

A fast numerical method for the operator solution of the generalized Rosen-Zener model

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Exploiting Algebraic and Geometric Structure in
Time-Integration Methods
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Schrödinger equation

In Nuclear Magnetic Resonance (NMR) applications, the quantum dynamic of particles is described by the Schrödinger equation

$$\hbar \frac{\partial |\Psi\rangle}{\partial t} = -iH|\Psi\rangle,$$

with H the (time-dependent) Hamiltonian and Ψ the wave function.

- Simulations are of great importance. They provide benchmarks for studies of new materials, and the development of new magnetic fields.
- H size **increases exponentially** with the number of particles.
- H is sparse and structured (Kronecker).

Extended Rosen-Zener model

- The Rosen-Zener (RZ) model [Rosen, Zener, 1932] is of the highest importance as representative of two-level quantum systems.
- Important in Nuclear Magnetic Resonance (NMR) [Silver, Joseph, Hoult, 1984; Hioe, 1984] and Magnetic Resonance Imaging (MRI) [Zhang, Garwood et al., 2017].
- In [Koyseva et al., 2007; Vitanov, 2010] the RZ model was extended to multiple degenerate sets of states in the framework of quantum-state engineering → **Large-size ODE**.
- The extended RZ model has been used as a **test model for numerical solvers** of non-autonomous evolutions equations [Blanes, Casas, Thalhammer, 2017; Blanes, Casas, Murua, 2017; Auzinger et al., 2019; Bader et al., 2022]

Extended Rosen-Zener model

Goal: compute $U(t) \in \mathbb{C}^{N \times N}$, $N = 2k$, the operator solution of:

$$\partial_t U(t) = -iH(t)U(t), \quad U(s) = I_N.$$

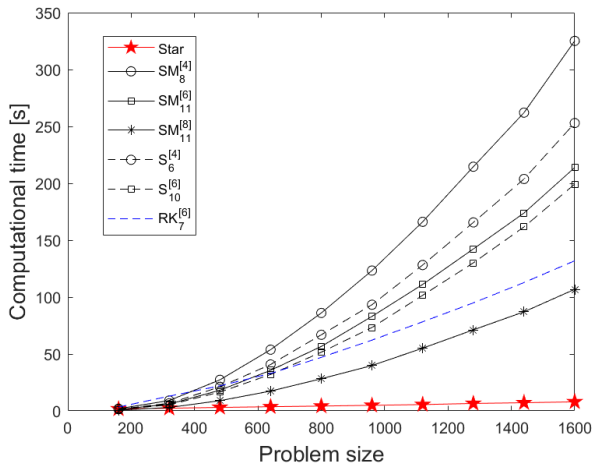
$$H(t) := \omega(t)\sigma_3 \otimes I_k + v(t)\sigma_1 \otimes M_k,$$

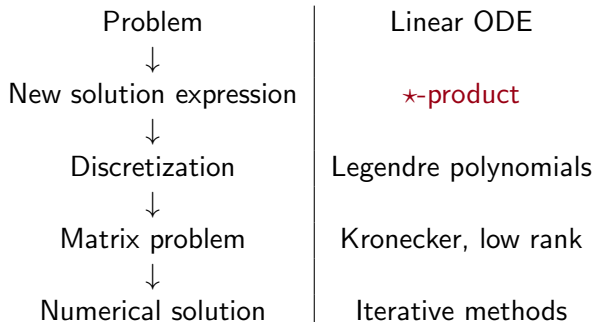
with the Pauli matrices σ_j and $M_k \in \mathbb{R}^{k \times k}$:

$$\sigma_1 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \sigma_2 = \begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}, \quad M_k = \begin{bmatrix} 0 & 1 & & \\ 1 & 0 & \ddots & \\ & \ddots & \ddots & 1 \\ & & 1 & 0 \end{bmatrix},$$

$$\sigma_3 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \quad \omega(t) := w_0 + \varepsilon \cos(\delta t), \quad v(t) := \frac{v_0}{\cosh(t/T_0)}.$$

A new (linear scaling?) algorithm: Preview





The problem: two systems of linear ODEs

We will solve two related problems.

First, the **quantum state vector** case. Compute the N -size vector $\psi(t)$ solving:

$$\frac{\partial}{\partial t}\psi(t) = -H(t)\psi(t), \quad \psi(t_0) = \psi_0 \in \mathbb{C}^N, \quad t \in I = [t_0, t_f].$$

Second, the **operator** case. Compute the $N \times N$ matrix-valued function $U(t)$ solving

$$\frac{\partial}{\partial t}U(t) = -H(t)U(t), \quad U(t_0) = I_N, \quad t \in I = [t_0, t_f].$$

Note that $\psi(t) = U(t)\psi_0$.

