Randomized Benchmarking

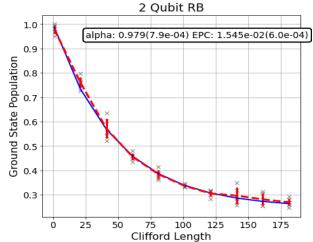
A key requirement for scalable quantum computing is that elementary quantum gates can be implemented with sufficiently low error. One method for determining the error behaviour of a gate implementation is to perform process tomography. However, standard process tomography is limited by errors in state preparation, measurement and one-qubit gates. It suffers from inefficient scaling with number of qubits and does not detect adverse error compounding when gates are composed in long sequences. An additional problem is due to the fact that desirable error probabilities for scalable quantum computing are of the order of 0.0001 or lower. Experimentally proving such low errors is challenging. We describe a randomized benchmarking method that yields estimates of the computationally relevant errors without relying on accurate state preparation and measurement. Since it involves long sequences of randomly chosen gates, it also verifies that error behaviour is stable when used in long computations. We implemented randomized benchmarking on 2-qubit simultaneous with 1-qubit, establishing a Error per Clifford (EPC) 1.320763e-02. In this particular experiment, we have 3 qubits Q0,Q1,Q2. We are running 2Q RB (on qubits Q0,Q2) and 1Q RB (on qubit Q1) simultaneously, where there are twice as many 1Q Clifford gates. We define a noise model for the simulator. To simulate decay, we add depolarizing error probabilities to the CNOT and U gates. We execute these sequences, but with a noise model extended with T1/T2 thermal relaxation error, and fit the exponentially decaying curve. We count the number of gates per Clifford, and calculate the two-qubit Clifford gate error, using the predicted primitive gate errors from the coherence limit.

What is Randomized Benchmarking?

• A proven protocol that provides an efficient and reliable estimate of an average error-rate for a set of quantum gate operations.

Consists of the following three stages:

- a) Generate RB sequences consisting of random elements from a Clifford group, including a computed reversal gate
- b) Run the RB sequences either on the device or on a simulator (with a noise model) and compare to the initial state
- c) Get the statistics and fit an exponential decaying curve: Ap^m+B Error per Clifford (EPC): r=(1-p)(d-1)/d (d=2n)

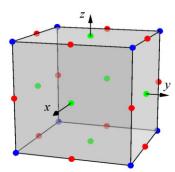


Clifford Group :

- The Clifford group consists of the quantum operators that can be efficiently simulated (in polynomial time) using a classical computer –Clifford simulation.
- It is generated by the gates: H, Sand CNOT:

$$H = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}, \qquad S = \begin{pmatrix} 1 & 0 \\ 0 & i \end{pmatrix}, \qquad CNOT = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

- The Clifford group on 1-qubit has 24 elements (the rotational symmetries of the cube)
- The Clifford group on n-qubit is of size: $2^{n^2+2n} \prod_{i=1}^{n} (4^{i}-1)$
- Efficient algorithms to generate and synthesize Clifford elements
- The Clifford group forms a unitary 2-design—twirling the finite Clifford group is equivalent to twirling the infinite unitary group

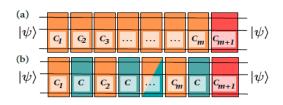


RB methods for estimating noise parameters :

Interleaved RB Estimating the average error of individual quantum gates

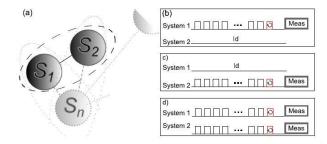
$$r_{\mathcal{C}}^{\mathrm{est}} = \frac{\left(d-1\right)\left(1-p_{\overline{\mathcal{C}}}/p\right)}{d},$$

Purity RB: Quantifies how coherent the errors are, namely



$$Tr(\rho^2) = 1 \leftrightarrow \rho \text{ is pure (coherent)}$$

- Leakage RB: Quantification and characterization of leakage errors (unwanted energy levels)
- Simultaneous RB: Running RB simultaneously on subsets of qubits, characterizing the amount of addressability between subsystems
- Correlated RB: Estimating correlated crosstalk error between qubits participating in separate gates



