \frac{s^2}{2} ds\right) = \exp\left(L \frac{t^3}{6}\right) \\ &= \left[\begin{array}{c|c} \Phi_{1,1}(t; 0)_{1 \times 1} & \Phi_{1,2}(t; 0)_{1 \times 3} \\ \hline \Phi_{2,1}(t; 0)_{3 \times 1} & \Phi_{2,2}(t; 0)_{3 \times 3} \end{array} \right]. \end{aligned} \quad (54)$$

323 It can be seen that, the block-entries $\Phi_{i,j}(t; 0)$, $1 \leq i, j \leq 2$, of $\Phi_L(t; 0)$ in (54) are

$$\Phi_{1,1}(t; 0)_{1 \times 1} = \exp(at^3/6), \quad (55)$$

$$\Phi_{1,2}(t; 0)_{3 \times 1}^\top = \left[\begin{array}{c} \frac{\exp(-t^3/6) \{b - ab + (2 + 2a + b + ab) \exp(t^3/3) - 2(1 + a + b) \exp(1/6(1 + a)t^3)\}}{2(-1 + a^2)} \\ 0 \\ \frac{b \exp(-t^3/6)(-1 + \exp(1/6(1 + a)t^3))}{1 + a} \end{array} \right], \quad (56)$$

$$\Phi_{2,1}(t; 0)_{3 \times 1} = \left[\begin{array}{c} 0 \\ -\frac{\exp(at^3/6) - \exp(-dt^3/6)}{a + d} \\ 0 \end{array} \right], \quad (57)$$

$$\Phi_{2,2}(t; 0)_{3 \times 3} = \left[\begin{array}{ccc} \Phi_{2,2}^1(t; 0) & \Phi_{2,2}^2(t; 0) & \Phi_{2,2}^3(t; 0) \end{array} \right], \quad (58)$$

324 where the column vectors $\Phi_{2,2}^j(t; 0)$, $1 \leq j \leq 3$, of block-entry $\Phi_{2,2}(t; 0)$ in (58) are the following expressions

$$\Phi_{2,2}^1(t; 0) = \begin{bmatrix} \exp(t^3/6) \\ \frac{b \exp(-t^3/6)}{2(1+a)(-1+d)} - \frac{(2+b) \exp(t^3/6)}{2(-1+a)(1+d)} + \frac{(1+a+b) \exp(at^3/6)}{(-1+a^2)(a+d)} + \frac{(-1-b+d) \exp(-dt^3/6)}{(a+d)(-1+d^2)} \\ -\sinh(t^3/6) \end{bmatrix}, \quad (59)$$

$$\Phi_{2,2}^2(t; 0) = \begin{bmatrix} 0 \\ \exp(-dt^3/6) \\ 0 \end{bmatrix}, \quad (60)$$

$$\Phi_{2,2}^3(t; 0) = \begin{bmatrix} 0 \\ -\frac{b \exp(-1/6)(1+d)t^3 \{(1+a) \exp(t^3/6) - (a+d) \exp(dt^3/6) + (-1+d) \exp(1/6(1+a+d)t^3)\}}{(1+a)(-1+d)(a+d)} \\ \exp(-t^3/6) \end{bmatrix}. \quad (61)$$

325 The p -differentiability of matrix s.p. $\Phi_L(t; 0)$ given by (54)–(61) and its inverse can be justified following an
326 analogous reasoning to the one shown in the Example 1.

327 **Step 2.** Construction of the solution s.p. of the random Riccati IVP (1) with data given in (51).

328 According to (36), (40) and (54)–(61), the solution s.p., $W(t) = [w_1(t) \ w_2(t) \ w_3(t)]^\top$, of the random Riccati IVP
329 (1) with the data (51), can be expressed in a closed form as follows

$$\begin{bmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \end{bmatrix} = V(t)(U(t))^{-1} = \left(\Phi_{2,1}(t; 0) + \Phi_{2,2}(t; 0) \begin{bmatrix} 0 \\ w_{2,0} \\ 0 \end{bmatrix} \right)_{3 \times 1} \left(\Phi_{1,1}(t; 0) + \Phi_{1,2}(t; 0) \begin{bmatrix} 0 \\ w_{2,0} \\ 0 \end{bmatrix} \right)_{1 \times 1}^{-1}. \quad (62)$$

330 Note that parameter $W_0 = \begin{bmatrix} 0 \\ w_{2,0} \\ 0 \end{bmatrix} \in L_{4p}^{3 \times 1}(\Omega)$ because r.v. $w_{2,0}$ verifies condition (24) since it is bounded.

