



Lorenzo Lazzarino

NUMERICAL APPROXIMATION OF THE TIME-ORDERED
EXPONENTIAL FOR SPIN DYNAMIC SIMULATION

Supervisor: Dr. S. Pozza

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Charles University, Prague



① INTRODUCTION

② ★-PRODUCT APPROACH

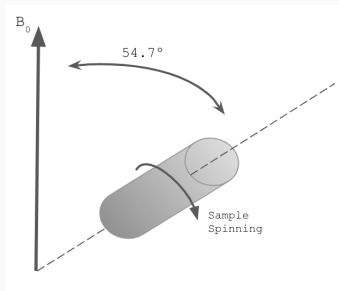
③ GEOMETRIC NUMERICAL INTEGRATORS

④ NUMERICAL COMPARISON

INTRODUCTION

Aim: First comparison between \star -product approach and well established numerical methods for the solution of non-autonomous ODEs.

Case Study: Solid-state Nuclear magnetic resonance (NMR) spectroscopy with magic-angle spinning (MAS).



Schrödinger equation

$$\begin{cases} \frac{d}{dt} \psi(t) = -i\mathcal{H}(t)\psi(t), & t \geq 0 \\ \psi(0) = \psi_0 \end{cases}$$

where \mathcal{H} is the time-dependent Hamiltonian operator.

**General Problem**

$$\begin{cases} \frac{d}{dt} u(t) = A(t)u(t), & t \in (t_0, T) \\ u(t_0) = u_0 \end{cases}$$

with time-dependent coefficients $A(t)$.

Difficulty: Analytic expression not always available

→ Role of numerical approaches is crucial

★-PRODUCT APPROACH



[Pozza, Van Buggenhout, 2023]

Problem

$$\frac{d}{dt} \tilde{u}(t) = \tilde{f}(t) \tilde{u}(t), \quad \tilde{u}(-1) = 1, \quad t \in [-1, 1]$$

- Heaviside step function: $\Theta(t-s) = \begin{cases} 0, & \text{if } t < s \\ 1, & \text{otherwise} \end{cases}$
- \mathcal{A}_Θ = set of all scalar distribution of the kind $f(t,s) = \tilde{f}(t,s)\Theta(t-s)$, with \tilde{f} analytic function
- \star -product:

$$f(t,s) \star g(t,s) := \int_{-1}^1 g(t,\tau) f(\tau,s) d\tau, \quad f, g \in \mathcal{A}_\Theta, \quad t, s \in [-1, 1]$$

- \star -identity: Dirac delta distribution $\delta(t-s)$
- \star -expression of the solution:

$$\frac{d}{dt} u(t,s) = f(t,s)u(t,s), \quad u(s,s) = 1, \quad t, s \in [-1, 1]$$

$$u(t,s) = \Theta(t-s) \star R_\star(f)(t,s), \quad R_\star(f)(t,s) = \delta(t-s) + \sum_{k \geq 1} f^{\star k}(t,s)$$

$$\tilde{u}(t) = u(t, -1)$$



Expansion in Legendre polynomials:

- For a function \tilde{f} : $\tilde{f}(t) = \sum_{d=0}^{\infty} \alpha_d p_d(t)$, with $\alpha_d = \int_{-1}^1 \tilde{f}(t) p_d(t) dt$
 → For \tilde{f} analytic, $|\alpha_d| \leq C \rho^{-d-1}$, $\rho > 1$
- For a distribution $f \in \mathcal{A}_\Theta$:

$$f(t, s) = \sum_{k=0}^{\infty} \sum_{\ell=0}^{\infty} f_{k,\ell} p_k(t) p_\ell(s), \quad \text{for every } t \neq s, \quad t, s \in [-1, 1]$$

$$\text{with } f_{k,\ell} = \int_{-1}^1 \int_{-1}^1 f(\tau, \rho) p_k(\tau) p_\ell(\rho) d\rho d\tau$$

$$\implies F := [f_{k,\ell}]_{k,\ell=0}^{\infty} = \begin{bmatrix} f_{0,0} & f_{0,1} & f_{0,2} & \dots \\ f_{1,0} & f_{1,1} & f_{1,2} & \dots \\ f_{2,0} & f_{2,1} & f_{2,2} & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$



We can express the coefficients $\{c_k\}_{k \geq 0}$ of the Legendre expansion of the **solution in terms of the coefficient matrix F** :

$$\begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ \vdots \end{bmatrix} = T(\mathbb{I} - F)^{-1} \begin{bmatrix} p_0(-1) \\ p_1(-1) \\ p_2(-1) \\ \vdots \end{bmatrix}$$

with T the coefficient matrix of the Heaviside function.

