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# Simulating fluid vortex interactions on a superconducting quantum processor

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Vortex interactions are commonly observed in atmospheric turbulence, plasma dynamics, and collective behaviors in biological systems. However, accurately simulating these complex interactions is highly challenging due to the need to capture fine-scale details over extended timescales, which places computational burdens on traditional methods. In this study, we introduce a quantum vortex method, reformulating the Navier-Stokes (NS) equations within a quantum mechanical framework to enable the simulation of multi-vortex interactions on a quantum computer. We construct the effective Hamiltonian for the vortex system and implement a spatiotemporal evolution circuit to simulate its dynamics over prolonged periods. By leveraging eight qubits on a superconducting quantum processor with gate fidelities of 99.97% for single-qubit gates and 99.76% for two-qubit gates, we successfully reproduce natural vortex interactions. Overall, we establish a framework that reformulates vortex dynamics into a normalized wavefunction representation compatible with quantum system unitary evolution, combined with the designed spatiotemporal encoding scheme, providing a concrete pathway toward leveraging quantum resources in fluid systems.

## INTRODUCTION

Vortices in fluids constitute a core component of complex flow behaviors, encompassing phenomena such as tropical cyclones [1–3], ocean currents [4–6], microfluidics [7, 8], as well as plasmas and magnetofluids [9–13]. Vortex interactions, which involve complex behaviors like vortex pairing and the leapfrogging effect (as shown in Fig. 1a and Fig. 1b), affect energy transport, momentum exchange, and the scale cascade process in fluids, ultimately determining turbulence characteristics and its evolution [14–17]. However, simulating these critical and intricate structures using classical computation is highly challenging, as achieving the necessary spatial and temporal resolution to capture fine-scale details over extended timescales demands massive computational resources [18–21], often exceeding practical limits. This complexity has spurred the development of advanced methods to address the computational bottlenecks while maintaining accuracy.

Recent progress in quantum computing presents a promising avenue to address these challenges, as emerging research on universal quantum partial differential equation (PDE) / ordinary differential equation (ODE) solvers [22–29] demonstrates potential for application in computational fluid dynamics (CFD) by leveraging quantum algorithms to replace key components of traditional solvers based on the fluid governing equations [30–37]. Additionally, alternative fluid dynamics descriptions optimized for quantum computing have been proposed, including quantum algorithms inspired by the lattice Boltzmann method [38–42], quantum simulations based on Schrödingerization [43–45], and the hydrodynamic Schrödinger equation [46–48], which is inherently more suitable for quantum computing than the conventional Navier-Stokes (NS) equations [49].

Although quantum computing has demonstrated its potential in fluid mechanics, simulating fluid motion on actual quantum devices based on existing algorithms remains challenging. Current research into complex phenomena like vortex interactions remains partially constrained by the reliance on Eulerian methods, whose high spatial resolution requirements for accurate fluid behavior capture consequently increase quantum resource demands as qubit needs scale with grid resolution, making such implementations challenging on present noisy intermediate-scale quantum (NISQ) hardware [50]. We adopt Lagrangian vortex methods (LVM) that circumvent the limitations of Eulerian formulations, which are commonly used in the CFD community [51]. Furthermore, their intrinsic conservation laws governing vorticity evolution in high-Reynolds-number flows exhibit inherent compatibility with unitary quantum evolution [52, 53], thereby establishing a promising pathway for developing quantum simulations that preserve the conservation laws of fluid systems.

Moreover, many quantum algorithms for simulating the time evolution of a system typically require a measurement at every time step to extract information necessary for studying dynamical behavior, computing physical quantities, and optimizing algorithms. However, since measurements collapse the quantum state, the quantum state at intermediate steps must be re-prepared to continue the computation. We design a novel spatiotemporal encoding scheme that embeds both spatial and temporal information directly into the quantum state. This approach prepares, in a single quantum-circuit structure, a quantum state that encodes information at multiple time steps in superposition, thereby eliminating the need for stepwise state preparation. We note that the measurement of a state for a specific time step requires repeated executions of the quantum circuit to collect samples, with the number

of realizations for a given accuracy increasing with temporal qubits.

