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NQSTI National Quantum Science and Technology Institute

Machine Learning assisted Quantum Sensing: Noise Classification and Plaquette Phase Detection

Luigi Giannelli[1,2], Shreyasi Mukherjee[1], Dario Fasone[1,3], Lorenzo Vitale [1], Elisabetta Paladino[1,2,4], Giuseppe A. Falci[1,2,4].
[1]DFA, Universitá di Catania, [2]INFN, [3]Università di Napoli, [4] CNR-IMM.

Terzo congresso nazionale NQSTI, Napoli, 2026-04-17

Università di Catania
Uni ct FISICA E ASTRONOMIA "ETTORE MAJORANA"
QuCaT Quantum Technologies at UniCT
INFN CATANIA

motivations

Quatum Control is a key tool for the development of quantum technologies: for enabling and optimizing quantum operations, for mitigate decoherence, ...

Machine Learning methods are a powerful tool for analysing and classifying data

Enable robust Quantum Sensing by combining Quantum Control protocols with Machine Learning

outline

1. noise classification in small quantum networks by machine learning
   1.1 essentials on control protocol STIRAP/CTAP
   1.2 noise models
   1.3 classification of noise correlations in a three-level system
   1.4 two-qubit quantum sensor for temporal and spatial correlations
2. sensing of the Plaquette phase in a three-level Δ system.
   2.1 STIRAP/CTAP in Δ systems
   $\rightarrow$ gauge invariant phase dependence
   2.2 detection of the Plaquette phase with Machine Learning
3. conclusion

STIRAP/CTAP in three-level systems

→ three-level system

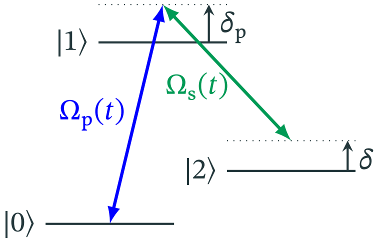
$$H_0 = \delta_p |1\rangle\langle 1| + \delta |2\rangle\langle 2|$$

→ time-dependent control

$$H_c(t) = \frac{\Omega_p(t)}{2}(|0\rangle\langle 1| + |1\rangle\langle 0|) + \frac{\Omega_s(t)}{2}(|1\rangle\langle 2| + |2\rangle\langle 1|)$$

Hamiltonian

$$H_0 + H_c(t) = \begin{pmatrix} 0 & \Omega_p(t)/2 & 0 \\ \Omega_p(t)/2 & \delta_p & \Omega_s(t)/2 \\ 0 & \Omega_s(t)/2 & \delta \end{pmatrix}$$



$$|\psi(t_i)\rangle = |0\rangle \longrightarrow |\psi(t_f)\rangle_{\text{target}} = |2\rangle, \quad \text{efficiency } \xi = |\langle\psi(t_f)|2\rangle|^2$$

STImulated Raman Adiabatic Passage (STIRAP)[1]
Coherent Tunnelling by Adiabatic Passage (CTAP)[2]

→ **counter-intuitive** pulse sequence

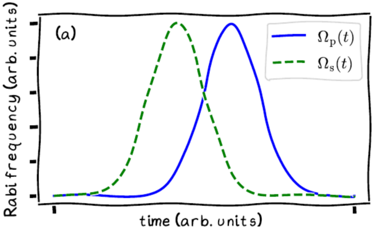
→ **adiabatic** protocol (robust and efficient)

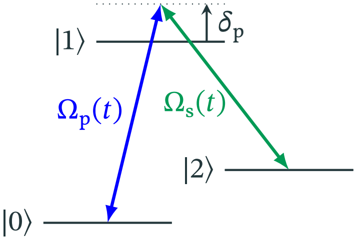
→ for $\delta \approx 0 \longrightarrow$ **trapped state**, no component on $|1\rangle$

$$|\phi_{\mathrm{D}}(t)\rangle = \cos\theta(t)|0\rangle - \sin\theta(t)|2\rangle, \quad \theta(t) = \tan^{-1}\left(\frac{\Omega_{\mathrm{p}}(t)}{\Omega_{\mathrm{s}}(t)}\right)$$

→ destructive interference

STIRAP/CTAP





[1] Phys. Rev. A 40 (11) (1989), Rev. Mod. Phys. 70 (3) (1998), Rev. Mod. Phys. 89 (1) (2017).
[2] Phys. Rev. B 70 235317 (2004), Phys. Rev. B 102 155404 (2020).

