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# UKAEA NEPTUNE Mathematical Support Project

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# Who we are

# STFC



Hussam

Rutherford Appleton  
Laboratory (RAL)

Hartree Centre



Sue

Numerical Linear  
Algebra

Data  
analytics

AI

HPC

Large-scale  
optimisation



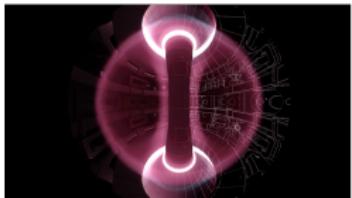
Tyrone



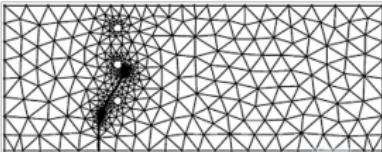
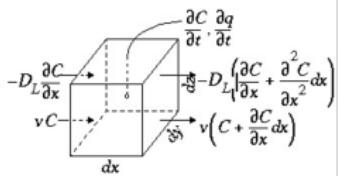
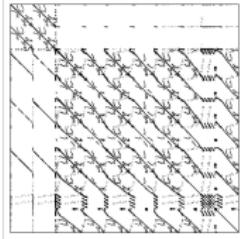
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# The big picture



$$\begin{aligned}\frac{du_1}{dx} &= \frac{-3u_1 + 4u_2 - u_3}{2h} \\ \frac{du_i}{dx} &= \frac{-u_{i+1} + u_{i-1}}{2h}, \quad i = 2(1)N-2 \\ \frac{du_{N-1}}{dx} &= \frac{u_{N-3} - 4u_{N-2} + 3u_{N-1}}{2h}.\end{aligned}$$

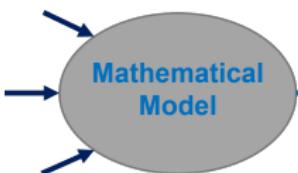


```
procedure pcp(A, ΘT, b)
1   Compute  $\Delta t_0$  as a guess of  $\Delta t^*$ ;
2    $r_0 := b - A\Theta^T A^\top \Delta t_0$ ;
3   solve  $Mz_0 = r_0$ ;
4    $p_0 := z_0$ ;
5    $i := 0$ ;
6   do stopping criterion not satisfied →
7        $q_i := A\Theta^T A^\top p_i$ ;
8        $\alpha_i := \frac{1}{2} r_i^\top p_i / q_i^\top$ ;
9        $\Delta y_{i+1} := \Delta y_i + \alpha_i q_i$ ;
10       $r_{i+1} := r_i - \alpha_i q_i$ ;
11      solve  $Mz_{i+1} = r_{i+1}$ ;
12       $\beta_i := \frac{r_{i+1}^\top p_{i+1}}{r_{i+1}^\top q_i}$ ;
13       $p_{i+1} := z_{i+1} + \beta_i p_i$ ;
14       $i := i + 1$ ;
15 od;
16  $\Delta t^* := \Delta y_i$ 
end pcp;
```

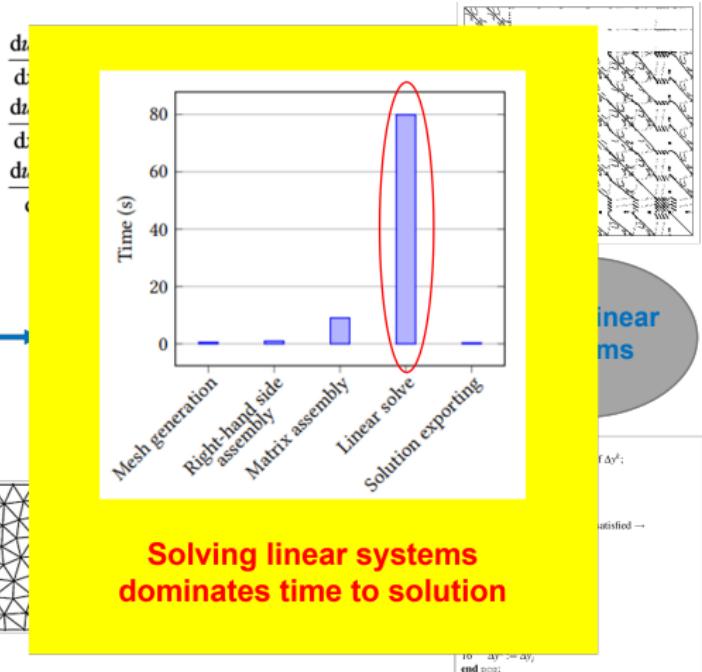


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# The big picture



$$-\dot{Q} = -D_L \frac{\partial C}{\partial x} + v C$$
$$\frac{\partial C}{\partial t} + \frac{\partial^2 C}{\partial x^2}$$