Truncated Matrix Problem

1. Construct $F_M = [f_{k,\ell}]_{k,\ell=0}^{M-1}$, i.e., construct the matrix of Fourier coefficients;
2. Solve $(\mathbb{I} - F_M)x = \phi(-1)$, i.e., solve a linear system;
3. Compute $T_M x = [c_0 \quad c_1 \quad c_2 \quad \cdots \quad c_{M-1}]^T$, i.e., compute a matrix-vector product.



Problem

$$\frac{d}{dt} u(t) = \tilde{A}(t)\Theta(t-s)u(t), \quad u(-1) = u_0, \quad t \in [-1, 1]$$

where $\tilde{A}(t)$ is an analytic matrix-valued function over $[-1, 1]$.

$$\rightarrow u(t) \approx (\mathbb{I}_N \otimes \phi_M(t))^T T_M (\mathbb{I}_{MN} - \mathcal{A}_M)^{-1} (u_0 \otimes \phi_M(-1))$$



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If $\tilde{A}(t) = \sum_{k=1}^d A_k \tilde{f}_k(t)$, then $\mathcal{A}_M = \sum_{k=1}^d A_k \otimes F_M^{(k)}$

$$X - \sum_{k=1}^d F_M^{(k)} X A_k^T = \phi_M(-1) u_0^T, \quad x = \text{vec}(X)$$

$$X_{n+1} = \sum_{k=1}^d F_M^{(k)} X_n A_k^T + \phi_M(-1) u_0^T$$

- Use **low-rank approximations**, i.e., $X_n \approx V_n W_n^H$, $V_n, W_n \in \mathbb{C}^{N \times r}$, $r \ll M$

[Pozza, Van Buggenhout, 2023]

GEOMETRIC NUMERICAL INTEGRATORS



The Magnus Expansion provides the **solution** of

$$\begin{cases} \frac{d}{dt} u(t) = A(t)u(t), & t \in (0, T) \\ u(0) = u_0 \end{cases}$$

as the **exponential of an infinite series**

$$u(t) = e^{\Omega(t)} u_0, \quad \Omega(t) = \sum_{m=1}^{\infty} \Omega_m(t)$$

where $\Omega_m(t)$ is the m -th nested integral containing $m - 1$ nested commutator of $A(t)$.

$$\Omega_1(t) = \int_0^t dt_1 A(t_1),$$

$$\Omega_2(t) = \frac{1}{2} \int_0^t dt_1 \int_0^{t_1} dt_2 [A(t_1), A(t_2)],$$

$$\Omega_3(t) = \frac{1}{6} \int_0^t dt \int_0^{t_1} dt_2 \int_0^{t_2} dt_3 [A(t_1), [A(t_2), A(t_3)]] + [[A(t_1), A(t_2)], A(t_3)]$$

[Alvermann, Fehske, 2011]



Idea

- **Truncate** the infinite series
- Use **quadrature formula** to estimate integrals in the Magnus Expansion

$$\rightarrow \tilde{u}^{(N)} = \exp \left[\sum_{m=1}^N \Omega_m(t) \right]$$

**Idea**

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Nested integrals \rightarrow Expand $A(t)$ in a series of (Shifted) Legendre Polynomials. For a fix τ :

$$A(t) = \frac{1}{\tau} \sum_{n=1}^N A_n P_{n-1} \left(\frac{t}{\tau} \right) + \mathcal{O}(\tau^{N+1}), \quad A_n = (2n-1) \int_0^\tau A(t) P_{n-1} \left(\frac{t}{\tau} \right) dt, \quad t \in [0, \tau].$$

\rightarrow **Reduce** the nested integrals to **single** integrals by symmetry and orthogonality

[Alvermann, Fehske, Blanes, Casas]



Generalization of the Splitting Methods, but with significantly less exponentials.

Aim

Avoid commutators to decrease the computational effort

$$\tilde{u}_{CF}^{(N)}(\tau) = e^{\Omega_1} e^{\Omega_2} \dots e^{\Omega_s}$$

$$\Omega_i = \sum_{n=1}^N f_{i,n} A_n, \quad \forall i = 1, \dots, s$$

- Completely determined by the choice of the coefficient $f_{i,n}$
- For a prescribed order, $f_{i,n}$ can be found through **order conditions**

[Alvermann, Fehske, Blanes, Casas]



Gauss - Legendre quadrature

$$\int_0^1 f(x) dx \approx \sum_{m=1}^M w_m f(x_m)$$

M nodes x_1, \dots, x_M which are the zeros of the (shifted) Legendre polynomial $P_M(x)$ and weights w_1, \dots, w_M



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\Rightarrow We can approximate the Legendre coefficients $A_n(t)$

$$A_n \approx (2n-1)\tau \sum_{m=1}^{N/2+1} w_m P_{n-1}(x_m) A(x_m\tau)$$

We **obtain** Ω_i as a linear combination of $A(t)$ at different time $x_m\tau$ with new coefficients

$$g_{i,m} = w_m \sum_{n=1}^{N/2+1} (2n-1) P_{n-1}(x_m) f_{i,n}.$$



We have **reduced** the problem of finding a solution to the non-autonomous ODE to a **computation of one or multiple exponentials of a matrix**.