RB methods for other groups and gates

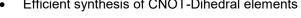
Non-Clifford Dihedral and CNOT-Dihedral RB

$$D_{m} = \langle X, Z_{m} \rangle$$

$$Z_{m} = \begin{bmatrix} 1 & 0 \\ 0 & e^{2\pi i/m} \end{bmatrix}$$

$$G_{m} = \langle CX(i, j), X(j), Z_{m}(j) \rangle$$

- Allows benchmarking of non-Clifford gates: T, CS, CCZ
- Efficient synthesis of CNOT-Dihedral elements



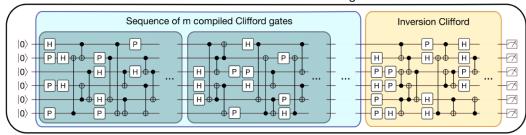


$$I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \qquad X = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \qquad Y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}, \qquad Z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

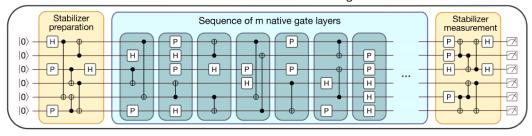
- Subgroups of the Clifford group
- More efficient synthesis compared to the Clifford group

• **Direct RB**: Directly benchmarking the native gates of a device

Clifford Randomized Benchmarking



Direct Randomized Benchmarking



Theoretical Background of RB:

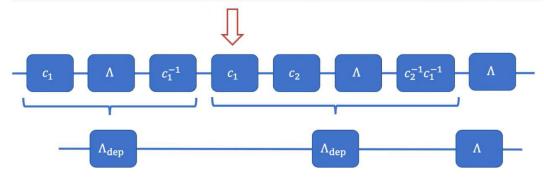
Ideal Clifford-gate Sequence



Noisy Clifford-gate sequence for Noisy channel Λ



Depolarizing channel: $\Lambda_{\mathrm{dep}}(ho) := rac{1}{|\mathcal{C}_d^n|} \sum_{l=1}^{|\mathcal{C}_d^n|} c_l^\dagger \Lambda\left(c_l ho c_l^\dagger\right) c_l$



- By independence, this factorizes into product of average channels ('Twirl')
- Sequence of Twirled noisy channels:



$$\Lambda \circ \Lambda_{\operatorname{dep}}^{\circ m-1}(
ho) =
ho^{m-1} \Lambda(
ho) + \left(1 -
ho^{m-1}\right) \Lambda(\mathbb{1}) / d^n$$

Depolarizing channel (Shur's Lemma):

$$\Lambda(\rho) = p\rho + (1-p)/d * I$$

• The average data looks like a product of depolarizing channels:

$$p^{m} \rho + (1 - p^{m})/d * I$$

 $p^{m} (d - 1)/d + 1/d$

• Fit the results:

$$Ap^m + B$$

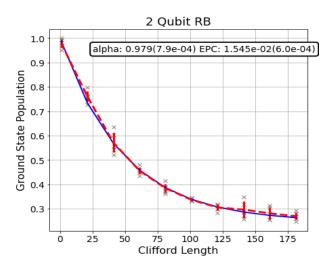
 Calculate the average Error per Clifford (EPC):

$$r = (1-p) - (1-p)/d$$

= $(1-p)(d-1)/d$

• Calculate the 2-qubit gate fidelity:

$$r_{cx} \approx r/n_{cx}$$
 $n_{cx} \approx 1.5$



Theoretical Background of the Clifford group:

• The Clifford group C_n on n-qubits is defined as the normalizer of the Pauli group P_n , when neglecting the global phase $U(1)=\mathbb{C}$

$$P_n/\mathbf{U}(\mathbf{1}) = \mathbf{F}_2^{2n}$$
$$C_n/P_n = Sp(2n)$$

- Sp(2n) denotes the group $2n \times 2n$ symplectic matrices over the field F_2 , which is simple when n > 2.
- 1-qubit Clifford group (24 elements):