In this work, we propose the quantum vortex method (QVM), which directly focuses on vortices themselves instead of relying on spatial discretization grids as in the Eulerian methods, thereby enabling the reformulation of complex vortex interactions in fluids within the framework of quantum computing. The QVM transforms the evolution of the vortex particle system into the evolution of a wavefunction. We adopt a data-driven strategy to train evolution modules that capture the dynamics of the wavefunction. Leveraging the trained modules, we then design an efficient spatiotemporal evolution circuit to implement the wavefunction propagation, where spatial qubits encode the spatial information of the vortex particle system, while auxiliary temporal qubits, initialized into a superposition state via Hadamard gates, act as placeholders for all time steps and later serve as control qubits to guide the evolution module in the spatial circuit. Building upon these theoretical developments, we implement the QVM on superconducting quantum processors to efficiently compute vortex interaction dynamics. This approach bridges classical fluid dynamics and quantum simulations, providing a new platform for exploring both quantum and classical vortex phenomena and offering a powerful tool for reinterpreting classical vortex dynamics from a quantum perspective.

## RESULTS

### Quantum vortex method

The fluid dynamics are governed by the NS equations for the velocity field  $\mathbf{u}(\mathbf{x}, t)$ , which describe the evolution of the flow under the influence of pressure  $p$ , viscosity  $\nu$ , and external forces  $\mathbf{f}$ :

$$\begin{cases} \frac{D \mathbf{u}}{D t} = -\frac{1}{\rho} \nabla p + \nu \nabla^2 \mathbf{u} + \mathbf{f}, \\ \nabla \cdot \mathbf{u} = 0, \end{cases} \quad (1)$$

where  $D / D t = \partial / \partial t + \mathbf{u} \cdot \nabla$  is the material derivative, and  $\rho$  is the constant fluid density.

To adapt the NS equations for quantum computing, we utilize the relationship between the vorticity field  $\omega$  and the velocity field  $\mathbf{u}$  ( $\omega = \nabla \times \mathbf{u}$ ), discretize the vorticity field into  $N_p$  point vortices, and map their coordinates to complex variables, leading to the generalized Schrödinger equation:

$$\frac{d \psi_j(t)}{d t} = i H_j(\psi_1(t), \dots, \psi_{N_p}(t)), \quad j = 1, \dots, N_p. \quad (2)$$

Here  $H_j$  denotes the  $j$ -th component of a vortex-interaction-dependent Hamiltonian.

The wave function  $\psi_j$  is transformed from the  $j$ -th vortex particle position  $\phi_j$  with

$$\psi_j = \lambda \left[ \phi_j - \left( \int_0^t c(\tau) d\tau + C_0 \right) \right], \quad (3)$$

where  $C_0$  is an arbitrary constant,  $j$  indexes the vortex particles, and  $\lambda$  is a scaling factor that ensures the normalization

condition:  $\sum_{j=1}^{N_p} |\psi_j|^2 = 1$  at  $t = 0$ . The time-dependent function  $c(t)$  is defined as:

$$c(t) = i \lambda \frac{1}{4\pi} \sum_{j \neq k, j=1, k=1}^{N_p} \Gamma_k \frac{\psi_j \psi_k^* - \psi_k \psi_j^*}{|\psi_j - \psi_k|^2 \left( \sum_i^{N_p} \psi_i^* \right)}, \quad (4)$$

where  $(\cdot)^*$  denotes complex conjugation, and  $\Gamma_k$  denotes the vortex strength of the  $k$ -th vortex.

The evolution of the quantum vortex system is governed by equations that ensure the normalization of the quantum state, facilitating accurate simulations of fluid flows with reduced computational costs. Furthermore, we observe that when the vortex particle system exhibits collective motion in a certain direction,  $c(t)$  tends to remain relatively stable, exhibiting only minor fluctuations around a constant value. Therefore, we also provide a random sampling approximation method, in which we randomly select a subset of time instances of  $c(t)$  and average them to approximate their complete set.

