

# Méthodes numériques pour des modèles hybrides fluide-cinétique de plasmas

Josselin Massot

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Directeur de thèse :	Nicolas	Crouseilles
Co-Directrice de thèse :	Anaïs	Crestetto

# Outline

- 1 Introduction
- 2 Numerical methods
- 3 Application to hybrid Vlasov-Maxwell model
  - With splitting method
  - With Lawson method
- 4 Numerical results
- 5 Conclusion

# Outline

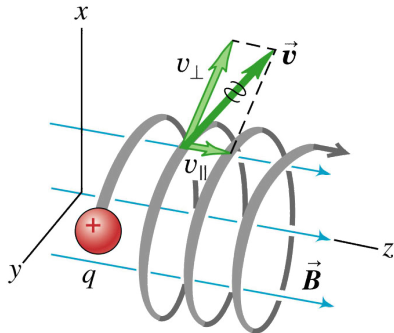
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# Vlasov-Maxwell $1dz - 3dv$ model

Transport of electron density distribution  $f = f(t, z, \mathbf{v})$ ,  
 $\mathbf{B}(t, z) = (B_x, B_y, 0)(t, z)$ ,  $\mathbf{E}(t, z) = (E_x, E_y, 0)(t, z) \in \mathbb{R}^2$ ,  
 $z \in [0, L]$  (periodic),  $\mathbf{B}_0 = (0, 0, B_0)^\top$ ,  $\mathbf{v} \in \mathbb{R}^3$ ,  $\mathbf{v}_\perp = (v_x, v_y, 0)^\top \in \mathbb{R}^2$ :

$$\begin{cases} \partial_t f + v_z \partial_z f - (\mathbf{E} + \mathbf{v} \times (\mathbf{B} + \mathbf{B}_0)) \cdot \nabla_{\mathbf{v}} f = 0 \\ \partial_t \mathbf{B} = J \partial_z \mathbf{E} \\ \partial_t \mathbf{E} = -J \partial_z \mathbf{B} + \int_{\mathbb{R}^3} \mathbf{v}_\perp f \, d\mathbf{v} \end{cases}$$

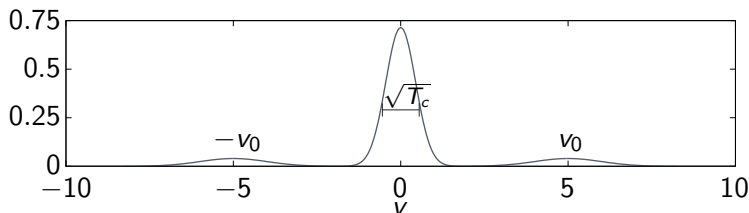
$$J = \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$



# Vlasov-Maxwell $1dz - 3dv$ model

Motivation:

- We want high order methods in  $(z, \mathbf{v})$ 
  - FFT in  $z$  + WENO in  $\mathbf{v}$
- We want high order methods in time  $t$ 
  - splitting method vs exponential integrator



- We consider an initial condition of the form  $f = f_c + f_h$  with:  
 $f_c(t=0, z, \mathbf{v}) = \rho_c(t, z) \delta_{\mathbf{v}=\mathbf{u}_c(t, z)}(\mathbf{v})$

# The idea

Grid methods can't have an initial condition like:

$$f_0(z, \mathbf{v}) = \underbrace{\rho_{c,0}(z) \delta_{\mathbf{v}-\mathbf{u}_{c,0}}(\mathbf{v})}_{f_{c,0}} + f_{h,0}(z, \mathbf{v})$$

The main idea is to derive a **linearized hybrid fluid/kinetic model**:

- Split  $f = f_c + f_h$  (2 Vlasov equations)
- Compute momentum of  $f_c$ 
  - Cold plasma approximation:  $\frac{T_c}{T_h} \ll 1 \rightarrow f_c(t, z, \mathbf{v}) \rightarrow \mathbf{j}_c(t, z)$
  - Fluid dynamic for cold particles (no velocity grid) ✓
  - Linearized fluid equations
- Hypothesis on hot particles:  $\int_{\mathbb{R}^3} f_h(t, z, \mathbf{v}) d\mathbf{v} \ll \rho_c(t, z)$ 
  - Kinetic dynamic for hot particles



Tronci et al. 2014, *Plasma Physics and Controlled Fusion*



Holderied et al. 2020, *Journal of Computational Physics*

# Linearized hybrid Vlasov-Maxwell $1dz - 3dv$ model

The new model: a nonlinear transport in  $(z, v_x, v_y, v_z) \in \Omega \times \mathbb{R}^3$  of:

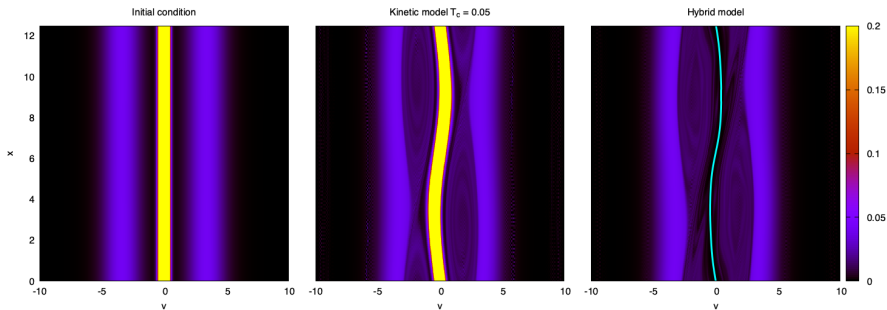
- a cold (fluid) electron density distribution, reconstruction from current variable  $\mathbf{j}_c(t, z) = q_e \rho_c(t, z) \mathbf{u}_c(t, z) = (j_{c,x}, j_{c,y}, 0)(t, z)$
- a hot (kinetic) electron density distribution  $f_h(t, z, \mathbf{v})$

$$\begin{cases} \partial_t \mathbf{j}_c = \Omega_{pe}^2 \mathbf{E} - J \mathbf{j}_c B_0 \\ \partial_t \mathbf{B} = J \partial_z \mathbf{E} \\ \partial_t \mathbf{E} = -J \partial_z \mathbf{B} - \mathbf{j}_c + \int_{\mathbb{R}^3} v_{\perp} f_h d\mathbf{v} \\ \partial_t f_h + v_z \partial_z f_h - (\mathbf{E} + \mathbf{v} \times (\mathbf{B} + \mathbf{B}_0)) \cdot \nabla_{\mathbf{v}} f_h = 0 \end{cases}$$

with:

$$J = \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

# Convergence when $T_c \rightarrow 0$ for 1dx-1dv model



**Figure:** Initial condition (left), solution at  $t = 200$  of the full kinetic model with  $T_c = 0.05$  (middle) and the hybrid model (right).

✓ Good agreement between kinetic ( $f$ ) model and hybrid model ( $f_h + u_c$ )



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Semi-discretization in space-velocity:

- In space  $z$ : we use a Fourier transform (FFT).
- In velocity  $\mathbf{v}$ : we use WENO5 or Lagrange 5.

Two time integrators to compute a numerical solution of abstract model:

$$\dot{u} = L(t, u) + N(t, u), \quad u(0) = u_0$$

$u \in \mathbb{R}^d$ ,  $L$  and  $N$  functions  $(t, u) \in \mathbb{R}_+ \times \mathbb{R}^d \mapsto \mathbb{R}^d$ ,  $d \in \mathbb{N}$ .