# Time dependent solvers

We consider fully IRK methods

- ▶ high order accuracy
- ▶ require solving classic LS as in backward Euler



# Solving linear systems – preconditioning

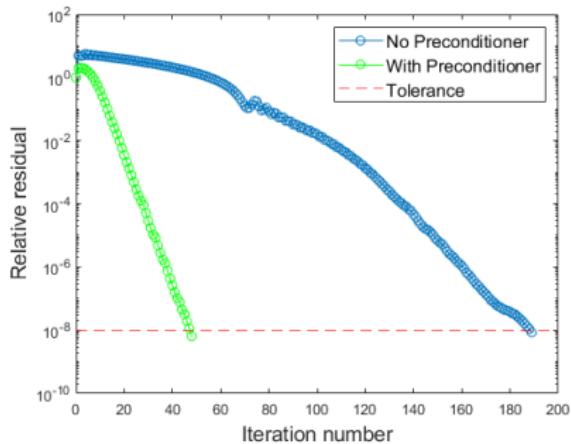
- ▶ Linear systems from discretised PDE models are typically very large and sparse
- ▶ Iterative methods are best suited to solve them
- ▶ However, properties degrade for real problems of interest (ill-conditioning prohibits convergence)
- ▶ Poor convergence avoided by having a good preconditioner

Solve

$$Ax = b$$

vs

$$\mathbf{P}Ax = \mathbf{P}b$$



# High-order finite elements

Solving is **particularly challenging** for **high-order finite elements**

Higher  $p$  gives better accuracy (exponential vs linear in # DOFs)  
but increased cost

|                    | Complexity              | Low order<br>( $p = 1$ ) | High order<br>( $p = 8$ ) |
|--------------------|-------------------------|--------------------------|---------------------------|
| DOFs per element   | $\mathcal{O}(p^d)$      | $\sim 1$                 | $\sim 8^d$                |
| # of couplings     | $\mathcal{O}(p^d)$      | $\sim 1$                 | $\sim 8^d$                |
| non-zeros (memory) | $\mathcal{O}(p^{2d})$   | $\sim 1$                 | $\sim 64^d$               |
| matrix-free memory | $\mathcal{O}(p^d)$      | $\sim 1$                 | $\sim 8^d$                |
| matrix-free action | $\mathcal{O}(dp^{d+1})$ | $\sim d$                 | $\sim d8^{d+1}$           |

# Preconditioners for HO FEM

Leverage well-established preconditioners such as Algebraic Multigrid and Domain Decomposition methods.

Should avoid as possible assembling the HO operator matrix Options

- ▶ use p-hierarchy of grids
- ▶ use the low-order operator matrix assembled on a refined mesh

If assembled, static condensation should be used



# Synthetic results

## Diffusion

Tests on orders up to  $p = 13$ , anisotropy (coef  $10^{-6} - 1$ , mesh  $0.3 - 1$ )

- ▶ Homogeneous diffusion: pMG scales perfectly
- ▶ Anisotropic diffusion (coef) : LOR AMG scales perfectly
- ▶ Anisotropic diffusion (mesh) : LOR AMG scales perfectly
- ▶ Anisotropic diffusion (coef&mesh): tough