We remark that the normalization mapping the evolution of the vortex particle system to the evolution of a wavefunction is mathematically equivalent to the conventional vortex method. To enable experiments on present hardware, approximations and linearization are introduced to preserve leading-order vortex interactions in a linear representation. A detailed description of the QVM is in SUPPLEMENTARY NOTE 1.

### Quantum encoding and evolution

The fluid dynamics are governed by Eq. (1), with vortex particle positions represented by  $\phi$ , which can be transformed into wave function  $\psi$  through Eq. (3), and  $\psi$  evolves according to Eq. (2). One may solve Eq. (1) on a grid, extract  $\phi$ , and apply the transformation to obtain  $\psi$ , thus creating the data needed for training the nonlinear model described by Eq. (2).

We investigate a system governed by Eq. (2) with  $N_p$  vortices, discretizing time evolution into evenly spaced  $N_t$  intervals. For the  $j$ -th vortex particle, its position in configuration space is mapped to a complex variable  $\phi_j$ , with  $j$  ranging from 1 to  $N_p$ . Subsequently, we introduce a transformation that shifts and scales the complex coordinates  $\phi_j$  to define new variables  $\psi_j$ . This transformation ensures that each component  $\psi_j$  of the wave function is properly normalized in terms of probability and remains conserved during the evolution governed by QVM. In the case of time discretization, the value of  $\psi_j$  at the  $i$ -th time step is denoted by  $\psi_j^i$ . At each time step, the collection of  $\psi_j^i$  forms a state vector  $|\psi^i\rangle = [\psi_1^i, \psi_2^i, \dots, \psi_{N_p}^i]^T$ .

To achieve efficient evolution, the initial flow field state  $|\psi^0\rangle$  is first encoded into a larger quantum system. Specifically, the system's initial state is prepared as a tensor product of the flow field's initial state, which is encoded in  $n_p = \lceil \log_2 N_p \rceil$  qubits, and a uniform superposition state encoded in  $n_t = \lceil \log_2 N_t \rceil$  qubits. This procedure effectively generates multiple replicas of the flow field's initial state, as shown in Fig. 1d. These replicas explore different

temporal evolutions simultaneously, and evolve in a branching manner as depicted in Fig. 1f, eventually yielding a superposition of flow field states at  $2^{nt}$  time steps  $|\psi\rangle = \frac{1}{\sqrt{N_t}} [|\psi^0\rangle, |\psi^1\rangle, \dots, |\psi^{N_t-1}\rangle]^T$ , as shown in Fig. 1e.

The evolution process is implemented with the quantum circuit illustrated in Fig. 2. The core element of this circuit is the evolution unitary  $\mathbf{F}_k$ , with  $k$  ranging from 1 to  $n_t$ , which evolves the state from  $i$ -th time step to  $(i + 2^{k-1})$ -th time step as  $|\psi^{i+2^{k-1}}\rangle = \mathbf{F}_k |\psi^i\rangle$ . At the beginning of the evolution, all qubits are initialized in the state  $|0\rangle$ . The system then undergoes spatiotemporal evolution through a layered quantum circuit architecture, evolving the quantum state into  $|\psi\rangle$ . Specifically, the spatial qubits are initialized to the desired initial state through the “State Prep.” module, while the temporal qubits are prepared into a uniform superposition state via Hadamard gates. The temporal qubits then act as control qubits, which sequentially control the implementation of evolution unitaries  $\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_k$  on the spatial qubits.

With this controlled-unitary scheme, the quantum state undergoes a tree-like branching evolution from the initial state shown in Fig. 1f, ultimately resulting in a superposition of all system states across  $2^{nt}$  time steps. This design fully leverages the parallelism of quantum computing, significantly improving the efficiency of the simulation. See SUPPLEMENTARY NOTE 2 for more details.

