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**Research article**

## **Pell coefficient polynomials for solving linear hyperbolic first-order partial differential equations via the Tau approach**

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**Abstract:** The main aims of this study are the introduction of Pell coefficient polynomials and their numerical treatment of the first-order hyperbolic partial differential equations. Our suggested numerical algorithm will be derived from the utilization of some novel formulas of the Pell coefficient polynomials, along with the application of the spectral tau method. For the proposed expansion, we investigate the convergence and error estimations in detail. The presented numerical results indicate that the suggested numerical method is accurate, converges exponentially, and is computationally efficient.

**Keywords:** Pell numbers; special polynomials; spectral methods; matrix system; convergence analysis

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### **1. Introduction**

Partial differential equations (PDEs) play important roles in modeling and analyzing various physical, biological, and engineering phenomena; see, for example, [1, 2]. These equations often do not admit analytical solutions, making it essential to solve them using various numerical algorithms. The authors of [3] used a quantum variational technique to solve certain nonlinear PDEs. In [4], a deep learning framework was proposed to handle nonlinear PDEs. Moreover, another approach for addressing such equations was developed in [5], where physics-informed neural networks were

utilized. Additionally, a method for approximating solutions to a class of PDEs was introduced in [6]. The authors of [7] developed some analytical and numerical solutions for certain nonlinear PDEs. Among the important PDEs are the hyperbolic partial differential equations (HPDEs). Many numerical algorithms were devoted to treating these types of equations. In [8], the authors introduced many-stage optimal stabilized Runge–Kutta methods. A matrix approach was followed using Vieta–Lucas polynomials in [9] to treat some HPDEs. In addition, a collocation algorithm was presented in [10] to handle the HPDEs. The method of lines combined with the Runge–Kutta integration method was employed in [11] for solving systems of certain delay HPDEs. Additionally, the authors of [12] presented an exponential Jacobi spectral method to handle HPDEs.

When dealing with differential equations (DEs) of various types, spectral approaches are very useful tools. These approaches are excellent for solving high-order ordinary DEs, PDEs, and other types of DEs. Their key benefit over the standard numerical approaches is their excellent performance for smooth problems, achieved by exponential or high-order convergence. These techniques provide an accurate approximation with few degrees of freedom by expressing the solution in terms of global basis functions, which are often particular functions or special polynomials. Spectral approaches have found useful applications in many domains, including models of biological systems, fluid dynamics, and quantum physics. One can refer to [13, 14] for some applications of these methods. Collocation, tau, and Galerkin methods are the three most common spectral approaches. One benefit of collocation techniques is that they can handle all DEs governed by any conditions; see, for example, [15–17]. Two sets of basis functions, trial and test, are required to apply both the Galerkin and Tau approaches. In the Galerkin method, these sets should be coincident; see, for example, [18–20], while the tau method has no restrictions in choosing the basis functions; see, for example, [21–23].

The sequences of numbers and polynomials have important roles in the different fields of applied sciences. For example, the sequences of Fibonacci and their generalized sequences are crucial [24]. Many polynomial sequences are beneficial in numerical analysis and, in particular, for treating all types of DEs. For example, the authors of [25] introduced telephone polynomials and utilized them to solve some models numerically. Shifted Lucas polynomials were utilized in [26] together with the collocation method to handle the fractional FitzHugh–Nagumo DEs. Fibonacci polynomials were employed in [27] to treat certain types of variable-order fractional DEs. Some specific Horadam polynomials were used in [28] to solve certain Korteweg–de Vries (KdV)-type equations. Bernstein polynomials were employed in [29] to solve some initial value problems. Multidimensional sinh–Gordon equations were treated in [30] using Lucas polynomials. In addition, modified Lucas polynomials were used in [31] to treat mixed-type fractional functional DEs. Vieta–Lucas polynomials were employed in [32] to handle certain types of fractional optimal control problems.

Among the important sequences that have roles in different disciplines is the Pell sequence. Many contributions were devoted to deriving formulas for the different Pell number sequences; see, for example, [33–35]. In addition, Pell polynomials were used in many articles related to numerical analysis to solve several important models. The authors of [36] followed a numerical approach based on Pell polynomials to solve certain stochastic fractional DEs. The authors of [37] utilized Pell polynomials to address nonlinear variable-order space fractional PDEs. The authors of [38] used the Pell polynomials to handle certain fractional DEs. The authors of [39] developed a Crank–Nicolson spectral Pell matrix algorithm to simulate the Rosenau–Burgers equations numerically.

The main objectives of this article are to introduce Pell coefficient polynomials and utilize them

numerically to treat the linear hyperbolic first-order PDEs. More definitely, we can list the goals in the following issues:

- Introducing Pell coefficient polynomials.
- Developing the inversion formula of these polynomials.
- Developing new moments, linearization, and derivative formulas of these polynomials.
- Utilizing the introduced polynomials to handle the linear hyperbolic first-order PDEs.
- Studying the error analysis of the suggested Pell coefficients expansion.
- Evaluating our numerical algorithm through some numerical examples.

Here are the main contributions and novelty of the current paper:

- Introducing new Pell coefficient polynomials: As far as we know, this is the first time that these kinds of polynomials have been defined and studied in the literature. This motivates us to study and utilize these polynomials.
- New theoretical results: Several new formulas concerning the Pell coefficient polynomials are introduced as the foundations to design the proposed numerical algorithm.
- Utilizing the spectral tau method: The suggested Pell coefficient polynomials are used as basis functions to numerically solve linear hyperbolic first-order PDEs.
- Convergence and error analysis: The proposed expansion is thoroughly examined to determine its convergence characteristics and error estimates.
- Numerical performance: The proposed method is tested by presenting some examples supported with comparisons with other schemes in the literature.

The contents of the paper are structured as follows. Section 2 gives some fundamental characteristic properties of the Pell numbers. In addition, we introduce the polynomials, namely, Pell coefficient polynomials. Some new formulas of these formulas are developed in Section 3. Section 4 is devoted to the numerical treatment of the one-dimensional linear HPDEs. Convergence and error analysis are investigated in Section 5. Illustrative examples are presented in Section 6 to ensure the accuracy and applicability of the proposed algorithm. Finally, some conclusions are given in Section 7.

## 2. Pell coefficient polynomials

In this section, we give an overview of the Pell numbers. In addition, we introduce polynomials whose coefficients are the Pell numbers.

The standard Pell numbers meet the following recursive formula [40]:

$$P_{j+2} = 2P_{j+1} + P_j, \quad P_0 = 0, P_1 = 1. \quad (2.1)$$

A few Pell numbers are 0, 1, 2, 5, 12, 29, 70, 169.

They have the following combinatorial formula [41]:

$$P_i = \sum_{m=0}^{\lfloor \frac{i-1}{2} \rfloor} 2^m \binom{i}{2m+1}. \quad (2.2)$$

Now, we define the new Pell coefficient polynomials  $P_i^*(\theta)$  as

$$P_i^*(\theta) = \sum_{k=0}^i P_{k+1} \theta^{i-k}, \quad (2.3)$$

where  $P_k$  represents the standard Pell numbers.

Formula (2.3) can also be written in the form

$$P_i^*(\theta) = \sum_{r=0}^i P_{i-r+1} \theta^r. \quad (2.4)$$

From the expression (2.4), it is evident that  $P_i^*(\theta)$  satisfies the following recurrence relation:

$$P_i^*(\theta) - \theta P_{i-1}^*(\theta) - P_{i+1} = 0. \quad (2.5)$$

**Remark 1.** *To the best of our knowledge, the introduced Pell coefficient polynomials are new, so their theoretical background is traceless in the literature.*

**Remark 2.** *The following theorem presents the inversion formula of  $P_i^*(\theta)$ . This formula, together with the power form representation, will be pivotal in yielding further properties of these polynomials in the next section.*

**Theorem 1.**  $\theta^i$  can be expanded as

$$\theta^i = \sum_{r=0}^i \mu_{r,i} P_r^*(\theta), \quad i \geq 0, \quad (2.6)$$

where

$$\mu_{r,i} = \begin{cases} 1, & \text{if } r = i, \\ -2, & \text{if } r = i-1, \\ -1, & \text{if } r = i-2, \\ 0, & \text{if } 0 \leq r \leq i-3. \end{cases} \quad (2.7)$$

*Proof.* We will prove that the following identity holds:

$$\theta^i = P_i^*(\theta) - 2 P_{i-1}^*(\theta) - P_{i-2}^*(\theta). \quad (2.8)$$

Assume the following polynomial:

$$\eta_i(\theta) = P_i^*(\theta) - 2 P_{i-1}^*(\theta) - P_{i-2}^*(\theta),$$

then, it is sufficient to show that

$$\eta_i(\theta) = \theta^i.$$

Based on the representation in (2.3),  $\eta_i(\theta)$  may be expressed in the form

$$\eta_i(\theta) = \sum_{r=0}^i P_{r+1} \theta^{i-r} - 2 \sum_{r=0}^{i-1} P_{r+1} \theta^{i-r-1} - \sum_{r=0}^{i-2} P_{r+1} \theta^{i-r-2}, \quad (2.9)$$

which is equal to

$$\eta_i(\theta) = \sum_{r=0}^i P_{r+1} \theta^{i-r} - 2 \sum_{r=1}^i P_r \theta^{i-r} - \sum_{r=2}^i P_{r-1} \theta^{i-r}, \quad (2.10)$$

and accordingly, we have

$$\eta_i(\theta) = \theta^i + \sum_{r=2}^i (P_{r+1} - 2P_r - P_{r-1}) \theta^{i-r}, \quad (2.11)$$

and therefore, the recurrence relation (2.1) leads to

$$\eta_i(\theta) = \theta^i. \quad (2.12)$$

This ends the proof.