classification of noise

our goal is NOT efficient population transfer,
but classification of time and energy correlation in noise (with ML)

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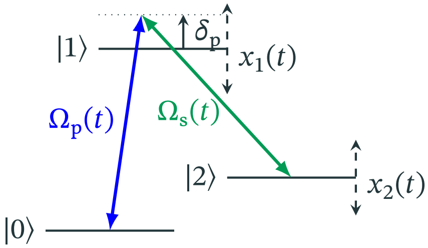
→ pure dephasing classical noise $x_i(t)$

$$H_{\text{noise}}(t) = x_1(t)|1\rangle\langle 1| + x_2(t)|2\rangle\langle 2|.$$

total Hamiltonian

$$H = \begin{pmatrix} 0 & \Omega_{\text{p}}(t)/2 & 0 \\ \Omega_{\text{p}}(t)/2 & \delta_{\text{p}} + x_1(t) & \Omega_{\text{s}}(t)/2 \\ 0 & \Omega_{\text{s}}(t)/2 & x_2(t) \end{pmatrix}$$



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→ pure dephasing classical noise $x_i(t)$

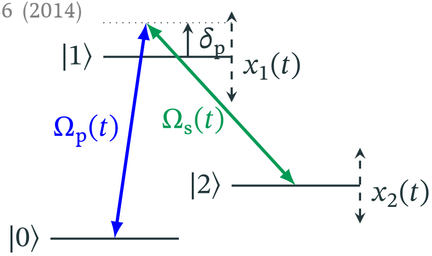
$$H_{\text{noise}}(t) = x_1(t)|1\rangle\langle 1| + x_2(t)|2\rangle\langle 2|.$$

- effective model of the leading decoherence effects in most AAs
- strategies like passive error avoidance, DD, QEC, depend critically on understanding and characterizing the underlying noise

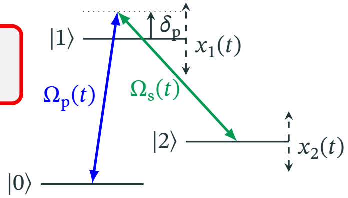
A. B. Zorin, *et al*, PRB 53 (1996) E. Paladino, *et al.*, RMP 86 (2014)
J. Yoneda, *et al*, Nat. Phys. (2023)

total Hamiltonian

$$H = \begin{pmatrix} 0 & \Omega_p(t)/2 & 0 \\ \Omega_p(t)/2 & \delta_p + x_1(t) & \Omega_s(t)/2 \\ 0 & \Omega_s(t)/2 & x_2(t) \end{pmatrix}$$



noise models



goal is the classification of noise correlations with ML

$$H_{\text{noise}}(t) = x_1(t)|1\rangle\langle 1| + x_2(t)|2\rangle\langle 2|.$$

→ **Non-Markovian quasistatic:**

1. correlated noise: $x_2(t) = \eta x_1(t)$, with $\eta > 0$,
2. anti-correlated noise: $x_2(t) = \eta x_1(t)$, with $\eta < 0$,
3. uncorrelated noise: $x_2(t)$ and $x_1(t)$, are independent.

→ **Markovian:**

4a. correlated noise: $x_2(t) = \eta x_1(t)$, with $\eta > 0$,
4b. anti-correlated noise: $x_2(t) = \eta x_1(t)$, with $\eta < 0$.

quasistatic → $x(t)$ constant during single evolution

calculation of efficiency

→ **non-Markovian (quasistatic) noise** → $\mathrm{i}\frac{\partial}{\partial t}|\psi(t)\rangle = H(t)|\psi(t)\rangle.$

$$\text{single trajectory efficiency } \xi^{(r)} = \xi(\{x_j\}^{(r)}) = |\langle\psi(t_\mathrm{f})|2\rangle|^2,$$

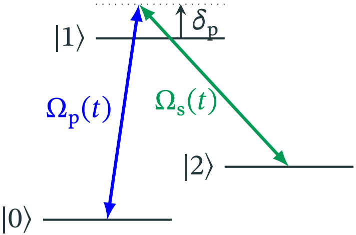
$$\text{efficiency } \xi = \int \xi(x_1, x_2)p(x_1, x_2)\mathrm{d}x_1\mathrm{d}x_2 \approx \frac{\sum_{r=1}^{N} \xi\big(x_1^{(r)}, x_2^{(r)}\big)p\big(x_1^{(r)}, x_2^{(r)}\big)}{\sum_{r=1}^{N} p\big(x_1^{(r)}, x_2^{(r)}\big)}.$$

