

Modelling and Control of a Reconfigurable Photonic Circuit using Deep Learning

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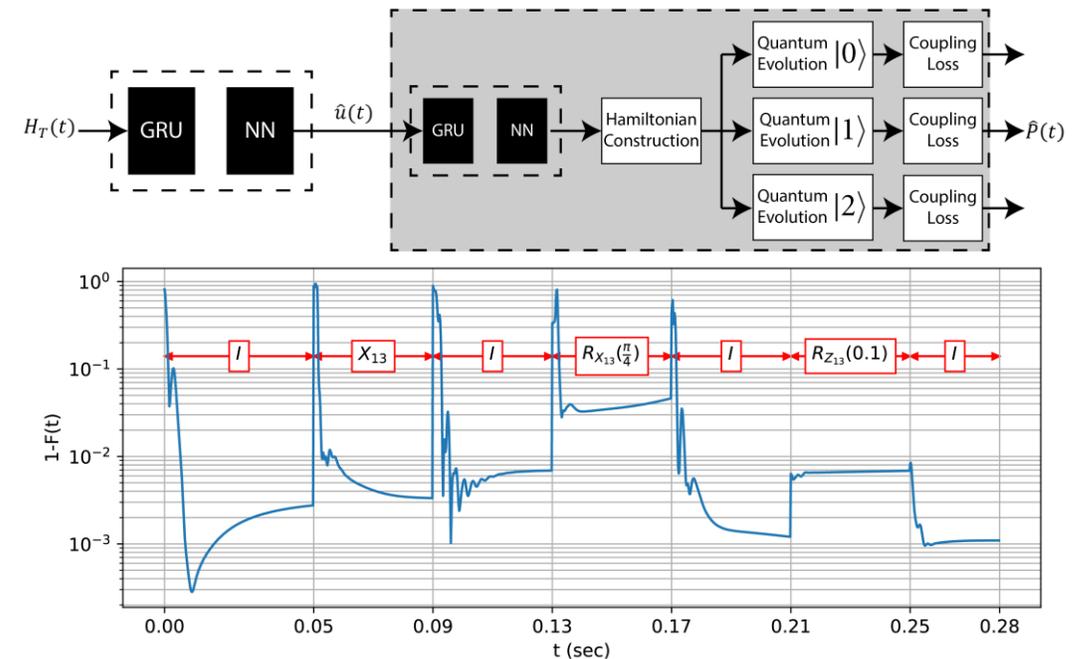
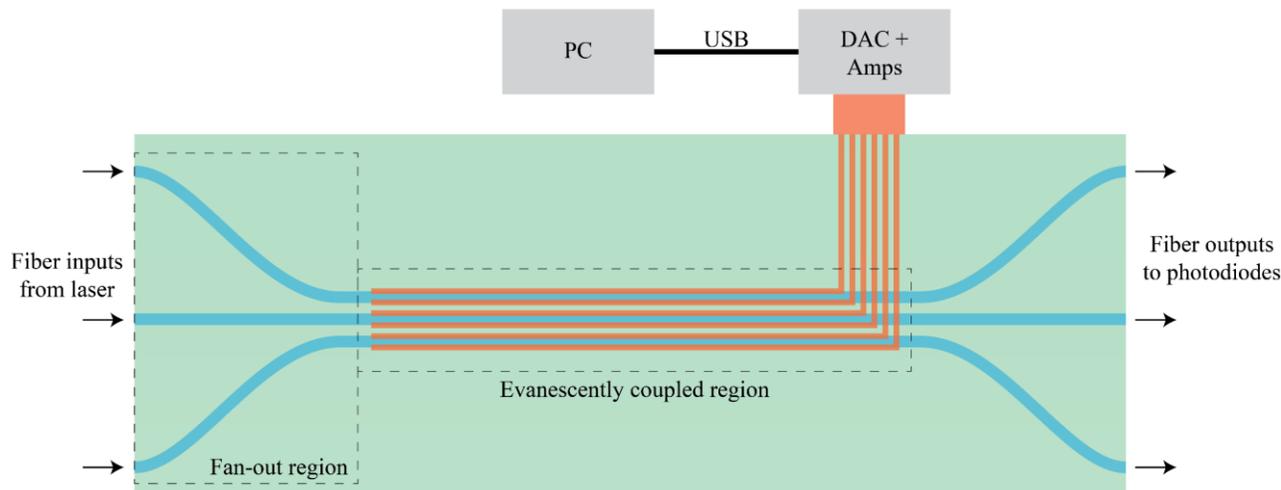
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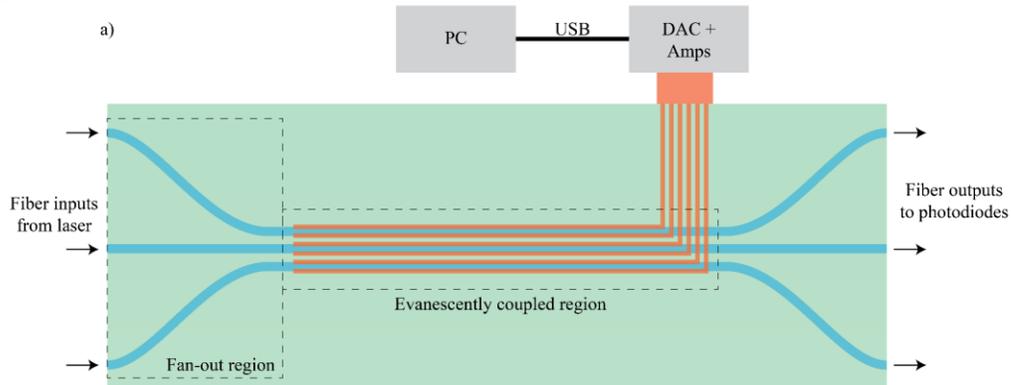
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Reconfigurable continuous-time quantum walk photonic circuit based on three evanescently coupled waveguides.



