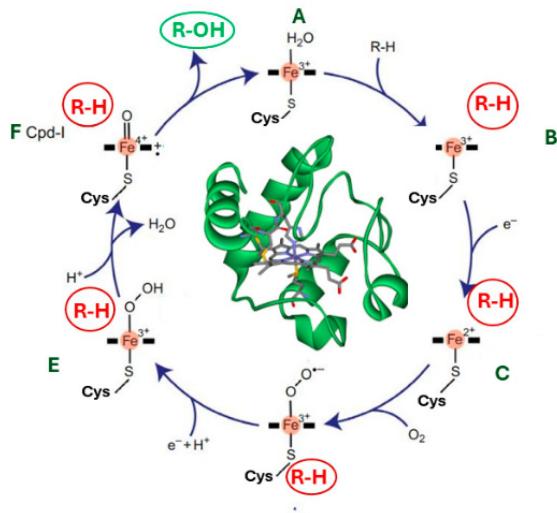


Quantum-Classical Auxiliary Field Quantum Monte Carlo with Matchgate Shadows on Trapped Ion Quantum Computer

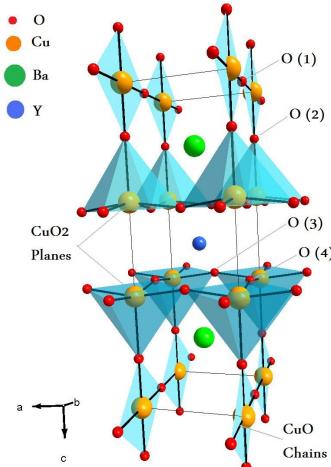


Luning Zhao
IonQ
Dec 10th, 2025

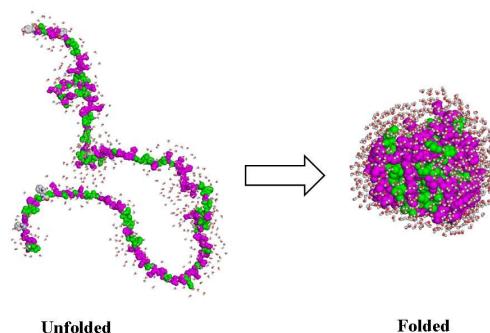
Quantum computers have the potential to solve difficult chemistry problems



Model complex chemical reactions

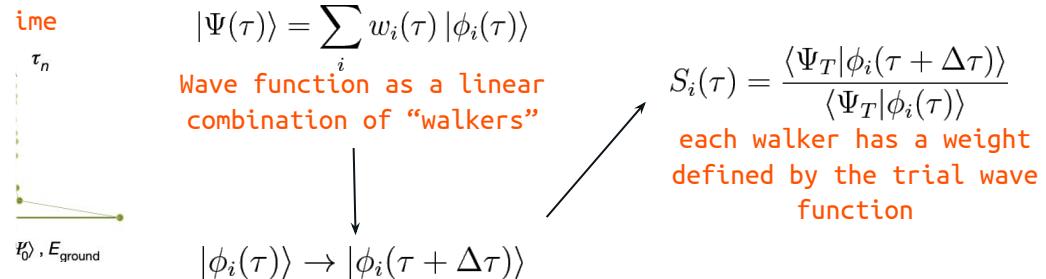
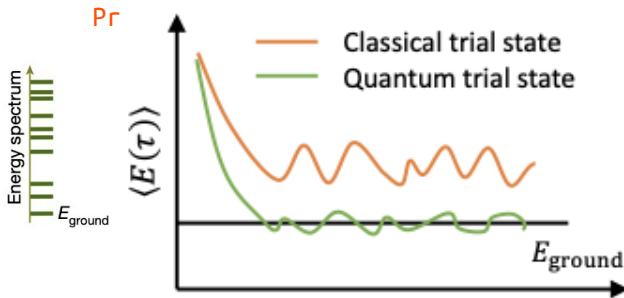


Strongly correlated materials



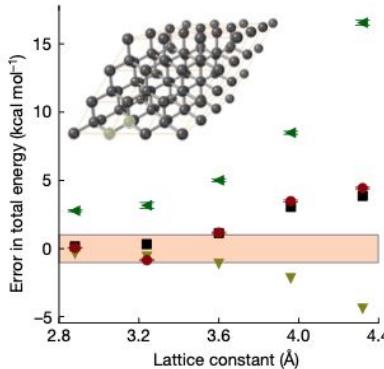
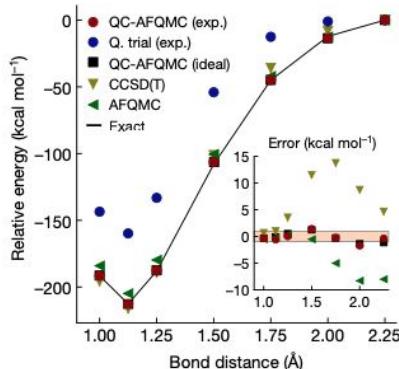
Protein folding