→ **Markovian noise** → $\dot{\rho}(t) = -[H_0 + H_\mathrm{c}(t), \rho(t)] - \frac{\gamma}{2}(\hat{O}^2\rho(t) + \rho(t)\hat{O}^2 - 2\hat{O}\rho(t)\hat{O}),$

with $\hat{O} = |1\rangle\langle 1| + \eta|2\rangle\langle 2|$, $\langle x_1(t)x_1(t')\rangle = \gamma\delta(t-t')$ and $\langle x(t)\rangle = 0$.

$$\text{efficiency } \xi = \mathrm{Tr}\{|2\rangle\langle 2|\rho(t_\mathrm{f})\}.$$

summary and input generation



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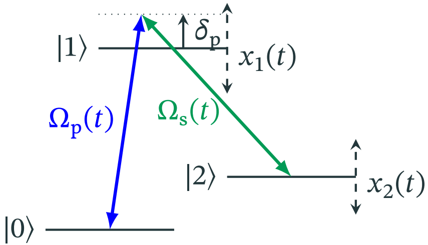

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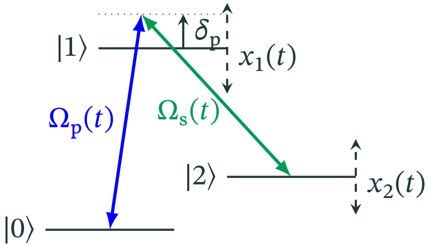
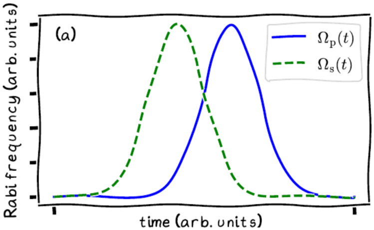


STIRAP/CTAP



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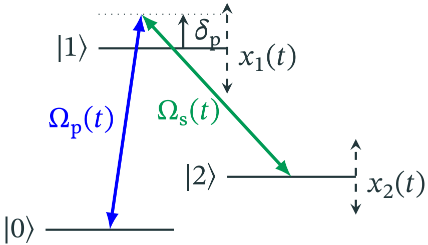

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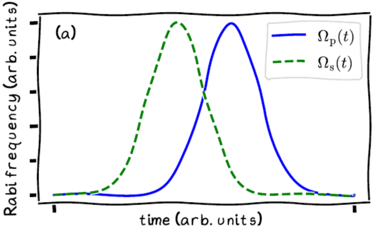

$$\Omega_p(t) = \Omega_p^{(\max)} e^{-\left(\frac{t-\tau}{T}\right)^2},$$

$$\Omega_s(t) = \Omega_s^{(\max)} e^{-\left(\frac{t+\tau}{T}\right)^2}.$$

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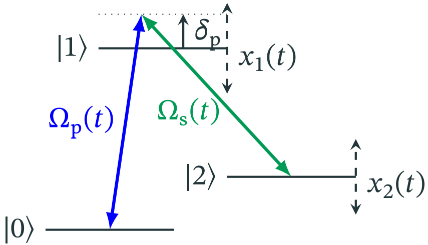

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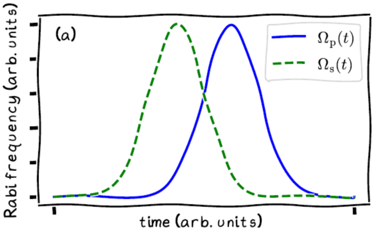

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efficiency under three pulse conditions:

1. $\Omega_p^{(\max)} = \Omega_s^{(\max)}$
2. $\Omega_p^{(\max)} > \Omega_s^{(\max)}$
3. $\Omega_p^{(\max)} < \Omega_s^{(\max)}$

data generation

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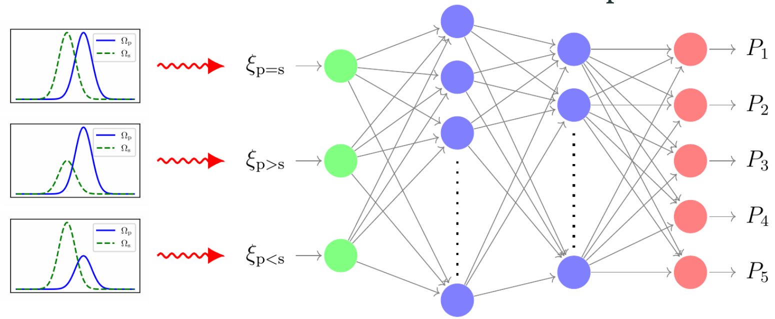
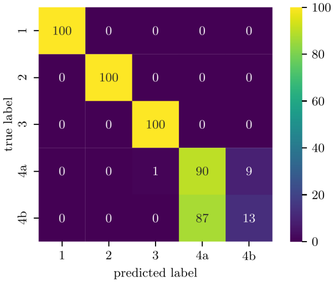
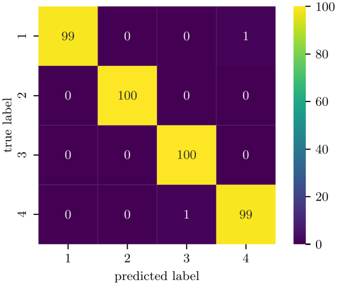
supervised learning



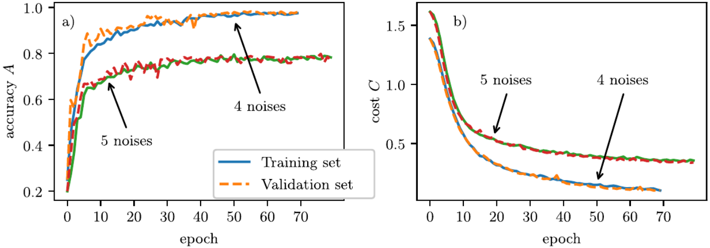
results

accuracy ≈ 0.80



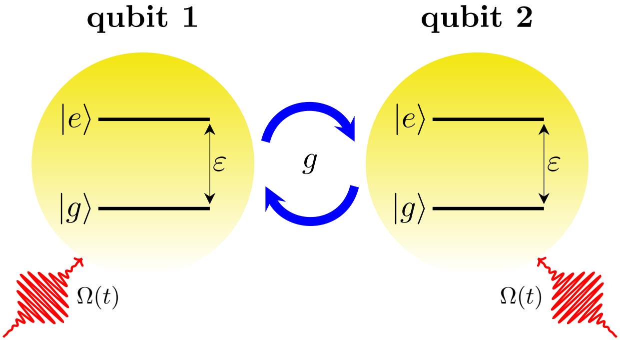


accuracy ≈ 1.00



S. Mukherjee, D. Penna, F. Cirinnà, M. Paternostro, E. Paladino, G. Falci, and LG, Mach. Learn.: Sci. Technol. 5 (2024)

ML-based quantum sensor for temporal and spatial correlations



$$H_0 = -\frac{\epsilon}{2}(\sigma_1^z + \sigma_2^z) + \frac{g}{2}\sigma_1^x\sigma_2^x, \quad H_c(t) = \frac{\Omega(t)}{\sqrt{2}}(\sigma_1^x + \sigma_2^x),$$

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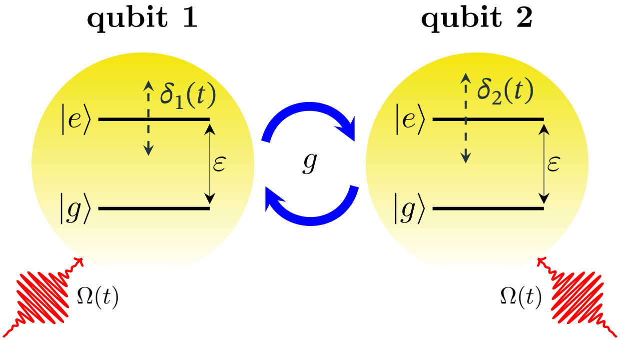

