

# Quantum Computational Fluid Dynamics D. Jaksch, University of Hamburg



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QSG 2025, Trento, 7<sup>th</sup> May 2025

#### Aerodynamic designs



• Edges reduce drags



Bulbous bows



• Gurney flaps



• Winglets



# Kolmogorov microscale and Reynolds number



- A simulation of fluid flow needs to cover a wide range of length scales
  - *L* the size of the largest eddies in the flow
  - $\eta$  the Kolmogorov length scale at which eddies are dissipated into heat
- The ratio of these two length scales is the Reynolds number defined as

$$\operatorname{Re} = \left(\frac{L}{\eta}\right)^{4/3} = \frac{\nu L}{\nu}$$

- Here *v* is the speed of the flow and *v* the kinematic viscosity
- Flows become turbulent when Re is greater than a couple of thousands
- Grid based methods typically scale with  $Re^{3K/4}$



 $\text{Re} \approx 10^9$ 

 $\text{Re} \approx \text{very large}$ 

# The challenge – Resolving a wide range of length-scales



• Typically, the largest eddy size *L* is

 $10m \le L \le 100m$ 

- Resolution up to the Kolmogorov length scale  $\eta,$  typically

 $0.1 \text{mm} \le \eta \le 10 \text{mm}$ 

• Necessary Grid Points N

 $1\ 000\ 000\ 000 \le N \le 1\ 000\ 000\ 000\ 000\ 000\ 000$ 

- Necessary memory *M* for storing a single velocity component  $8 \text{ Mbyte} \le M \le 8 000 \text{ Pbyte} = 8 000 000 \text{ Tbyte}$
- Additionally, very small time steps are often necessary
- one usually works with approximations
  - Can work very well especially with known configurations
  - Unfortunately, they also deliver qualitatively incorrect results



Winglets



#### Bulbous bows

#### CFD Vision 2030 Research Roadmap



"There is steady progress on fabricating practical quantum computers, and such systems may be available in 2030. However, while a quantum computer can be used for some linear algebra calculations ..., a quantum computer is not necessarily a faster computer for CFD calculations." (CFD Vision 2030 Study Report)



#### **Incompressible Navier-Stokes equation**



• We solve the 2D and 3D equations for simple fluid flows

$$\frac{\partial \vec{v}}{\partial t} = -(\vec{v} \cdot \nabla)\vec{v} - \nabla p + \frac{1}{\text{Re}} \nabla^2 \vec{v}$$
$$\nabla \cdot \vec{v} = 0$$

- 2D  $\rightarrow$  weather forecast
- 3D → aerodynamics, combustion physics, …



#### The energy cascade – two and three spatial dimensions





#### Outline







- Consider a scalar field  $u(r_q)$  on a  $2^N \times 2^N$  of size  $L \times L$ .
- We decompose the field into functions on a coarse L/2 grid (red dots  $X_k$ ) and a fine grid (black dots) as

$$u(\mathbf{r}_q) = \sum_{\alpha=1}^{\chi(1)} \lambda_{\alpha} \mathbf{R}_{\alpha}(\mathbf{X}_k) f_{\alpha}(\mathbf{x}_l) \text{ where } \mathbf{r}_q = \mathbf{X}_k + \mathbf{x}_l$$

• The maximum number of terms in this sum is

$$\chi_{\max}(1) = 4$$

- The actually required number of terms  $\chi(1)$  in this sum is the so-called Schmidt number. It is a measure of correlations between L/2 and other length scales.
- The terms in the sum are weighted by  $\lambda_{\alpha}$  which is the entanglement spectrum.

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• We encode the grid positions into basis states of two qubits

 $|00\rangle$   $|01\rangle$   $|10\rangle$   $|11\rangle$ 

• The function values are basis state amplitudes

 $\begin{aligned} |f_{\alpha}\rangle &= R_{\alpha}(\boldsymbol{X_{00}})|00\rangle + R_{\alpha}(\boldsymbol{X_{01}})|01\rangle + \\ R_{\alpha}(\boldsymbol{X_{10}})|10\rangle + R_{\alpha}(\boldsymbol{X_{11}})|11\rangle \end{aligned}$ 

• The 2 qubit state may be entangled, so all required  $R_{\alpha}$  can be encoded into just 2 qubits.

$$|\psi
angle = \sum_{lpha} \lambda_{lpha} |f_{lpha}
angle \otimes |\phi_{lpha}
angle$$

• Here,  $|\phi_{\alpha}\rangle$  will be used to encode the rest of the function.