Quantum-Classical Auxiliary-Field Quantum Monte Carlo Carlo



The choice of the trial state is crucial:

- classically only HF could be used efficiently
- HF is not accurate enough
- one could use VQE state as the trial state
- more accurate trial state -> more accurate predictions



Nature 2021, 603, 416-420

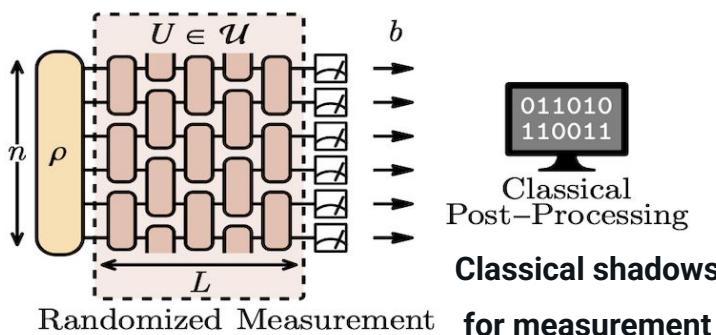
Quantum-Classical Auxiliary-Field Quantum Monte Carlo

Prepare the quantum state

$$\rho = \frac{1}{2}(|0\rangle + |\Psi_T\rangle)(\langle 0| + \langle \Psi_T|)$$

Overlaps become expectation values

$$\langle \Psi_T | \phi_i \rangle = 2\text{tr}(|\phi_i\rangle \langle 0| \rho)$$



Number of Measurement on Quantum Computers

$$\sqrt{N} \log(N)/\varepsilon^2$$

Cost of Classical Post-Processing

Evaluation of Overlaps (need for every time step): $O(N^{4.5})$

Evaluation of Energies (only need at the end of propagation): $O(N^{8.5})$

The Post-Processing Bottleneck

Overlap between the trial state and a determinant $\langle \Psi | \phi_p \rangle$

$$\mathbf{B}_{p|b\rangle} = \mathbf{W}^* \mathbf{M}_\phi \mathbf{Q}_p^T \mathbf{C}_{|b\rangle} \mathbf{Q}_p \mathbf{M}_\phi^T \mathbf{W}^\dagger$$

$$\mathbf{A}_{p|b\rangle}(z) = \mathbf{C}_{|0\rangle}^{(s)} + z \cdot \mathbf{B}_{p|b\rangle}^{(s)}$$

$$\text{Pfaffian of } \mathbf{A}_{p|b\rangle}(z) = \sum_x^l c_{p|b\rangle x} z^x$$

Force bias and local energy

$$\frac{\langle \Psi_T | v_\gamma | \phi \rangle}{\langle \Psi_T | \phi \rangle} = i \frac{\langle \Psi_T | \sum_{pq} L_{pq}^\gamma a_p^\dagger a_q | \phi \rangle}{\langle \Psi_T | \phi \rangle}$$

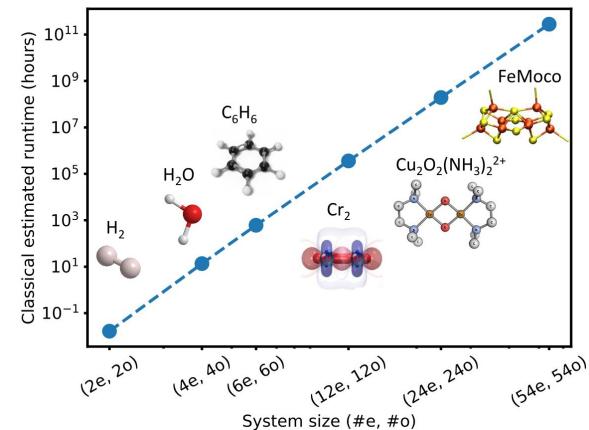
$$\sum_\gamma \frac{\langle \Psi_T | \sum_{pqrs} L_{pq}^\gamma L_{rs}^\gamma a_p^\dagger a_q a_r^\dagger a_s | \phi \rangle}{\langle \Psi_T | \phi \rangle}$$



Matrix product : $O(N^3) \times O(N^{0.5}) = O(N^{3.5})$
Pfaffian : $O(N^{3.5}) \times O(N) = O(N^{4.5})$