- Splitting method (Lie, Strang, Suzuki)
- Lawson method (LRK(4,4), LDP4(3))

# Splitting method

Successive resolution of:

$$\dot{u} = L(t, u) \quad \rightarrow \tilde{u}_t = \varphi_t^{[L]}(u_0)$$

$$\dot{u} = N(t, u) \quad \rightarrow \tilde{u}_t = \varphi_t^{[N]}(u_0)$$

Solution at time  $t$ :

**Lie:** order 1 method, composition of sub-steps:

$$\varphi_t(u_0) \approx \varphi_t^{[L]} \circ \varphi_t^{[N]}(u_0)$$

**Strang:** order 2 method:  $\varphi_t(u_0) \approx \mathcal{S}_t(u_0) = \varphi_{t/2}^{[L]} \circ \varphi_t^{[N]} \circ \varphi_{t/2}^{[L]}(u_0)$



Strang 1968, *SIAM Journal on Numerical Analysis*

**Suzuki:** order 4 method, composition of 5 Strang methods:

$$\varphi_t(u_0) \approx \mathcal{S}_{\alpha_1 t} \circ \mathcal{S}_{\alpha_2 t} \circ \mathcal{S}_{\alpha_3 t} \circ \mathcal{S}_{\alpha_2 t} \circ \mathcal{S}_{\alpha_1 t}(u_0)$$

with:  $\alpha_1 = \alpha_2 = \frac{1}{4 - \sqrt[3]{4}}$  and  $\alpha_3 = \frac{1}{1 - 4\sqrt[3]{2}}$



Suzuki 1990, *Physics Letters A*

# Splitting method

## Pros & Cons

- ✓ Good splitting leads to good long time behavior
- ✓ Error in time only depends on splitting method
- ✓ Split a difficult problem into small easier sub-problems
- ✗ Numerical cost for high order method

$$\dot{u} = Lu + N(t, u)$$

Change of variable:  $v = e^{-tL}u$ , we obtain:

$$\begin{aligned}\dot{v}(t) &= -Le^{-tL}u(t) + e^{-tL} \underbrace{(Lu(t) + N(t, u))}_{\dot{u}(t)} \\ &= e^{-tL}N(t, e^{tL}v)\end{aligned}$$

which can be solved with a **Runge-Kutta method** in  $v$ , that can be rewritten in  $u$ . For example with Euler method:

$$v(t^n + \Delta t) \approx v^{n+1} = v^n + \Delta t e^{-t^n L} N(t^n, e^{t^n L} v^n)$$

which can be rewritten, in terms of  $u$ :

$$u^{n+1} = e^{\Delta t L} u^n + \Delta t e^{\Delta t L} N(t^n, u^n)$$

 Lawson 1967, *SIAM Journal on Numerical Analysis*

 Hochbruck and Ostermann 2010, *Acta Numerica*

 Hochbruck, Leibold, and Ostermann 2020, *Numerische Mathematik*

# Lawson method

## Pros & Cons

- ✓ Numerically efficient (order increases linearly-ish with the number of stages)
- ✓ Literature on Runge-Kutta method (embedded-RK, low storage methods, IMEX methods, DIRK methods. . .)
- ✓ Linear part is solved exactly
- ✗ Stability constraint (not from the linear part ✓)
- ✗ Long time behavior
- ~ Needs to compute (efficiently)  $e^{\tau L}$  for any  $\tau = c_j \Delta t$  and  $L$

# Main idea of adaptive time step methods (error estimate)

For a generic ODE  $\dot{u} = f(t, u)$ , adaptive time step method needs 2 numerical approximations of  $u(t^{n+1})$  of different order,  $p$  and  $p + 1$ :

$$u_{[p]}^{n+1} = u(t^{n+1}) + \mathcal{O}(\Delta t^{p+1}), \quad u_{[p+1]}^{n+1} = u(t^{n+1}) + \mathcal{O}(\Delta t^{p+2})$$

Estimate of local error:  $L_{[p]}^{n+1} = \left| u_{[p+1]}^{n+1} - u_{[p]}^{n+1} \right|$

**If**  $L_{[p]}^{n+1} > \text{tol}$ : we reject the step and start again from time  $t^n$ . **Else** we accept the step. **In both cases**, the optimal new time step is:

$$\Delta t_{\text{opt}} = \sqrt[p]{\frac{\text{tol}}{L_{[p]}^{n+1}}} \Delta t^n$$

In practice  $u_{[p]}^{n+1}$  is computed from sub-steps of  $u_{[p+1]}^{n+1}$ .



Dormand and Prince 1978, *Celestial mechanics* (for RK method)



Blanes, Casas, and Thalhammer 2019, *Applied Numerical Mathematics* (for splitting method)

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# Linearized hybrid Vlasov-Maxwell model

$$U = (\mathbf{j}_c, \mathbf{B}, \mathbf{E}, f_h)^\top, \mathbf{j}_c(t, z), \mathbf{B}(t, z), \mathbf{E}(t, z) \in \mathbb{R}^2, f_h(t, z, \mathbf{v}) \in \mathbb{R}$$

$$\begin{cases} \partial_t \mathbf{j}_c = \Omega_{pe}^2 \mathbf{E} - J \mathbf{j}_c B_0 \\ \partial_t \mathbf{B} = J \partial_z \mathbf{E} \\ \partial_t \mathbf{E} = -J \partial_z \mathbf{B} - \mathbf{j}_c + \int v_\perp f_h d\mathbf{v}_\perp \\ \partial_t f_h + v_z \partial_z f_h - (\mathbf{E} + \mathbf{v} \times (\mathbf{B} + \mathbf{B}_0)) \cdot \nabla_{\mathbf{v}} f_h = 0 \end{cases}$$

we define the Hamiltonian as :

$$\begin{aligned} \mathcal{H} = & \underbrace{\frac{1}{2} \int \|\mathbf{E}\|^2 dz}_{\mathcal{H}_E} + \underbrace{\frac{1}{2} \int \|\mathbf{B}\|^2 dz}_{\mathcal{H}_B} + \underbrace{\frac{1}{2} \int \frac{1}{\Omega_{pe}^2} \|\mathbf{j}_c\|^2 dz}_{\mathcal{H}_{j_c}} \\ & + \underbrace{\frac{1}{2} \int \int \|\mathbf{v}\|^2 f_h d\mathbf{v} dz}_{\mathcal{H}_{f_h}} \end{aligned}$$

This Hamiltonian is the basis of a splitting.