Input State

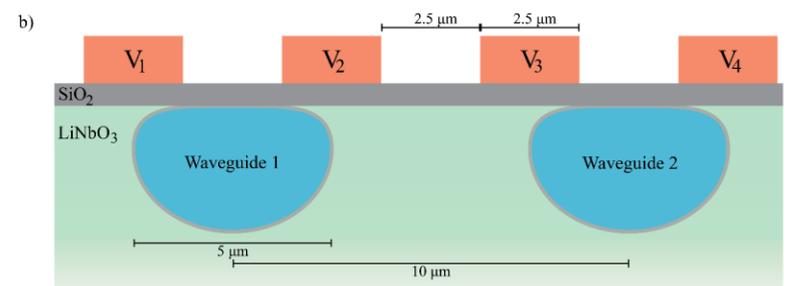
$$|\psi_{in}\rangle, |0\rangle = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, |1\rangle = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, |2\rangle = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Chip Hamiltonian

$$H = \begin{pmatrix} \beta_1 & C_{1,2} & 0 \\ C_{2,1} & \beta_2 & C_{2,3} \\ 0 & C_{3,2} & \beta_3 \end{pmatrix}$$

$$\beta_i = \frac{2\pi}{\lambda}(n_0 + \Delta n \Delta V_i)$$

$$C_{i,j} = C_0 + \Delta C_1 \Delta V_{i,j} + \Delta C_2 (\Delta V_i + \Delta V_j)$$



State Evolution

$$U = e^{-iHl}$$

$$|\psi_{out}\rangle = U |\psi_{in}\rangle$$

$$P_i = |\langle i | \psi_{in} \rangle|^2$$

Output Coupling Losses

$$\hat{P}_k = \frac{\epsilon_k P_k}{\sum_{i=1}^n \epsilon_i P_i}$$

Challenges in modelling and controlling quantum photonic circuits:

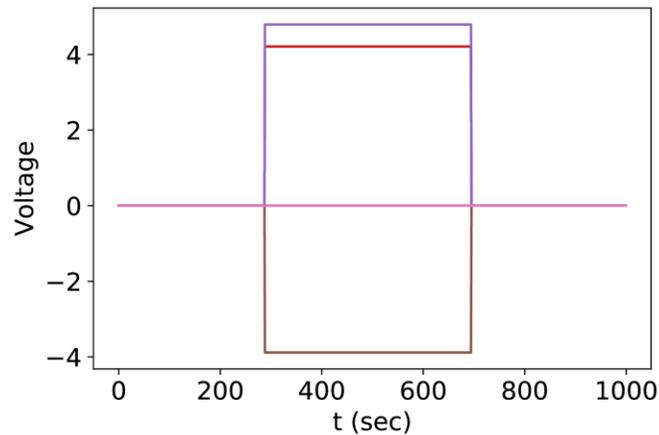
1. Uncertain description of the waveguide circuit Hamiltonian H
2. Distortion and drift of the optical response to applied control voltages.
3. Coupling losses in measuring the output of each waveguide.
4. This experiment uses a generalized circuit simulator based on the parameters of a physical device under investigation.

Reconfigurable continuous-time quantum walk photonic circuit:

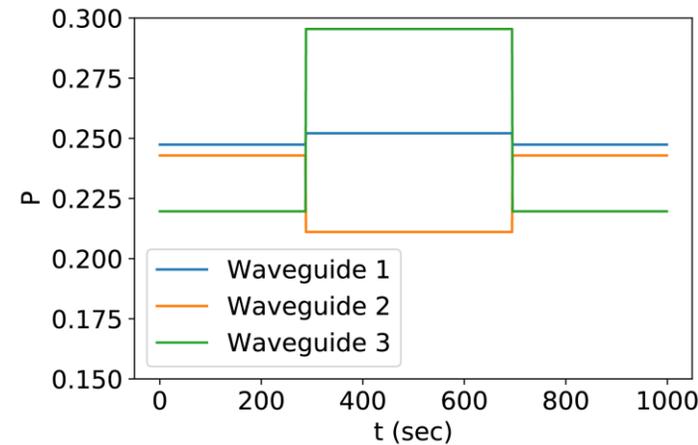
1. Three titanium-diffused lithium niobate waveguides are evanescently coupled to implement a continuous-time quantum walk.
2. Applying a voltage between the waveguides causes a change in refractive index, independently altering the propagation and coupling coefficients.
3. The device can implement a wide range of interesting quantum photonic circuits and can be readily scaled up to larger numbers of waveguides.

DC drift for fixed voltage setting as a result of trapped charges leading to an unstable optical signal.

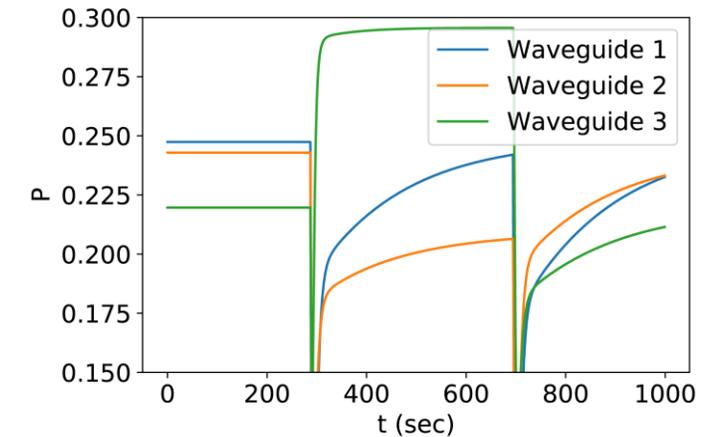
An example of voltage set on the chip electrodes



An expected output signal without any voltage drift



A typical signal measured with the optical device.