Since $C_1/P_1=Sp(2)=S_3$, we can explicitly present each elements of C_1 as a product AB where:

$$A \ in \ \{I,V,W,H,HV,HW\} (V=S^{\dagger}H,W=HS) \quad , \quad B \ in \ P_l=\{I,X,Y,Z\}$$

• n-qubit Clifford group:

Algorithms to efficiently select random elements of C_n of size: $2^{n^2+2n}\prod_{j=1}^n(4^j-1)$ Algorithms to synthesize elements of C_n (optimized for n=1,2,3)

Appendix

Python Code for Simulations

Created on Wed Jul 06 14:56:59 2022 UTC

#Import general libraries (needed for functions)

import numpy as np

import matplotlib.pyplot as plt

from IPython import display

#Import Qiskit classes

import qiskit

from qiskit.providers.aer.noise import NoiseModel

from qiskit.providers.aer.noise.errors.standard errors import depolarizing error, thermal relaxation error

#Import the RB Functions

import qiskit.ignis.verification.randomized_benchmarking as rb

#Number of qubits

nQ = 3

#There are 3 qubits: Q0,Q1,Q2.

#Number of seeds (random sequences)

nseeds = 5

#Number of Cliffords in the sequence (start, stop, steps)

nCliffs = np.arange(1,200,20)

#2Q RB on Q0,Q2 and 1Q RB on Q1

 $rb_pattern = [[0,2],[1]]$

#Do three times as many 1Q Cliffords

length_multiplier = [1,3]

rb_opts = {}

rb_opts['length_vector'] = nCliffs

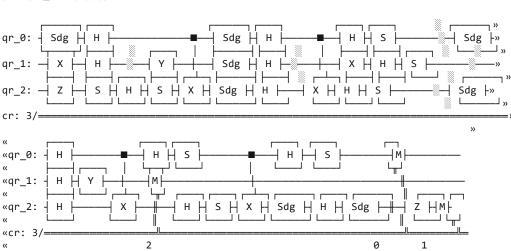
rb_opts['nseeds'] = nseeds

rb_opts['rb_pattern'] = rb_pattern

rb_opts['length_multiplier'] = length_multiplier

rb_circs, xdata = rb.randomized_benchmarking_seq(**rb_opts)

print(rb_circs[0][0])