Solution expression: \star -product

We define the \star -product as [Giscard, P., Ryckebusch]

$$(f_2 \star f_1)(t, s) := \int_I f_2(t, \tau) f_1(\tau, s) d\tau, \quad \Theta(t - s) = \begin{cases} 1, & t \geq s, \\ 0, & t < s \end{cases}$$

where $f_1(t, s), f_2(t, s)$ comes from a specific class of distributions:
 $f_j(t, s) = \tilde{f}_j(t, s)\Theta(t - s)$, f_j analytic in $t, s \in I$.

Then the solution to the problems are:

$$U(t) = \hat{U}(t, t_0), \quad \psi(t) = \hat{U}(t, t_0)\psi_0,$$

with

$$\hat{U}(t, s) = \Theta(t - s) \star (I_N \delta(t - s) + iH(t)\Theta(t - s))^{-\star}.$$

§ 4. — Risoluzione generale di equazioni integrali.

9. Abbiassi una funzione analitica del tipo (1)

$$(1') \quad \mathbf{F}(s_1, s_2, \dots, s_n).$$

Scriviamo l'equazione

$$(4) \quad \mathbf{F}(s_1, s_2, \dots, s_n) = 0.$$

$$S(x, y) = R(x, y) - \frac{1}{2} R^2(x, y) + \frac{1}{3} R^3(x, y) - \dots + \frac{(-1)^n}{n} R^n(x, y) + \dots$$

ove

$$R^n(x, y) = \int_x^y R^{n-1}(x, \xi) R(\xi, y) d\xi.$$

e non dovremo porre alcuna limitazione per i valori assoluti di $S(x, y)$, $R(x, y)$, purchè siano finiti.

10. Supponiamo in particolare che la (4') sia un polinomio razionale e

[Volterra, Rend Lincei, 1910]

Discretization: Legendre polynomial expansion

If $I = [-1, 1]$, $f(t, s)$ can be expanded in a 2D series:

$$f(t, s) = \tilde{f}(t)\Theta(t - s) \approx \sum_{k=0}^{m-1} \sum_{\ell=0}^{m-1} \alpha_{k,\ell} p_k(t) p_\ell(s),$$

with p_k the **orthonormal Legendre polynomials**:

$$\int_{-1}^1 p_k(\tau) p_\ell(\tau) d\tau = \delta_{k\ell},$$

and

$$\alpha_{k,\ell} = \int_{-1}^1 p_k(\rho) \left(\int_{-1}^1 f(\tau, \rho) p_\ell(\tau) d\tau \right) d\rho.$$

Discretization: Legendre polynomial coefficients

The function is then represented by the matrix:

$$f(t, s) \rightarrow \begin{bmatrix} \alpha_{0,0} & \alpha_{0,1} & \dots & \alpha_{0,m-1} \\ \alpha_{1,0} & \alpha_{1,1} & \dots & \alpha_{1,m-1} \\ \vdots & \vdots & & \vdots \\ \alpha_{m-1,0} & \alpha_{m-1,1} & \dots & \alpha_{m-1,m-1} \end{bmatrix} =: F$$

Note that

$$\begin{aligned} f(t, s) &\approx \sum_{k=0}^{m-1} \sum_{\ell=0}^{m-1} \alpha_{k,\ell} p_k(t) p_\ell(s) = \varphi_m(t)^T F \varphi_m(s) \\ &\approx [p_0(t) \quad \dots \quad p_{m-1}(t)] F \begin{bmatrix} p_0(s) \\ \vdots \\ p_{m-1}(s) \end{bmatrix}. \end{aligned}$$

Matrix problem: the resolvent

The discretized \star -product translates into the usual matrix algebra.

$$\begin{array}{l|l} f(t, s) & F_m \\ 1_\star = \delta(t - s) & I_m \\ f^{\star-1} & F_m^{-1} \\ g(t, s) & G_m \\ f \star g & F_m G_m \\ f + g & F_m + G_m \\ \Theta(t - s) & T_m \\ R_\star(f) & (I_m - F_m)^{-1} \\ \hat{U}(t, s) & T_m (I_m - F_m)^{-1} \end{array}$$