Approximation of the matrix exponential e^M

- Padé Approximation $R_{pq}(M) = [D_{pq}(M)]^{-1}N_{pq}(M)$
- Scaling and Squaring $e^M = \left(e^{\frac{M}{n}}\right)^n$

[Moler, Van Loan, 2003]

Approximation of the action of the matrix exponential on a vector $e^M \xi$

- Scaling/Squaring - like strategy $Z_{i+1} = r_m(s^{-1}M)Z_i, \quad Z_0 = \xi$
- Krylov subspace methods $e^M \xi \approx \|\xi\|_2 V_m e^{H_m} e_1$
- Chebyshev technique $e^{-i\tau M} \approx \sum_{n=0}^m c_n Q_n(\tau M)$

[Al-Mohy, Higham, Saad]

NUMERICAL COMPARISON



$$\frac{d}{dt}u(t) = -i\mathcal{H}_{BS}(t)u(t), \quad u(0) = u_0, \quad t \in [0, 2\pi/\omega_r]$$

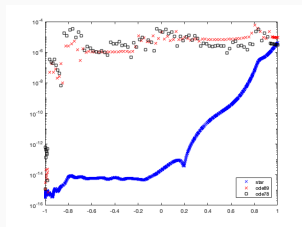
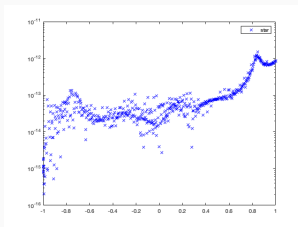
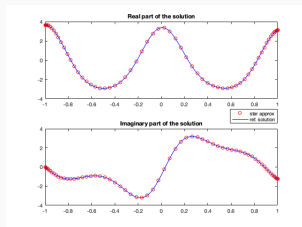
$$\mathcal{H}_{BS} = \begin{bmatrix} \omega_0/2 & 2\beta \cos(\omega_r t) \\ 2\beta \cos(\omega_r t) & -\omega_0/2 \end{bmatrix}$$

- Resonant: $\omega_0 = \omega_r$
- Strong-coupling $\beta/\omega_r > 1$
- $\omega_r = 20000$ and $\beta = 1.2\omega_r$
- $u_0 =$ random vector (`randn`)

[Giscard, Bonhomme, 2020]



Taking the Runge-Kutta (8,9) method with tolerance 10^{-12} (ode9) as reference, we see that the \star -solution computed with tolerance 10^{-12} is reliable



- Reference: \star -solution with $tol = 10^{-12}$
- \star -process with $tol = 10^{-4}$
- Runge-Kutta (8,9) with $tol = 10^{-3}$
- Runge-Kutta (7,8) with $tol = 10^{-3}$



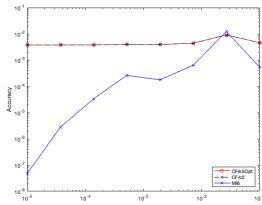
$$\mathcal{H}(t) = \mathcal{H}_{ICS} + \mathcal{H}_{DD}(t), \quad t \in [0, \frac{1}{10\omega_r}]$$

$$\mathcal{H}_{ICS} = \sum_{k=1}^{N_s} \Omega_k I_{k_z}$$

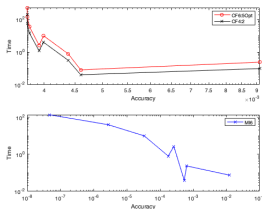
$$\mathcal{H}_{DD} = \delta \sum_{k=1}^{N_s-1} \sum_{q=k+1}^{N_s} \left(\sum_{n=-2}^2 e^{in(\gamma+\omega_r t)} C_n(\beta) \right) \cdot \frac{1}{r_{kq}^3} [2I_{k_z} I_{q_z} - (I_{k_x} I_{q_x} + I_{k_y} I_{q_y})]$$

- N_s = number of spins
- $C_1(\beta) = C_{-1}(\beta) = -\frac{1}{2\sqrt{2}} \sin(2\beta)$
 $C_2(\beta) = C_{-2}(\beta) = \frac{1}{4} \sin^2(\beta)$
- δ = fixed constant
- u_0 randomly generated
- Ω_k = chemical shift differences
 (\rightarrow randomly generated)
- r_{kq} = interspin distance between spins
 k and q (\rightarrow cationic tin oxo-cluster)
- $\omega_r = 20000$, $\beta = \pi/4$ and $\gamma = \pi$