$O(N^3)$ Pfaffians : $O(N^{7.5})$

$O(N^4)$ Pfaffians : $O(N^{8.5})$



Phys. Rev. Research 6, 043063, 2024

The Post-Processing Bottleneck

Improvements using finite difference: (Tong et al)

Force bias is a first order derivative of overlaps

$$\frac{\langle \Psi_T | v_\gamma | \phi \rangle}{\langle \Psi_T | \phi \rangle} = i \frac{\langle \Psi_T | \sum_{pq} L_{pq}^\gamma a_p^\dagger a_q | \phi \rangle}{\langle \Psi_T | \phi \rangle} = i \frac{\partial}{\partial \lambda} \ln \langle \Psi_T | e^{\lambda \sum_{pq} L_{pq}^\gamma a_p^\dagger a_q} | \phi \rangle \big|_{\lambda=0} = i \frac{\partial}{\partial \lambda} \ln \langle \Psi_T | \tilde{\phi}(\lambda) \rangle \big|_{\lambda=0}$$

Local energy is a second order derivative of overlaps

$$\begin{aligned} & \sum_\gamma \frac{\langle \Psi_T | \sum_{pqrs} L_{pq}^\gamma L_{rs}^\gamma a_p^\dagger a_q a_r^\dagger a_s | \phi \rangle}{\langle \Psi_T | \phi \rangle} \\ &= \sum_\gamma \frac{\partial^2}{\partial \lambda_1 \partial \lambda_2} \langle \Psi_T | e^{\lambda_1 \sum_{pq} L_{pq}^\gamma a_p^\dagger a_q} e^{\lambda_2 \sum_{rs} L_{rs}^\gamma a_r^\dagger a_s} | \phi \rangle \big|_{\lambda_1=0, \lambda_2=0} / \langle \Psi_T | \phi \rangle \\ &= \sum_\gamma \frac{\partial^2}{\partial \lambda_1 \partial \lambda_2} \langle \Psi_T | \tilde{\phi}(\lambda_1, \lambda_2) \rangle \big|_{\lambda_1=0, \lambda_2=0} / \langle \Psi_T | \phi \rangle, \end{aligned}$$

Evaluating with finite difference

Force Bias : $O(N^{5.5})$

Local Energy : $O(N^{5.5})$

The Post-Processing Bottleneck

Improvements using algorithmic differentiation: (This work)

Force bias

$$\frac{\partial \text{Pf}(\mathbf{A}(\lambda))}{\partial \lambda} = \frac{\text{Pf}(\mathbf{A}(\lambda))}{2} \text{Tr}(\mathbf{A}(\lambda)^{-1} \frac{\partial \mathbf{A}}{\partial \lambda})|_{\lambda=0},$$

Local energy

$$\begin{aligned} & \frac{\partial^2 \text{Pf}(\mathbf{A}(\lambda_1, \lambda_2))}{\partial \lambda_1 \partial \lambda_2} \\ &= \frac{\text{Pf}(\mathbf{A}(\lambda_1, \lambda_2))}{2} \left\{ \text{tr} \left[\mathbf{A}^{-1}(\lambda_1, \lambda_2) \frac{\partial^2 \mathbf{A}(\lambda_1, \lambda_2)}{\partial \lambda_1 \partial \lambda_2} \right] \right. \\ & \quad - \text{tr} \left[\mathbf{A}^{-1}(\lambda_1, \lambda_2) \frac{\partial \mathbf{A}(\lambda_1, \lambda_2)}{\partial \lambda_1} \mathbf{A}^{-1}(\lambda_1, \lambda_2) \frac{\partial \mathbf{A}(\lambda_1, \lambda_2)}{\partial \lambda_2} \right] \\ & \quad \left. + \frac{1}{2} \text{tr} \left[\mathbf{A}^{-1}(\lambda_1, \lambda_2) \frac{\partial \mathbf{A}(\lambda_1, \lambda_2)}{\partial \lambda_1} \right] \text{tr} \left[\mathbf{A}^{-1}(\lambda_1, \lambda_2) \frac{\partial \mathbf{A}(\lambda_1, \lambda_2)}{\partial \lambda_2} \right] \right\} |_{\lambda_1=0, \lambda_2=0} \end{aligned}$$

Evaluating with algorithmic differentiation

Force Bias : $O(N^{5.5}) \rightarrow O(N^{4.5})$

Local Energy : $O(N^{5.5}) \rightarrow O(N^{5.5})$

- No errors due to finite differences
- Computational bottleneck transferred from Pfaffians to matrix products