## Experimental setup

The algorithm is implemented with eight frequency-tunable transmon qubits on a flip-chip superconducting quantum processor, as shown in Fig. 1c, where blue circles represent the spatial qubits and green circles represent the temporal qubits. Each qubit can be controlled and readout individually. The nearest-neighbouring qubits are connected with a tunable coupler for tuning on and off the effective coupling strength of the two qubits. The single qubit gate with a length of 24 ns is realized by applying a Gaussian-shaped microwave pulse with DRAG correction [54]. The two-qubit CZ gate, with a duration of around 40 ns, is realized by tuning the frequencies and coupling strength of the two qubits to achieve a close-cycle diabatic transition, a global process involving both qubits as a combined system, between  $|11\rangle$  (both qubits in their excited states) and  $|02\rangle$  (the first qubit in the ground state and the second qubit in its second excited state), accumulating a  $\pi$  phase shift that transforms  $|11\rangle$  into  $-|11\rangle$ . The median parallel single-qubit gate and two-qubit gate fidelities are 99.97% and 99.76% respectively. See SUPPLEMENTARY NOTE 6 for details.

## Nonlinear interactions in vortex systems

The leapfrog vortex phenomenon [55], described by the NS<sub>2D</sub> equation, refers to a mode of motion that occurs when two or more vortex rings interact, corresponding to four or more vortex particles in two dimensions. We consider the evolution of a four-vortex-particle system under Eq. (2), with the positions of the four particles initialized to be  $(0, 1), (0, 0.3), (0, -1)$ ,

and  $(0, -0.3)$ , respectively. We then apply the transformation defined in Eq. (3), with  $C_0 = -1.7903$  and  $\Gamma = (1, 1, -1, -1)$  to obtain the corresponding quantum state. To learn the Hamiltonian of the vortex system, we select 100 vortex state pairs at time  $(t_i, t_i + 1)$  to form the training set. Here,  $t_i = 0.18(i - 1)$  with  $i = 1, \dots, 100$  is equally sampled from a time range of  $[0, 18]$ , which roughly corresponds to the period of a full leapfrogging cycle.

In our experiment, we use two qubits to encode spatial information of the four vortex particles. Additionally, six qubits are used to represent 64 time steps in the evolution. We then apply the QVM circuit based on the learned Hamiltonian to prepare the quantum state that encodes the spatiotemporal dynamics of the entire evolution process. To obtain the evolution trajectories of the vortex particles, we perform quantum state tomography (QST) on the two spatial qubits, while simultaneously conducting projective measurements on all temporal qubits. For each time step, we postselect the QST data for the respective temporal state to reconstruct the density matrix, from which the positions of the vortex particles can be extracted (see Methods). Note that additional global phases, which are experimentally unobservable, are numerically applied at each time step to preserve the symmetry of the system and constrain particle motion along the positive real axis.

For comparison, we conduct ideal (noiseless) and noisy simulations using the same circuit as in the experiments. In the noisy simulation, we consider error models including depolarizing error of the single- and two-qubit gates, the qubit decoherence, and readout error, with the error rates obtained from experiments (see SUPPLEMENTARY NOTE 6). In Fig. 3a, we plot the experimentally extracted trajectory of the four vortex particles for time steps outside of the training set, i.e., after  $t = 18$ . The results demonstrate a decent agreement between experimental data and noisy simulation. To characterize the experimental performance, we compare the reconstructed state of the spatial qubits and positions of the vortex particles with those obtained from noiseless numerical simulation (Fig. 3b). The state fidelity values exceed 97% for all time steps (Fig. 3b, upper panel). Besides, the position deviations of all four vortex particles from the noiseless simulated values remain below 0.2 throughout the evolution (Fig. 3b, lower panel). Moreover, using the vortex particle position data from both experimental and noiseless simulation results, we reconstruct the velocity field for each time step based on the Biot-Savart formula and visualize it in Fig. 3c and Fig. 3d, respectively. For all illustrated time steps, the velocity fields from experimental data are in close agreement with those of the noiseless simulation, demonstrating that two vortex rings, corresponding to four point vortices in 2D, alternately pass through and move forward in a real flow field while maintaining a degree of symmetry. An additional leapfrogging-type example in SUPPLEMENTARY NOTE 5 empirically probes how the learned evolution module  $\mathbf{F}_k$  responds to small perturbations of the initial condition, where we observe indications of generalization beyond the training trajectory.