Note: For the whole grid only 2N qubits are required





- We repeat this decomposition to get correlations between neighbouring length scales.
- For instance, for correlations between the length scale L/4 and lengths scale L/8 we decompose each of the functions  $f_{\alpha}(x_l)$  from before.
- This gives a representation of the field as

$$u = \sum_{\alpha=1}^{\chi(1)} \lambda_{\alpha} R_{\alpha} \sum_{\beta=1}^{\nu} \lambda_{\beta} R_{\alpha\beta} f_{\alpha\beta}$$

• The maximum Schmidt number  $\chi(2)$  is the total number of terms in these sums

$$\chi_{\rm max}(2) = 4^2 = 16$$

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• In general, Schmidt numbers  $\chi(n)$  and  $\lambda_{\alpha}^{(n)}$  characterize the amount of correlations between length scales

 $L \times 2^{-n}$  and  $L \times 2^{-n-1}$ 

 The repeated application of Schmidt decompositions with increasing n gives a compact Matrix-Product-State (MPS) representation of the scalar field

 $u(\boldsymbol{r}_{\boldsymbol{q}}) = A^{q_1} A^{q_2} A^{q_3} A^{q_4} \cdots A^{q_N}$ 

- Here  $A^{q_i}$  is a  $\chi(i-1) \times \chi(i)$  matrix.
- The index  $q_i$  labels the position in the *i*-th 2 × 2 subgrid 00, 01, 10, 11.
- In principle the maximum  $\chi$  can grow exponentially with the fineness of the grid.

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#### MPS – Turbulence Correlations

DNS,  $t/T_0 = 0.25$   $\mathcal{S}$ , 1024<sup>2</sup> grid DNS,  $t/T_0 = 0.75$   $\mathcal{M}$ ,  $\chi_{\text{max}} = 26$ B С DNS,  $t/T_0=0.8$   $\mathcal{M}, \chi_{\max}=190$ DNS,  $t/T_0=1.4$   $\mathcal{W}, 16^3$  grid box DNS,  $t/T_0 = 1.25$   $\mathcal{W}$ ,  $64^2$  grid the DNS,  $t/T_0 = 1.75$ DNS,  $t/T_0=2$  $4^5$  $8^{4}$ characteristic time to transverse  $4^{4}$  $8^3$  $4^3$  $\chi_{2\mathrm{D}}$  $\overset{(2)}{\times} \overset{(2)}{\times} \overset{(2$  $4^2$ 8 8 6 23 56 9 54  $T_0$ *n*-th Bipartition *n*-th Bipartition

30 (2022). N. Gourianov, et al., Nature Computational Science 2,

2D developing jet, Re=1000

3D Taylor-Green vortex, Re=800

#### Entanglement entropy





• The entanglement entropy is different for 2D and 3D flows

- For 2D the entropy shifts to coarser length scales with increasing time, consistent with the inverse energy cascade
- In 3D the opposite happens consistent with energy cascade energising small length scales.

2D developing jet, Re=1000

3D Taylor-Green vortex, Re=800

Outline





### MPS algorithm for evolving a 2D fluid flow in time

- We illustrate this by considering a simple Euler step to move forward in time by  $\Delta t$ .
- For this we minimize the cost function

$$\Theta(\vec{v}^*) = \mu |\overline{\nabla} \cdot \vec{v}^*|^2 + \left| \frac{\vec{v}^* - \vec{v}}{\Delta t} + (\vec{v} \cdot \overline{\nabla})\vec{v} - \nu \overline{\nabla}^2 \vec{v} \right|^2$$