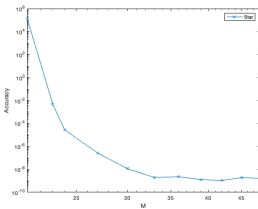
$$I_{k_x} := \mathbb{I}_{2^{k-1}} \otimes \sigma_x \otimes \mathbb{I}_{2^{N_s-k}}, \quad \sigma_x = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad \sigma_y = \begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}, \quad \sigma_z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$



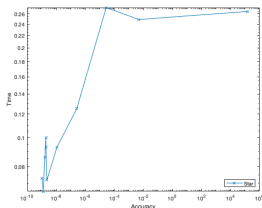
Accuracy vs τ



GNI: Accuracy vs Time



Accuracy vs M



*-process: Accuracy vs Time

- $N_s = 6$
- The accuracy is governed by the parameter τ, M
- Reference:
 - ★-process, $tol = 10^{-13}$
 - ★-process, $tol = 10^{-4}$
 - 6-th order CFEI with 5 exponentials
 - 4-th order CFEI with 2 exponentials
 - 6-th order Magnus Integrator

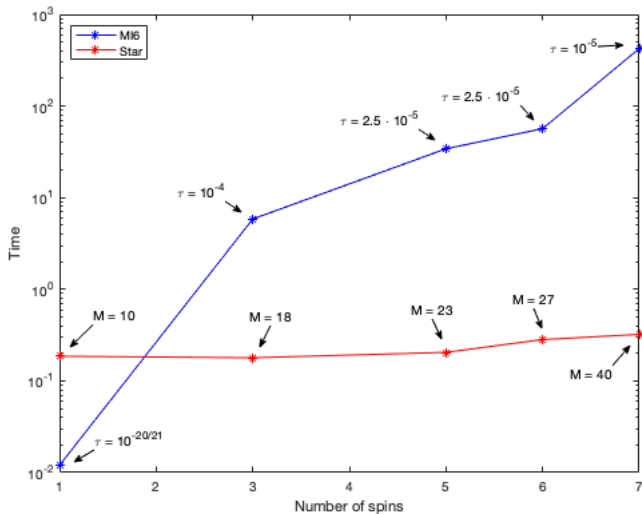


- $N_s = 6$

Accuracy	Method	Parameter	Total computational time
10^{-3}	* -process	$M = 23$	0.1969s
	MI6	$\tau = 10^{-\frac{20}{21}}$	0.0463s
	CF6:5Opt	$\tau = 10^{-1}$	0.1324s
	CF4:2	$\tau = 10^{-1}$	0.0701s
10^{-5}	* -process	$M = 24$	0.1370s
	MI6	$\tau = 1.4 \cdot 10^{-4}$	10.3845s
	CF6:5Opt	$\tau < 10^{-5}$	> 540s
	CF4:2	$\tau < 10^{-5}$	> 220s
10^{-8}	* -process	$M = 30$	0.0766s
	MI6	$\tau = 10^{-5}$	149.9658s



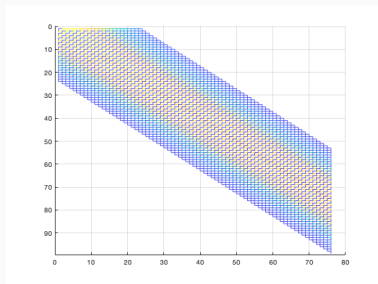
MI6 and *-process: Time vs Number of spins



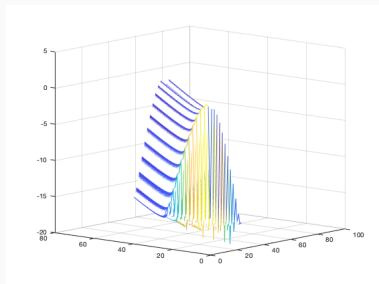


- Use more efficient **implementations** of Geometric Numerical **Integrators**
- Consider **other methods** for comparison
- Consider **more complicated** NMR **problems**
- Comparison with commonly-used **software** in quantum chemistry, e.g. SIMPSON
- Consider experiment **data** totally linked to **real-world problems**

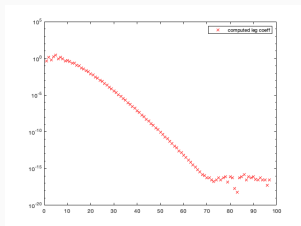
Thank you!



Banded Property



Decay phenomenon



Decay of the Legendre coefficients

- Tolerance: 10^{-12}
- $M = 100$
- $N = 24$