# Splitting method

4 subsystems  $\varphi^{[E]}$ ,  $\varphi^{[B]}$ ,  $\varphi^{[j_c]}$ ,  $\varphi^{[f_h]}$

- Solution with Lie splitting method:

$$U^{n+1} = \varphi_{\Delta t}^{[E]} \circ \varphi_{\Delta t}^{[B]} \circ \varphi_{\Delta t}^{[j_c]} \circ \varphi_{\Delta t}^{[f_h]}(U^n)$$

- or Strang method:

$$U^{n+1} = \varphi_{\Delta t/2}^{[E]} \circ \varphi_{\Delta t/2}^{[B]} \circ \varphi_{\Delta t/2}^{[j_c]} \circ \varphi_{\Delta t}^{[f_h]} \circ \varphi_{\Delta t/2}^{[j_c]} \circ \varphi_{\Delta t/2}^{[B]} \circ \varphi_{\Delta t/2}^{[E]}(U^n)$$

## Numerical cost:

- $\varphi^{[B]}$  and  $\varphi^{[j_c]}$ : almost free ( $\mathcal{O}(N_z)$ )
- $\varphi^{[E]}$ : moderately expensive ( $\mathcal{O}(N_z)$  + loop on phase space)
- $\varphi^{[f_h]}$ : extremely expensive (multiple loops on phase space)

# Splitting method

Example with:  $\varphi^{[E]}$

One of sub-steps of Hamiltonian splitting:

$$\varphi^{[E]}(U) = \begin{cases} \partial_t \mathbf{j}_c = \Omega_{pe}^2 \mathbf{E} \\ \partial_t \mathbf{B} = J \partial_z \mathbf{E} \\ \partial_t \mathbf{E} = 0 \\ \partial_t f_h = \mathbf{E} \cdot \nabla_{v_\perp} f_h \end{cases} \rightarrow \varphi_t^{[E]}(U^0) = \begin{pmatrix} \mathbf{j}_c(0) + t\Omega_{pe}^2 \mathbf{E}(0) \\ \mathbf{B}(0) + tJ\partial_z \mathbf{E}(0) \\ \mathbf{E}(0) \\ f_h(0, z, v_\perp + t\mathbf{E}(0), v_z) \end{pmatrix}$$

## Numerical tools:

- 2D interpolation using two 5th-Lagrange interpolations to approximate  $f_h(0, z, v_\perp + t\mathbf{E}(0), v_z)$

# Lawson method

$$U = (\mathbf{j}_c, \mathbf{B}, \mathbf{E}, f_h)^\top$$

$$\dot{U} = LU + N(t, U)$$

with:

$$L = \begin{pmatrix} 0 & -B_0 & 0 & 0 & \Omega_{pe}^2 & 0 & 0 \\ B_0 & 0 & 0 & 0 & 0 & \Omega_{pe}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \partial_z & 0 \\ 0 & 0 & 0 & 0 & -\partial_z & 0 & 0 \\ -1 & 0 & 0 & -\partial_z & 0 & 0 & 0 \\ 0 & -1 & \partial_z & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -v_z \partial_z \end{pmatrix}, \quad N:(t, U) \mapsto \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \int v_x f_h d\mathbf{v} \\ \int v_y f_h d\mathbf{v} \\ (\mathbf{E} + \mathbf{v} \times \mathbf{B}) \cdot \nabla_{\mathbf{v}} f_h \end{pmatrix}$$

But  $e^{\tau L}$  can't be computed even with symbolic computation software.

# How to compute $e^{\tau L}$ ?

2 solutions are proposed:

- 1 Remove some terms of the linear part  $L$  and put them in nonlinear part  $N$ .
  - ✓ symbolic computation to write efficient code
  - ✗ add CFL stability condition
- 2 Approximate  $e^{\tau L}$  with Taylor series or Padé approximant.
  - ✓ no CFL stability from all (local) linear terms
  - ✗ add error of approximation

# Remove terms

Remove Maxwell equations from linear part  $L$ , and add them in nonlinear term  $N$ :

$$L = \begin{pmatrix} 0 & -B_0 & 0 & 0 & \Omega_{pe}^2 & 0 & 0 \\ B_0 & 0 & 0 & 0 & 0 & \Omega_{pe}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -v_z \partial_z \end{pmatrix}, \quad N(t, U) = \begin{pmatrix} 0 \\ 0 \\ \partial_z E_y \\ -\partial_z E_x \\ -\partial_z B_y + \int v_x f_h d\mathbf{v} \\ \partial_z B_x + \int v_y f_h d\mathbf{v} \\ (\mathbf{E} + \mathbf{v} \times \mathbf{B}) \cdot \nabla_{\mathbf{v}} f_h \end{pmatrix}$$

- ✓  $e^{\tau L}$  is exactly computed with symbolic computation
- ✗ Add a CFL stability condition in  $z$  (coming from explicit resolution of [Maxwell equations](#)) which can be estimated.

# Approximation of $e^{\tau L}$

Complete linear part  $L$ , after Fourier transform in  $z$ :  $\partial_z \mapsto i\kappa$

$$L = \begin{pmatrix} 0 & -B_0 & 0 & 0 & \Omega_{pe}^2 & 0 & 0 \\ B_0 & 0 & 0 & 0 & 0 & \Omega_{pe}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & i\kappa & 0 \\ 0 & 0 & 0 & 0 & -i\kappa & 0 & 0 \\ -1 & 0 & 0 & -i\kappa & 0 & 0 & 0 \\ 0 & -1 & i\kappa & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -i\kappa v_z \end{pmatrix}$$

We have:

$$\forall \kappa, \sigma(L(\kappa)) \subset i\mathbb{R}$$

So that :  $\text{sp}(e^{\tau L(\kappa)}) \subset \mathcal{C}(0,1)$  **IMPORTANT** for numerical stability !

# Taylor series

Simplest approximation:

$$T_p(\tau L) = \sum_{k=0}^p \frac{\tau^k}{k!} L^k = e^{\tau L} + \mathcal{O}(\tau^{p+1})$$

## Proposition

Bad behavior of eigenvalues of Taylor series

*Proof:* compute Taylor series outside of its convergence radius

## Conclusion:

- ✗ Bad behavior of eigenvalues
- ✗ Numerical instability in scheme



# Padé approximant

Best rational approximation of exponential function.

Defined (for order  $(p, q)$ ) as:

$$h_{p,q}(M) = \sum_{i=0}^p \frac{\frac{p!}{(p-i)!}}{\frac{(p+q)!}{(p+q-i)!}} \frac{M^i}{i!} \quad , \quad k_{p,q}(M) = \sum_{j=0}^q (-1)^j \frac{\frac{q!}{(q-j)!}}{\frac{(p+q)!}{(p+q-j)!}} \frac{M^j}{j!}$$

Finally Padé approximant is:

$$P_{p,q}(\tau L) = h_{p,q}(\tau L) (k_{p,q}(\tau L))^{-1} = e^{\tau L} + \mathcal{O}(\tau^{p+q+1})$$

## Theorem

$$sp(L) \subset i\mathbb{R} \implies sp(P_{p,p}(tL)) \subset \mathcal{C}(0, 1)$$

## Conclusion:

✗ Needs matrix inversion, or some tricks:



Li, Zhu, and Gu 2011, *Applied Mathematics*

- ✓ Best approximation for this numerical cost
- ✓ Preserves eigenvalues

$L$  diagonalizable  $\rightarrow$  study only on diagonal terms ( $iy, y \in \mathbb{R}$ )

$$P_{p,p}(iy) = \left( \sum_{k=0}^p \frac{1}{k!} (iy)^k \right) \cdot \left( \sum_{\ell=0}^p (-1)^\ell \frac{1}{\ell!} (iy)^\ell \right)^{-1}$$

$$\begin{aligned} \sum_{k=0}^p \frac{1}{k!} (iy)^k &= \sum_{k=0}^{\lfloor \frac{p}{2} \rfloor} (-1)^k \frac{y^{2k}}{(2k)!} + i \sum_{k=0}^{\lfloor \frac{p}{2} \rfloor - 1} (-1)^k \frac{y^{2k+1}}{(2k+1)!} \\ \sum_{\ell=0}^p (-1)^\ell \frac{1}{\ell!} (iy)^\ell &= \sum_{\ell=0}^{\lfloor \frac{p}{2} \rfloor} (-1)^\ell \frac{y^{2\ell}}{(2\ell)!} - i \sum_{\ell=0}^{\lfloor \frac{p}{2} \rfloor - 1} (-1)^\ell \frac{y^{2\ell+1}}{(2\ell+1)!} \end{aligned}$$

$$\lambda^- = \overline{\lambda^+} \text{ so } \left| \frac{\lambda^+}{\lambda^-} \right| = 1.$$

# Eigenvalues of symmetric Padé approximants

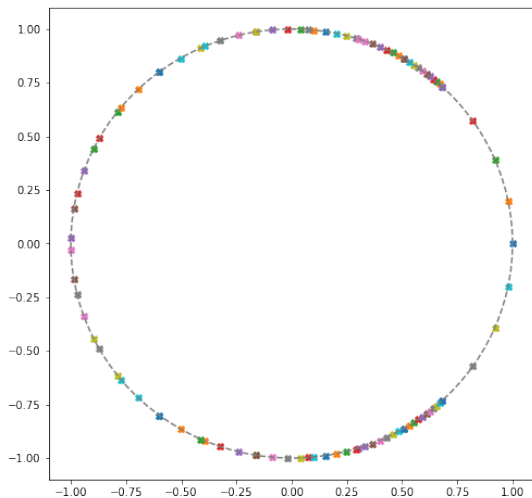


Figure:  $P_{2,2}(iy)$   $y \in [-5, 5]$

# Eigenvalues of asymmetric Padé approximants

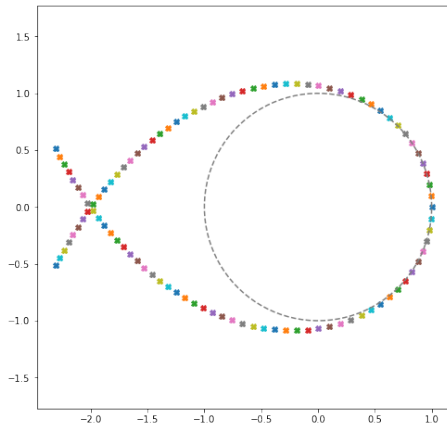


Figure:  $P_{2,1}(iy)$   $y \in [-5, 5]$

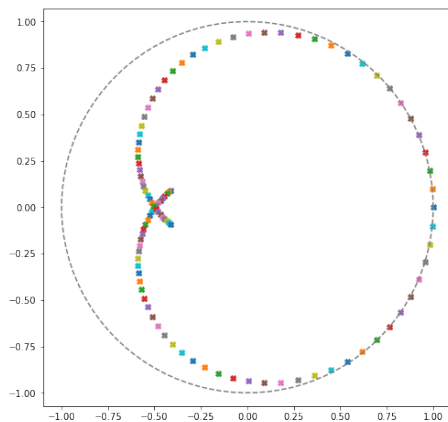


Figure:  $P_{1,2}(iy)$   $y \in [-5, 5]$

We can also approximate  $e^{\tau L}$  with truncated BCH formula (or splitting method):

$$L = \underbrace{\begin{pmatrix} 0 & -B_0 & 0 & 0 & \Omega_{pe}^2 & 0 & 0 \\ B_0 & 0 & 0 & 0 & 0 & \Omega_{pe}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -iV_Z\kappa \end{pmatrix}}_{L_1} + \underbrace{\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & i\kappa & 0 \\ 0 & 0 & 0 & 0 & -i\kappa & 0 & 0 \\ 0 & 0 & 0 & -i\kappa & 0 & 0 & 0 \\ 0 & 0 & i\kappa & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}}_{L_2}$$

$$S_\tau(L) = e^{\frac{\tau}{2}L_1} e^{\tau L_2} e^{\frac{\tau}{2}L_1} = e^{\tau L} + \mathcal{O}(\tau^3)$$

# Error on approximate Lawson method

We note  $P_{p,q}(z) = \epsilon^z$ . We recall:

$$\epsilon^{\tau L} = e^{\tau L} + \mathcal{O}(\tau^{r+1}), \quad \text{with } r = p + q$$

After some calculations, Lawson RK(3,3) rewrites:

$$\begin{aligned} u^{(1)} &= \epsilon^{\Delta t L} u^n + \Delta t \epsilon^{\Delta t L} N(t^n, u^n) \\ u^{(2)} &= \frac{3}{4} \epsilon^{\frac{\Delta t}{2} L} u^n + \frac{1}{4} \epsilon^{-\frac{\Delta t}{2} L} u^{(1)} + \frac{\Delta t}{4} \epsilon^{-\frac{\Delta t}{2} L} N(t^n + \Delta t, u^{(1)}) \\ u^{n+1} &= \frac{1}{3} \epsilon^{\Delta t L} u^n + \frac{2}{3} \epsilon^{\frac{\Delta t}{2} L} u^{(2)} + \frac{2}{3} \Delta t \epsilon^{\frac{\Delta t}{2} L} N(t^n + \frac{\Delta t}{2}, u^{(2)}) \end{aligned}$$

**If**  $L$  and  $N$  commute:  $u^{n+1} = \epsilon^{\Delta t L} \left( I + N + \frac{N^2}{2} + \frac{N^3}{6} \right) u^n$ , stability is same as RK(3,3).



Crouseilles, Einkemmer, and Massot 2020, *Journal of Computational Physics*  
study of Lawson stability in scalar case

**Else...**

# Error on approximate Lawson method

If  $L$  and  $N$  don't commute:

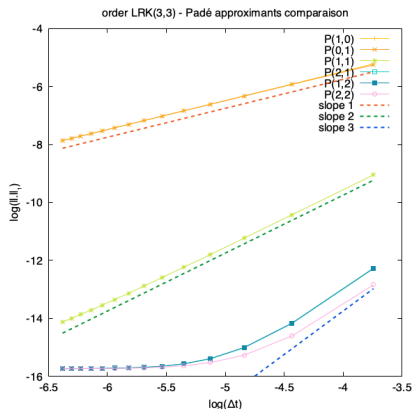
$$\begin{aligned} u^{n+1} &= \left[ e^{\Delta t L} + \Delta t \left( \frac{2}{3} e^{\frac{\Delta t}{2} L} N e^{\frac{\Delta t}{2} L} + \frac{1}{6} e^{\Delta t L} N + \frac{1}{6} N e^{\Delta t L} \right) \right. \\ &\quad \rightsquigarrow e^{\Delta t L} \Delta t N + \mathcal{O}(\Delta t^{r+1}) \\ &\quad + \frac{\Delta t^2}{2} \left( \frac{1}{3} N e^{\Delta t L} N + \frac{1}{3} e^{\frac{\Delta t}{2} L} N e^{\frac{\Delta t}{2} L} N + \frac{1}{3} e^{\frac{\Delta t}{2} L} N e^{-\frac{\Delta t}{2} L} N e^{\Delta t L} \right) \\ &\quad \rightsquigarrow e^{\Delta t L} \frac{(\Delta t N)^2}{2} + \mathcal{O}(\Delta t^{r+1}) \\ &\quad \left. + \frac{\Delta t^3}{6} e^{\frac{\Delta t}{2} L} N e^{-\frac{\Delta t}{2} L} N e^{\Delta t L} N \right] u^n \rightsquigarrow e^{\Delta t L} \frac{(\Delta t N)^3}{6} + \mathcal{O}(\Delta t^{r+1}) \end{aligned}$$

## Lemma

Truncature error of modified Lawson RK( $s, m$ ) is  $\mathcal{O}(\Delta t^{\min(r, m)})$

# Test 1: measure of order

Simulation of  $\partial_t u + a\partial_x u + b\partial_y u = 0$  (2D translation test case).