**Remark 3.** *Formula (2.6) can be written in the following alternative form:*

$$\theta^i = \sum_{r=0}^i G_{r,i} P_{i-r}^*(\theta), \quad (2.13)$$

with

$$G_{r,i} = \begin{cases} 1, & \text{if } r = 0, \\ -2, & \text{if } r = 1, \\ -1, & \text{if } r = 2, \\ 0, & \text{if } r \geq 3. \end{cases} \quad (2.14)$$

### 3. Some further new formulas of the Pell coefficient polynomials

This section is confined to deriving some new formulas for the Pell coefficient polynomials, which will be useful in determining our proposed algorithm.

The following two theorems give the expressions of the moment and linearization formulas of the  $P_i^*(\theta)$ .

**Theorem 2.** *The following moment formula holds for every nonnegative integers  $r$  and  $s$ :*

$$x^r P_s^*(\theta) = \sum_{m=0}^{s+r} M_{m,s} P_{s+r-m}^*(\theta), \quad (3.1)$$

with

$$M_{m,s} = \sum_{r=0}^{\min(m,s)} P_{r+1} G_{m-r, s+r-k}, \quad (3.2)$$

and  $G_{r,i}$  are given in (2.14).

*Proof.* The analytic form in (2.3) gives

$$\theta^r P_s^*(\theta) = \sum_{k=0}^s P_{k+1} \theta^{s-k+r}. \quad (3.3)$$

Applying formula (2.13) leads to the following identity:

$$\theta^r P_s^*(\theta) = \sum_{k=0}^s P_{k+1} \sum_{t=0}^{s-k+r} G_{t,s+r-k} P_{s+r-k-t}^*(\theta),$$

which can be rearranged to give

$$\theta^r P_s^*(\theta) = \sum_{m=0}^{s+r} \left( \sum_{r=0}^{\min(m,s)} P_{r+1} G_{m-r, s+r-k} \right) P_{s+r-m}^*(\theta). \quad (3.4)$$

This proves Theorem 2.

**Theorem 3.** For every two nonnegative integers  $i$  and  $r$ , the following linearization formula is valid:

$$P_i^*(\theta) P_r^*(\theta) = \sum_{m=0}^{r+i} \zeta_{m,i,r} P_{r+i-m}^*(\theta), \quad (3.5)$$

with the linearization coefficients  $\zeta_{m,i,r}$  given as

$$\zeta_{m,i,r} = \sum_{s=0}^{\min(i,m)} P_{s+1} \sum_{L=0}^{\min(m-s,r)} P_{L+1} G_{m-L-s, r+i-s+L}. \quad (3.6)$$

*Proof.* Starting with the representation (2.3) leads to

$$P_i^*(\theta) P_r^*(\theta) = \sum_{s=0}^i P_{s+1} \theta^{i-s} P_r^*(\theta). \quad (3.7)$$

With the aid of the moment formula (3.4), the last formula turns into

$$P_i^*(\theta) P_r^*(\theta) = \sum_{s=0}^i P_{s+1} \sum_{m=0}^{r+i-s} R_{m,r} P_{r+i-m-s}^*(\theta), \quad (3.8)$$

where

$$R_{m,r} = \sum_{L=0}^{\min(m,r)} P_{L+1} G_{m-L, r+i-s+L}.$$

Formula (3.8) can be written alternatively in the form

$$P_i^*(\theta) P_r^*(\theta) = \sum_{m=0}^{r+i} \left( \sum_{s=0}^{\min(i,m)} P_{s+1} R_{m-s,r} \right) P_{r+i-m}^*(\theta), \quad (3.9)$$

and accordingly, Formula (3.5) can be obtained.

**Corollary 1.** The following integral formula holds:

$$\int_0^\ell P_i^*(\theta) P_r^*(\theta) d\theta = \sum_{m=0}^{r+i} \zeta_{m,i,r} J_{i+r-m}, \quad (3.10)$$

where

$$J_s = \sum_{r=0}^s \frac{\ell^{s-r+1}}{s-r+1} P_{s+1}, \quad (3.11)$$

and the coefficients  $\zeta_{m,i,r}$  are those given in (3.6).

*Proof.* From the explicit expression (2.3), we can write

$$\int_0^\ell P_r^*(\theta) d\theta = \sum_{k=0}^r P_{k+1} \int_0^\ell \theta^{r-k} d\theta, \quad (3.12)$$

and thus, we can write

$$\int_0^\ell P_r^*(\theta) d\theta = J_r, \quad (3.13)$$

with

$$J_r = \sum_{k=0}^r \frac{P_{k+1} \ell^{r-k+1}}{r-k+1}. \quad (3.14)$$

Now, integrating both sides of the linearization formula (3.5), we get

$$\int_0^\ell P_i^*(\theta) P_r^*(\theta) d\theta = \sum_{m=0}^{r+i} \zeta_{m,i,r} \int_0^\ell P_{r+i-m}^*(\theta) d\theta. \quad (3.15)$$

Using the integral in (3.13), the following integral formula can be obtained:

$$\int_0^\ell P_i^*(\theta) P_r^*(\theta) d\theta = \sum_{m=0}^{r+i} \zeta_{m,i,r} J_{r+i-m}. \quad (3.16)$$

This ends the proof.

The first-order derivatives are given in the following theorem in a closed form.

**Theorem 4.** *The first derivative of  $P_i^*(\theta)$  can be expressed as*

$$\frac{d P_i^*(\theta)}{d\theta} = \sum_{m=0}^{i-1} H_{m,i} P_m^*(\theta), \quad i \geq 1, \quad (3.17)$$

where

$$H_{m,i} = -(m+3) P_{i-m-2} - 2(m+2) P_{i-m-1} + (m+1) P_{i-m}. \quad (3.18)$$

*Proof.* The power form representation of  $P_i^*(\theta)$  in (2.3) enables one to write

$$\frac{d P_i^*(\theta)}{d\theta} = \sum_{k=0}^{i-1} P_{k+1} (i-k) \theta^{i-k-1}. \quad (3.19)$$

Inserting the inversion formula (2.8) into the last formula leads to

$$\frac{d P_i^*(\theta)}{d\theta} = \sum_{k=0}^{i-1} P_{k+1} (i-k) (P_{i-k-1}^*(\theta) - 2P_{i-k-2}^*(\theta) - P_{i-k-3}^*(\theta)), \quad (3.20)$$

which can be written as

$$\begin{aligned} \frac{d P_i^*(\theta)}{d\theta} = & i P_{i-1}^*(\theta) - 2 P_{i-2}^*(\theta) \\ & + \sum_{L=2}^{i-1} ((L-i-2) P_{L-1} + 2(L-i-1) P_L + (i-L) P_{L+1}) P_{i-L-1}^*(\theta), \end{aligned} \quad (3.21)$$

and accordingly, we can write

$$\frac{dP_i^*(\theta)}{d\theta} = \sum_{L=0}^{i-1} ((L-i-2)P_{L-1} + 2(L-i-1)P_L + (i-L)P_{L+1}) P_{i-L-1}^*(\theta). \quad (3.22)$$

An alternative formula for (3.22) is

$$\frac{dP_i^*(\theta)}{d\theta} = \sum_{m=0}^{i-1} (-(m+3)P_{i-m-2} - 2(m+2)P_{i-m-1} + (m+1)P_{i-m}) P_m^*(\theta). \quad (3.23)$$

This proves Theorem 4.

**Corollary 2.** *The following integral formula holds:*

$$\int_0^\ell \frac{dP_i^*(\theta)}{d\theta} P_r^*(\theta) d\theta = \sum_{m=0}^{i-1} H_{m,i} S_{m,r}, \quad (3.24)$$

where  $H_{m,i}$  are those given in (3.18),  $S_{m,r}$  are given by

$$S_{m,r} = \sum_{p=0}^{r+m} \zeta_{p,m,r} J_{r+m-p},$$

and the coefficients  $\zeta_{p,m,r}$ , and  $J_m$  are, respectively, given by (3.6) and (3.11).

*Proof.* Making use of the first-order derivative in (3.17), we get

$$\frac{dP_i^*(\theta)}{d\theta} P_r^*(\theta) = \sum_{m=0}^{i-1} H_{m,i} P_m^*(\theta) P_r^*(\theta). \quad (3.25)$$

If we integrate both sides of the last formula, and make use of formula (3.25), then the following formula can be obtained:

$$\int_0^\ell \frac{dP_i^*(\theta)}{d\theta} P_r^*(\theta) d\theta = \sum_{m=0}^{i-1} H_{m,i} S_{m,r}. \quad (3.26)$$

This ends the proof.