- We use eighth-order central finite difference stencils and represent the Laplace operator as an MPO.
- We write out explicitly  $\vec{v} = u_1 \vec{e}_1 + u_2 \vec{e}_2$  and  $\vec{v}^* = u_1^* \vec{e}_1 + u_2^* \vec{e}_2$  and write the components as bold vectors on the grid, e.g.  $u_1 = \{u_1(r_1), u_1(r_1) \dots\}$  and rewrite the cost function as

$$\begin{split} \Theta(\mathbf{V}^*) &= \sum_{i,j=1}^2 \left\{ \mu \left( \frac{\Delta \mathbf{u}_i^*}{\Delta x_i} \right)^t \frac{\Delta \mathbf{u}_j^*}{\Delta x_j} \right\} + \sum_{i=1}^2 \left\{ \frac{(\mathbf{u}_i^*)^t \mathbf{u}_i^*}{\Delta t^2} + \frac{(\mathbf{u}_i^*)^t}{\Delta t} \left( \frac{-\mathbf{u}_i}{\Delta t} + \sum_{j=1}^2 \left\{ \mathbf{u}_j \frac{\Delta \mathbf{u}_i}{\Delta x_j} - \nu \frac{\Delta^2 \mathbf{u}_i}{\Delta x_j^2} \right\} \right) \right. \\ &+ \left( \frac{-\mathbf{u}_i}{\Delta t} + \sum_{j=1}^2 \left\{ \mathbf{u}_j \frac{\Delta \mathbf{u}_i}{\Delta x_j} - \nu \frac{\Delta^2 \mathbf{u}_i}{\Delta x_j^2} \right\} \right)^t \frac{\mathbf{u}_i^*}{\Delta t} \right\} + \left[ \dots \right], \end{split}$$

• The terms in […] are constant and thus irrelevant for the optimization, a step scales like  $O(N\chi^4)$  or  $O(\chi^4 \log L)$ .

#### **CFD Examples – Jet Formation**



#### **CFD Examples – Jet Formation**



#### CFD Examples – Taylor Green Vortex





#### CFD Examples – Taylor Green Vortex





• Scaling is often assessed as a function of characteristic numbers like the Reynolds number

$$Re = \left(\frac{L}{\eta}\right)^4$$

/3

- Here *L* is the largest size of the energy containing eddies and  $\eta$  is the Kolmogorov microscale.
- Typically, numerically exact methods are expected to scale like  $Re^{3K/4}$  where *K* is the number of spatial dimensions.
- The runtime scales as  $\operatorname{Re}^{4\chi_{99}}$  which means favourable scaling for TDJ with K = 2 where  $\chi_{99} \approx const$ . but not for the TGV with K = 3 where  $\chi_{99} \approx 0.71$  for the two examples studied above.
- Note: we do not know the general scaling.



 $10^{2}$ 

Re

◆ TGV (3-D)

 $-\chi_{99} \sim \mathrm{Re}^{0.71}$ 

• TDJ (2-D)

 $10^{3}$ 



 $10^{1}$ 

#### Gaining a computational advantage in runtime?



#### Incompressible flow – boundary conditions

• Time evolution starting from the fluid and the lid at rest.

W. Y. Soh and J. W. Goodrich, Journal of Computational Physics **79**, 113 (1988).



#### Tensor Network CFD algorithms





- Black: only top lid moves
- Red: top and bottom lid move

Operation	Algorithm	Scaling	
Addition	Variational addition of MPS (see Sec. 4.5 in [10]).	$\chi^3$	3
Multiplication	Multiplication algorithm in [22] combined with variational com- pression [10] of the product MPS.	$\chi^4$ >	ſ≁
Poisson solver	MPS algorithm for solving the Poisson equation in [23].	$\chi^3$	
Matrix-vector multiplication	MPO-MPS contraction combined with variational compression (see Sec. 5 in [10]). For the system considered here, the MPO bond di- mension $D \leq 6$ and thus $D \ll \chi$ .	$D\chi^3$	

M. Kiffner and DJ, *Tensor network reduced order models for wall-bounded flows*, Phys. Rev. Fluids **8**, 124101 (2023).



Nature Comp. Science 2, 30 (2022).

Outline





#### Hybrid Optimization – Hardware Architecture





A. Peruzzo, et al., Nat. Commun. 5, 4213 (2014).

#### Hybrid Optimization – Hardware Architecture





A. Peruzzo, et al., Nat. Commun. 5, 4213 (2014).

#### Hybrid Optimization – Hardware Architecture





#### The QNPU Quantum Network for cost function $\ensuremath{\mathcal{C}}$



 $C = f^{(1)^*} \prod_{j=1}^r (O_j f^{(j)})$ 

M. Lubasch, J. Joo, P. Moinier, M. Kiffner & DJ, Phys. Rev. A **101**, 010301(R) (2020).





#### Tensor networks as a quantum programming paradigm





#### **23** Modified Variational Quantum Algorithm



### O Amplitude encoding of discrete functions





Quantum superposition

$$\psi\rangle = \sum_{i} f_{i} |\vec{\iota}\rangle$$

*n*-qubit register stores  $2^n$  function values  $f_j$ 



### O Amplitude encoding of discrete functions



#### QCFD – required depth of the variational network

• Tensor Networks are a **programming paradigm** for quantum computers [Phys. Rev. A **101**, 010301(R) (2020)]