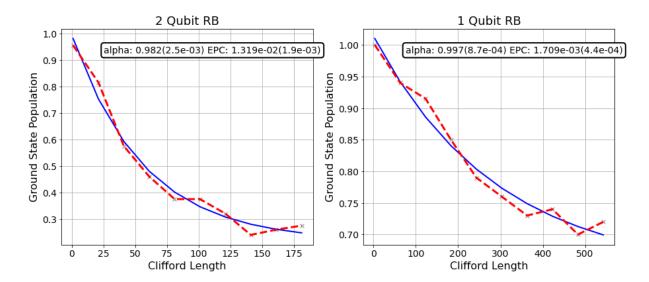
```
#Create a new circuit without the measurement
qc = qiskit.QuantumCircuit(*rb_circs[0][-1].qregs,*rb_circs[0][-1].cregs)
for i in rb_circs[0][-1][0:-nQ]:
  qc.data.append(i)
#The Unitary is an identity (with a global phase)
backend = qiskit.Aer.get backend('unitary simulator')
basis_gates = ['u1', 'u2', 'u3', 'cx'] # use U,CX for now
job = qiskit.execute(qc, backend=backend, basis_gates=basis_gates)
print(np.around(job.result().get unitary(), 3))
[[-1.+0.j -0.-0.j -0.-0.j -0.-0.j 0.+0.j 0.-0.j -0.-0.j 0.+0.j]
 [ 0.-0.j -1.+0.j -0.+0.j -0.-0.j -0.+0.j -0.+0.j -0.-0.j 0.+0.j]
 [ 0.-0.j -0.-0.j -1.+0.j -0.-0.j -0.-0.j -0.+0.j -0.+0.j -0.-0.j]
 [-0.-0.j 0.+0.j 0.-0.j -1.+0.j 0.-0.j -0.-0.j -0.+0.j 0.-0.j]
 [-0.+0.j 0.+0.j 0.+0.j -0.-0.j -0.-0.j 0.+0.j 0.+0.j -1.+0.j]]
noise model = NoiseModel()
p1Q = 0.002
p2Q = 0.01
noise_model.add_all_qubit_quantum_error(depolarizing_error(p1Q, 1), 'u2')
noise model.add all qubit quantum error(depolarizing error(2*p1Q, 1), 'u3')
noise model.add all qubit quantum error(depolarizing error(p2Q, 2), 'cx')
backend = qiskit.Aer.get_backend('qasm_simulator')
basis gates = ['u1','u2','u3','cx'] # use U,CX for now
shots = 200
result list = []
transpile_list = []
import time
for rb_seed,rb_circ_seed in enumerate(rb_circs):
  print('Compiling seed %d'%rb seed)
  rb circ transpile = qiskit.transpile(rb circ seed, basis gates=basis gates)
  print('Simulating seed %d'%rb_seed)
  job = qiskit.execute(rb_circ_transpile, noise_model=noise_model, shots=shots, backend=backend,
backend options={'max parallel experiments': 0})
  result_list.append(job.result())
  transpile_list.append(rb_circ_transpile)
print("Finished Simulating")
Compiling seed 0
Simulating seed 0
Compiling seed 1
Simulating seed 1
Compiling seed 2
Simulating seed 2
Compiling seed 3
Simulating seed 3
Compiling seed 4
Simulating seed 4
Finished Simulating
#Create an RBFitter object with 1 seed of data
rbfit = rb.fitters.RBFitter(result_list[0], xdata, rb_opts['rb_pattern'])
plt.figure(figsize=(15, 6))
```

```
for i in range(2):
    ax = plt.subplot(1, 2, i+1)
    pattern_ind = i

# Plot the essence by calling plot_rb_data
    rbfit.plot_rb_data(pattern_ind, ax=ax, add_label=True, show_plt=False)

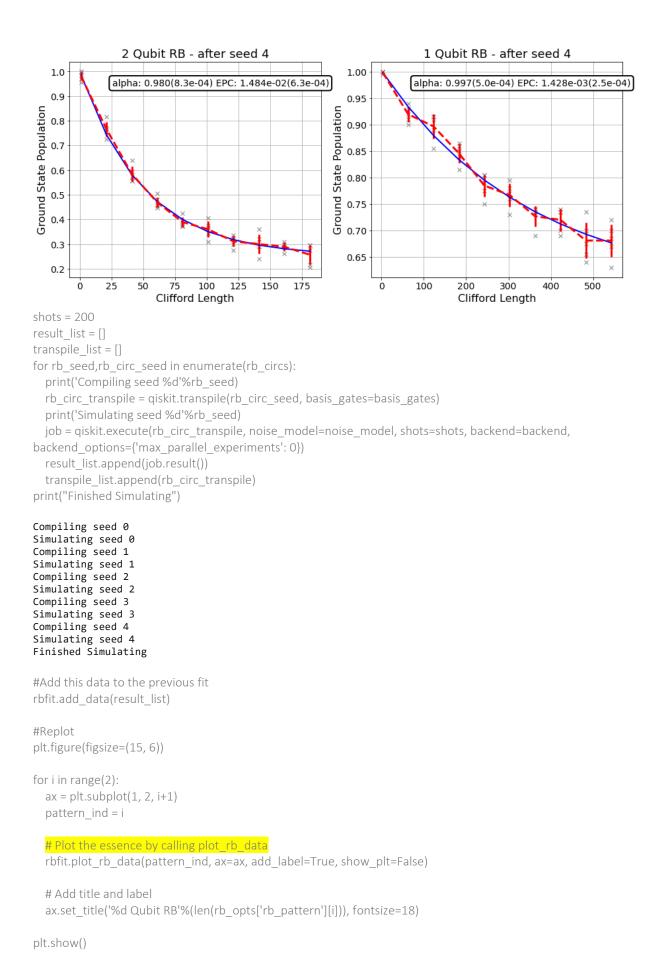
# Add title and label
    ax.set_title('%d Qubit RB'%(len(rb_opts['rb_pattern'][i])), fontsize=18)

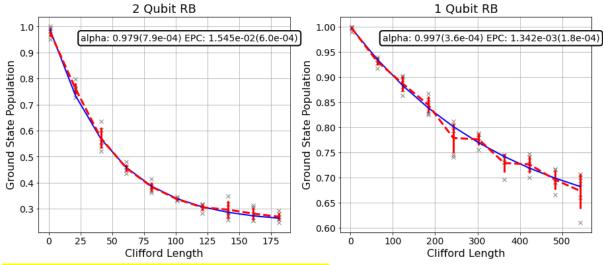
plt.show()
```