## Turbulent vortex particle system

To demonstrate the robustness of our method, we further implement it to simulate the dynamics of an eight-vortex-particle system. The positions and vortex strengths of the eight vortex particles are initialized randomly, akin to a turbulent vortex particle system. We numerically perform the simulation using MindQuantum [56], an open-source quantum computing framework for simulating and implementing quantum algorithms. We use three spatial qubits and nine temporal qubits to encode the positions and time steps, and then simulate the dynamics of the system under Eq. (2). Specifically, we select 64 equally spaced time steps, namely,  $N_t \in \{0, 4, 8, \dots, 252\}$ , within the time range [0, 256] as training data to directly learn the implementation circuit using the variational quantum algorithm (VQA) described in the Methods. Applying the learned circuit to the first frame, we construct the wavefunctions for all time steps from 0 to 511. Fig. 4(a–d) visualizes the results at time steps 128 and 384, respectively. The progression from (a) to (c) illustrates how vortex dynamics evolve while maintaining coherent structures, whereas the corresponding velocity distributions from (b) to (d) quantitatively capturing the spatial variations in flow velocity magnitude and direction.

## Viscous vortex particle systems

We now turn to a viscous system containing two vortex particles. For viscous vortex particle systems, our data-driven approach enables viscosity terms to be encoded within normalized quantum state vectors that preserve their physical properties during evolution. Vortex particle strengths are implicitly incorporated within the evolution module during training and rollout, and the velocity field can be recovered by applying empirical relations for the time evolution of strength. A detailed description can be found in SUPPLEMENTARY NOTE 1. In this simple two-vortex system, both particle positions and viscous interactions can be represented through normalized wavefunctions, enabling our QVM to compute viscous evolution directly from the learned circuit using VQA on MindQuantum. In contrast, the classical Lagrangian vortex method faces limitations in directly incorporating viscosity terms into the vortex particle evolution.

We employ high-precision grid-based Eulerian methods for solving the NS equation to compute the two-dimensional flow field and extract vortex particle positions as the dataset. The spatial information is encoded using  $n_p = 1$  qubits, while  $n_t = 4$  qubits are allocated for encoding the temporal steps, with the first four frames used to optimize the variational circuit parameters. A comparison of the computational results between the QVM and LVM in Fig. 4e and Fig. 4f reveals that the former exhibits perfect agreement with ground truth data, whereas the latter demonstrates significant positional deviations indicative of strong viscous dissipation effects. Although 16 frames, corresponding to 4 qubits, are actually computed, only frames 0, 2, ..., 14 are visualized due to space limitations.

We remark that our method extends the idealized frame

work by learning viscous diffusion from data; the example of two co-rotating vortices in Fig. 4 shows vortex pre-merging dynamics. Although we implicitly handle vortex particle strengths, how to address topological changes induced by viscosity [57], such as vortex splitting, merging, or reconnection, has not yet been investigated due to the fixed structure of the quantum representation. In conventional vortex methods, various particle reseeding and local re-meshing techniques, including vortex element splitting, merging, and deletion, have been developed to handle vortex reconnection [58, 59]. From an implementation perspective, we could initialize partially empty vortex element data structures to accommodate variations in vortex element count, suggesting that incorporating auxiliary registers might provide a potential solution for handling vortex reconnection in future work. We provide a more detailed discussion in SUPPLEMENTARY NOTE 1.