## Advection-diffusion

Tests on orders up to  $p = 8$ , viscosity  $10^{-4} - 1$

- ▶ LOR AMG scales well



# Numerical experiments

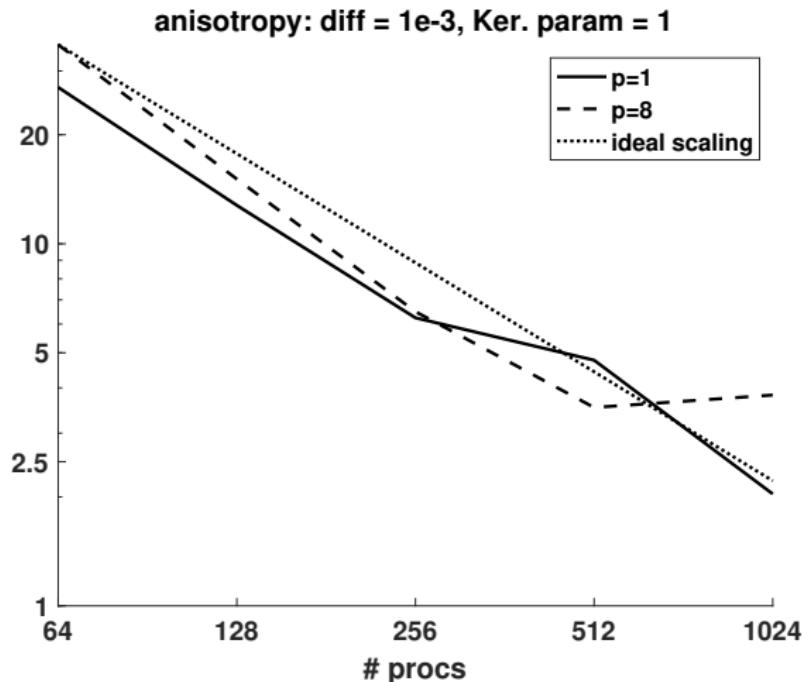


Figure: #DOFs  $\approx 67M$ . # iter<sub>p=1</sub> = 11. # iter<sub>p=8</sub> = 15

# Numerical experiments

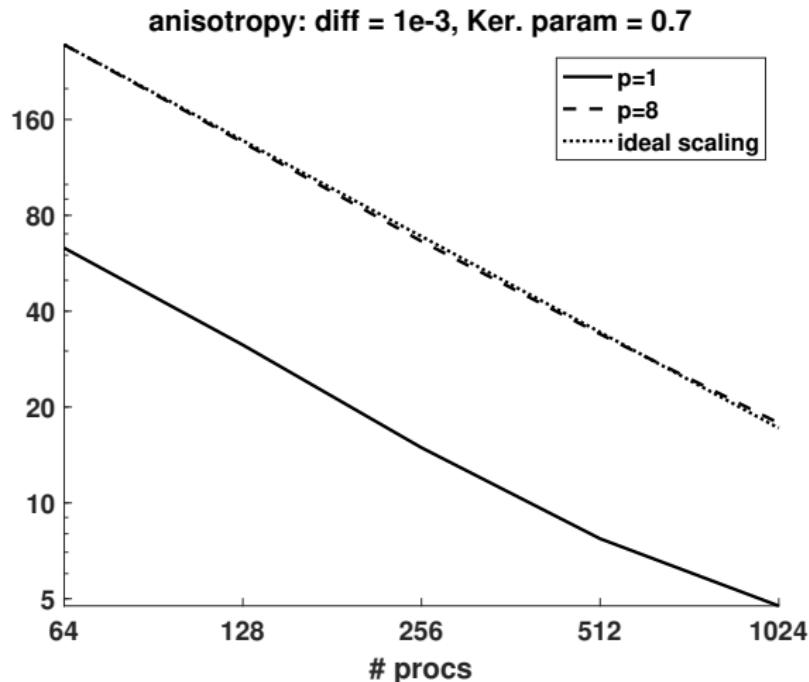


Figure: #DOFs  $\approx$  67M. # iter<sub>p=1</sub> = 53. # iter<sub>p=8</sub> = 317

# Numerical experiments

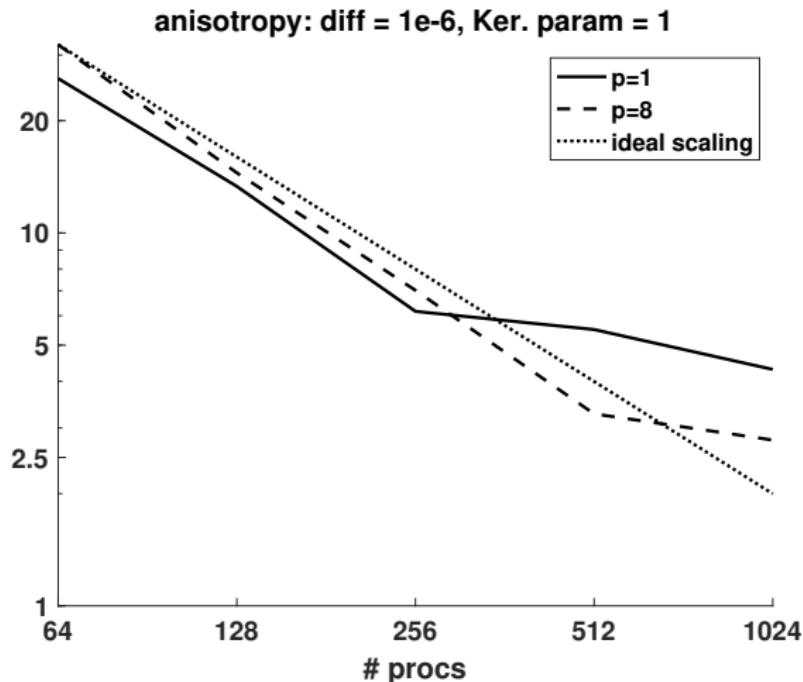


Figure: #DOFs  $\approx 67M$ . # iter <sub>$p=1$</sub>  = 11. # iter <sub>$p=7$</sub>  = 17