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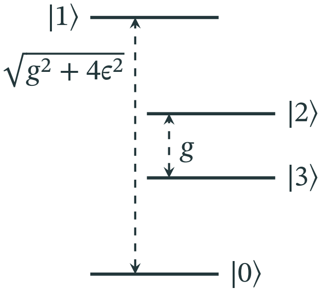
$$H_{\text{noise}}(t) = -\frac{\delta_1(t)}{2}\sigma_1^z - \frac{\delta_2(t)}{2}\sigma_2^z$$

eigenstates of

$$H_0 = -\frac{\epsilon}{2}(\sigma_1^z + \sigma_2^z) + \frac{g}{2}\sigma_1^x\sigma_2^x$$



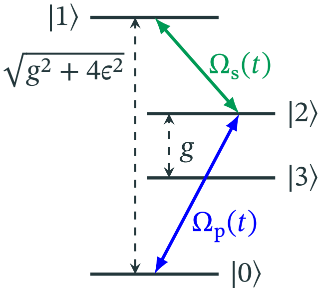
Eigenv.	Eigenstate
$-\varepsilon_e$	$\|0\rangle \equiv -\cos(\theta_e/2)\|gg\rangle + \sin(\theta_e/2)\|ee\rangle$
ε_e	$\|1\rangle \equiv \sin(\theta_e/2)\|gg\rangle + \cos(\theta_e/2)\|ee\rangle$
$-\varepsilon_o$	$\|3\rangle \equiv \frac{1}{\sqrt{2}}(\|ge\rangle - \|eg\rangle)$
ε_o	$\|2\rangle \equiv \frac{1}{\sqrt{2}}(\|ge\rangle + \|eg\rangle)$

$$\tan\theta_\mathrm{e} = \frac{g}{2\epsilon}$$

design of the sensor

eigenstates of

$$H_0 = -\frac{\epsilon}{2}(\sigma_1^z + \sigma_2^z) + \frac{g}{2}\sigma_1^x\sigma_2^x$$



simmetrically driven

$$H_c(t) = \frac{\Omega(t)}{\sqrt{2}}(\sigma_1^x + \sigma_2^x)$$

$\Longrightarrow$ level $|3\rangle$ uncoupled

two-tone AC field + USC

$$\Omega(t) = \frac{\Omega_p(t)}{\alpha}\cos(\omega_p t) + \frac{\Omega_s(t)}{\beta}\cos(\omega_s t),$$

AND

$g \sim \epsilon$ (UltraStrong Coupling)

design of the sensor

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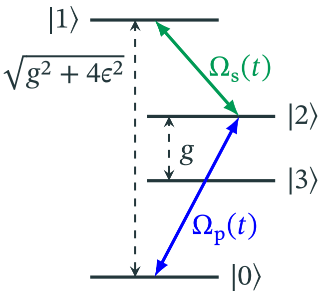

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→ noise introduces energy shifts of $|0\rangle$ and $|1\rangle$ and coupling between $|2\rangle$ and $|3\rangle$ and between $|0\rangle$ and $|1\rangle$

design of the sensor

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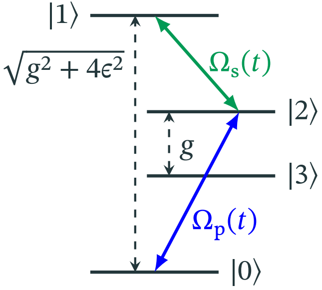

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→ noise introduces energy shifts of $|0\rangle$ and $|1\rangle$ and coupling between $|2\rangle$ and $|3\rangle$ and between $|0\rangle$ and $|1\rangle$ ⟶ beneficial for classification