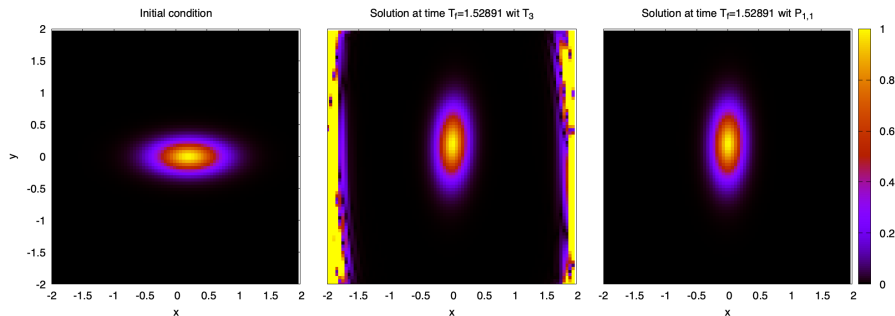


**Figure:** Convergence order of modified Lawson RK(3,3) methods with Padé approximant ( $p, q = 0, 1, 2$ )



## Test 2: illustration of instability or stability

Simulation of  $\partial_t u - y\partial_x u + x\partial_y u = 0$  (2D rotation)



**Figure:** Solution of the modified Lawson RK(3,3) methods with Taylor  $T_3$  (middle) and Padé  $P_{1,1}$  (right).

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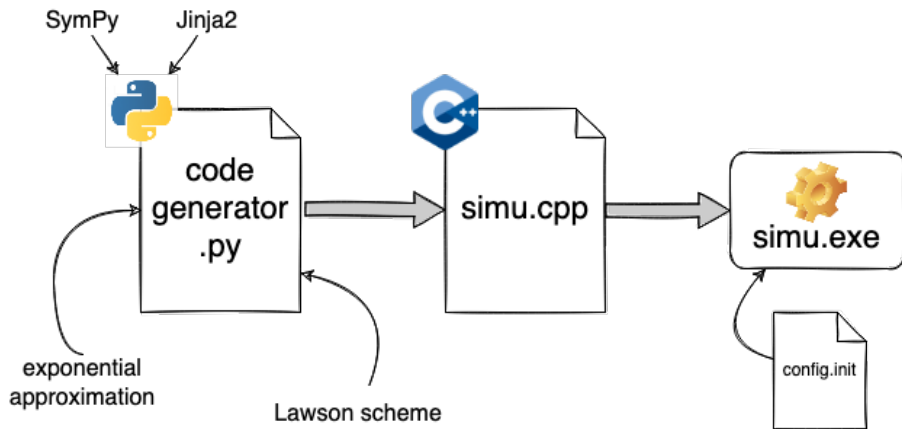
# Numerical results

We compare:

- Splitting method:
  - Strang (order 2)
  - Suzuki (order 4)
- Lawson method:
  - LRK(4,4) (order 4)
  - LDP4(3) (adaptive time step method)
- Modified Lawson method with Padé:
  - LRK(4,4) with Padé (2,2) (order 4 + approximation of order  $2 + 2 = 4$ )
  - LDP4(3) with Padé (2,2) (adaptive time step method)

**But** Padé approximant implies a huge rational function (with invert of matrix), high order Lawson methods have a lot of coefficients, with 7 variables problem... → bug source !!!

# Code generator



# Numerical test

Anisotropic equilibrium, Weibel instability:

$$\begin{cases} \mathbf{j}_c(t=0, z) = 0 \\ \mathbf{B}(t=0, z) = (\epsilon \sin(Kz), 0, 0) \\ \mathbf{E}(t=0, z) = 0 \\ f_h(t=0, z, \mathbf{v}) = \frac{\rho_h}{(2\pi)^{3/2} \bar{v}_\perp^2 \bar{v}_\parallel} \exp\left(-\frac{v_z^2}{2\bar{v}_\parallel^2} - \frac{(v_x^2 + v_y^2)}{2\bar{v}_\perp^2}\right) \end{cases}$$

with  $z \in [0, \frac{2\pi}{K}]$ ,  $\mathbf{v} \in [-3.6, 3.6] \times [-3.6, 3.6] \times [-2.4, 2.4]$ ,  $K = 2$ ,  $\bar{v}_\parallel = 0.2$ ,  $\bar{v}_\perp = 0.6$ ,  $\rho_h = 0.2$  and  $\epsilon = 10^{-5}$ .

**Compare energies:**

$$\mathcal{H}_E(t) = \frac{1}{2} \int \|\mathbf{E}(t, z)\|^2 dz \quad \mathcal{H}_B(t) = \frac{1}{2} \int \|\mathbf{B}(t, z)\|^2 dz$$

$$\mathcal{H}_c(t) = \frac{1}{2\Omega_{pe}^2} \int \|\mathbf{j}_c(t, z)\|^2 dz$$

# Numerical results: splitting vs Lawson

$$N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$$

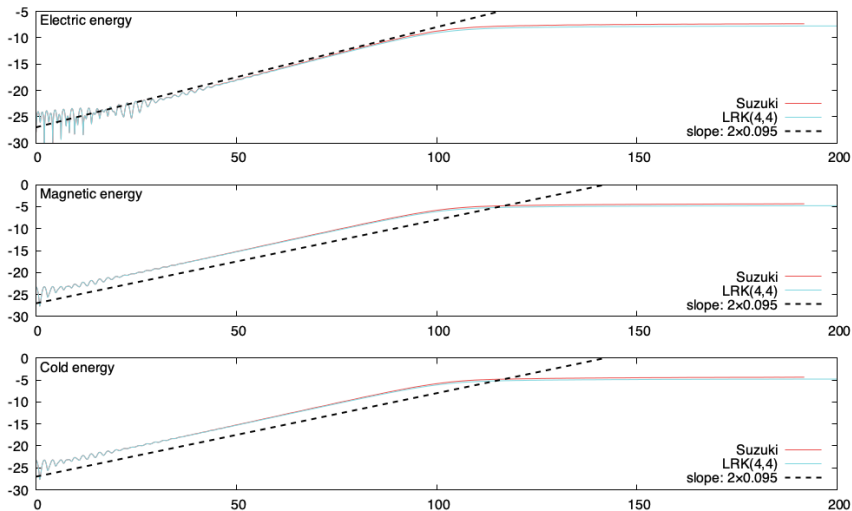


Figure: Energies evolution,  $\Delta t = 0.05$

# Numerical results: splitting vs Lawson

$$N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$$

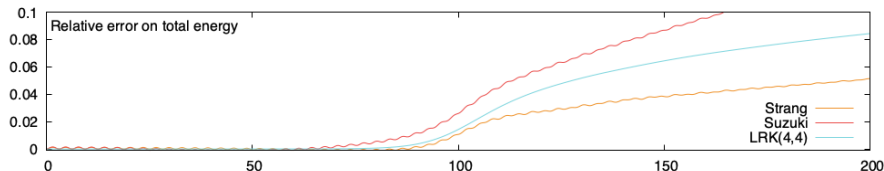


Figure: Relative error on total energy,  $\Delta t = 0.05$

# Numerical results: splitting vs Lawson

$$N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$$

time integrator	simulation time
Lie splitting	13 h 25 min 10 s
Strang splitting	17 h 09 min 54 s
Suzuki splitting	3 j 03 h 05 min 24 s
LRK(3,3)	11 h 29 min 09 s
LRK(4,4)	14 h 06 min 15 s

**Table:** Computational time for the different methods, on mesh  $N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$  and time step  $\Delta t = 0.05$ .