# Numerical experiments

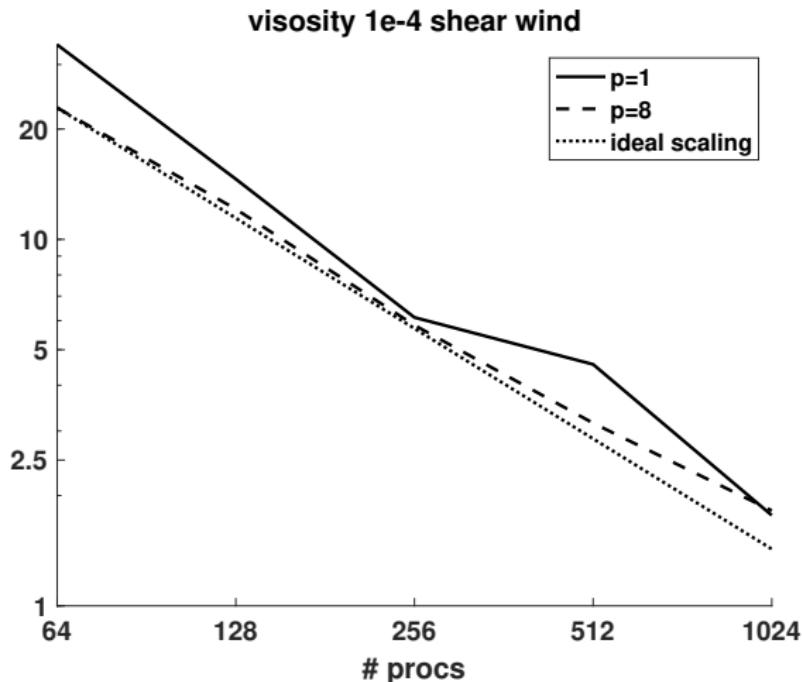


Figure: #DOFs  $\approx 67M$ . # iter $_{p=1} = 20$ . # iter $_{p=8} = 17$

# Code coupling Fluid–Particle

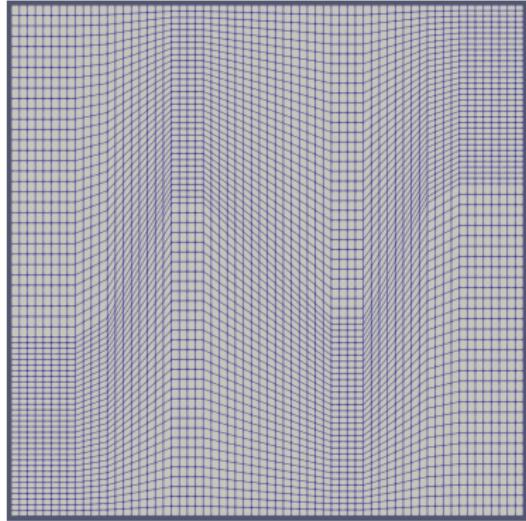
- ▶ Suggested Spatial Hybridization (SpH) Approach
- ▶ Identified several lightweight and efficient coupling software (MUI, CWIPI, preCICE)

Since NESO particle-in-cell solver not yet available in Nektar++, current proxyapp plan is to represent particle-in-cell solver by sampling a travelling sine wave, the fluid model by an advection equation, in Nektar++

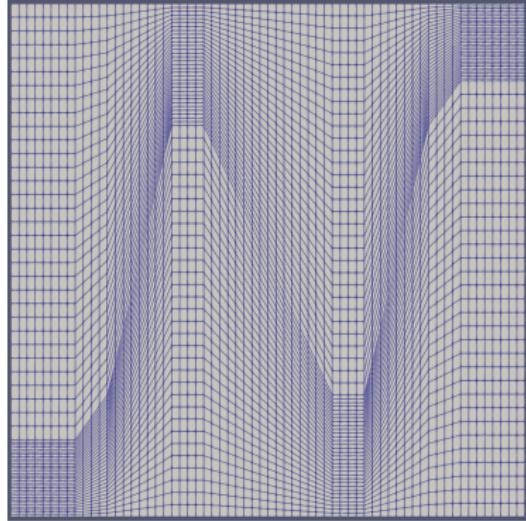
- ▶ 1-D model with variable overlap region
- ▶ At each timestep combine particle contribution with existing density using an indicator function



# Kershaw mesh



(a) Ker. param: 0.7



(b) Ker. param: 0.3

Figure: Anisotropic mesh