Kronecker structure and low-rank

In many applications, $H(t)$ is given as a sum of products:

$$H(t) = \sum_{j=0}^s H_j \times \tilde{f}_j(t),$$

with H_j sparse matrices, and $\tilde{f}_j(t)$ analytic scalar functions. Our approach reformulates the problem as the linear system

$$\left(I_{Nm} + i \sum_{j=0}^s H_j \otimes F_j \right) \text{vec}(X) = \psi_0 \otimes \varphi_m(-1),$$

with vec the vectorization transformation and F_j the Legendre discretization matrices. Equivalently, we have the **matrix equation** with a low-rank rhs (state vector case)

$$X + i \sum_{j=0}^s F_j X H_j^T = \varphi_m(-1) \psi_0^T.$$

Matrix equation and the Rosen-Zener model

In the Rosen-Zener model for the state vector case we get the approximant:

$$\psi(t) \approx \text{vec} \left(\phi_M(t)^T T_M X \right), \quad t \in [-1, 1],$$

where $X \in \mathbb{C}^{M \times N}$ is the solution of the matrix equation

$$X + i \Omega_M X (\sigma_3 \otimes I_k) + i V_M X (\sigma_1 \otimes M_k) = \phi_M(-1) \psi_0^T,$$

with Ω_M and V_M the $M \times M$ coefficient matrices of, respectively, $\omega(t)$ and $v(t)$.

Numerical solution: Iterations for the state vector ODE

At this scope, we can derive from (18) the (implicit) iterates:

$$X_{n+1} + i\Omega_M X_{n+1}(\sigma_3 \otimes I_k) = -i V_M X_n(\sigma_1 \otimes M_k) + \phi_M(-1)\psi_0^T.$$

Thanks to the simple diagonal structure of the matrix $\sigma_3 \otimes I_k$, we get the *stationary iterative method*:

$$\begin{aligned} X_{n+1/2} &= -i V_M X_n(\sigma_1 \otimes M_k) + \phi_M(-1)\psi_0^T; \\ X_{n+1} &= G_1 X_{n+1/2} D_1 + G_2 X_{n+1/2} D_2, \end{aligned}$$

with $X_0 = \phi_M(-1)\psi_0^T$ and

$$\begin{aligned} G_1 &= (I_M + i\Omega_M)^{-1}, & D_1 &= \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \otimes I_k, \\ G_2 &= (I_M - i\Omega_M)^{-1}, & D_2 &= \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \otimes I_k. \end{aligned}$$

Algorithm for the state vector

Require: Error tolerance $tol > 0$ and svd truncation tolerance $trunc > 0$.

$$L = \phi_M(-1); \quad R = \psi_0;$$

$$g = [G_1L, G_2L]; \quad d = [D_1R, D_2R];$$

while $err \geq tol$ **do**

$$L = -iV_M L; \quad R = (\sigma_1 \otimes M_k)R; \quad \triangleright \text{Iteration (6)}$$

$$L = [G_1L, G_2L, g]; \quad R = [D_1R, D_2R, d]; \quad \triangleright \text{Iteration (7)}$$

$$L = Q_L R_L; \quad \triangleright \text{Economy-size QR decomposition}$$

$$R_L = USV^H; \quad \triangleright \text{Economy-size SVD decomposition}$$

$$r = \min\{j : \sigma_j < trunc\}, \text{ with } \text{diag}(\sigma_j) = S;$$

$$L = Q_L U(:, 1:r) S(1:r, 1:r); \quad \triangleright \text{Truncation}$$

$$R = R \text{ conjugate}(V(:, 1:r)); \quad \triangleright \text{Truncation}$$

$$b = L(R^T \text{ conjugate}(\psi_0)); \quad \triangleright b = (\psi_0^H \otimes I_M) \text{vec}(LR^T)$$

$$err = \|b - b_{old}\|_2 \quad \triangleright \text{Cheap error estimate}$$

$$b_{old} = b;$$

end while

$$X \approx LR^T$$

Matrix equation and the Rosen-Zener model

In the Rosen-Zener model for the operator case we get the approximant:

$$U_{:,j}(t) \approx \text{vec} \left(\phi_M(t)^T T_M X^{(j)} \right),$$

where $U_{:,j}(t)$ is the j th column of $U(t)$. Here, $H^{(j)}$ is the solution of the equation

$$X + i \Omega_M X (\sigma_3 \otimes I_k) + i V_M X (\sigma_1 \otimes M_k) = \phi_M(-1) e_j,$$

i.e, the state vector equation with initial state $\psi_0 = e_j$.