#### 4. Approximate solution of the one-dimensional linear HPDEs of first-order

Consider the following one-dimensional linear HPDEs of first-order [42]:

$$\partial_t Z(\theta, t) - \nu_1 \partial_\theta Z(\theta, t) - \nu_2 Z(\theta, t) = f(\theta, t), \quad 0 < \theta < \ell, \quad 0 < t < \tau, \quad (4.1)$$

subject to the following initial and boundary conditions:

$$Z(\theta, 0) = Z_0(\theta), \quad 0 < \theta < \ell, \quad (4.2)$$

$$Z(0, t) = Z_1(t), \quad 0 < t < \tau, \quad (4.3)$$

where  $f(\theta, t)$ ,  $Z_0(\theta)$ , and  $Z_1(t)$  are given functions, and  $a, b$  are positive constants. Moreover,  $f(\theta, t) \neq 0$ . If we define the following space:

$$\Delta^N = \text{span}\{\mathbf{P}_i^*(\theta) \mathbf{P}_j^*(t) : 0 \leq i, j \leq N\},$$

then any function  $Z^N(\theta, t) \in \Delta^N$  may be assumed to have the following expression:

$$Z^N(\theta, t) = \sum_{i=0}^N \sum_{j=0}^N c_{ij} \mathbf{P}_i^*(\theta) \mathbf{P}_j^*(t) = \mathbf{P}^*(\theta) \mathbf{C} \mathbf{P}^*(t)^T, \quad (4.4)$$

where  $\mathbf{P}^*(\theta) = [\mathbf{P}_0^*(\theta), \mathbf{P}_1^*(\theta), \dots, \mathbf{P}_N^*(\theta)]$ ,  $\mathbf{P}(t)^T = [\mathbf{P}_0^*(t), \mathbf{P}_1^*(t), \dots, \mathbf{P}_N^*(t)]^T$ , and  $\mathbf{C} = (c_{ij})_{0 \leq i, j \leq N}$  is the unknown matrix of dimension  $(N + 1)^2$ .

The residual  $\mathcal{R}(\theta, t)$  of Eq (4.1) can be expressed as

$$\mathcal{R}(\theta, t) = \partial_t Z^N(\theta, t) - a \partial_\theta Z^N(\theta, t) - b Z^N(\theta, t) - f(\theta, t). \quad (4.5)$$

Now, the application of the Tau method leads to

$$(\mathcal{R}(\theta, t), \mathbf{P}_r^*(\theta) \mathbf{P}_s^*(t)) = 0, \quad 0 \leq r, s \leq N - 1. \quad (4.6)$$

Now, if we let

$$\mathbf{F} = (f_{r,s})_{N \times N}, \quad f_{rs} = (f(\theta, t), \mathbf{P}_r^*(\theta) \mathbf{P}_s^*(t)), \quad (4.7)$$

$$\mathbf{G} = (g_{i,r})_{(N+1) \times N}, \quad g_{ir} = (\mathbf{P}_i^*(\theta), \mathbf{P}_r^*(\theta)), \quad (4.8)$$

$$\mathbf{H} = (h_{ir})_{(N+1) \times N}, \quad h_{ir} = \left( \frac{d \mathbf{P}_i^*(\theta)}{d \theta}, \mathbf{P}_r^*(\theta) \right), \quad (4.9)$$

then Eq (4.6) can be rewritten as

$$\sum_{i=0}^N \sum_{j=0}^N c_{ij} g_{i,r} h_{j,s} - \nu_1 \sum_{i=0}^N \sum_{j=0}^N c_{ij} h_{i,r} g_{j,s} - \nu_2 \sum_{i=0}^N \sum_{j=0}^N c_{ij} g_{i,r} g_{j,s} = f_{rs}, \quad 0 \leq r, s \leq N - 1, \quad (4.10)$$

or in matrix form as

$$\mathbf{G}^T \mathbf{C} \mathbf{H} - \nu_1 \mathbf{H}^T \mathbf{C} \mathbf{G} - \nu_2 \mathbf{G}^T \mathbf{C} \mathbf{G} = \mathbf{F}. \quad (4.11)$$

In addition, the conditions (4.2) and (4.3) lead to

$$\sum_{i=0}^N \sum_{j=0}^N c_{ij} g_{i,r} \mathbf{P}_j^*(0) = (Z_0(\theta), \mathbf{P}_r^*(\theta)), \quad 0 \leq r \leq N, \quad (4.12)$$

$$\sum_{i=0}^N \sum_{j=0}^N c_{ij} g_{j,s} \mathbf{P}_i^*(0) = (Z_1(t), \mathbf{P}_s^*(t)), \quad 0 \leq s \leq N - 1. \quad (4.13)$$

An appropriate method may now be employed to solve the resultant algebraic system of equations of order  $(N + 1)^2$ , including Eqs (4.11)–(4.13).

**Remark 4.** The elements  $g_{i,r}$  and  $h_{i,r}$  in (4.10) are given in Corollaries 1 and 2, where

$$(a) \quad g_{i,r} = \int_0^\ell \mathbf{P}_i^*(\theta) \mathbf{P}_r^*(\theta) d\theta. \quad (4.14)$$

$$(b) \quad h_{i,r} = \int_0^\ell \frac{d \mathbf{P}_i^*(\theta)}{d \theta} \mathbf{P}_r^*(\theta) d\theta.$$

## 5. Convergence and error analysis

This section is interested in analyzing in detail the expansion in terms of  $P_i^*(\theta)$ . Thus, some important lemmas and theorems are presented and proved.

**Lemma 1.** *Let  $\theta \in [0, \ell]$ ,  $\ell > 0$ . This inequality holds:*

$$|P_i^*(\theta)| \leq (\ell \varepsilon)^{i+2}, \quad \forall i \geq 0, \quad (5.1)$$

where  $\varepsilon = \sqrt{2} + 1$ .

*Proof.* The application of Eq (2.4) enables us to write

$$|P_i^*(\theta)| = \sum_{r=0}^i |\lambda_{i-r}| |\theta^r|. \quad (5.2)$$

Now,  $\lambda_{i-r}$  can be summed as

$$\lambda_{i-r} = \frac{(\sqrt{2} + 1)^{i-r+1}}{2\sqrt{2}}. \quad (5.3)$$

Therefore,  $|P_i^*(\theta)|$  is given by

$$|P_i^*(\theta)| = \sum_{r=0}^i \left| \frac{(\sqrt{2} + 1)^{i-r+1}}{2\sqrt{2}} \right| |\theta^r|. \quad (5.4)$$

The previous equation can be summed and written after using  $|\theta^r| \leq \ell^r$  as

$$|P_i^*(\theta)| = \frac{(\sqrt{2} + 2) \left( (\sqrt{2} + 1)^{i+1} - \ell^{i+1} \right)}{4(-\ell + \sqrt{2} + 1)}. \quad (5.5)$$

At the end, using the following estimation:

$$\frac{(\sqrt{2} + 2) \left( (\sqrt{2} + 1)^{i+1} - \ell^{i+1} \right)}{4(-\ell + \sqrt{2} + 1)} \leq (\ell \varepsilon)^{i+2}, \quad \forall i \geq 0, \quad (5.6)$$

where  $\varepsilon = \sqrt{2} + 1$ , we get the desired result.

**Lemma 2.** *Let  $g(\theta)$  be an infinitely differentiable function at the origin that may be expressed as*

$$g(\theta) = \sum_{n=0}^{\infty} \sum_{s=n}^{\infty} \frac{g^s(0) \mu_{n,s}}{s!} P_n^*(\theta), \quad (5.7)$$

where  $\mu_{n,s}$  is defined in Eq (2.7).

*Proof.* First, write  $g(\theta)$  as

$$g(\theta) = \sum_{n=0}^{\infty} \frac{g^{(n)}(0)}{n!} \theta^n. \quad (5.8)$$

Thanks to the inversion formula (2.6), the previous expansion turns into

$$g(\theta) = \sum_{n=0}^{\infty} \sum_{r=0}^n \frac{g^{(n)}(0) \mu_{r,n}}{n!} P_r^*(\theta), \quad (5.9)$$

which can be transformed again into the following form, based on some algebraic computations:

$$g(\theta) = \sum_{n=0}^{\infty} \sum_{s=n}^{\infty} \frac{g^s(0) \mu_{n,s}}{s!} P_n^*(\theta). \quad (5.10)$$

This ends the proof.

**Theorem 5.** If  $g(\theta)$  is defined on  $[0, \ell]$ , and  $|g^{(i)}(0)| \leq \lambda^i$ ,  $i > 0$ , where  $\lambda > 0$ , and  $g(\theta) = \sum_{i=0}^{\infty} \hat{g}_i P_i^*(\theta)$ , then we get

$$|\hat{g}_i| \leq \frac{2 e^{\lambda} \lambda^i}{i!}, \quad \forall i > 0. \quad (5.11)$$

Furthermore, the series is absolutely convergent.

*Proof.* Using Lemma 2, we can write

$$|\hat{g}_i| = \left| \sum_{s=i}^{\infty} \frac{f^s(0) \mu_{i,s}}{s!} \right| = \sum_{s=i}^{\infty} \frac{|f^s(0)| |\mu_{i,s}|}{s!}. \quad (5.12)$$

The application of the assumption  $|g^{(i)}(0)| \leq \lambda^i$ ,  $i > 0$  enables us to write

$$|\hat{g}_i| \leq \sum_{s=i}^{\infty} \frac{2 \lambda^s}{s!} = \frac{2 e^{\lambda} ((i-1)! - \Gamma(i, \lambda))}{(i-1)!}, \quad (5.13)$$

where  $\Gamma(i, \lambda)$  is the incomplete gamma function.

If we make use of the following inequality:

$$\frac{2 e^{\lambda} ((i-1)! - \Gamma(i, \lambda))}{(i-1)!} \leq \frac{2 e^{\lambda} \lambda^i}{i!}, \quad \forall i > 0, \quad (5.14)$$

then the inequality in (5.13) leads to

$$|\hat{g}_i| \leq \frac{2 e^{\lambda} \lambda^i}{i!}. \quad (5.15)$$

To prove the second part of this theorem, using inequalities (5.1) and (5.11), we can write

$$\begin{aligned} \left| \sum_{i=0}^{\infty} \hat{g}_i P_i(\theta) \right| &= \sum_{i=0}^{\infty} |\hat{g}_i| |P_i^*(\theta)| \\ &\leq \sum_{i=0}^{\infty} \frac{2 e^{\lambda} \lambda^i (\ell \varepsilon)^{i+2}}{i!} \\ &= 2 \varepsilon^2 \ell^2 e^{\lambda(1+\varepsilon\ell)}, \end{aligned} \quad (5.16)$$

so the series converges absolutely.