Again the $2p$ -differentiable of the s.p. $U(t) \in L_{2p}(\Omega)$

$$U(t) = \frac{\exp(-t^3/6)}{2(-1+a^2)} \left\{ 2(1+a) \left[\exp(t^3/3) + (-2+a) \exp(1/6(1+a)t^3) \right] \right. \\ \left. + b \left[1 - a + (1+a) \exp(t^3/3) - 2 \exp(1/6(1+a)t^3) \right] \right\},$$

331 and its inverse, $(U(t))^{-1} \in L_{2p}(\Omega)$, follows in broad outline the same arguments shown in Example 1. Here,
332 details are omitted because they are quite cumbersome.

333 **Step 3.** Computation of the expectation of the solution s.p. of the IVP (1) with the data given in (51).

334 Compute the expectation of each one of the three components of the solution s.p. $W(t) = [w_1(t) \ w_2(t) \ w_3(t)]^\top$
335 obtained from (62), as follows

$$E[w_i(t)] = \int_{\mathbb{R}^4} w_i(t) f_a(a) f_b(b) f_d(d) f_{w_{2,0}}(w_{2,0}) da db dd dw_{2,0}, \quad i = 1, 2, 3, \quad (63)$$

336 where we denote by, $f_a(a)$, $f_b(b)$, $f_d(d)$ and $f_{w_{2,0}}(w_{2,0})$, the probability density functions of r.v.'s a , b , d and $w_{2,0}$,
337 respectively.

338 **Step 4.** Computation of the standard deviation of solution s.p. of the IVP (1) with data given in (51).

339

Compute the following expectations

$$E[(w_i(t))^2] = \int_{\mathbb{R}^4} (w_i(t))^2 f_a(a)f_b(b)f_d(d)f_{w_{2,0}}(w_{2,0}) da db dd dw_{2,0}, \quad i = 1, 2, 3.$$

340

Afterwards, computing the standard deviations according to

$$\sigma[w_i(t)] = +\sqrt{E[(w_i(t))^2] - (E[w_i(t)])^2}, \quad i = 1, 2, 3, \tag{64}$$

341

where $E[w_i(t)]$ is given by (63).

342

In Figure 3, we have plotted the expectations $E[w_i(t)]$, $i = 1, 2, 3$, and plus/minus the standard deviations, $E[w_i(t)] \pm \sigma[w_i(t)]$, $i = 1, 2, 3$, of the three components of the vector solution s.p. $W(t) = [w_1(t) w_2(t) w_3(t)]^T$, given by (62), of the random Riccati IVP (1) with the data (51).