rbfit = rb.fitters.RBFitter(result_list[0], xdata, rb_opts['rb_pattern'])

```
for seed num, data in enumerate(result list):#range(1,len(result list)):
  plt.figure(figsize=(15, 6))
  axis = [plt.subplot(1, 2, 1), plt.subplot(1, 2, 2)]
  # Add another seed to the data
  rbfit.add_data([data])
  for i in range(2):
    pattern_ind = i
    # Plot the essence by calling plot_rb_data
    rbfit.plot_rb_data(pattern_ind, ax=axis[i], add_label=True, show_plt=False)
    # Add title and label
    axis[i].set title('%d Qubit RB - after seed %d'%(len(rb opts['rb pattern'][i]), seed num), fontsize=18)
  # Display
  display.display(plt.gcf())
  # Clear display after each seed and close
  display.clear_output(wait=True)
  time.sleep(1.0)
  plt.close()
```





#Count the number of single and 2Q gates in the 2Q Cliffords

 $gates_per_cliff = rb.rb_utils.gates_per_clifford(transpile_list,xdata[0],basis_gates,rb_opts['rb_pattern'][0]) \\ for basis_gate in basis_gates:$

Number of u1 gates per Clifford: 0.142174 Number of u2 gates per Clifford: 1.643696 Number of u3 gates per Clifford: 0.166957 Number of cx gates per Clifford: 1.468913

Error per gate from noise model

epgs_1q = {'u1': 0, 'u2': p1Q/2, 'u3': 2*p1Q/2}
epg_2q = p2Q*3/4
pred_epc = rb.rb_utils.calculate_2q_epc(
 gate_per_cliff=gates_per_cliff,
 epg_2q=epg_2q,
 qubit_pair=[0, 2],
 list_epgs_1q=[epgs_1q, epgs_1q])

Calculate the predicted epc

print("Predicted 2Q Error per Clifford: %e"%pred_epc)

Predicted 2Q Error per Clifford: 1.565697e-02

```
rb_opts2 = rb_opts.copy()
rb_opts2['rb_pattern'] = [[0,1]]
rb_opts2['length_multiplier'] = 1
rb_circs2, xdata2 = rb.randomized_benchmarking_seq(**rb_opts2)
```