**Theorem 6.** Let  $Z^N(\theta, t) = f_1(\theta) f_2(t) = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} c_{ij} P_i^*(\theta) P_j^*(t)$ , with  $|f_1^{(i)}(0)| \leq Q_1^i$  and  $|f_2^{(j)}(0)| \leq Q_2^j$ , where  $Q_1$  and  $Q_2$  are positive constants. One has

$$|c_{ij}| \leq \frac{4 e^{Q_1+Q_2} Q_1^i Q_2^j}{i! j!}. \quad (5.17)$$

Moreover, the series converges absolutely.

*Proof.* The application of Lemma 2, along with the assumption  $Z^N(\theta, t) = f_1(\theta) f_2(t)$ , enables us to write

$$c_{ij} = \sum_{p=i}^{\infty} \sum_{q=j}^{\infty} \frac{f_1^p(0) f_2^q(0) \mu_{j,q} \mu_{i,p}}{p! q!}. \quad (5.18)$$

If we make use of the assumption  $|f_1^{(i)}(0)| \leq Q_1^i$  and  $|f_2^{(j)}(0)| \leq Q_2^j$ , then we can write

$$|c_{ij}| \leq \sum_{p=i}^{\infty} \frac{Q_1^p \mu_{i,p}}{p!} \times \sum_{q=j}^{\infty} \frac{Q_2^q \mu_{j,q}}{q!}. \quad (5.19)$$

Ultimately, by replicating the methods analogous to the proof of Theorem 5, we obtain

$$|c_{ij}| \leq \frac{4 e^{Q_1+Q_2} Q_1^i Q_2^j}{i! j!}. \quad (5.20)$$

**Theorem 7.** The following upper estimation holds if  $Z^N(\theta, t)$  satisfies the assumptions of Theorem 6.

$$|Z(\theta, t) - Z^N(\theta, t)| < \frac{4 \ell^2 \tau^2 \varepsilon^{N+4} e^{Q_1(1+\varepsilon\ell)} e^{Q_2(1+\varepsilon\tau)} \left[ (\ell Q_1)^N + (\tau Q_2)^N \right]}{N!}. \quad (5.21)$$

*Proof.* The application of definitions  $Z(\theta, t)$  and  $Z^N(\theta, t)$  enables us to write

$$\begin{aligned} |Z(\theta, t) - Z^N(\theta, t)| &= \left| \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} c_{ij} P_i^*(\theta) P_j^*(t) - \sum_{i=0}^N \sum_{j=0}^N c_{ij} P_i^*(\theta) P_j^*(t) \right| \\ &\leq \left| \sum_{i=0}^N \sum_{j=N+1}^{\infty} c_{ij} P_i^*(\theta) P_j^*(t) \right| + \left| \sum_{i=N+1}^{\infty} \sum_{j=0}^{\infty} c_{ij} P_i^*(\theta) P_j^*(t) \right|. \end{aligned} \quad (5.22)$$

With the help of Theorem 6 along with Lemma 1, the following estimations may be obtained.

$$\begin{aligned}
\sum_{i=0}^N \frac{2e^{Q_1} Q_1^i (\ell \varepsilon)^{i+2}}{i!} &= \frac{2\varepsilon^2 \ell^2 e^{\lambda \varepsilon \ell + Q_1} \Gamma(N+1, Q_1 \varepsilon \ell)}{N!} < 2\varepsilon^2 \ell^2 e^{Q_1(1+\varepsilon \ell)}, \\
\sum_{j=N+1}^{\infty} \frac{2e^{Q_2} Q_2^j (\tau \varepsilon)^{j+2}}{j!} &= \frac{2(N+1)Q_2^N e^{Q_2 \varepsilon \tau + Q_2} (\varepsilon \tau)^{N+2} (Q_2 \varepsilon \tau)^{-N} (N! - \Gamma(N+1, Q_2 \varepsilon \tau))}{(N+1)!} \\
&< \frac{2Q_2^N e^{Q_2(1+\varepsilon \tau)} (\varepsilon \tau)^{N+2}}{N!}, \\
\sum_{i=N+1}^{\infty} \frac{2e^{Q_1} Q_1^i (\ell \varepsilon)^{i+2}}{i!} &= \frac{2(N+1)Q_1^N e^{Q_1 \varepsilon \ell + Q_1} (\varepsilon \ell)^{N+2} (Q_1 \varepsilon \ell)^{-N} (N! - \Gamma(N+1, Q_1 \varepsilon \ell))}{(N+1)!} \\
&< \frac{2Q_1^N e^{Q_1(1+\varepsilon \ell)} (\varepsilon \ell)^{N+2}}{N!}, \\
\sum_{j=0}^{\infty} \frac{2e^{Q_2} Q_2^j (\tau \varepsilon)^{j+2}}{j!} &= 2\varepsilon^2 \tau^2 e^{Q_2(1+\varepsilon \tau)}.
\end{aligned} \tag{5.23}$$

Using the estimations in (5.23), we get the following estimation:

$$|Z(\theta, t) - Z^N(\theta, t)| < \frac{4\ell^2 \tau^2 \varepsilon^{N+4} e^{Q_1(1+\varepsilon \ell)} e^{Q_2(1+\varepsilon \tau)} [(Q_1)^N + (Q_2)^N]}{N!}, \tag{5.24}$$

which is the desired result.

## 6. Some illustrative examples

This section presents three illustrative examples to ensure the proposed algorithm's applicability and accuracy.

**Test Problem 1.** [43, 44]. Consider the following equation:

$$\partial_t Z(\theta, t) + \partial_\theta Z(\theta, t) + Z(\theta, t) = (\theta - t)^2, \quad 0 < \theta, t < 1, \tag{6.1}$$

with the following conditions:

$$Z(\theta, 0) = \theta^2, \quad Z(0, t) = t^2, \quad 0 < \theta, t < 1, \tag{6.2}$$

whose exact solution is given as:  $Z(\theta, t) = (\theta - t)^2$ .

For  $N = 2$ , applying Theorem 4 yields

$$\begin{aligned}
\mathcal{G} &= \begin{pmatrix} 1 & \frac{5}{2} \\ \frac{5}{2} & \frac{19}{3} \end{pmatrix}, \\
\mathcal{H} &= \begin{pmatrix} 0 & 0 \\ 1 & \frac{5}{2} \end{pmatrix}.
\end{aligned} \tag{6.3}$$

Therefore, Eq (4.11) can be rewritten as

$$\begin{aligned}
 & \left( \begin{array}{ccc} 1 & \frac{5}{2} & \frac{19}{12} \\ \frac{5}{2} & \frac{19}{3} & \frac{193}{12} \end{array} \right) \left( \begin{array}{ccc} c_{00} & c_{01} & c_{02} \\ c_{10} & c_{11} & c_{12} \\ c_{20} & c_{21} & c_{22} \end{array} \right) \left( \begin{array}{cc} 0 & 0 \\ 1 & \frac{5}{2} \\ 3 & \frac{23}{3} \end{array} \right) \\
 & + \left( \begin{array}{ccc} 0 & 1 & 3 \\ 0 & \frac{5}{2} & \frac{23}{3} \end{array} \right) \left( \begin{array}{ccc} c_{00} & c_{01} & c_{02} \\ c_{10} & c_{11} & c_{12} \\ c_{20} & c_{21} & c_{22} \end{array} \right) \left( \begin{array}{cc} 1 & \frac{5}{2} \\ \frac{5}{2} & \frac{19}{12} \\ \frac{19}{3} & \frac{193}{12} \end{array} \right) \\
 & + \left( \begin{array}{ccc} 1 & \frac{5}{2} & \frac{19}{12} \\ \frac{5}{2} & \frac{19}{3} & \frac{193}{12} \end{array} \right) \left( \begin{array}{ccc} c_{00} & c_{01} & c_{02} \\ c_{10} & c_{11} & c_{12} \\ c_{20} & c_{21} & c_{22} \end{array} \right) \left( \begin{array}{cc} 1 & \frac{5}{2} \\ \frac{5}{2} & \frac{19}{12} \\ \frac{19}{3} & \frac{193}{12} \end{array} \right) = \left( \begin{array}{cc} \frac{1}{6} & \frac{5}{12} \\ \frac{5}{12} & \frac{37}{36} \end{array} \right). \tag{6.4}
 \end{aligned}$$

Moreover, conditions (4.12) and (4.13), after putting  $Z_0(\theta) = \theta^2$  and  $Z_1(t) = t^2$  enable us to write

$$\left( \begin{array}{c} c_{00} + 2c_{01} + 5c_{02} + \frac{5}{2}c_{10} + 5c_{11} + \frac{25}{2}c_{12} + \frac{19}{3}c_{20} + \frac{38}{3}c_{21} + \frac{95}{3}c_{22} \\ \frac{5}{2}c_{00} + 5c_{01} + \frac{25}{2}c_{02} + \frac{19}{3}c_{10} + \frac{38}{3}c_{11} + \frac{95}{3}c_{12} + \frac{193}{12}c_{20} + \frac{193}{6}c_{21} + \frac{965}{12}c_{22} \\ \frac{19}{3}c_{00} + \frac{38}{3}c_{01} + \frac{95}{3}c_{02} + \frac{193}{12}c_{10} + \frac{193}{6}c_{11} + \frac{965}{12}c_{12} + \frac{613}{15}c_{20} + \frac{1226}{15}c_{21} + \frac{613}{3}c_{22} \end{array} \right) = \left( \begin{array}{c} \frac{1}{3} \\ \frac{11}{12} \\ \frac{71}{30} \end{array} \right), \tag{6.5}$$

and

$$\left( \begin{array}{c} c_{00} + \frac{5}{2}c_{01} + \frac{19}{3}c_{02} + 2c_{10} + 5c_{11} + \frac{38}{3}c_{12} + 5c_{20} + \frac{25}{2}c_{21} + \frac{95}{3}c_{22} \\ \frac{5}{2}c_{00} + \frac{19}{3}c_{01} + \frac{193}{12}c_{02} + 5c_{10} + \frac{38}{3}c_{11} + \frac{193}{6}c_{12} + \frac{25}{2}c_{20} + \frac{95}{3}c_{21} + \frac{965}{12}c_{22} \end{array} \right) = \left( \begin{array}{c} \frac{1}{3} \\ \frac{11}{12} \end{array} \right). \tag{6.6}$$