Comparison of Algorithms

Algorithm	Overlap	Force Bias	Local Energy	Bottleneck	GPU?
Huggins et al (2022)	$O(e^N)$	$O(e^N)$	$O(e^N)$	Matrix Product	No
* a theory paper was published later by the Google team to address the exponential scaling, which is used on all later studies, including ours					
Huang et al (2024), first implementation of matchgate post-processing	$O(N^{4.5})$	$O(N^{7.5})$	$O(N^{8.5})$	Matrix Pfaffian	No
Tong et al (2024), numerical differentiation					
Tong et al (2024), numerical differentiation	$O(N^{4.5})$	$O(N^{5.5})$	$O(N^{5.5})$	Matrix Pfaffian	No
Our work (2025), analytical differentiation + GPUs					
Our work (2025), analytical differentiation + GPUs	$O(N^{4.5})$	$O(N^{4.5})$	$O(N^{5.5})$	Matrix Product	Yes

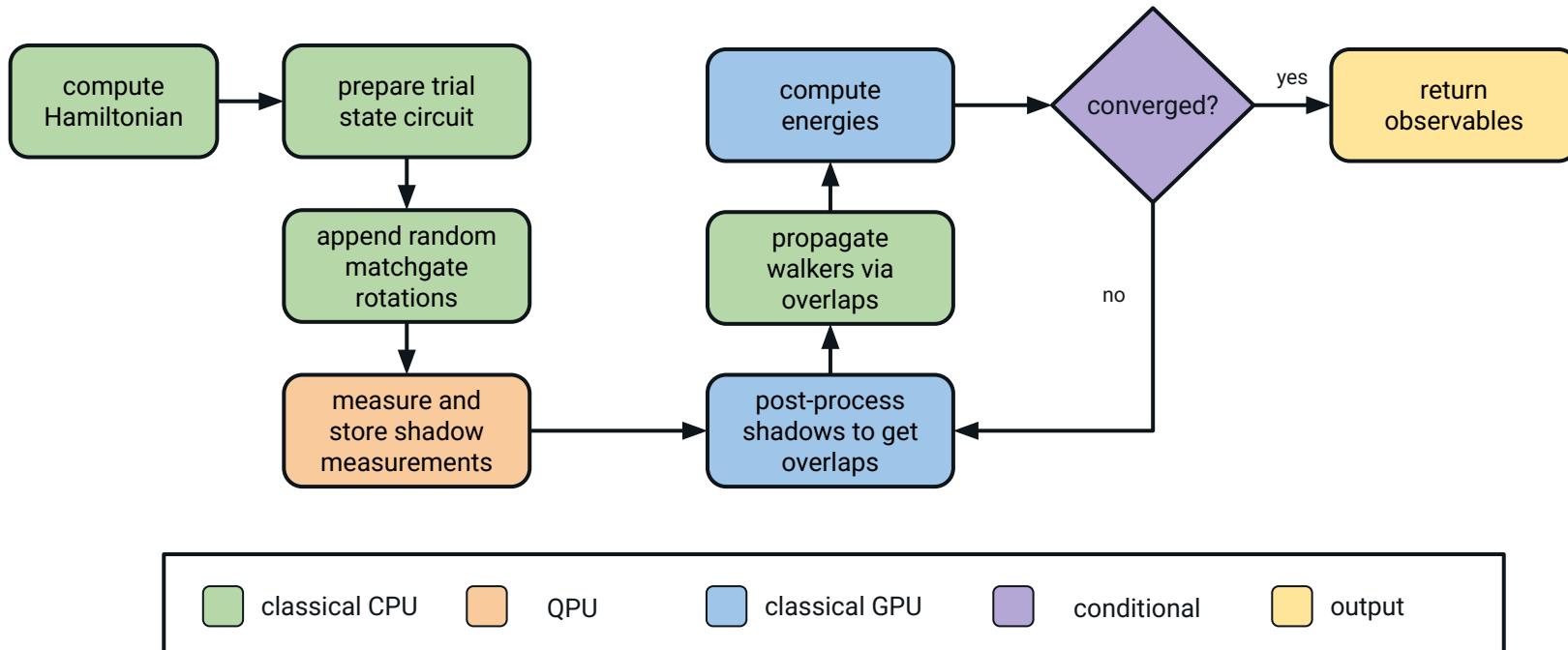
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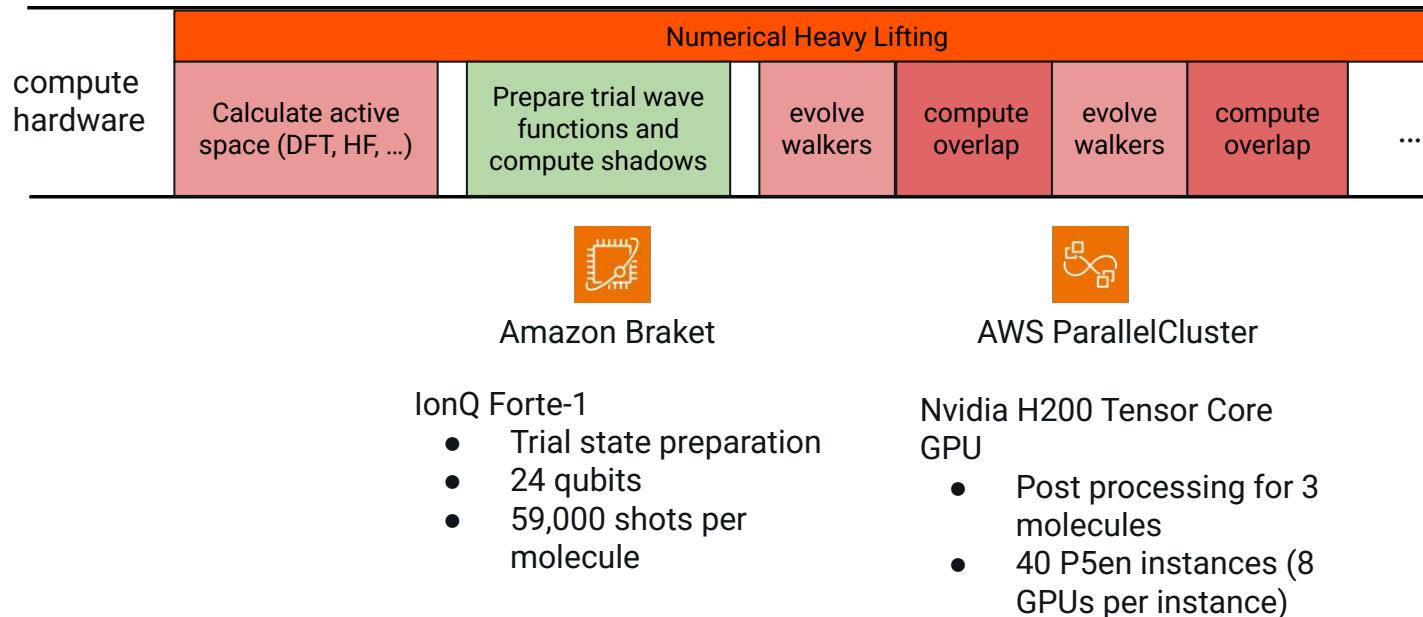
Phys. Rev. Research 7, 012038, 2024