344

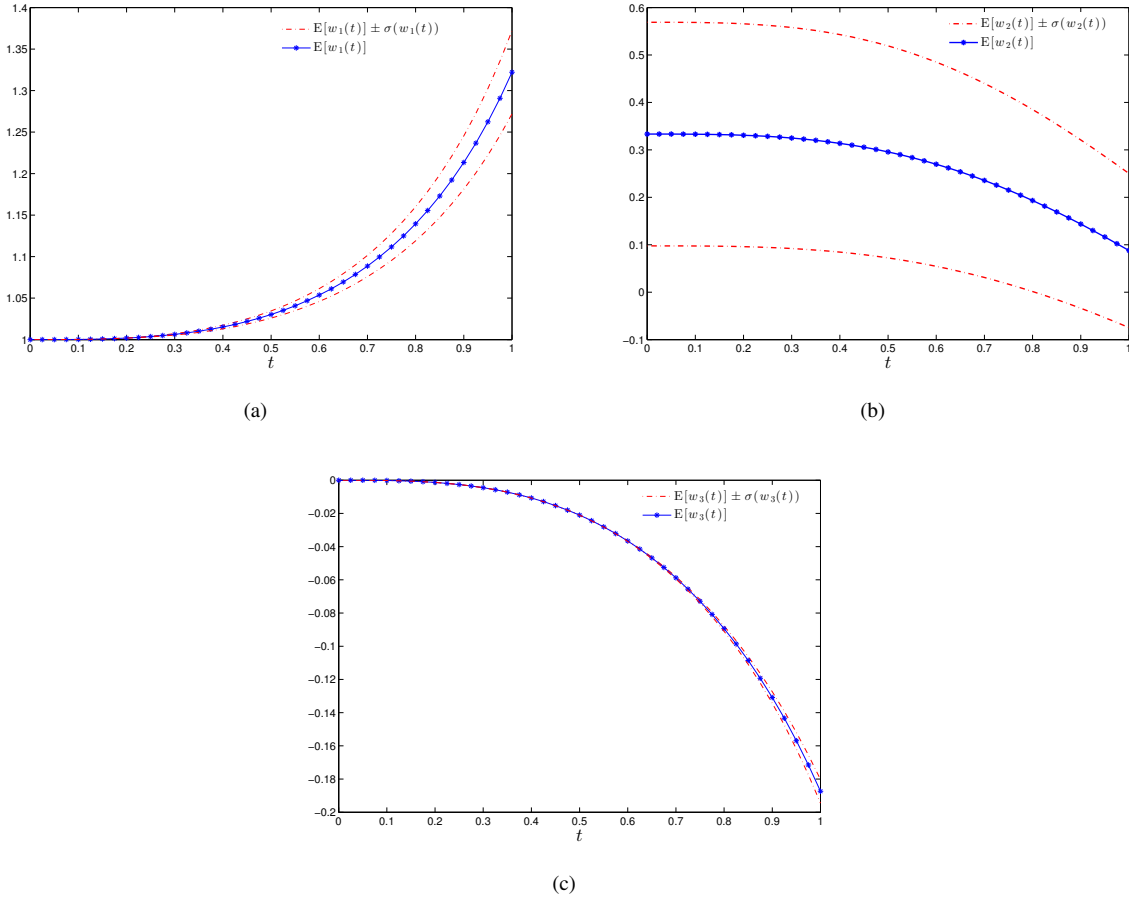


Figure 3: Evolution of the expectations $E[w_1(t)]$ (plot(a)), $E[w_2(t)]$ (plot(b)) and $E[w_3(t)]$ (plot(c)), of the solution s.p. $W(t) = [w_1(t) w_2(t) w_3(t)]^T$ of the Riccati (1), given by (62), on the time domain $t \in [0, 1]$ in the context of Example 6.

345

Finally, we are going to compare the values of expectation and standard deviation of the solution s.p. $W(t)$, defined in (62) as a closed form, versus the numerical approximations, W_k , obtained by the particular random multistep matrix method (43)–(44). Note that in (43), it must be guaranteed the existence of the inverse of the matrices

347

$$\left(I_{n+m} - \frac{h}{2} L(t_{k-j}) \right), \quad 1 \leq k - j \leq N, \quad n = 1, \quad m = 3, \tag{65}$$

348 where matrix s.p.'s $L(t_{k-j})$ are defined by (53). In fact, the matrices of (65) are invertible due to the positivity of the
 349 time-step h and the r.v.'s a , b and d .

350 In Table 1, we collected the exact values of the expectations and standard deviations, in a fixed time T (so we
 351 use the so-called "approximation in the fixed station sense"), for the three components of solution s.p. $W(t) =$
 352 $[w_1(t) w_2(t) w_3(t)]^T$, denoted by $E[w_i(t)]$, $i = 1, 2, 3$, and $\sqrt{\text{Var}[w_i(T)]}$, $i = 1, 2, 3$, respectively. Those values have been
 353 compared with their respective numerical expectations and numerical standard deviations, denoted by $E[w_{i,N}(T)]$ and
 354 $\sqrt{\text{Var}[w_{i,N}(T)]}$, respectively, in the same fixed time $T = Nh$, considering $N = 50$ fixed. Then, for the following values
 355 of $T \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$, and $N = 50$, the time-step h has been determined. The components
 356 $w_{i,N}(T)$, $i = 1, 2, 3$, of the numerical solution $W_k(T)$, have been computed in each time instant T using (43)–(44) for
 357 $k = N = 50$, that is

$$W_N = \{[O_{3 \times 1}, I_3]Y_N\} \{[I_1, O_{1 \times 3}]Y_N\}^{-1}, \quad N = 50, \quad (66)$$