Now, we get a system of nine equations from (6.4), (6.5), and (6.6), and this system can be solved exactly to give:

$$c_{00} \rightarrow -10, c_{01} \rightarrow 2, c_{02} \rightarrow 1, c_{10} \rightarrow 2, c_{11} \rightarrow -2, c_{12} \rightarrow 0, c_{20} \rightarrow 1, c_{21} \rightarrow 0, c_{22} \rightarrow 0,$$

and, therefore:  $Z_2(\theta, t) = (\theta - t)^2$ , which is the exact solution.

**Test Problem 2.** [44] Consider the following equation:

$$\partial_t Z(\theta, t) + \partial_\theta Z(\theta, t) + Z(\theta, t) = \cos(\theta + t) - 2 \sin(\theta + t), \quad 0 < \theta, t < 1, \tag{6.7}$$

with the following conditions:

$$Z(\theta, 0) = \cos(\theta), \quad Z(0, t) = \cos(t), \quad 0 < \theta, t < 1, \tag{6.8}$$

whose exact solution is given as:  $Z(\theta, t) = \cos(\theta + t)$ .

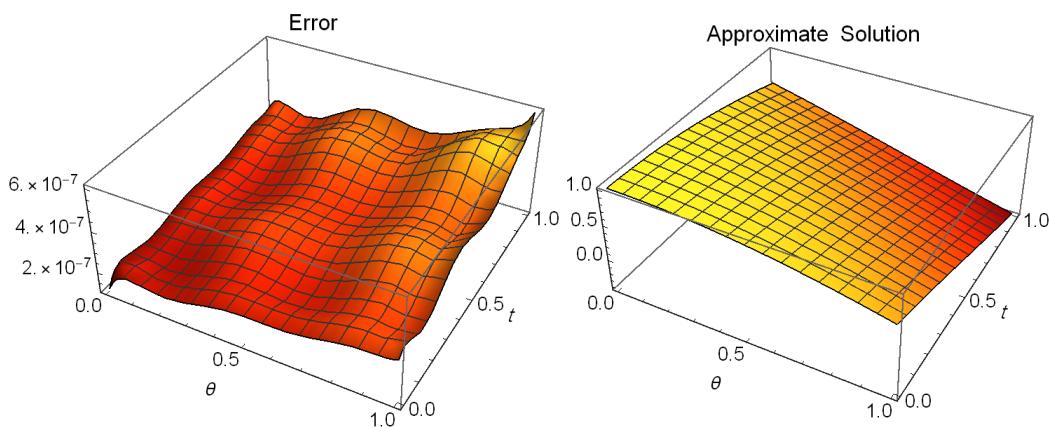
In Table 1, we give a comparison of absolute errors (AEs) between our method and the method in [44] at various  $\theta$  and  $t$ . Table 2 shows the maximum absolute errors (MAEs),  $L_\infty$ -errors, and  $L_2$ -errors at different values of  $N$ . Figure 1 shows the AEs (left) and approximate solution (right) at  $N = 6$ . Figure 2 shows the AEs at  $\theta = t$  and different values of  $N$ . Finally, Figure 3 shows the stability  $|Z_{N+1}(\theta, 0.3) - Z_N(\theta, 0.3)|$  at different values of  $N$ .

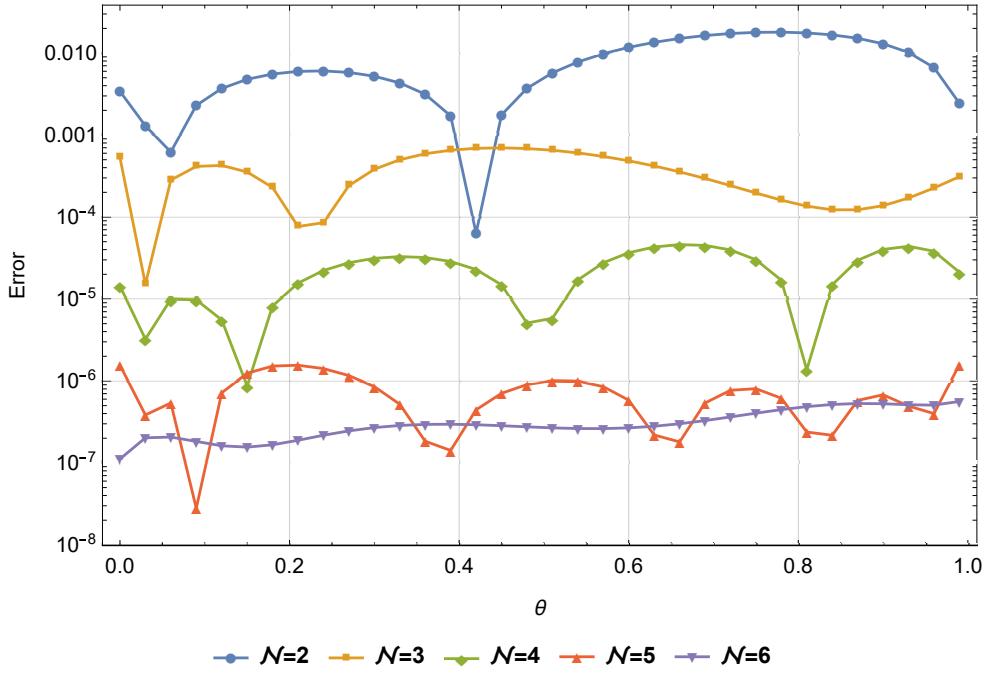
**Table 1.** Comparison of the AEs for Example 2.

| $(\theta, t)$ | Legendre wavelet at $M = 6$ [44] | Chebyshev wavelet at $M = 6$ [44] | Present method at $N = 6$ |
|---------------|----------------------------------|-----------------------------------|---------------------------|
| (0.1,0.1)     | $9.12 \times 10^{-5}$            | $4.53 \times 10^{-4}$             | $1.74541 \times 10^{-7}$  |
| (0.2,0.2)     | $3.36 \times 10^{-5}$            | $2.07 \times 10^{-4}$             | $1.80389 \times 10^{-7}$  |
| (0.3,0.3)     | $1.86 \times 10^{-5}$            | $6.92 \times 10^{-5}$             | $2.69712 \times 10^{-7}$  |
| (0.4,0.4)     | $2.42 \times 10^{-5}$            | $1.39 \times 10^{-4}$             | $2.95508 \times 10^{-7}$  |
| (0.5,0.5)     | $8.30 \times 10^{-5}$            | $2.64 \times 10^{-4}$             | $2.69978 \times 10^{-7}$  |
| (0.6,0.6)     | $1.38 \times 10^{-4}$            | $7.62 \times 10^{-5}$             | $2.67529 \times 10^{-7}$  |
| (0.7,0.7)     | $9.90 \times 10^{-5}$            | $2.10 \times 10^{-5}$             | $3.3939 \times 10^{-7}$   |
| (0.8,0.8)     | $1.20 \times 10^{-6}$            | $2.01 \times 10^{-5}$             | $4.73848 \times 10^{-7}$  |
| (0.9,0.9)     | $9.00 \times 10^{-5}$            | $3.00 \times 10^{-4}$             | $5.27481 \times 10^{-7}$  |

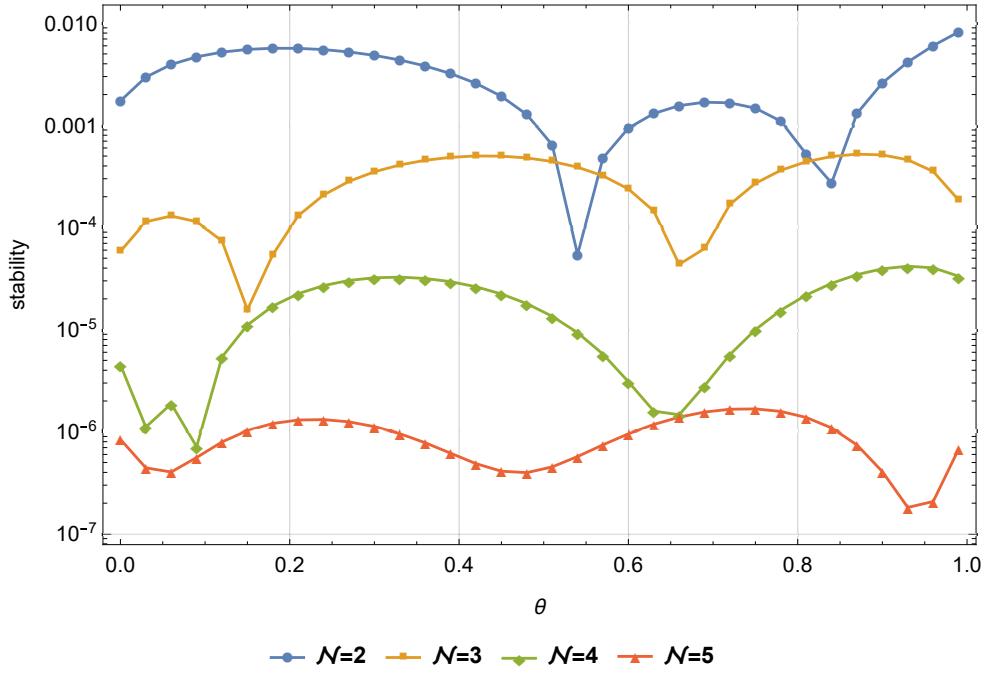
**Table 2.** Errors of Example 2.