arXiv:2506.22408v1, 2025

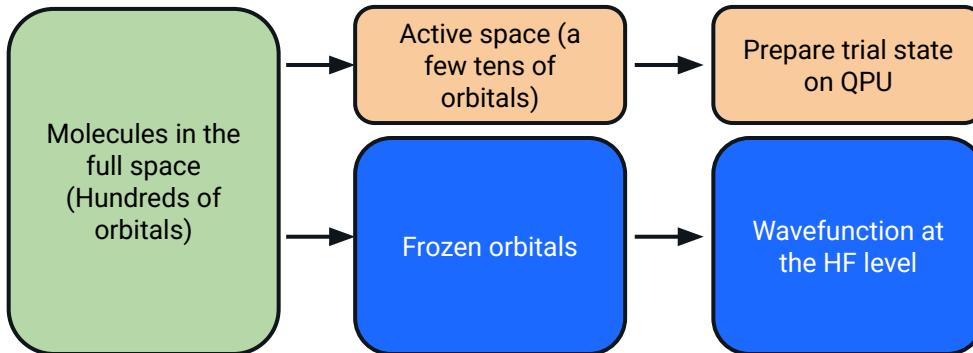
Quantum-Classical Auxiliary-Field Quantum Monte Carlo



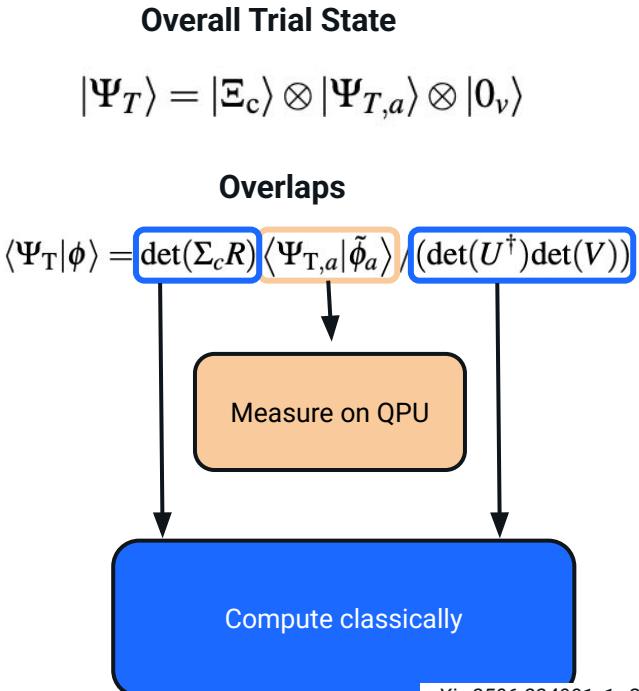
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The Virtual Correlation Energy