## DISCUSSION

This study introduces a quantum algorithmic framework designed to simulate intricate vortex interactions in fluid dynamics. By directly encoding vortex information into quantum states, the approach circumvents the inherent challenges associated with quantum encoding of fluid fields. The proposed algorithm is validated through numerical simulations of turbulent and viscous flows, as well as experimental simulation of the leapfrogging vortex phenomenon on a superconducting quantum processor. The present QVM is most effective when the flow admits a compact Lagrangian description with a small number of coherent vortices. In such cases, the qubit count scales with the number of vortices rather than a spatial grid; time-parallel encoding reduces repeated state preparations; and measured observables can be tailored to vortex-level quantities. By contrast, when smooth potential fields are of primary interest or full-field observables are essential, Schrödinger/Madelung-based formulations provide a natural Eulerian pathway and remain preferable. We therefore view the two families of approaches as complementary, and we outline extending our framework with data-driven reduced operators and improved measurement strategies as a path toward bridging more complex scenarios. We provide a detailed discussion in SUPPLEMENTARY NOTE 1.

The theoretical benefit in circuit evolution primarily depends on the complexity of the evolution module  $F_k$  and its count  $O(\log N_t)$ , where  $N_t$  denotes the number of discrete time steps. For different temporal qubit indices  $k$ , the complexity of  $F_k$  shows no significant difference; as such, we characterize each module as  $O(\bar{g}_{CZ})$ . We conclude that the overall complexity of the quantum circuit execution is  $O(\bar{g}_{CZ} \log N_t)$ , demonstrating a quantum benefit for predicting long-time flow evolution as the algorithmic complexity grows logarithmically with  $N_t$ . We provide a detailed discussion in SUPPLEMENTARY NOTE 4.

Our spatiotemporal encoding approach leverages both spatial and temporal degrees of freedom to expand the Hilbert space available for information storage, enabling an expo-

ential increase in capacity compared to classical systems of similar scale. Specifically, our method processes all time steps in a quantum superposition within a single workflow, requiring  $\log N_p + \log N_t$  qubits compared with the classical  $N_p N_t$  units of storage for the same functionality. For sequential time-stepping dynamics, classical methods require storage scaling linearly with system size  $N_p$ , while our quantum approach exploits superposition and entanglement to encode spatial information efficiently. Despite logarithmic overhead from the time register, the quantum method still maintains a benefit as problem size increases. This high-density encoding scheme is particularly well-suited for storing dynamic or high-dimensional data such as neural network parameters or physical trajectories. It also aligns naturally with quantum memory architectures, allowing efficient data retrieval via quantum algorithms including Grover's search and quantum random access memory [60]. Applications span a wide range of fields, including artificial intelligence [61], where data and models can be encoded and processed in parallel, scientific simulations involving complex many-body or time-evolving systems, and quantum cryptography [62], where secure and scalable storage of large keys or quantum states is essential.

Phenomena governed by viscosity and small scale physics, such as splitting, co-rotating merging, are not yet fully modeled. A complete quantum vortex particle solver for the incompressible NS equations remains a subject for further study. Future advances in measurement techniques and error mitigation strategies, such as quantum error correction [63], noise filtering, and more efficient tomography [64], along with the development of novel quantum algorithms that reduce the need for intensive measurements, could further alleviate the computational burden and enhance the efficiency of quantum simulations.

## METHODS

### Implementing the evolution modules

To implement the quantum circuit module, we leverage a data-driven approach. We approximate the  $N_p$ -particle system as a linear system described by a parameterized effective Hamiltonian  $\mathbf{H}_{\text{eff}}(\theta)$ , expressed as an  $N_p \times N_p$  complex Hermitian matrix. The training time range  $T_{\text{train}}$  is uniformly divided into  $N_{\text{train}}$  ( $N_{\text{train}} \geq N_p^2$ ) segments, based on which we extract  $N_{\text{train}}$  state pairs separated by a step size  $\Delta t_{\text{train}}$  as our training data. While  $\Delta t_{\text{train}}$  typically matches the evolution step size, it can be adjusted for specific purposes such as data interpolation.