| $N$                | 2                        | 3                        | 4                        | 5                        | 6                        |
|--------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| MAEs               | $1.78021 \times 10^{-2}$ | $6.68349 \times 10^{-4}$ | $4.37397 \times 10^{-5}$ | $2.65074 \times 10^{-6}$ | $6.09552 \times 10^{-7}$ |
| $L_\infty$ -errors | $1.80157 \times 10^{-2}$ | $6.98176 \times 10^{-4}$ | $4.39709 \times 10^{-5}$ | $1.67709 \times 10^{-6}$ | $6.09552 \times 10^{-7}$ |
| $L_2$ -errors      | $7.18447 \times 10^{-3}$ | $3.14754 \times 10^{-4}$ | $1.89696 \times 10^{-5}$ | $7.28894 \times 10^{-7}$ | $3.05884 \times 10^{-7}$ |

**Figure 1.** The AEs (left) and approximate solution (right) of Example 2 at  $N = 6$ .



**Figure 2.** The AEs of Example 2 at  $\theta = t$  and different values of  $\mathcal{N}$ .



**Figure 3.** Stability  $|Z_{N+1}(\theta, 0.3) - Z_N(\theta, 0.3)|$  of Example 2.

**Test Problem 3.** [45] Consider the following equation:

$$\partial_t Z(\theta, t) + \partial_\theta Z(\theta, t) + Z(\theta, t) = -\sqrt{2} e^{-\sqrt{2}t-\theta}, \quad 0 < \theta, t < 1, \quad (6.9)$$

with the following conditions:

$$Z(\theta, 0) = e^{-\theta}, \quad Z(0, t) = e^{-\sqrt{2}t}, \quad 0 < \theta, t < 1, \quad (6.10)$$

whose exact solution is given as:  $Z(\theta, t) = e^{-(\sqrt{2}t+\theta)}$ .

In Table 3, we give a comparison of AEs between our method and the method in [45] at different values of  $\theta$  when  $t = 0.1$ . Also, Table 4 presents a comparison of AEs between our method and the method in [45] at different values of  $\theta$  when  $t = 0.5$ . Table 5 shows the MAEs,  $L_\infty$ -errors, and  $L_2$ -errors at different values of  $N$ . Figure 4 shows the AEs (left) and approximate solution (right) at  $N = 6$ . Figure 5 shows the AEs at different values of  $N$  and  $\theta$  when  $t = 0.1$ . Finally, Figure 6 shows the AEs at different values of  $N$  and  $\theta$  when  $t = 0.9$ .

**Table 3.** Comparison of the AEs for Example 3 at  $t = 0.1$ .

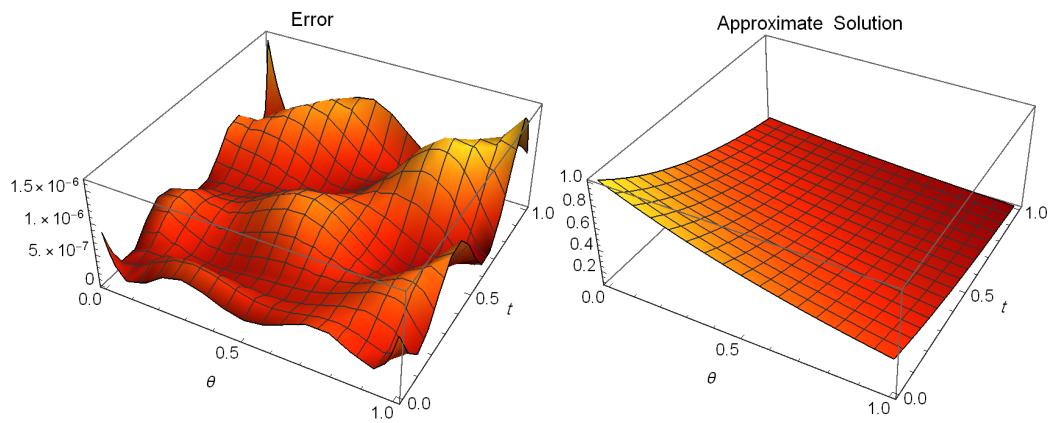
| $\theta$ | Method in [45] at $M = N = 16$ | Present method at $N = 6$ |
|----------|--------------------------------|---------------------------|
| 0.1      | $2.84 \times 10^{-7}$          | $2.7611 \times 10^{-7}$   |
| 0.2      | $8.79 \times 10^{-6}$          | $4.1743 \times 10^{-7}$   |
| 0.3      | $1.20 \times 10^{-5}$          | $4.40967 \times 10^{-7}$  |
| 0.4      | $1.12 \times 10^{-5}$          | $3.70131 \times 10^{-7}$  |
| 0.5      | $7.95 \times 10^{-6}$          | $3.0252 \times 10^{-7}$   |
| 0.6      | $3.29 \times 10^{-6}$          | $3.26524 \times 10^{-7}$  |
| 0.7      | $1.78 \times 10^{-6}$          | $4.40008 \times 10^{-7}$  |
| 0.8      | $6.53 \times 10^{-6}$          | $5.26572 \times 10^{-7}$  |
| 0.9      | $1.04 \times 10^{-5}$          | $4.39639 \times 10^{-7}$  |

**Table 4.** Comparison of the AEs for Example 3 at  $t = 0.5$ .

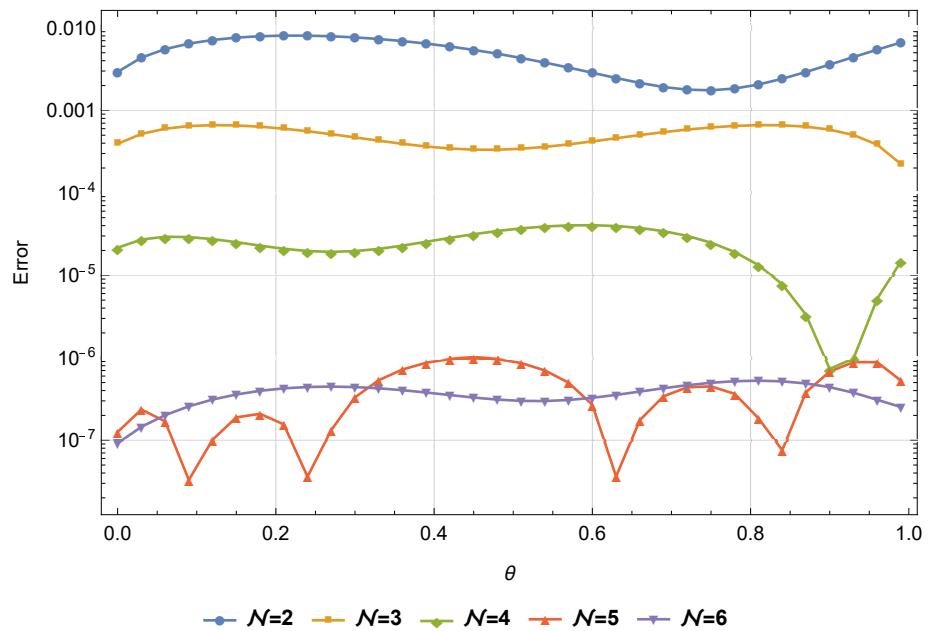
| $\theta$ | Method in [45] at $M = N = 16$ | Present method at $N = 6$ |
|----------|--------------------------------|---------------------------|
| 0.1      | $8.95 \times 10^{-6}$          | $2.82859 \times 10^{-7}$  |
| 0.2      | $4.10 \times 10^{-6}$          | $3.28433 \times 10^{-7}$  |
| 0.3      | $1.39 \times 10^{-5}$          | $5.28007 \times 10^{-7}$  |
| 0.4      | $2.07 \times 10^{-5}$          | $7.55095 \times 10^{-7}$  |
| 0.5      | $2.47 \times 10^{-5}$          | $8.30558 \times 10^{-7}$  |
| 0.6      | $2.62 \times 10^{-5}$          | $6.76593 \times 10^{-7}$  |
| 0.7      | $2.55 \times 10^{-5}$          | $3.66795 \times 10^{-7}$  |
| 0.8      | $2.31 \times 10^{-5}$          | $1.03841 \times 10^{-7}$  |
| 0.9      | $1.93 \times 10^{-5}$          | $1.53321 \times 10^{-7}$  |