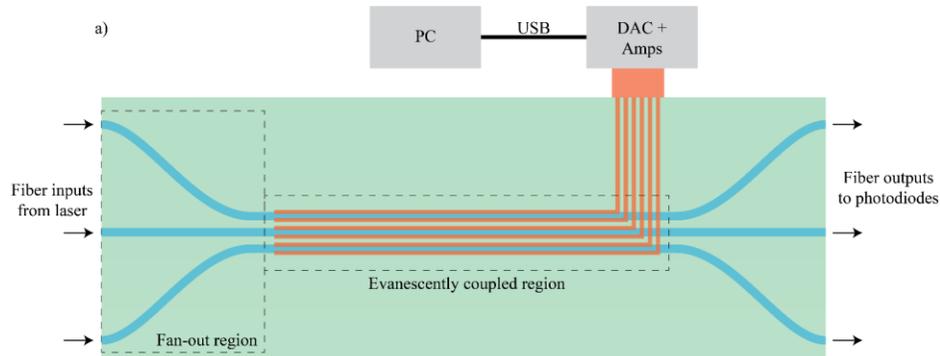
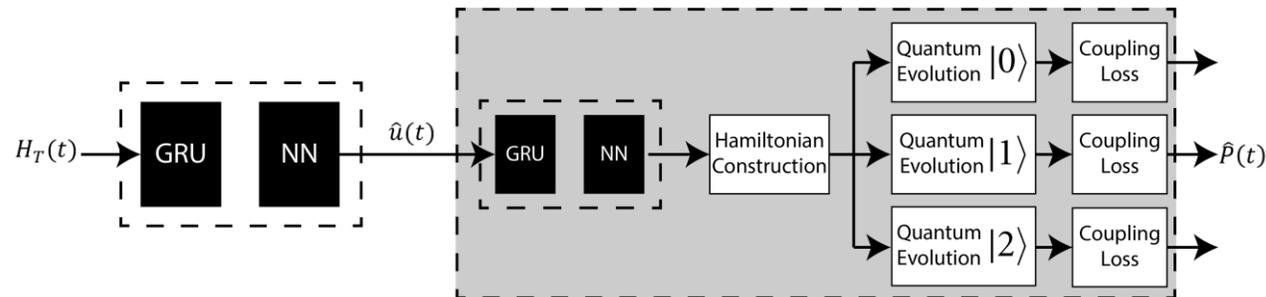
The output optical signal drifts in time as a result of:

1. The output of the chip is distorted by drifting voltages arising from trapped charges at the $\text{LiNbO}_3 / \text{SiO}_2$ interface.
2. These trapped charges result in a long-term instability of the optical output, even when the voltage is set to zero.
3. This creates a highly unstable system with configurations that are very difficult to reproduce.

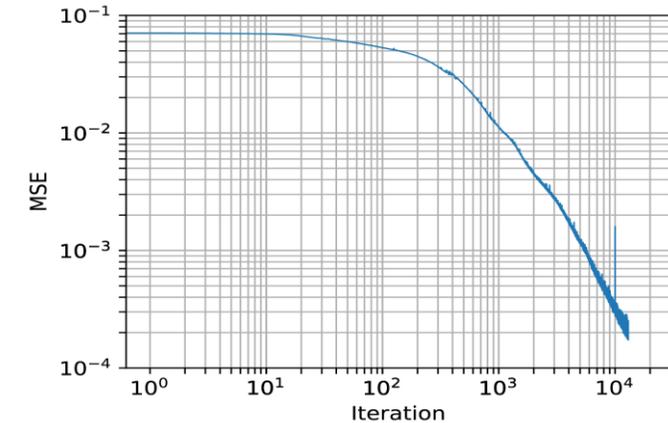
We develop a novel neural network approach to control the voltages of the chip such that the output optical signal is stable.

The “grey-box” machine learning approach to model the photonic circuit.