# Numerical results: Padé-Lawson

$$N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$$

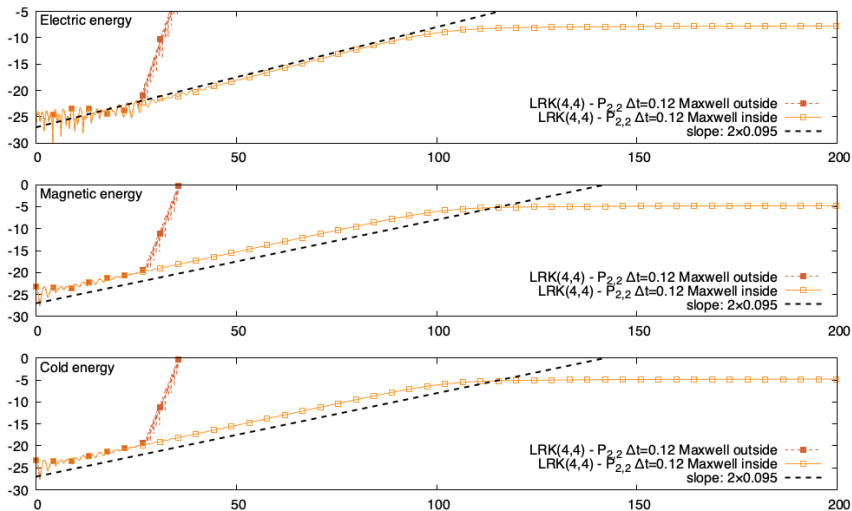


Figure: Energies evolution, Lawson with Padé approximation,  $\Delta t = 0.12$

# Numerical results: Padé-Lawson adaptive time step

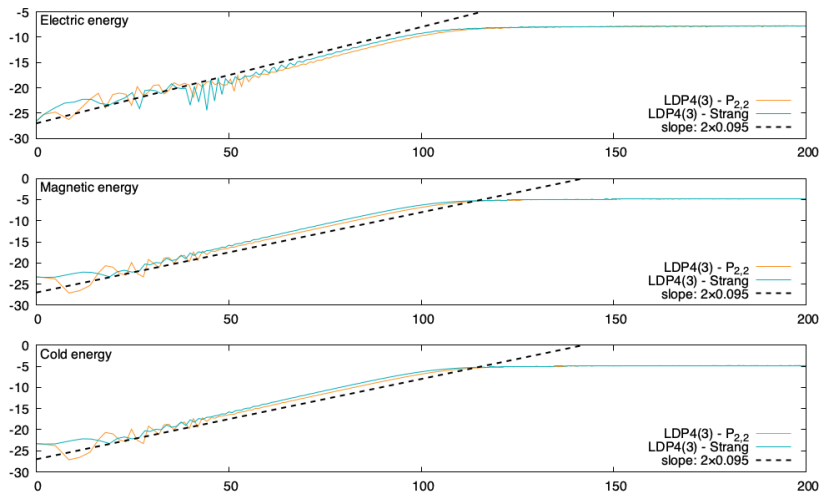


Figure: Energies evolution, Lawson with Padé approximation,  $\Delta t^n$

# Numerical results: Padé-Lawson adaptive time step

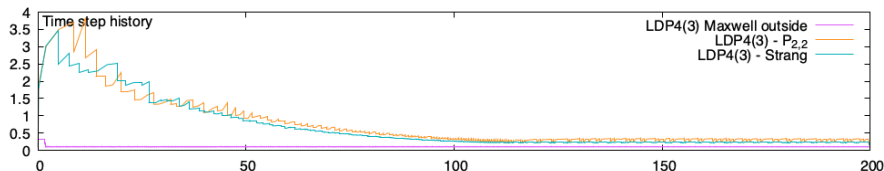


Figure: Time step evolution, classic Lawson (Maxwell outside) and approximate Lawson with Padé or Strang approximation,  $\Delta t_n$

method	# of iterations	# of succeeded	ratio
LDP4(3) (Maxwell outside)	2794	1970	0.705
LDP4(3)-P <sub>2,2</sub>	919	464	0.504
LDP4(3)-Strang	1131	583	0.515

# Computational time

time integrator	simulation time
LRK(3,3)	11 h 29 min 09 s
LRK(3,3) - $P_{1,1}$	10 h 54 min 11 s
LRK(3,3) - $P_{2,2}$	10 h 55 min 26 s
LRK(4,4)	14 h 06 min 15 s
LRK(4,4) - $P_{2,2}$	13 h 59 min 59 s
LDP4(3)	11 h 44 min 04 s
LDP4(3) - $P_{2,2}$	04 h 09 min 44 s
LDP4(3) - Strang	04 h 42 min 25 s

**Table:** Computational time for the different methods, on mesh  $N_z \times N_{v_x} \times N_{v_y} \times N_{v_z} = 27 \times 32 \times 32 \times 41$  and time step  $\Delta t = 0.05$  (initial time step for adaptive time step strategy).

# Outline

- 1 Introduction
- 2 Numerical methods
- 3 Application to hybrid Vlasov-Maxwell model
  - With splitting method
  - With Lawson method
- 4 Numerical results
- 5 Conclusion

# Conclusion

- ✓ Numerical estimation of CFL with Python package: Ponio<sup>1</sup>
- ✓ Comparison between kinetic model and hybrid model thanks dispersion relation and simulations
- ✗ Numerical cost of splitting methods (not bad in  $1dz - 1dv$  but very bad in  $1dz - 3dv$ , must be very very very bad in  $3dx - 3dv$ )
- ✓ Numerical cost of Lawson methods
- ~ Behavior of total energy of Lawson method (but we can use high order method easily)
- ✓ Error of approximation with Padé approximant can be lower than time integrator
- ✓ Adaptive time step method with any linear part thanks to approximation of exponential function

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<sup>1</sup><http://jmassot.perso.math.cnrs.fr/ponio.html>

- Add  $\int \mathbf{v} f_h d\mathbf{v}$  in linear part (for  $1dx - 1dv$  model) **WIP**
- Improve code generator (easy to use for other problem) **WIP**
- Parallelized with OpenMP or OpenACC (GPU)
- Combining Lawson integrator to semi-Lagrangian methods
- Comparison with PIC simulation (code developed in IPP Max Planck, Garching)
- Construction of energy preserving Lawson method