**Table 5.** Errors of Example 3.

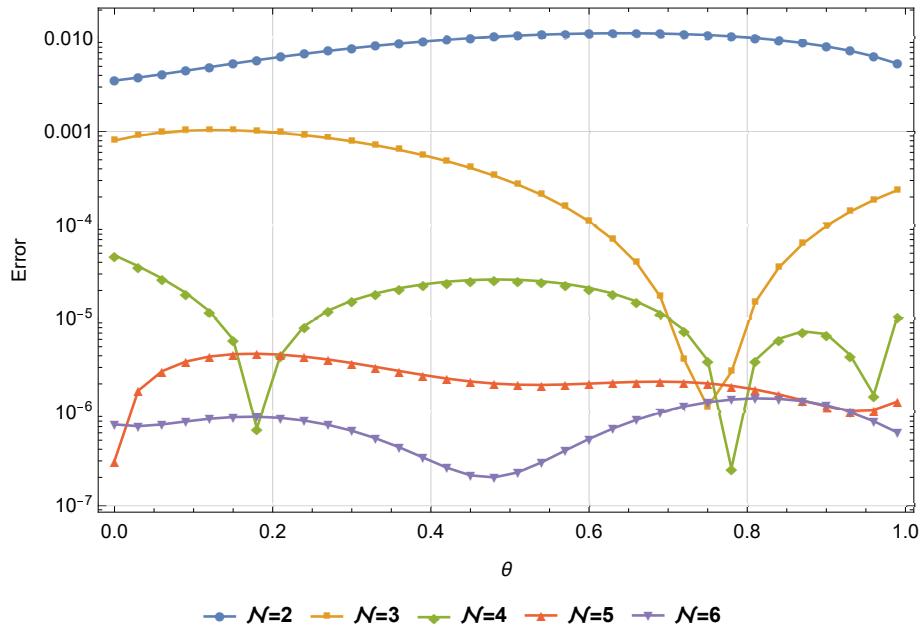
| $N$                | 2                        | 3                        | 4                        | 5                        | 6                        |
|--------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| MAEs               | $1.05726 \times 10^{-2}$ | $9.47791 \times 10^{-4}$ | $6.56318 \times 10^{-5}$ | $3.56142 \times 10^{-6}$ | $1.39114 \times 10^{-6}$ |
| $L_\infty$ -errors | $1.13462 \times 10^{-2}$ | $9.94362 \times 10^{-4}$ | $4.70445 \times 10^{-5}$ | $3.71657 \times 10^{-6}$ | $1.63616 \times 10^{-6}$ |
| $L_2$ -errors      | $6.10254 \times 10^{-3}$ | $5.10838 \times 10^{-4}$ | $3.37253 \times 10^{-5}$ | $1.87435 \times 10^{-6}$ | $5.93552 \times 10^{-7}$ |



**Figure 4.** AEs (left) and approximate solution (right) of Example 3 at  $\mathcal{N} = 6$ .



**Figure 5.** The AEs of Example 3 at  $t = 0.1$  and different values of  $\mathcal{N}$ .



**Figure 6.** The AEs of Example 3 at  $t = 0.9$  and different values of  $N$ .

**Test Problem 4.** Consider the following equation:

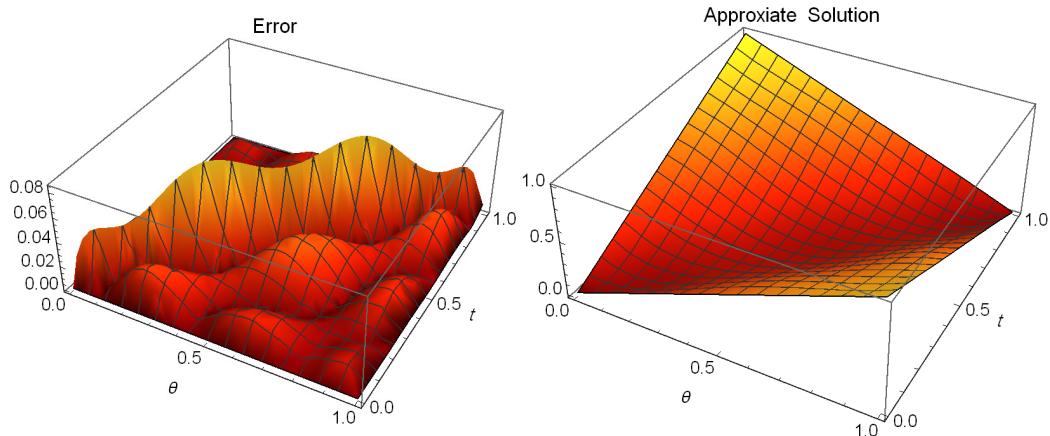
$$\partial_t Z(\theta, t) + \partial_\theta Z(\theta, t) + Z(\theta, t) = f(\theta, t), \quad 0 < \theta, t < 1, \quad (6.11)$$

with the following conditions:

$$Z(\theta, 0) = |\theta|, \quad Z(0, t) = |t|, \quad 0 < \theta, t < 1, \quad (6.12)$$

where  $f(\theta, t)$  is chosen such that the exact solution of this problem is  $Z(\theta, t) = |\theta - t|$ .

Figure 7 shows the AEs (left) and approximate solution (right) at  $N = 4$ . Table 6 shows the  $L_\infty$ -errors and  $L_2$ -errors at different values of  $t$  when  $N = 4$ .



**Figure 7.** The AEs (left) and approximate solution (right) of Example 4 at  $N = 4$ .

**Table 6.** Errors of Example 4 at  $N = 4$ .

| $t$                | 0.1                  | 0.2                  | 0.3                  | 0.4                  | 0.5                  | 0.6                  | 0.7                  | 0.8                  | 0.9                  |
|--------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| $L_\infty$ -errors | $2.7 \times 10^{-2}$ | $2.4 \times 10^{-2}$ | $3.0 \times 10^{-2}$ | $3.6 \times 10^{-2}$ | $2.4 \times 10^{-2}$ | $3.6 \times 10^{-2}$ | $2.9 \times 10^{-2}$ | $2.5 \times 10^{-2}$ | $2.8 \times 10^{-2}$ |
| $L_2$ -errors      | $1.6 \times 10^{-2}$ | $1.5 \times 10^{-2}$ | $2.6 \times 10^{-2}$ | $2.5 \times 10^{-2}$ | $2.0 \times 10^{-2}$ | $2.5 \times 10^{-2}$ | $2.6 \times 10^{-2}$ | $1.5 \times 10^{-2}$ | $1.6 \times 10^{-2}$ |

**Remark 5.** According to the error analysis section, the solutions need to be smooth enough. For a non-smooth solution, it is better to be constructed fractional-order Pell coefficient polynomials as basis functions.

## 7. Concluding remarks

This work was confined to introducing new polynomials whose coefficients are the celebrated Pell numbers. New formulas regarding these polynomials, such as moment, linearization, and derivative formulas of these polynomials, have been found and used to design a numerical algorithm to treat the linear hyperbolic first-order partial differential equations. The spectral tau method was utilized for such a purpose. The numerical results demonstrated the high accuracy of our proposed numerical algorithm. The use of these polynomials in numerical analysis is novel to the best of our knowledge. In future work, we aim to introduce other polynomials that generalize our introduced polynomials. In addition, we believe that these polynomials can be utilized to solve other types of differential equations.

## Author contributions

Waleed Mohamed Abd-Elhameed: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Writing—original draft preparation, Writing—review and editing, Supervision; Mohamed A. Abdelkawy: Methodology, Validation, Investigation, Funding acquisition; Omar Mazen Alqubori: Methodology, Validation, Investigation; Ahmed Gamal Atta: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing—original draft preparation, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

## Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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## Conflict of interest

The authors declare there is no conflict of interest.

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## References

1. J. Ockendon, S. Howison, A. Lacey, A. Movchan, *Applied Partial Differential Equations*, Oxford University Press, Oxford, 2003. <https://doi.org/10.1093/oso/9780198527701.001.0001>
2. T. Roubíček, *Nonlinear Partial Differential Equations with Applications*, 2013.
3. A. Sarma, T. W. Watts, M. Moosa, Y. Liu, P. L. McMahon, Quantum variational solving of nonlinear and multidimensional partial differential equations, *Phys. Rev. A*, **109** (2024), 062616. <https://doi.org/10.1103/PhysRevA.109.062616>
4. B. Bhaumik, S. De, S. Changdar, Deep learning based solution of nonlinear partial differential equations arising in the process of arterial blood flow, *Math. Comput. Simul.*, **217** (2024), 21–36. <https://doi.org/10.1016/j.matcom.2023.10.011>
5. S. Tang, X. Feng, W. Wu, H. Xu, Physics-informed neural networks combined with polynomial interpolation to solve nonlinear partial differential equations, *Comput. Math. Appl.*, **132** (2023), 48–62. <https://doi.org/10.1016/j.camwa.2022.12.008>
6. L. Zada, R. Nawaz, K. S. Nisar, M. Tahir, M. Yavuz, M. K. A. Kaabar, et al., New approximate-analytical solutions to partial differential equations via auxiliary function method, *Partial Differ. Equations Appl. Math.*, **4** (2021), 100045. <https://doi.org/10.1016/j.padiff.2021.100045>
7. G. Sarma, Vezhopalu, Analytical and numerical investigation of nonlinear differential equations: A comprehensive study, *J. Comput. Anal. Appl.*, **34** (2025), 213–222.
8. D. Doehring, G. J. Gassner, M. Torrilhon, Many-stage optimal stabilized Runge–Kutta methods for hyperbolic partial differential equations, *J. Sci. Comput.*, **99** (2024), 28. <https://doi.org/10.1007/s10915-024-02478-5>
9. S. Sharma, A. Bala, S. Aeri, R. Kumar, K. S. Nisar, Vieta–Lucas matrix approach for the numeric estimation of hyperbolic partial differential equations, *Partial Differ. Equations Appl. Math.*, **11** (2024), 100770. <https://doi.org/10.1016/j.padiff.2024.100770>
10. S. Malik, S. T. Ejaz, A. Akgül, Subdivision collocation method: a new numerical technique for solving hyperbolic partial differential equation in non-uniform medium, *Bol. Soc. Mat. Mex.*, **31** (2025), 50. <https://doi.org/10.1007/s40590-025-00731-x>
11. S. Karthick, V. Subburayan, R. P. Agarwal, Solving a system of one-dimensional hyperbolic delay differential equations using the method of lines and Runge–Kutta methods, *Computation*, **12** (2024), 64. <https://doi.org/10.3390/computation12040064>
12. Y. H. Youssri, R. M. Hafez, Exponential Jacobi spectral method for hyperbolic partial differential equations, *Math. Sci.*, **13** (2019), 347–354. <https://doi.org/10.1007/s40096-019-00304-w>
13. J. P. Boyd. *Chebyshev & Fourier Spectral Methods*, Springer-Verlag Berlin, 2001.
14. J. Shen, T. Tang, L. L. Wang, *Spectral Methods: Algorithms, Analysis and Applications*, Springer, 2011. <https://doi.org/10.1007/978-3-540-71041-7>
15. M. Kashif, M. Singh, T. Som, E. M. Craciun, Numerical study of variable order model arising in chemical processes using operational matrix and collocation method, *J. Comput. Sci.*, **80** (2024), 102339. <https://doi.org/10.1016/j.jocs.2024.102339>