Classical complexity  $\propto \chi^4$ 

• Quantum speed-up like in **Grover's algorithm** 

Quantum complexity  $\propto \chi^2$ 

QCFD – required depth of the variational network





• Quantum speed-up like in Grover's algorithm

#### QCFD – required depth of the variational network



#### • Further possible quantum advantages

- Systematic approach via re-compilation of circuits [Quantum Sci. Technol. 5 034015 (2020)]
- Works entirely on quantum computers (work in progress)
- Problem-specific quantum Ansatz [Phys. Rev. A 101, 010301(R) (2020)]
- Exponential reduction of variational parameters?





# Burgers equation in 1D $\frac{\partial f}{\partial t} = v \frac{\partial^2 f}{\partial x^2} - f \frac{\partial f}{\partial x}$

1D Burgers' equation requires 17 qubits in ideal computer Porting the software to quantum hardware

- Platform optimized quantum circuits

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q₂	•		•	Ģ	+
qı			-	•	+
<b>q</b> 4		-	-	-	+
с	1				

 Required quantum device and further optimizations





#### Gaining a quantum advantage in practice?







*Computational Fluid Dynamics on Quantum Computers*, arXiv:2406.18749 • Using HHL based linearized equation solvers

Flow past a sphere  $10^{22}$  to  $10^{28}$  T-gate calls



Feasibility of accelerating incompressible computational fluid dynamics simulations with fault-tolerant quantum computers, arxiv:2406.06323

### The QCFD workflow



- Nonlinear PDE
- Discretize in space and time
- Residual as cost function



# Q-circuit

- Ansatz and QNPU
   q-circuits
- Classical feedback
- Platform optimize

#### Tensor Network

- Gate level emulation
- Quantum computation





#### QCFD consortium and collaborations beyond







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QCFD (qcfd-h2020.eu)



### **Related** publications

#### MPS encoding and Multigrid Renormalization

- M. Lubasch, P. Moinier and D. Jaksch, *Multigrid Renormalization*, J. Comp. Phys. **372**, 587 (2018)
- Quantum Algorithms for nonlinear optimization
  - M. Lubasch, J. Joo, P. Moinier, M. Kiffner and D. Jaksch, *Variational Quantum Algorithms for Nonlinear Problems,* Phys. Rev. A **101**, 010301(R) (2020)
- QCFD and tensor network algorithms
  - N. Gourianov, M. Lubasch, S. Dolgov, Q.Y. van den Berg, H. Babaee, P. Givi, M. Kiffner and D. Jaksch, *A quantum-inspired approach to exploit turbulence structures,* Nature Computational Science **2**, 30 (2022).
  - D. Jaksch, P. Givi, A.J. Daley and T. Rung, *Variational Quantum Algorithms for Computational Fluid Dynamics*, AIAA Journal **61**, 1885 (2023)
  - M. Kiffner and D. Jaksch, *Tensor network reduced order models for wall-bounded flows*, Phys. Rev. Fluids **8**, 124101 (2023)
  - P. Over, S. Bengoechea, T. Rung, F. Clerici, L. Scandurra, E. de Villiers, D. Jaksch, *Boundary treatment for variational quantum simulations of partial differential equations on quantum computers,* Computers & Fluids **288**, 106508 (2025)
  - N. Gourianov, P. Givi, D. Jaksch, and S.B. Pope, *Tensor networks enable the calculation of turbulence probability distributions*, Sci. Adv. **11**, eads5990 (2025)
  - S. Bengoechea, P. Over, D. Jaksch, and T. Rung, *Towards Variational Quantum Algorithms for generalized linear and nonlinear transport phenomena*, arXiv:2411.14931 (2024)
  - P. Siegl, G.S. Reese, T. Hashizume, N.-L. van Hülst, and D. Jaksch, *Tensor-Programmable Quantum Circuits for Solving Differential Equations*, arXiv:2502.04425 (2025)