data generation

$$\Omega_p(t) = \Omega_p^{(\max)} e^{-\left(\frac{t-\tau}{T}\right)^2},$$

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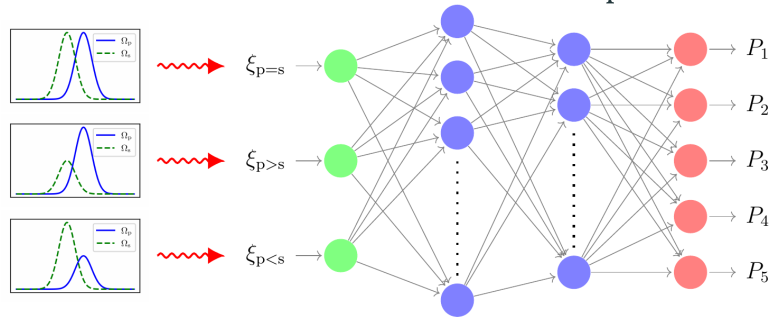
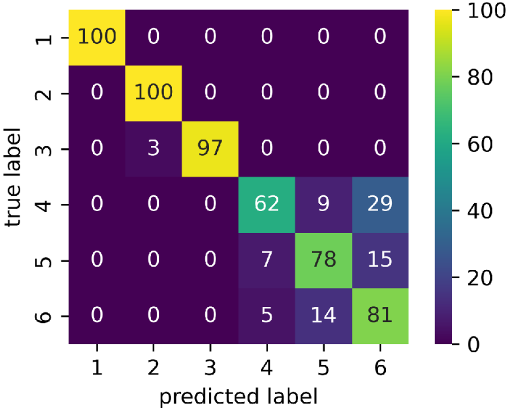
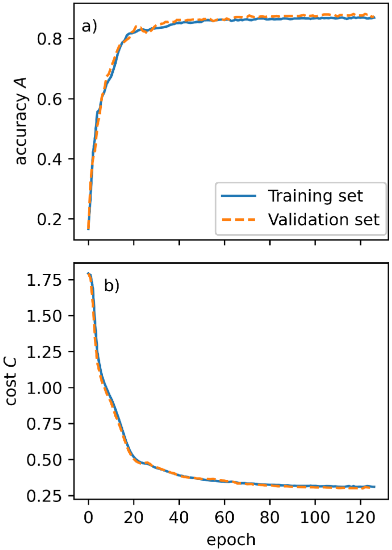


results

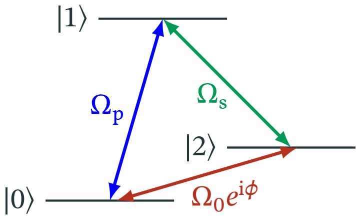


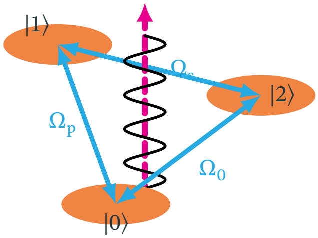


overall accuracy ≈ 0.86
temporal class. accuracy ≈ 1.00

D. Fasone, S. Mukherjee, D. Penna, F. Cirinnà, M. Paternostro, E. Paladino, LG, and G.A. Falci, APL Quantum 3, 026108 (2026)

plaquette phase





emergence of a plaquette phase

→ in general, the couplings are comples $\Omega_k = |\Omega_k| e^{\imath\phi_k}$

→ local phase redefinitions remove two phases, one phase persist

$$\phi = \phi_0 + \phi_s - \phi_p$$

→ gauge-invarian quantity → observable

→ dynamics of an electron hopping in a Δ network fo three electronic states in the presence of a magnetic field → tunnelling amplitudes aquire complex phases

non-conventional STIRAP in Δ systems

Hamiltonian

$$H = \begin{pmatrix} 0 & \Omega_\mathrm{p}(t)/2 & \Omega_0(t)e^{\mathrm{i}\phi}/2 \\ \Omega_\mathrm{p}(t)/2 & \delta_\mathrm{p} & \Omega_\mathrm{s}(t)/2 \\ \Omega_0(t)e^{-\mathrm{i}\phi}/2 & \Omega_\mathrm{s}(t)/2 & \delta \end{pmatrix}$$

$$\phi = \phi_0 + \phi_s - \phi_p$$

Trapping condition:

$$\delta(t) = \frac{\Omega_0}{\Omega_\mathrm{p}\Omega_\mathrm{s}}\left(\Omega_\mathrm{s}^2 e^{-\mathrm{i}\phi} - \Omega_\mathrm{p}^2 e^{\mathrm{i}\phi}\right)$$

→ for $\phi = 0, \pi$

- δ-modulated protocol equivalent to STIRAP

→ for $\phi \neq 0, \pi$

- complex detuning → non-hermicity
- the dynamics of the dark state is no longer decoupled
- mixing term $\propto \sin\phi$
- breaking of coherent trapping
- population leackage
- efficiency depends on phase ϕ