Thank you for your attention







Blanes, Casas, and Thalhammer 2019, *Applied Numerical Mathematics* for Suzuki splitting method

$$u_{[4]}^{n+1} = \mathcal{S}_{\Delta t}(u^n) = S_{\alpha_1 \Delta t} \circ S_{\alpha_2 \Delta t} \circ S_{\alpha_3 \Delta t} \circ S_{\alpha_2 \Delta t} \circ \underbrace{S_{\alpha_1 \Delta t}(u^n)}_{u^{(1)}}.$$

$$\underbrace{\hspace{15em}}_{u^{(2)}}$$

$$\underbrace{\hspace{15em}}_{u^{(3)}}$$

$$\underbrace{\hspace{15em}}_{u^{(4)}}$$

We compute an order 3 approximation from  $U^n$  and  $U^{(s)}$ ,  $s = 1, 2, 3, 4$  :

$$u_{[3]}^{n+1} = -u^n + w_1(u^{(1)} + u^{(4)}) + w_2(u^{(2)} + u^{(3)})$$

with:

$$w_1 = \frac{g_2(1 - g_2)}{g_1(g_1 - 1) - g_2(g_2 - 1)}, \quad w_2 = 1 - w_1, \quad \begin{aligned} g_1 &= \alpha_1 \\ g_2 &= \alpha_1 + \alpha_2 \end{aligned}$$

and  $L_{[3]}^n = \left\| u_{[4]}^{n+1} - u_{[3]}^{n+1} \right\|_2$



For two given functionals  $\mathcal{F}, \mathcal{G}$  of  $\mathbf{j}_c, \mathbf{B}, \mathbf{E}, f_h$ , the Poisson bracket is given by

$$\begin{aligned}
 \{\mathcal{F}, \mathcal{G}\}[\mathbf{j}_c, \mathbf{B}, \mathbf{E}, f_h] = & \frac{1}{m_e} \int_{\Omega} \int_{\mathbb{R}^3} f_h \left[ \frac{\delta \mathcal{F}}{\delta f_h}, \frac{\delta \mathcal{G}}{\delta f_h} \right]_{\mathbf{x}\mathbf{v}} d\mathbf{v} d\mathbf{x} \\
 & + \frac{q_e}{m_e \varepsilon_0} \int_{\Omega} \int_{\mathbb{R}^3} f_h \left( \nabla_{\mathbf{v}} \frac{\delta \mathcal{F}}{\delta f_h} \cdot \frac{\delta \mathcal{G}}{\delta \mathbf{E}} - \nabla_{\mathbf{v}} \frac{\delta \mathcal{G}}{\delta f_h} \cdot \frac{\delta \mathcal{F}}{\delta \mathbf{E}} \right) d\mathbf{v} d\mathbf{x} \\
 & + \frac{q_e}{m_e^2} \int_{\Omega} \int_{\mathbb{R}^3} f_h (\mathbf{B} + \mathbf{B}_0) \cdot \left( \nabla_{\mathbf{v}} \frac{\delta \mathcal{F}}{\delta f_h} \times \nabla_{\mathbf{v}} \frac{\delta \mathcal{G}}{\delta f_h} \right) d\mathbf{v} d\mathbf{x} \\
 & + \frac{1}{\varepsilon_0} \int_{\Omega} \left( \nabla \times \frac{\delta \mathcal{F}}{\delta \mathbf{E}} \cdot \frac{\delta \mathcal{G}}{\delta \mathbf{B}} - \nabla \times \frac{\delta \mathcal{G}}{\delta \mathbf{E}} \cdot \frac{\delta \mathcal{F}}{\delta \mathbf{B}} \right) d\mathbf{x} \\
 & + \int_{\Omega} \Omega_{pe}^2 \left( \frac{\delta \mathcal{F}}{\delta \mathbf{j}_c} \cdot \frac{\delta \mathcal{G}}{\delta \mathbf{E}} - \frac{\delta \mathcal{G}}{\delta \mathbf{j}_c} \cdot \frac{\delta \mathcal{F}}{\delta \mathbf{E}} \right) d\mathbf{x} \\
 & + \frac{q_e \varepsilon_0}{m_e} \int_{\Omega} \Omega_{pe}^2 \mathbf{B}_0 \cdot \left( \frac{\delta \mathcal{F}}{\delta \mathbf{j}_c} \times \frac{\delta \mathcal{G}}{\delta \mathbf{j}_c} \right) d\mathbf{x}.
 \end{aligned}$$

$$\varphi^{[j_c]}(U) = \begin{cases} \partial_t \mathbf{j}_c = -J \mathbf{j} B_0 \\ \partial_t \mathbf{B} = 0 \\ \partial_t \mathbf{E} = -\mathbf{j}_c \\ \partial_t f_h = 0 \end{cases} \rightarrow \varphi_t^{[j_c]}(U^0) = \begin{pmatrix} e^{-tJ} \mathbf{j}_c(0) B_0 \\ \mathbf{B}(0) \\ \mathbf{E}(0) - J(e^{-tJ} - I) \mathbf{j}_c(0) \\ f_h(0) \end{pmatrix}$$

Obtain because:  $\int_0^t \exp(-sJ) \mathbf{j}_c(0) ds = J(\exp(-tJ) - I) \mathbf{j}_c(0)$ , with:

$$\exp(-tJ) = \begin{pmatrix} \cos(t) & -\sin(t) \\ \sin(t) & \cos(t) \end{pmatrix}$$

$$\varphi^{[B]}(U) = \begin{cases} \partial_t \mathbf{j}_c = 0 \\ \partial_t \mathbf{B} = 0 \\ \partial_t \mathbf{E} = -J \partial_z \mathbf{B} \\ \partial_t f_h = 0 \end{cases} \rightarrow \varphi_t^{[B]}(U^0) = \begin{pmatrix} \mathbf{j}_c(0) \\ \mathbf{B}(0) \\ \mathbf{E}(0) - tJ \partial_z \mathbf{B}(0) \\ f_h(0) \end{pmatrix}$$

### Numerical tools:

- Solve in Fourier space

$$\varphi^{[E]}(U) = \begin{cases} \partial_t \mathbf{j}_c = \Omega_{pe}^2 \mathbf{E} \\ \partial_t \mathbf{B} = J \partial_z \mathbf{E} \\ \partial_t \mathbf{E} = 0 \\ \partial_t f_h = \mathbf{E} \cdot \nabla_{\mathbf{v}} f_h \end{cases} \rightarrow \varphi_t^{[E]}(U^0) = \begin{pmatrix} \mathbf{j}_c(0) + t\Omega_{pe}^2 \mathbf{E}(0) \\ \mathbf{B}(0) + tJ\partial_z \mathbf{E}(0) \\ \mathbf{E}(0) \\ f_h(0, z, \mathbf{v} + t\mathbf{E}(0), v_z) \end{pmatrix}$$

### Numerical tools:

- 2D interpolation with 2 Lagrange 5 interpolations to approximate  $f_h(0, z, \mathbf{v} + t\mathbf{E}(0), v_z)$

$$\varphi^{[f_h]}(U) = \begin{cases} \partial_t \mathbf{j}_c = 0 \\ \partial_t \mathbf{B} = 0 \\ \partial_t \mathbf{E} = \int \mathbf{v} f_h \, d\mathbf{v} \\ \partial_t f_h = -v_z \partial_z f_h + (\mathbf{v} \times (\mathbf{B} + \mathbf{B}_0)) \cdot \nabla_{\mathbf{v}} f_h \end{cases}$$