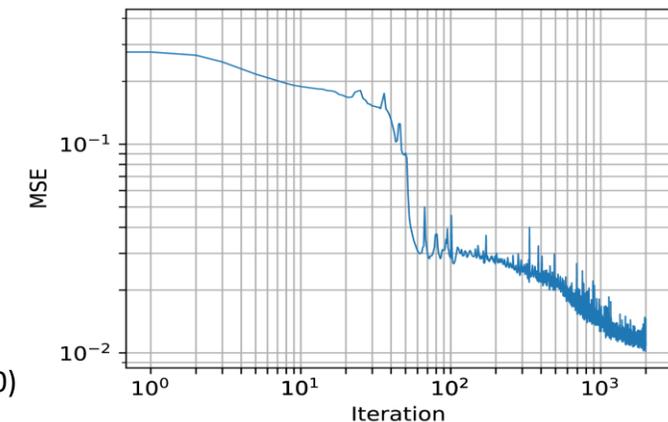
1. A gated recurrent units (GRU) and neural network (NN) is a black-box layers that are trained with a large data-set.
2. The construction of the Hamiltonian, quantum evolution, coupling losses and state measurement are structured as custom white-box layers.
3. An additional GRU and NN is used



The first NN is trained on data taken from a full simulation of the photonic circuit. This enables the NN to predict the drifting optical signal as a result of the drifting charges in the device.



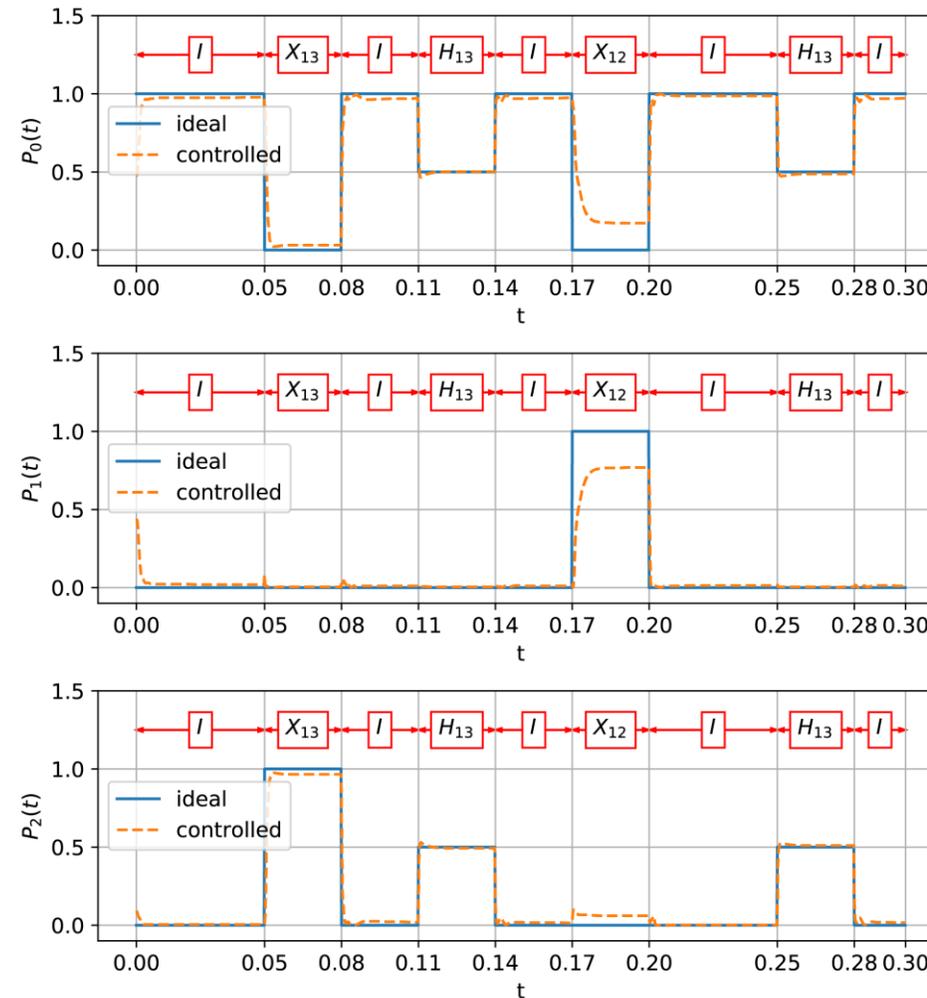
The second NN is then trained to produce a stable optical output given the uncontrolled voltage drift. This takes into account the memory effect of the previous voltage settings.