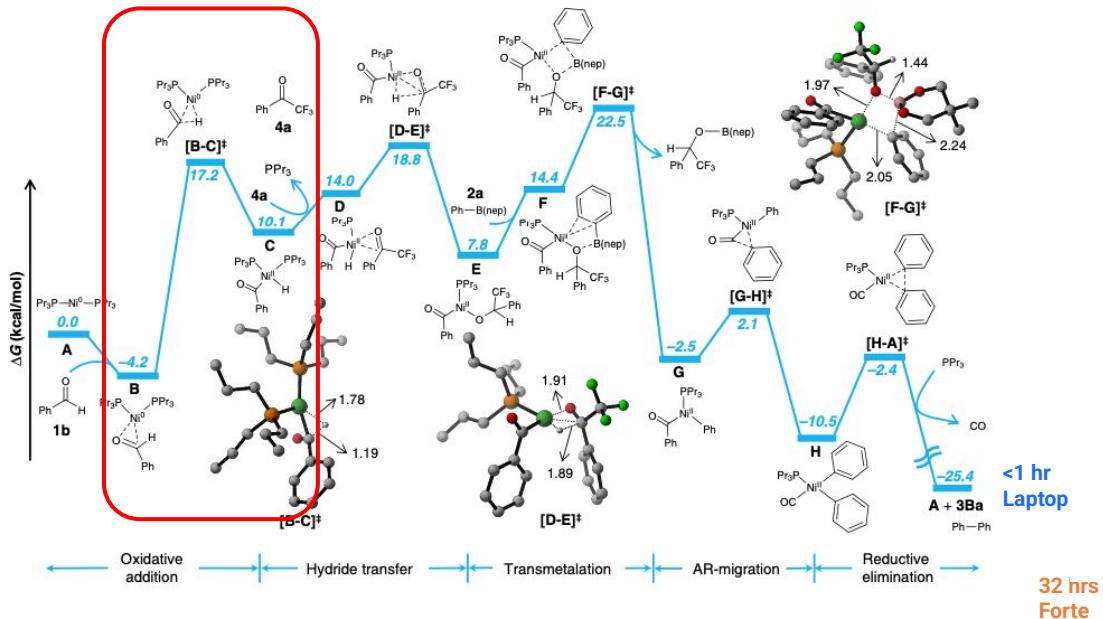


- Allows one to incorporate dynamic correlation outside of the active space
- Minimum computational overhead