For the training process, we construct a temporary unitary evolution operator  $U(\theta; \Delta t_{\text{train}}) = e^{-i \mathbf{H}_{\text{eff}}(\theta) \Delta t_{\text{train}}}$  based on the chosen step size  $\Delta t_{\text{train}}$ . We optimize the parameterized unitary matrix to match the evolution for all state pairs in the training set, thereby obtaining a linear dynamics. The evolution matrices  $\mathbf{F}_k$  are then constructed similarly through  $e^{-i \mathbf{H}_{\text{eff}}(\theta) 2^{k-1} \Delta t_{\text{predict}}}$ , where the time step  $\Delta t_{\text{predict}}$  can be theoretically arbitrary. With the determined evolution matrices  $\mathbf{F}_k$ , the CPFlow method [65] is then employed to obtain the

quantum circuit implementation with the optimal fidelity and number of CZ gates corresponding to  $\mathbf{F}_k$ . The complexity of the operator  $\mathbf{F}_k$  is heuristic and scales empirically with the system size, as in the quantum approximate optimization algorithm (QAOA) [66, 67]. Further details on the practical implementation and complexity of  $\mathbf{F}_k$  are provided in SUPPLEMENTARY NOTE 3.

In addition to introducing a Hamiltonian as an intermediary to accommodate hardware limitations, the evolution module can alternatively be implemented by designing a parameterized quantum circuit ansatz and employing VQA to minimize the loss function, thereby learning vortex dynamics directly from data. We theoretically derive the complete quantum circuit for loss evaluation and gradient computation methods in SUPPLEMENTARY NOTE 3.

To validate the generalization and practical implementability of our QVM, we evaluate the transfer performance of its evolution module  $\mathbf{F}_k$  to nearby initial conditions against a configuration-space dynamic mode decomposition (DMD) surrogate trained on identical data. Results demonstrate that the solution error of our method remains stable across varying initial conditions, indicating that the trained operators can be effectively reused for systems with the same vortex count and similar configurations. Both methods show comparable performance within the training horizon under small deviations, while QVM exhibits slower error growth and tighter uncertainty bands under larger perturbations. We hypothesize that the normalization and unitary propagation act as an implicit regularizer under distribution shift, improving robustness at the cost of a small in-distribution bias. Future work could explore a hybrid approach combining DMD's interpretability with QVM's hardware-native generalization for enhanced performance and adaptability. A detailed configuration and representation is provided in SUPPLEMENTARY NOTE 5.

### Extracting the spatial information

In our experiment, we use QST to obtain the density matrix of the spatial qubits. We then extract the spatial information of the vortex particles from the eigenstate of the density matrix with the maximum eigenvalue. The method is valid for the depolarization error with a sufficiently small error rate  $p$ . Under the depolarizing error channel, the experimental density matrix can be modeled as  $\rho_{\text{exp}} \rightarrow (1-p)\rho + (p/2^N)I$ , where  $\rho = |\psi\rangle\langle\psi|$  is the ideal density matrix and  $N$  is the number of qubits. Thus,  $|\psi\rangle$  is also the eigenstate of the experimental density matrix with an eigenvalue of  $1 - p + p/2^N$ , which remains the largest among all eigenvalues for a small  $p$ . However, in our experiment, there are also coherent error channels, which can change the eigenstates of  $\rho_{\text{exp}}$ , introducing additional errors during the spatial information extraction procedure. To mitigate this error, we apply Pauli Twirling [68], which can effectively transform all errors into depolarizing errors. Specifically, we average the QST data obtained from 50 equivalent circuits, which are generated by randomly replacing the CZ gates in the original circuit with 16 equivalent gates realized by applying additional Pauli gates before and

after the CZ gate.

## Data availability

The data generated in this study have been deposited in the Figshare database under accession code <https://doi.org/10.6084/m9.figshare.30698342>

## Code availability

The codes for numerical simulations are available at <https://doi.org/10.6084/m9.figshare.30698342>

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## Author contributions

S.X. conceived the theoretical ideas. J.Z. and K.W. carried out the experiment under the supervision of C.S.; Z.W. and J.Z. designed the digital quantum circuits under the supervision of C.S.; Z.W., S.X., C.Z., W.Z., Y.Z. and Y.Y. conducted the theoretical analysis. J.Z., K.W., Z.Z., and Z.B. contributed to the experimental setup. All authors contributed to data analysis, discussion of the results, and writing of the manuscript.