16. G. Manohara, S. Kumbinarasaiah, An innovative Fibonacci wavelet collocation method for the numerical approximation of Emden–Fowler equations, *Appl. Numer. Math.*, **201** (2024), 347–369. <https://doi.org/10.1016/j.apnum.2024.03.016>

17. E. Gebril, M. S. El-Azab, M. Sameeh, Chebyshev collocation method for fractional Newell–Whitehead–Segel equation, *Alexandria Eng. J.*, **87** (2024), 39–46. <https://doi.org/10.1016/j.aej.2023.12.025>

18. W. M. Abd-Elhameed, M. M. Alsuyuti, New spectral algorithm for fractional delay pantograph equation using certain orthogonal generalized Chebyshev polynomials, *Commun. Nonlinear Sci. Numer. Simul.*, **141** (2025), 108479. <https://doi.org/10.1016/j.cnsns.2024.108479>

19. W. M. Abd-Elhameed, A. M. Al-Sady, O. M. Alqubori, A. G. Atta, Numerical treatment of the fractional Rayleigh–Stokes problem using some orthogonal combinations of Chebyshev polynomials, *AIMS Math.*, **9** (2024), 25457–25481. <https://doi.org/10.3934/math.20241243>

20. O. E. Hepson, Numerical simulations of Kuramoto–Sivashinsky equation in reaction-diffusion via Galerkin method, *Math. Sci.*, **15** (2021), 199–206. <https://doi.org/10.1007/s40096-021-00402-8>

21. A. A. El-Sayed, S. Boulaaras, N. H. Sweilam, Numerical solution of the fractional-order logistic equation via the first-kind Dickson polynomials and spectral tau method, *Math. Methods Appl. Sci.*, **46** (2023), 8004–8017. <https://doi.org/10.1002/mma.7345>

22. W. M. Abd-Elhameed, O. M. Alqubori, A. K. Al-Harbi, M. H. Alharbi, A. G. Atta, Generalized third-kind Chebyshev tau approach for treating the time fractional cable problem, *Electron. Res. Arch.*, **32** (2024), 6200–6224. <https://doi.org/10.3934/era.2024288>

23. W. M. Abd-Elhameed, A. F. Abu Sunayh, M. H. Alharbi, A. G. Atta, Spectral tau technique via Lucas polynomials for the time-fractional diffusion equation, *AIMS Math.*, **9** (2024), 34567–34587. <https://doi.org/10.3934/math.20241646>

24. T. Koshy, *Fibonacci and Lucas Numbers With Applications*, John Wiley & Sons, 2019. <https://doi.org/10.1002/9781118742297>

25. R. M. Hafez, H. M. Ahmed, O. M. Alqubori, A. K. Amin, W. M. Abd-Elhameed, Efficient spectral Galerkin and collocation approaches using telephone polynomials for solving some models of differential equations with convergence analysis, *Mathematics*, **13** (2025), 918. <https://doi.org/10.3390/math13060918>

26. W. M. Abd-Elhameed, O. M. Alqubori, A. G. Atta, A collocation procedure for treating the time-fractional FitzHugh–Nagumo differential equation using shifted Lucas polynomials, *Mathematics*, **12** (2024), 3672. <https://doi.org/10.3390/math12233672>

27. M. H. Heydari, Z. Avazzadeh, Fibonacci polynomials for the numerical solution of variable-order space-time fractional Burgers–Huxley equation, *Math. Methods Appl. Sci.*, **44** (2021), 6774–6786. <https://doi.org/10.1002/mma.7222>

28. W. M. Abd-Elhameed, O. M. Alqubori, A. G. Atta, A collocation approach for the nonlinear fifth-order KdV equations using certain shifted Horadam polynomials, *Mathematics*, **13** (2025), 300. <https://doi.org/10.3390/math13020300>

29. E. Aourir, H. L. Dastjerdi, M. Oudani, K. Shah, T. Abdeljawad, Numerical technique based on Bernstein polynomials approach for solving auto-convolution VIEs and the initial value problem of auto-convolution VIDEs, *J. Appl. Math. Comput.*, **71** (2025), 4697–4727. <https://doi.org/10.1007/s12190-025-02400-8>

30. Ö. Oruç, A new numerical treatment based on Lucas polynomials for 1D and 2D sinh–Gordon equation, *Commun. Nonlinear Sci. Numer. Simul.*, **57** (2018), 14–25. <https://doi.org/10.1016/j.cnsns.2017.09.006>

31. B. P. Moghaddam, A. Dabiri, A. M. Lopes, J. A. T. Machado, Numerical solution of mixed-type fractional functional differential equations using modified Lucas polynomials, *Comput. Appl. Math.*, **38** (2019), 46. <https://doi.org/10.1007/s40314-019-0813-9>

32. M. Pourbabae, A. Saadatmandi, A numerical schemes based on Vieta–Lucas polynomials for evaluating the approximate solution of some types of fractional optimal control problems, *Iran. J. Sci. Technol. Trans. Electr. Eng.*, **49** (2025), 873–895. <https://doi.org/10.1007/s40998-025-00791-9>

33. S. Çelik, I. Durukan, E. Özkan, New recurrences on Pell numbers, Pell–Lucas numbers, Jacobsthal numbers, and Jacobsthal–Lucas numbers, *Chaos, Solitons Fractals*, **150** (2021), 111173. <https://doi.org/10.1016/j.chaos.2021.111173>

34. Z. Şiar, R. Keskin, k-Generalized Pell numbers which are concatenation of two repdigits, *Mediterr. J. Math.*, **19** (2022), 180. <https://doi.org/10.1007/s00009-022-02099-y>

35. J. J. Bravo, J. L. Herrera, F. Luca, On a generalization of the Pell sequence, *Math. Bohemica*, **146** (2021), 199–213. <https://doi.org/10.21136/MB.2020.0098-19>

36. P. K. Singh, S. S. Ray, A numerical approach based on Pell polynomial for solving stochastic fractional differential equations, *Numer. Algorithms*, **97** (2024), 1513–1534. <https://doi.org/10.1007/s11075-024-01760-9>

37. H. C. Yaslan, Pell polynomial solution of the nonlinear variable order space fractional PDEs, *J. Fract. Calc. Appl.*, **16** (2025), 1–16. <https://doi.org/10.21608/jfca.2024.255438.1052>

38. H. C. Yaslan, Pell polynomial solution of the fractional differential equations in the Caputo–Fabrizio sense, *Indian J. Pure Appl. Math.*, (2024), 1–12. <https://doi.org/10.1007/s13226-024-00684-3>

39. M. Izadi, H. M. Srivastava, K. Mamehrashi, Numerical simulations of Rosenau–Burgers equations via Crank–Nicolson spectral Pell matrix algorithm, *J. Appl. Math. Comput.*, **71** (2025), 1009–1033. <https://doi.org/10.1007/s12190-024-02273-3>

40. T. Koshy, *Pell and Pell–Lucas Numbers with Applications*, Springer, 2014. <https://doi.org/10.1007/978-1-4614-8489-9>

41. G. B. Djordjevic, G. V. Milovanovic, *Special Classes of Polynomials*, University of Nis, Faculty of Technology Leskovac, 2014.

42. A. G. Atta, W. M. Abd-Elhameed, G. M. Moatimid, Y. H. Youssri, Shifted fifth-kind Chebyshev Galerkin treatment for linear hyperbolic first-order partial differential equations, *Appl. Numer. Math.*, **167** (2021), 237–256. <https://doi.org/10.1016/j.apnum.2021.05.010>

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- 43. S. Kumbinarasaiah, M. Mulimani, A novel scheme for the hyperbolic partial differential equation through Fibonacci wavelets, *J. Taibah Univ. Sci.*, **16** (2022), 1112–1132. <https://doi.org/10.1080/16583655.2022.2143636>
- 44. S. Singh, V. K. Patel, V. K. Singh, Application of wavelet collocation method for hyperbolic partial differential equations via matrices, *Appl. Math. Comput.*, **320** (2018), 407–424. <https://doi.org/10.1016/j.amc.2017.09.043>
- 45. A. H. Bhrawy, R. M. Hafez, E. Alzahrani, D. Baleanu, A. A. Alzahrani, Generalized Laguerre–Gauss–Radau scheme for first order hyperbolic equations on semi-infinite domains, *Rom. J. Phys.*, **60** (2015), 918–934. Available from: <http://hdl.handle.net/20.500.12416/1554>.



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