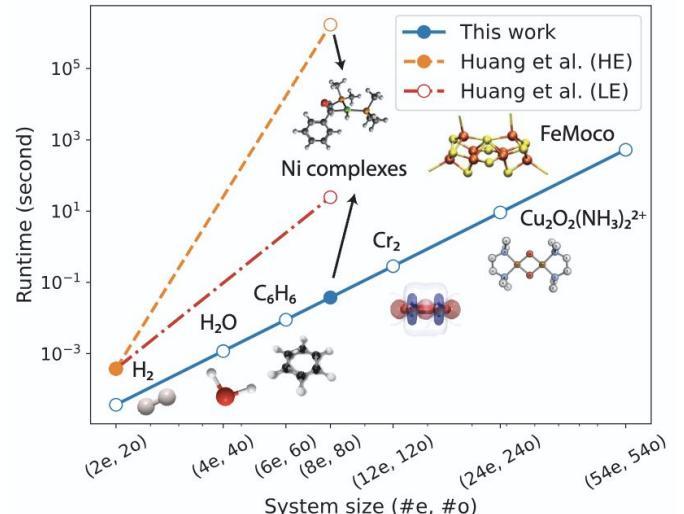


The Suzuki-Miyaura Reaction

130 orbitals in total , 16 qubits in active space

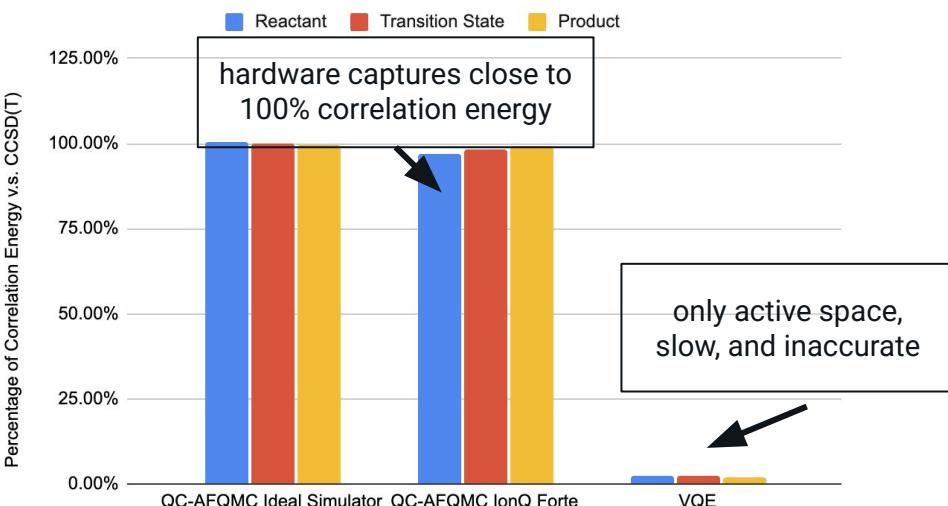


Ni-catalyzed deformylative Suzuki–Miyaura cross coupling



Results on QPU and Simulators

Percentage of Correlation Energy Captured



Reaction barrier

Method	B → [B-C] [‡]	C → [B-C] [‡]
DFT ^a	21.4	7.1
RHF	77.4	85.3
CCSD(T)	53.3	45.4
VQE/upCCD	75.1	80.5
ph-AFQMC ^b	62(4)	76(5)
QC-AFQMC (Ideal simulator)	57(4)	44(4)
QC-AFQMC (Forte QPU)	43(3)	55(3)

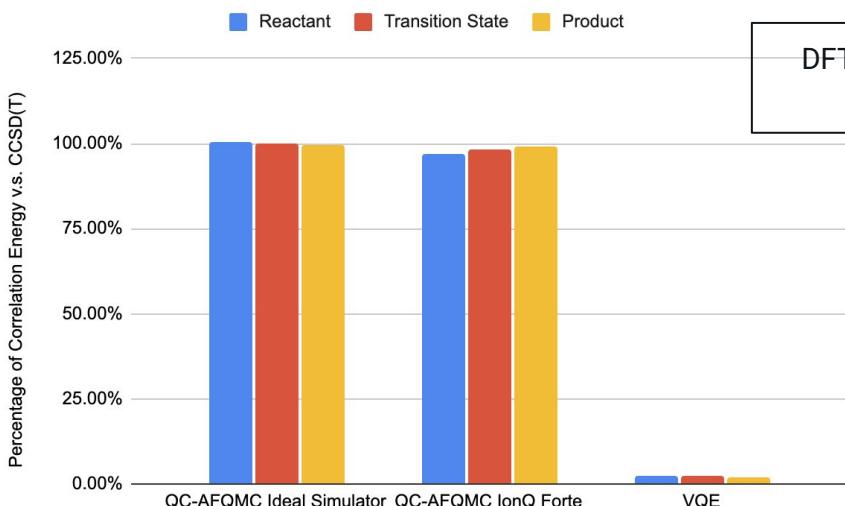
^a Free energies in solution [SMD (1,4-Dioxane)] evaluated with

M06/Def2-TZVPP//ωB97xD/Def2-TZVP(Ni)/Def2-SVP(non-metal).[47]

^b Using a single RHF Slater determinant as a trial state.