## Competing interests

<sup>749</sup> The authors declare no competing interests.

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Fig. 1. **Overview for implementing vortex interactions using a superconducting quantum chip.** **a**, Vortex pairs generated by paddling in natural fluid systems. **b**, Laboratory-induced vortex interactions, leading to a leapfrogging configuration (Reprinted from Lim (1997) [69], with the permission of AIP Publishing.). **c**, Schematic of our superconducting quantum chip, where all qubits are arranged in a square lattice with nearest-neighbor couplings. Blue and green circles represent the spatial and temporal qubits used in our experiment. **d**, The initial state of a four-vortex-particle system, which can be expressed as the tensor product of  $|\psi^0\rangle$  that encodes the initial spatial information of the vortex particles and a uniform superposition state that encodes the temporal information. The quantum state is prepared with  $n_p$  spatial qubits and  $n_t$  temporal qubits. Here, we take  $n_p = 2$  and  $n_t = 3$  for illustration. **e**, System's final state, where each basis state of the temporal qubits is entangled with the corresponding spatial state,  $|\psi^i\rangle$ , with  $i$  indexing the time step. **f**, The quantum parallel evolution enabled by our circuit.  $\mathbf{F}_k$  represents the unitary that evolves the system for  $2^{k-1}$  time steps, with  $k$  ranging from 1 to  $n_t$ .

Fig. 2. **The evolution circuit of the QVM method.** The circuit consists of  $n_p$  spatial qubits encoding the spatial state of vortex particles and  $n_t$  temporal qubits encoding the temporal information. The spatial qubits are initialized via the "State Prep." module, while the temporal qubits are prepared in a uniform superposition state using Hadamard gates. The quantum parallel evolution illustrated in Fig. 1f is achieved through sequentially applying the controlled- $\mathbf{F}_k$  operations to the system, with the temporal and spatial qubits being the control and target, respectively.

Fig. 3. **Experimental results of nonlinear interactions in vortex systems.** **a**, Trajectories of vortex particles obtained from ideal (noiseless) simulation, noisy simulation, and experimental data. **b**, Fidelity and the position deviations as functions of time. The fidelity  $F$  at each time step  $t$  is defined as  $F = |\langle \psi_{\text{ideal}}^t | \psi_{\text{exp}}^t \rangle|^2$ , where  $|\psi_{\text{exp}}^t\rangle$  and  $|\psi_{\text{ideal}}^t\rangle$  denote the state vector of the spatial qubits obtained through experiment and noiseless numerical simulation, respectively. The position deviation is defined as the Euclidean distance between the vortex particles in the experiment and that in noiseless simulation  $d = \sum_{n=1}^{N_p} |\vec{r}_{\text{exp}}^{n,t} - \vec{r}_{\text{ideal}}^{n,t}|$ , where  $\vec{r}_{\text{exp}}^{n,t}$  and  $\vec{r}_{\text{ideal}}^{n,t}$  denote the coordinates of the vortex particle  $n$  at time  $t$  obtained through experiment and noise-free simulation, respectively. **c,d**, Velocity fields and streamlines induced by vortex particles at  $t = 24, 44, 62$ , and  $81$ , obtained in the experiment (**c**) and noiseless simulation (**d**).

Fig. 4. **The simulation results of turbulent vortex particle system and viscous vortex particle system.** **a**, Flow field visualization rendered based on vortex particle position data from initial time to  $t = 128$ . **b**, Velocity distribution of the flow field at  $t = 128$ . **c**, Flow field visualization rendered based on vortex particle position data from the initial time to  $t = 384$ . **d**, Velocity distribution of the flow field at  $t = 384$ . **e,f** Evolution of vortex particles in a viscous fluid computed using QVM (**e**) and LVM (**f**).







