



Wang, J., Paesani, S., Santagati, R., Knauer, S., Gentile, A. A., Wiebe, N., ... Thompson, M. (2017). Learning nitrogen-vacancy electron spin dynamics on a silicon quantum photonic simulator. In *2017 Conference on Lasers and Electro-Optics (CLEO): Proceedings of a meeting held 16-18 May 2017, San Jose, California, USA* [FTu1F.5] Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1364/CLEO_QELS.2017.FTu1F.5

Peer reviewed version

Link to published version (if available):
[10.1364/CLEO_QELS.2017.FTu1F.5](https://doi.org/10.1364/CLEO_QELS.2017.FTu1F.5)

[Link to publication record in Explore Bristol Research](#)
PDF-document

This is the author accepted manuscript (AAM). The final published version (version of record) is available online via OSA at https://www.osapublishing.org/abstract.cfm?uri=CLEO_QELS-2017-FTu1F.5. Please refer to any applicable terms of use of the publisher.

University of Bristol - Explore Bristol Research

General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available:
<http://www.bristol.ac.uk/pure/about/ebr-terms>

Learning nitrogen-vacancy electron spin dynamics on a silicon quantum photonic simulator

J. Wang¹, S. Paesani¹, R. Santagati¹, S. Knauer¹, A. A. Gentile¹, N. Wiebe², M. Petruzzella³, A. Laing¹, J. G. Rarity¹, J. L. O’Brien¹, and M. G. Thompson¹

¹ *Quantum Engineering Technology Labs, H. H. Wills Physics Laboratory and Department of Electrical and Electronic Engineering, University of Bristol, BS8 1FD, UK.*

² *Quantum Architectures and Computation Group, Microsoft Research, Redmond, Washington 98052, USA.*

³ *Department of Applied Physics, Eindhoven University of Technology, P.O. Box 513, NL-5600MB Eindhoven, The Netherlands.*

Please correspondence to: mark.thompson@bristol.ac.uk

Abstract: We report the learning of electron spin Hamiltonian in a diamond nitrogen-vacancy centre using a silicon-photonics quantum simulator with classical machine learning, showing a new ability of efficient characterisation and verification of quantum devices/systems.

OCIS codes: 270.5585, 130.0130

1. Introduction

Predicting the behaviour of quantum physical processes normally requires simulation of model Hamiltonians. Understanding the model approximation to actual quantum system is crucial to characterise quantum devices and systems, to engineer quantum technologies and to study quantum foundations [1,2]. However, this problem in the exponentially large quantum systems is thought to be intractable to classical computers [3]. Efficiently characterising and verifying complex Hamiltonians is therefore a central challenge.

A new method, quantum Hamiltonian learning (QHL), was recently proposed to exploit quantum simulation with classical machine learning to efficiently validate Hamiltonian models and the predictions of quantum systems or devices [4]. In this approach, the exponential speed-up in reproducing the dynamics of the quantum system is given by the combination of quantum simulation with machine learning that enables to estimate the best Hamiltonian parameters among those accessible by the simulator.

Our experimental demonstration of QHL here uses a programmable silicon-photonics quantum simulator (Fig.1a) to learn the electron spin dynamics of a negatively charged nitrogen-vacancy (NV^-) centre in bulk diamond (Fig.1b). This work shows a new approach for efficiently verifying real quantum physical systems by enhancing established classical computational techniques with quantum processing power.

2. Results

Integrated silicon photonic quantum simulator — We realise the controllable quantum simulator on the silicon quantum photonics platform [5–7]. This device includes functions of entangled-photons generation, projective measurements, and single-qubit and two-qubit operations (Fig.1a). The signal and idler photons are generated by spontaneous four-wave mixing and used to prepare the path-encoded maximally entangled state [6]. The idler photon passes through a state preparation $|\varphi\rangle$ stage and an unitary, \hat{U} or \hat{V} , controlled by the state of the signal, yielding the post-selected entangled state $(|0\rangle\hat{U}|\varphi\rangle + |1\rangle\hat{V}|\varphi\rangle)/\sqrt{2}$ [7]. The quantum operations are achieved by thermo-optical phase gates. Projective measurements \hat{M} allow us to estimate the likelihoods function for the QHL implementations.

Electronic spin in diamond nitrogen-vacancy centre — We study the dynamics of the negatively charged NV^- centre’s ground-state electron spin, see Fig.1b [8,9]. The spin dynamics under study are between the state $m_s = 0$ and $m_s = -1$ of the ground-state triplet (see Fig.1d). The optical addressing and read-out, and microwave (MW) manipulation of the electron spin were performed with a confocal microscope setup. The electron spin is optically initialised into the $m_s = 0$ state, and then driven in a single Rabi sequence (Fig.1c) by applying MW pulses of a fixed power but arbitrarily chosen. The photo-luminescence (PL) identifying the spin state is collected and used to obtain the output probability, which are fed into the quantum simulator to perform the likelihoods estimation.