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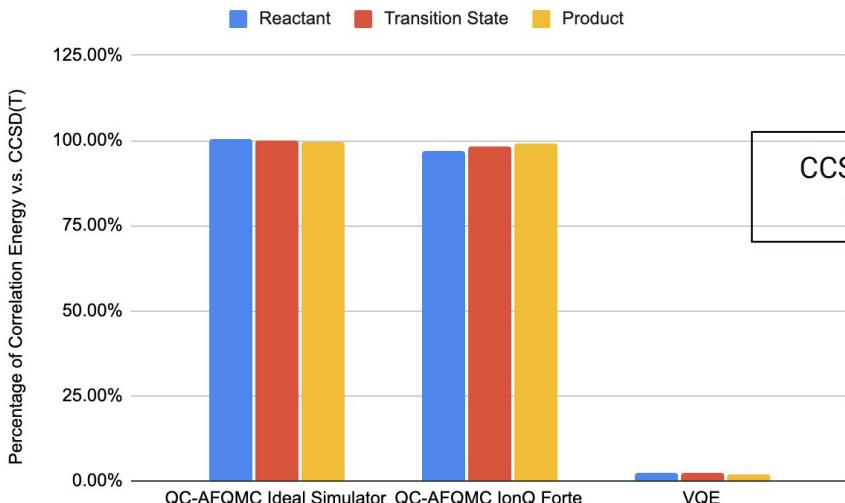
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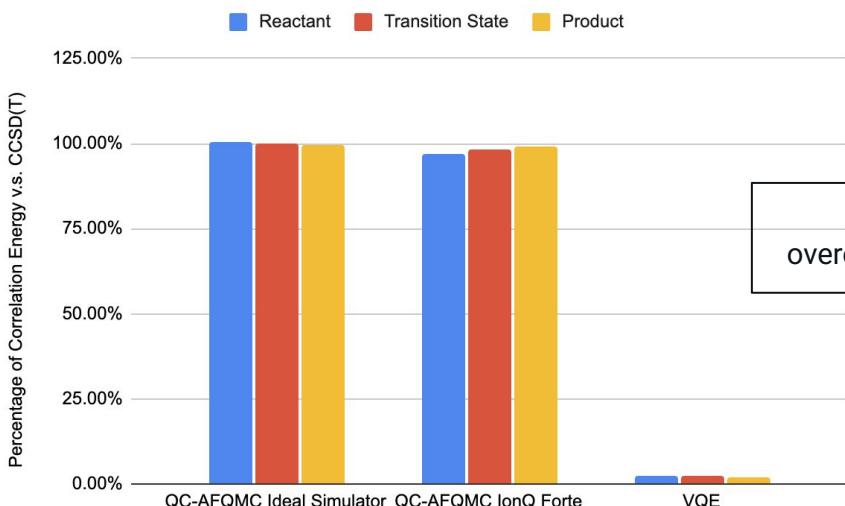
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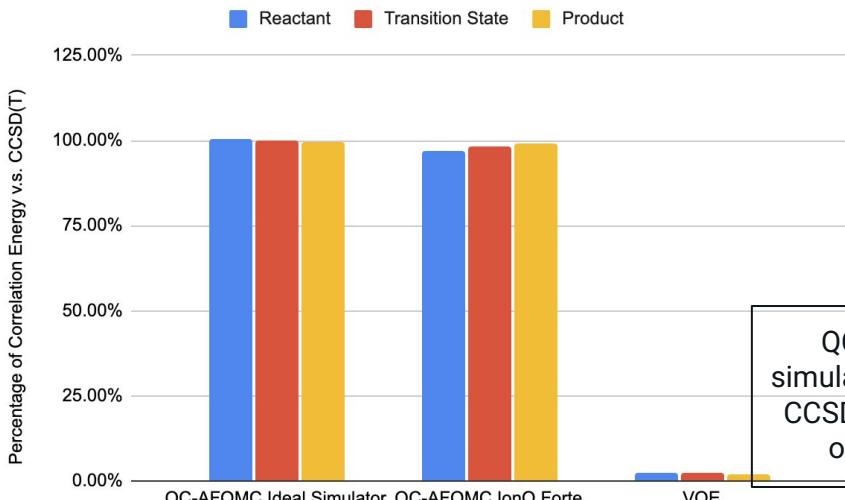
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QC-AFQMC on ideal simulator closes agree with CCSD(T), but some errors occur on hardware

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^b Using a single RHF Slater determinant as a trial state.

Conclusions

What are the advantages of QC-AFQMC and future research directions?



Efficient quantum and classical processing

Improved algorithmic improvements in this work made the method more practical and becomes comparable to classical counterparts



Leverage QPU + CPU + GPU

QC-AFQMC is a perfect method for QPU + CPU + GPU hybrid computing



Noise resilient and efficient

Compared with VQE, QC-AFQMC is much more noise resilient and efficient (no feedback loops between the QPU and CPU)



Can treat large systems

with the aid of virtual correlation energy, QC-AFQMC is able to capture correlations inside and outside the active space



Error Mitigation needed

To deliver chemical accuracy, one still needs to apply error mitigation techniques

Acknowledgements



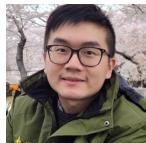
Joshua J. Goings



Arseny Kovyrshin



Jeff Hammond



Tim Chen



Michael Brett



Evgeny Epifanovsky



Lars Tornberg



Zohim Chandani



Benchen Huang



Tyler Y. Takeshita



Martin Roetteler



Anders Broo



Elica Kyoseva



Eric Kessler

and many others!