Use of multiple driving-detuning configurations

Transfer efficiencies are evaluated using 8 driving conditions

Three driving conditions

$$\Omega_p^{\max} = \Omega_s^{\max}, \quad \Omega_p^{\max} > \Omega_s^{\max}, \quad \Omega_p^{\max} < \Omega_s^{\max}$$

with $\sqrt{(\Omega_p^{\max})^2 + (\Omega_s^{\max})^2} = \text{constant}$

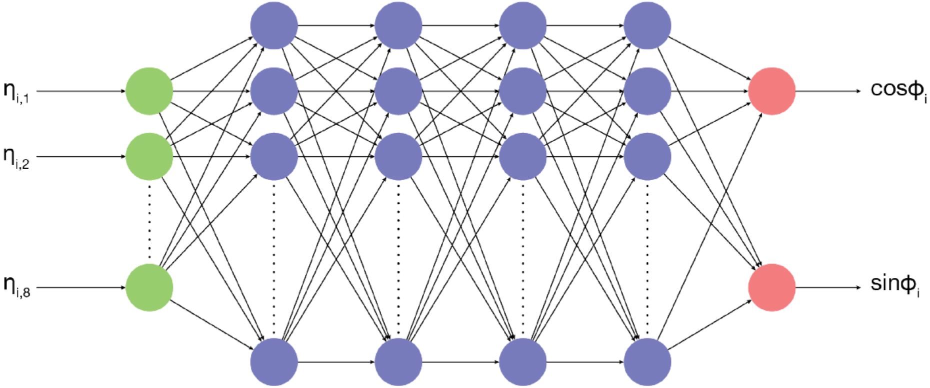
Two detuning strategies

$$\delta = 0 \quad \delta = \frac{\Omega_0}{\Omega_p \Omega_s}\left(\Omega_s^2 - \Omega_p^2\right)$$

Selected configurations

Driving condition	$\delta(t) = 0$	$\delta_{p=s}(t)$	$\delta_{p>s}(t)$	$\delta_{p<s}(t)$
$\Omega_p^{\max} = \Omega_s^{\max}$	✓	✓	–	–
$\Omega_p^{\max} > \Omega_s^{\max}$	✓	✓	✓	–
$\Omega_p^{\max} < \Omega_s^{\max}$	✓	✓	–	✓

structure of the NN



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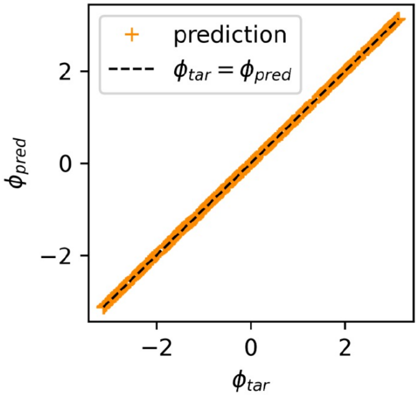
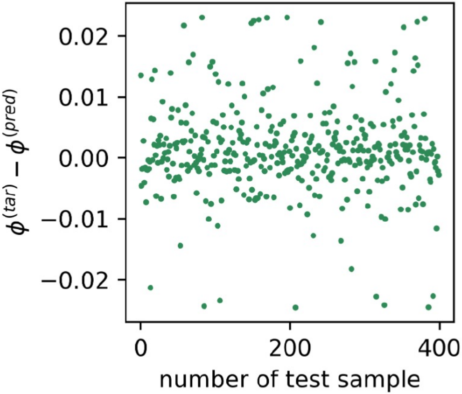

prediction
$\phi_{tar} = \phi_{pred}$
2
0
−2
−2
0
2
ϕ_{pred}
ϕ_{tar}


0.02
0.01
0.00
−0.01
−0.02
0
200
400
$\phi^{(tar)} - \phi^{(pred)}$
number of test sample

conclusion

Quantum Control + Machine Learning → detection of noise correlations

→ exploit the sensitivity of STIRAP/CTAP to classify noise correlations

→ in a three-level system

- ✓ non-Markovian vs Markovian → $A \approx 1$
- ✓ correlations in non-Markovian → $A \approx 1$
- ✗ unsensitive to correlations in Markovian noise

→ two-qubits quantum sensor

- ✓ non-Markovian vs Markovian → $A \approx 1$
- ✓ correlations in **both non-Markovian and Markovian noise** with overall accuracy $A \approx 0.86$

Quantum Control + Machine Learning → detection of Plaquette phase

→ use of δ-modulated non-conventional STIRAP/CTAP with 8 driving conditions

✓ Detection of the phase with error $\propto$ 0.01rad.

Thank You!!

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