Using the deep neural network, we can predict and control the optical output of the photonic circuit simulation.

Predicting and correcting the optical output using the deep neural network.

1. The NN gives a (not constant) voltage configuration that combats the drifting optical signal.
2. This enables a stable optical signal to be prepared despite the drifting voltage state due to trapped charges.
3. We can prepare certain photonic quantum gates using the NN to stabilise the optical signal.



$$I \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$X_{13} \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

$$H_{13} \begin{pmatrix} \frac{1}{\sqrt{2}} & 0 & \frac{1}{\sqrt{2}} \\ 0 & 1 & 0 \\ \frac{1}{\sqrt{2}} & 0 & -\frac{1}{\sqrt{2}} \end{pmatrix}$$

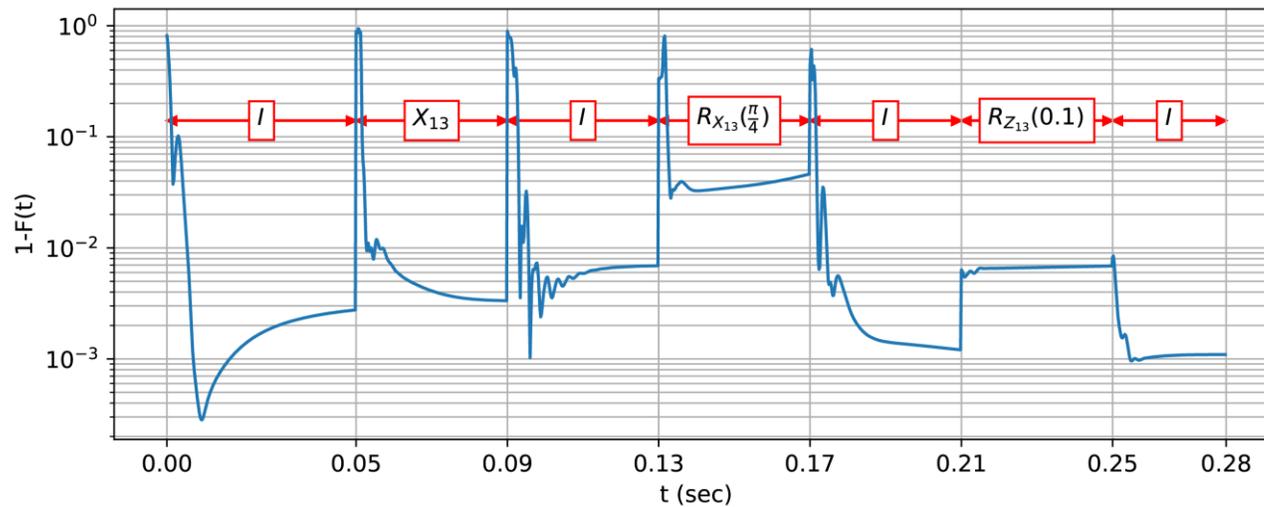
$$X_{12} \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$R_{X_{13}}(\theta) \exp(-i\theta X_{13})$$

$$R_{Z_{13}}(\theta) \exp(-i\theta Z_{13})$$

We can prepare a range of quantum logic gates and plan to implement this algorithm on waveguide arrays with from 3 to 13 coupled waveguides.

We can prepare important quantum logic gates on an array of three coupled waveguide. This could enable more compact optical circuits based on reconfigurable quantum walks.



We aim to implement this algorithm to control circuits of much greater complexity and implement single qubit and entangling gates.