358 where the time T is reached. Note that in (66), the scalar r.v. $[I_1, O_{1 \times 3}]Y_N$ is invertible, and both $[O_{3 \times 1}, I_3]Y_N$ and
 359 $[I_1, O_{1 \times 3}]Y_N$ lie in $L_{2p}^{3 \times 1}(\Omega)$ and $L_{2p}(\Omega)$, respectively.

360 In Table 1, the numerical values of the relative errors for the expectations, $\text{RelErr}_{\mu_i}(T)$, $i = 1, 2, 3$, and the standard
 361 deviations, $\text{RelErr}_{\sigma_i}(T)$, $i = 1, 2, 3$, have been computed according to the following expressions

$$\text{RelErr}_{\mu_i}(T) = \left| \frac{E[w_i(T)] - E[w_{i,N}(T)]}{E[w_i(T)]} \right|, \quad \text{RelErr}_{\sigma_i}(T) = \left| \frac{\sqrt{\text{Var}[w_i(T)]} - \sqrt{\text{Var}[w_{i,N}(T)]}}{\sqrt{\text{Var}[w_i(T)]}} \right|, \quad i = 1, 2, 3. \quad (67)$$

362 Computations have been carried out using different fixed stations T and time steps h . From the numerical values, we
 363 observe that both relative errors, for every component of the solution s.p., take very small values. This shows that
 364 the numerical values for the expectation and the standard deviations obtained from the closed form solution (62) are
 365 quite good.

366 6. Conclusions

367 In this paper one completes the closed form solution of the random non-autonomous Riccati matrix type IVP's,
 368 initiated in [1] for the autonomous case. The study of the random non-autonomous matrix linear case has required
 369 the random analogous of the Abel-Liouville-Jacobi's formula that is interesting itself and will be used in forthcoming
 370 works. The potential application to develop numerical methods starting from the analytic solution has been shown
 371 through appropriate results and numerical examples.