This step is split again onto 3 parts.



$$\varphi^{[f_{h,x}]}(U) = \begin{cases} \partial_t \mathbf{j}_c = 0 \\ \partial_t \mathbf{B} = 0 \\ \partial_t E_x = \int v_x f_h d\mathbf{v} \\ \partial_t E_y = 0 \\ \partial_t f_h = -v_x B_0 \partial_{v_y} f_h + v_x B_y \partial_{v_z} f_h \end{cases} \rightarrow \varphi_t^{[f_{h,x}]}(U^0) = \begin{pmatrix} \mathbf{j}_c(0) \\ \mathbf{B}(0) \\ E_x(0) + t \int v_x f_h(0) d\mathbf{v} \\ E_y(0) \\ f_h(0, z, v_x, v_y - t v_x B_0, v_z + t B_y v_x) \end{pmatrix}$$

### Numerical tools:

- 2D interpolation with Lagrange 5 interpolation to approximate  $f_h(0, z, v_x, v_y - t v_x B_0, v_z + t B_y v_x)$

Same thing for  $\varphi^{[f_{h,y}]}$  in  $v_y$  direction.

$$\varphi^{[f_{h,z}]}(U) = \begin{cases} \partial_t \mathbf{j}_c = 0 \\ \partial_t \mathbf{B} = 0 \\ \partial_t \mathbf{E} = 0 \\ \partial_t f_h = -v_z \partial_z f_h + (-v_z B_y \partial_{v_x} f_h + v_z B_x \partial_{v_y} f_h) \end{cases}$$

## Numerical tools:

- Split **again** onto 3 parts, with change of variable  $g(t, z, \mathbf{v}) := f(t, z + tv_z, \mathbf{v})$
- 2D interpolation with Lagrange 5 interpolation to approximate  $g(0, z, v_x - \sum_k \hat{B}_y(0, k) \frac{1}{ik} e^{ikz} (e^{iktv_z} - 1), v_y + \sum_k \hat{B}_x(0, k) \frac{1}{ik} e^{ikz} (e^{iktv_z} - 1), v_z)$
- Revert change of variable with Fourier transform

For Lie method:

$$U^{n+1} = \varphi_{\Delta t}^{[j_c]} \circ \varphi_{\Delta t}^{[B]} \circ \varphi_{\Delta t}^{[E_{v_x}]} \circ \varphi_{\Delta t}^{[E_{v_y}]} \circ \varphi_{\Delta t}^{[f_{h,x,v_x}]} \circ \varphi_{\Delta t}^{[f_{h,x,v_z}]} \circ \varphi_{\Delta t}^{[f_{h,y,v_y}]} \circ \varphi_{\Delta t}^{[f_{h,y,v_z}]} \circ \varphi_{\Delta t}^{[f_{h,z,1}]} \circ \varphi_{\Delta t}^{[f_{h,z,2}]} \circ \varphi_{\Delta t}^{[f_{h,z,3}]}(U^n)$$

# backup Suzuki vs Lawson (adaptive time step)

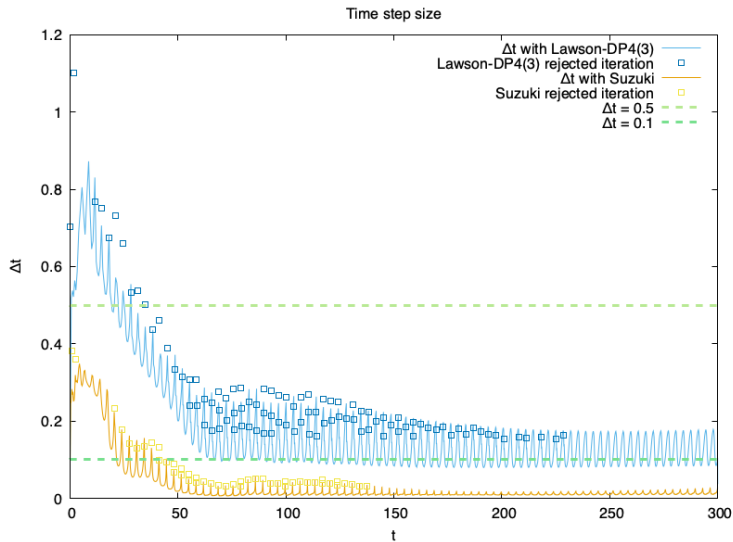


Figure: Time step size in 1dx-1dv

# backup Suzuki vs Lawson (adaptive time step)

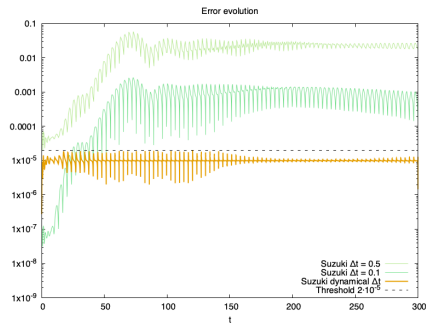
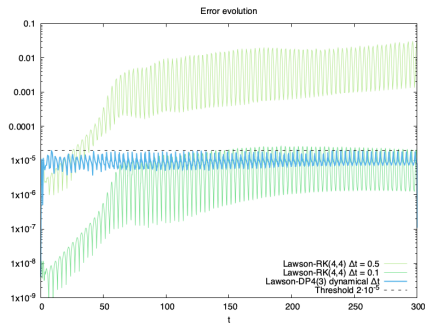


Figure: Local error estimate Lawson (left) and Suzuki (right)

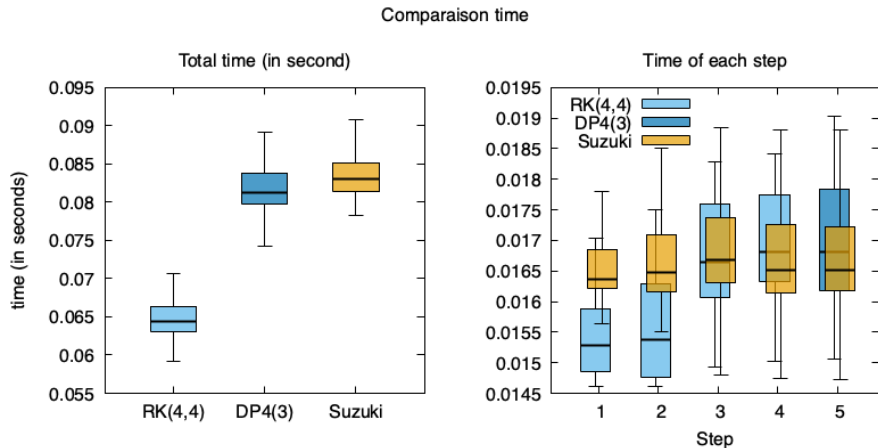


Figure: Simulation time of each step

Language	Files	Lines	Code	Comments	Blanks
C header	16	6010	4352	870	788
C++	67	39837	28463	5428	5946
Makefile	1	120	84	9	27
Python	13	2747	2149	221	377
Shell	1	35	21	8	6
Total	98	48749	35069	6536	7144