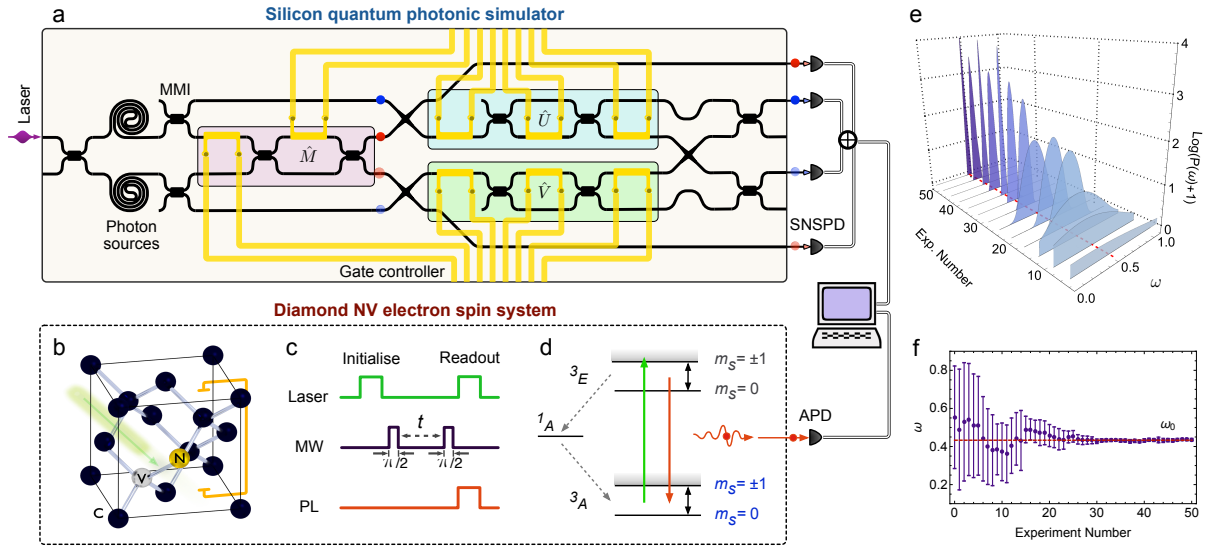


Fig. 1. **a.** Schematic of a silicon quantum photonic simulator. **b.** Schematic of a diamond nitrogen-vacancy centre. **c.** Initialisation, manipulation and read-out of the electron spin state. **d.** Energy-level diagram of a NV centre in diamond. **e.** The learning of the spin Hamiltonian represented by a rescaled Rabi frequency ω . **f.** Evolution of the mean and standard deviation of the distribution of ω .

Implementation of quantum Hamiltonian learning — The photonic quantum simulator and NV electronic spin system are linked by a classical computer. Adopting classical Bayesian inference the Hamiltonian learning problem is reduced to the problem of simulating the experiment with a Hamiltonian $\hat{H}(\vec{x})$ and enables to obtain the likelihood function $\Pr(D|\vec{x})$ from the measurement statistics. The spin Hamiltonian studied here can be modelled as $\hat{H}(f) = \hat{\sigma}_x f/2$. The quantum simulator simulates the model and estimate the likelihoods. Iterating the Bayesian updating allows to infer the Hamiltonian parameter, that is the Rabi frequency f in this case. Figs. 1e and f show the learning of the rescaled frequency ($\omega = f/\Delta f$) of the NV spin, progressively approaching the correct value of ω_0 . The ultimately learned value corresponds to $f = (6.93 \pm 0.09)$ MHz, which is well consistent with that from the fit of Rabi oscillations.

3. Conclusions

We have represented the quantum Hamiltonian learning, demonstrating the learning of the NV electronic spin dynamics by the quantum photonic simulator. This shows the new ability to characterise, verify and validate future large-scale quantum devices and systems with a hybridisation of quantum-classical information processing techniques.

References

1. M. P. da Silva *et al.* Practical characterization of quantum devices without tomography. *Phys. Rev. Lett.* 107, 210404, 2011.
2. S. Barz *et al.* Experimental verification of quantum computation. *Nat. Phys.* 9, 727-731, 2013.
3. R. P. Feynman. Simulating physics with computers. - *International J. of theoretical physics*, 21, 467-488, 1982.
4. N. Wiebe *et al.* Hamiltonian learning and certification using quantum resources. *Phys. Rev. Lett.* 112, 190501, 2014.
5. J. Silverstone *et al.* On-chip quantum interference between silicon photon-pair sources. *Nat. Photon.* 8, 104-108, 2014.
6. J. Wang *et al.* Chip-to-chip quantum photonic interconnect by path-polarization interconversion. *Optica* 3, 407-413, 2016.
7. R. Santagati *et al.* Quantum simulation of Hamiltonian spectra on a silicon chip, arXiv:1611.03511, 2016.
8. F. Jelezko *et al.* Observation of coherent oscillations in a single electron spin. *Phys. Rev. Lett.* 92, 1-4, 2004.
9. Y. C. Chen *et al.* Laser writing of coherent colour centres in diamond. *Nat. Photon.* 236, 2016.