#Add T1/T2 noise to the simulation

noise_model2 = NoiseModel()

```
t1 = 100.

t2 = 80.

gate1Q = 0.1

gate2Q = 0.5

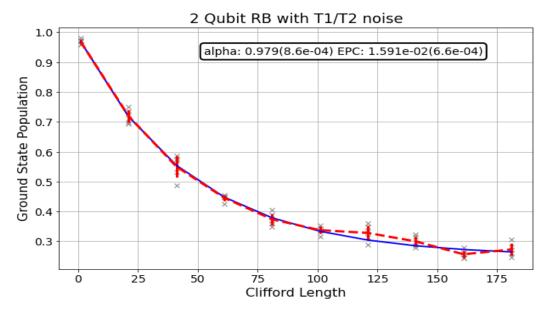
noise_model2.add_all_qubit_quantum_error(thermal_relaxation_error(t1,t2,gate1Q), 'u2')

noise_model2.add_all_qubit_quantum_error(thermal_relaxation_error(t1,t2,2*gate1Q), 'u3')

noise_model2.add_all_qubit_quantum_error(

thermal_relaxation_error(t1,t2,gate2Q).tensor(thermal_relaxation_error(t1,t2,gate2Q)), 'cx')
```

```
backend = qiskit.Aer.get backend('qasm simulator')
basis_gates = ['u1','u2','u3','cx'] # use U,CX for now
shots = 500
result list2 = []
transpile list2 = []
for rb_seed,rb_circ_seed in enumerate(rb_circs2):
  print('Compiling seed %d'%rb seed)
  rb_circ_transpile = qiskit.transpile(rb_circ_seed, basis_gates=basis_gates)
  print('Simulating seed %d'%rb_seed)
  job = qiskit.execute(rb circ transpile, noise model=noise model, shots=shots, backend=backend,
backend_options={'max_parallel_experiments': 0})
  result_list2.append(job.result())
  transpile_list2.append(rb_circ_transpile)
print("Finished Simulating")
Compiling seed 0
Simulating seed 0
Compiling seed 1
Simulating seed 1
Compiling seed 2
Simulating seed 2
Compiling seed 3
Simulating seed 3
Compiling seed 4
Simulating seed 4
Finished Simulating
#Create an RBFitter object
rbfit = rb.RBFitter(result_list2, xdata2, rb_opts2['rb_pattern'])
plt.figure(figsize=(10, 6))
ax = plt.gca()
# Plot the essence by calling plot_rb_data
rbfit.plot_rb_data(0, ax=ax, add_label=True, show_plt=False)
# Add title and label
ax.set_title('2 Qubit RB with T1/T2 noise', fontsize=18)
plt.show()
```



#Count the number of single and 2Q gates in the 2Q Cliffords

```
gates_per_cliff = rb.rb_utils.gates_per_clifford(transpile_list2,xdata[0],basis_gates,rb_opts2['rb_pattern'][0]) for basis_gate in basis_gates:
```

```
Number of u1 gates per Clifford: 0.119674
Number of u2 gates per Clifford: 1.655000
Number of u3 gates per Clifford: 0.181848
Number of cx gates per Clifford: 1.500652
```

Predicted primitive gate errors from the coherence limit

```
u2_error = rb.rb_utils.coherence_limit(1,[t1],[t2],gate1Q)
u3_error = rb.rb_utils.coherence_limit(1,[t1],[t2],2*gate1Q)
epg_2q = rb.rb_utils.coherence_limit(2,[t1,t1],[t2,t2],gate2Q)
epgs_1q = {'u1': 0, 'u2': u2_error, 'u3': u3_error}
pred_epc = rb.rb_utils.calculate_2q_epc(
    gate_per_cliff=gates_per_cliff,
    epg_2q=epg_2q,
    qubit_pair=[0, 1],
    list_epgs_1q=[epgs_1q, epgs_1q])
```

Calculate the predicted epc

print("Predicted 2Q Error per Clifford: %e"%pred_epc)

Predicted 2Q Error per Clifford: 1.320763e-02

import qiskit.tools.jupyter %qiskit_version_table %qiskit_copyright

Qiskit Software Version

qiskit-terra	0.20.2
qiskit-aer	0.10.4
qiskit-ignis	0.7.1
qiskit-ibmq-provider	0.19.1
qiskit	0.36.2
qiskit-nature	0.4.1
qiskit-finance	0.3.3
qiskit-optimization	0.4.0
qiskit-machine-learning	0.4.0

System information

```
Python version 3.8.13

Python compiler GCC 10.3.0

Python build default, Mar 25 2022 06:04:10

OS

Linux

CPUs8Memory (Gb) 31.211315155029297

Wed Jul 06 14:56:59 2022 UTC
```

References

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 2.Mahnaz Jaafarzadeh Randomized Benchmarking For Qudit Clifford Gates et al 2020 New J. Phys.. 22 063014 https://iopscience.iop.org/article/10.1088/1367-2630/ab8ab1
 3.Timothy J. Proctor, Arnaud Carignan-Dugas, Kenneth Rudinger, Erik Nielsen, Robin Blume-Kohout, and Kevin Young, Direct randomized benchmarking for multi-qubit devices, Phys. Rev. Lett. 12(030503) 2019,https://arxiv.org/abs/1807.07975
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 5. https://giskit.org/documentation/stable/0.24/tutorials/noise/4_randomized_benchmarking.html