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		$E[w_i(T)]$	$E[w_{i,N}(T)]$	$\text{RelErr}_{\mu_i}(T)$	$\sqrt{\text{Var}[w_i(T)]}$	$\sqrt{\text{Var}[w_{i,N}(T)]}$	$\text{RelErr}_{\sigma_i}(T)$
$T = 0.1$ ($h = 0.002$)	$i = 1$	1.0002e+00	1.0002e+00	4.6728e-08	0	0	0
	$i = 2$	3.3302e-01	3.3302e-01	0	2.3560e-01	2.3560e-01	3.0000e-07
	$i = 3$	-1.6668e-04	-1.6671e-04	2.0001e-04	0	0	0
$T = 0.2$ ($h = 0.004$)	$i = 1$	1.0019e+00	1.0019e+00	3.7725e-07	0	0	0
	$i = 2$	3.3085e-01	3.3085e-01	1.4000e-06	2.3489e-01	2.3489e-01	3.0000e-07
	$i = 3$	-1.3340e-03	-1.3343e-03	2.0011e-04	0	0	0
$T = 0.3$ ($h = 0.006$)	$i = 1$	1.0063e+00	1.0064e+00	1.3048e-06	8.4591e-04	8.4600e-04	2.3257e-04
	$i = 2$	3.2499e-01	3.2499e-01	4.8000e-06	2.3297e-01	2.3297e-01	2.0000e-06
	$i = 3$	-4.5083e-03	-4.5092e-03	2.0041e-04	3.7895e-06	3.7910e-06	4.3172e-04
$T = 0.4$ ($h = 0.008$)	$i = 1$	1.0152e+00	1.0152e+00	3.2403e-06	2.1527e-03	2.1532e-03	2.0995e-04
	$i = 2$	3.1375e-01	3.1375e-01	1.1000e-05	2.2931e-01	2.2931e-01	4.8000e-06
	$i = 3$	-1.0714e-02	-1.0716e-02	2.0113e-04	2.2719e-05	2.2728e-05	4.0788e-04
$T = 0.5$ ($h = 0.01$)	$i = 1$	1.0302e+00	1.0303e+00	6.8135e-06	4.3292e-03	4.3302e-03	2.1189e-04
	$i = 2$	2.9569e-01	2.9569e-01	2.0100e-05	2.2348e-01	2.2348e-01	8.7000e-06
	$i = 3$	-2.1022e-02	-2.1027e-02	2.0273e-04	8.8339e-05	8.8375e-05	4.0785e-04
$T = 0.6$ ($h = 0.012$)	$i = 1$	1.0537e+00	1.0537e+00	1.3066e-05	7.7370e-03	7.7387e-03	2.2050e-04
	$i = 2$	2.6978e-01	2.6977e-01	3.0600e-05	2.1524e-01	2.1524e-01	1.1000e-05
	$i = 3$	-3.6600e-02	-3.6607e-02	2.0611e-04	2.6874e-04	2.6885e-04	4.1359e-04
$T = 0.7$ ($h = 0.014$)	$i = 1$	1.0886e+00	1.0886e+00	2.3758e-05	1.2835e-02	1.2838e-02	2.3680e-04
	$i = 2$	2.3556e-01	2.3555e-01	3.8000e-05	2.0459e-01	2.0458e-01	1.3600e-05
	$i = 3$	-5.8807e-02	-5.8819e-02	2.1294e-04	6.9563e-04	6.9365e-04	2.8458e-03
$T = 0.8$ ($h = 0.016$)	$i = 1$	1.1395e+00	1.1396e+00	4.1890e-05	2.0500e-02	2.0505e-02	2.6277e-04
	$i = 2$	1.9321e-01	1.9320e-01	3.1800e-05	1.9180e-01	1.9180e-01	6.2000e-06
	$i = 3$	-8.9393e-02	-8.9413e-02	2.2617e-04	1.6113e-03	1.6089e-03	1.4978e-03
$T = 0.9$ ($h = 0.018$)	$i = 1$	1.2134e+00	1.2135e+00	7.2653e-05	3.2097e-02	3.2107e-02	3.0664e-04
	$i = 2$	1.4355e-01	1.4355e-01	1.5000e-05	1.7747e-01	1.7747e-01	1.4800e-05
	$i = 3$	-1.3088e-01	-1.3091e-01	2.5006e-04	3.4613e-03	3.4638e-03	7.2867e-04
$T = 1$ ($h = 0.02$)	$i = 1$	1.3220e+00	1.3222e+00	1.2535e-04	5.0139e-02	5.0158e-02	3.8335e-04
	$i = 2$	8.7824e-02	8.7842e-02	2.0260e-04	1.6245e-01	1.6246e-01	6.8930e-05
	$i = 3$	-1.8738e-01	-1.8743e-01	2.9568e-04	7.1046e-03	7.1104e-03	8.1559e-04

Table 1: Values of the exact expectations, $E[w_i(T)]$, $i = 1, 2, 3$, and exact standard deviations, $\sqrt{\text{Var}[w_i(T)]}$, $i = 1, 2, 3$, using (63)–(64), for the three components of the solution s.p., $W(T)$, given by (62), to the random Riccati matrix IVP (1) in the context of Example 6. These values are computed in some time instants $T \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$ using the corresponding time-step h such as $Nh = T$ for $N = 50$ fixed. Numerical expectations, $E[w_{i,N}(T)]$, $i = 1, 2, 3$, and numerical standard deviations, $\sqrt{\text{Var}[w_{i,N}(T)]}$, $i = 1, 2, 3$, of the vector numerical solution $W_N(T)$, computed by (43)–(44) and (66), are shown too. To compare the numerical values of both approximations to the expectation and the standard deviation, their relative errors, $\text{RelErr}_{\mu_i}(T)$, $i = 1, 2, 3$ and $\text{RelErr}_{\sigma_i}(T)$, $i = 1, 2, 3$, respectively, have also been computed using (67).

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