Algorithm for the operator solution

Require: Error tolerance $tol > 0$ and svd truncation tolerance $trunc > 0$.

$$L = \phi_M(-1); \quad R = I_n;$$

$$g = [G_1L, G_2L]; \quad d = [D_1, D_2];$$

while $err \geq tol$ **do**

$$L = -iV_M L; \quad R = (\sigma_1 \otimes M_k)R; \quad \triangleright \text{Iteration (6)}$$

$$L = [G_1L, G_2L, g]; \quad R = [D_1R, D_2R, d]; \quad \triangleright \text{Iteration (7)}$$

$$L = Q_L R_L; \quad \triangleright \text{Economy-size QR decomposition}$$

$$R_L = USV^H; \quad \triangleright \text{Economy-size SVD decomposition}$$

$$r = \min\{j : \sigma_j < trunc\}, \text{ with } \text{diag}(\sigma_j) = S;$$

$$L = Q_L U(:, 1:r) S(1:r, 1:r); \quad \triangleright \text{Truncation}$$

$$K = \text{conjugate}(V(:, 1:r)) \otimes I_N;$$

$$R = RK; \quad \triangleright \text{Truncation}$$

$$b = L(R(1, 1:N : 1 + (r-1)N))^T; \quad \triangleright b = \mathcal{X}(:, 1)$$

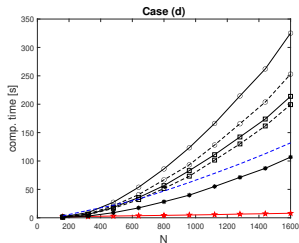
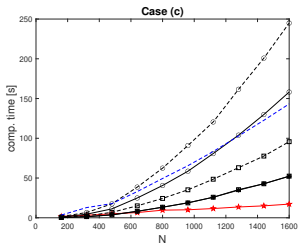
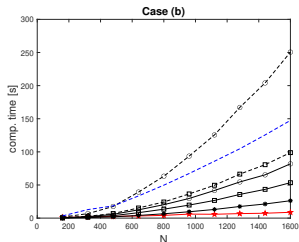
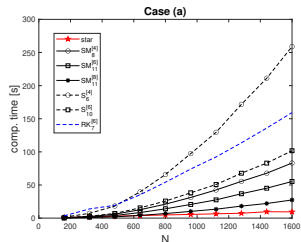
$$err = \|b - b_{old}\|_2 \quad \triangleright \text{Cheap error estimate}$$

$$b_{old} = b;$$

end while

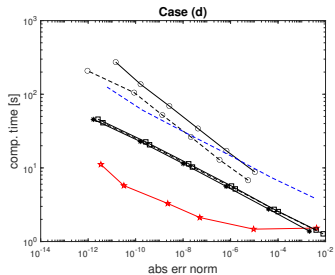
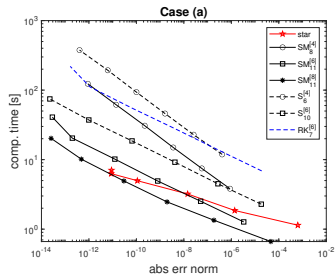
$$X^{(j)} \approx L(R(:, j : N : j + (r-1)N))^T, \quad j = 1, \dots, N.$$

Comparison: size



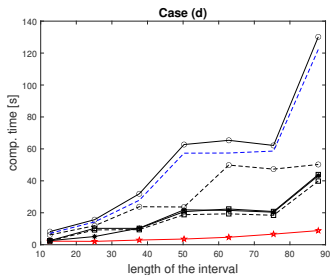
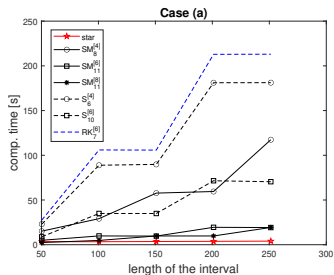
Error order $1e - 7$. Examples and methods for the comparison
from: [Blanes, Casas, Murua, The Journal of Chemical Physics, 2017]

Comparison: accuracy







$N = 400$

Comparison: interval length



$N = 400$, Error order $1e - 7$.

- 1 We introduce a new method for the operator solution of the Rosen-Zener model whose computational cost appears to scale linearly with the size of the problem.
- 2 The method seems to scale linearly also with the length of the domain if we do not include the discretization cost.
- 3 Probably because of the system condition number, the method cannot reach too high accuracy.
- 4 A method for the state vector case has also been introduced.
- 5 This proves that the new \star -approach to ODEs can play a crucial role in the resolution of increasingly large problems from quantum chemistry.

-  P. L. Giscard and S. Pozza, *Appl. Math.* **65**(6), 807–827 (2020).
-  P. L. Giscard and S. Pozza, *Boll. Unione Mat. Ital.* **16**(1), 81–102 (2023).
-  S. Pozza, *arXiv:2302.11375 [math.NA]* (2023).
-  S. Pozza and N. Van Buggenhout, *arXiv:2209.13322, 2209.15533, 2210.07052 [math.NA]* (2022).

Projects

- Charles University PRIMUS research project: *A Lanczos-like Method for the Time-Ordered Exponential*, www.starlanczos.cz.
- French ANR research project: *MAGICA (MAGnetic resonance techniques and Innovative Combinatorial Algebra)*.