

# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## QFlux: Quantum Circuit Implementations of Molecular Dynamics

Victor S Batista

*Yale University, Department of Chemistry and Yale Quantum Institute*

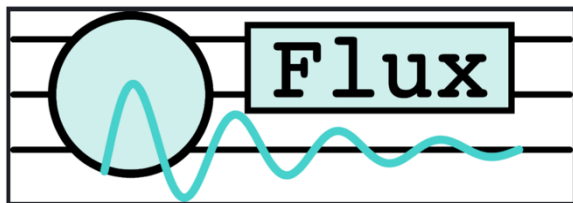
### Part III: The QFlux Synthesis Pipeline

*Every quantum algorithm depends on two operations:  
preparing a state and implementing a unitary.*

*These are not physical problems — they're synthesis problems.  
How linear algebra is compiled as pulses applied to quantum hardware*

<https://qflux.batistalab.com>

[Part\\_III.ipynb](#)



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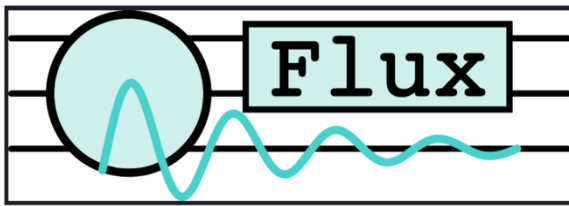
**This tutorial is based on the manuscript**

**QFlux: Quantum Circuit Implementations for Molecular Dynamics**

**Part III – State Initialization and Unitary Decomposition**

**Authors:**

Alexander V. Soudackov, Delmar G. A. Cabral, Brandon C. Allen, Xiaohan Dan, Nam P. Vu, Cameron Ciani, Rishab Dutta, Sabre Kais, Eitan Geva, and Victor S. Batista



# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

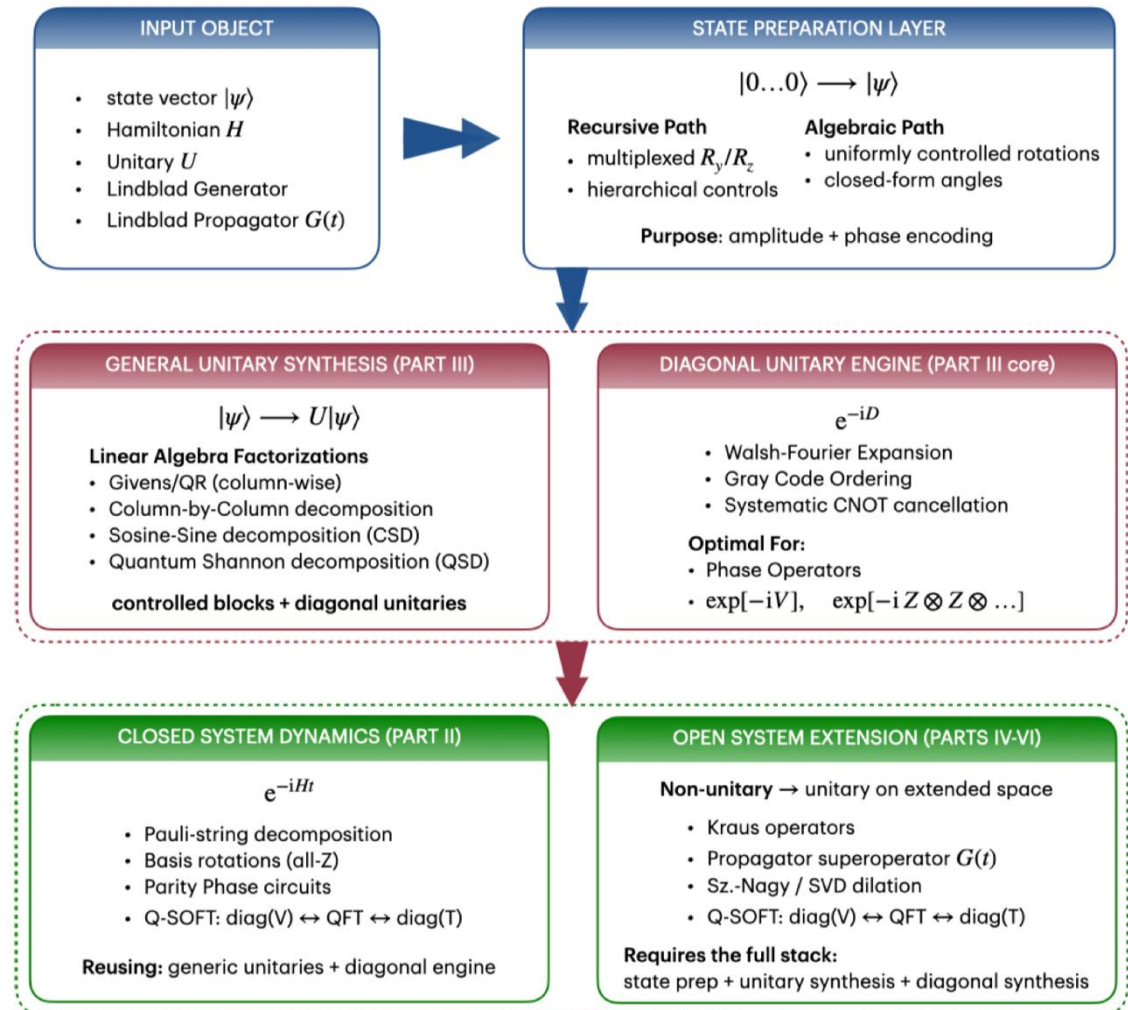
## The QFlux Synthesis Pipeline

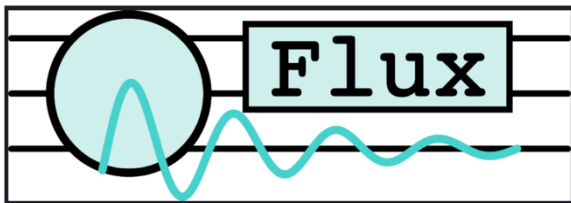
*The backbone of QFlux*

One pipeline for all simulations

- State vectors  $\rightarrow$  state preparation
- Generic unitaries  $\rightarrow$  linear-algebra factorizations
- Diagonal operators  $\rightarrow$  Walsh synthesis

*Reused across  
closed and open systems*





# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## Method Selection: Which Tool When?

### State preparation:

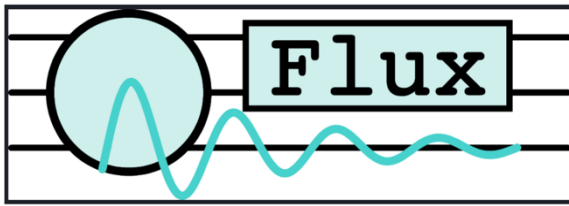
- Multiplexors → transparent, good for debugging
- UCRs → compact, compiler-friendly

### Unitaries:

- Givens / QR → pedagogical baseline
- Column-by-column → practical
- CSD / QSD → asymptotically optimal

### Diagonal:

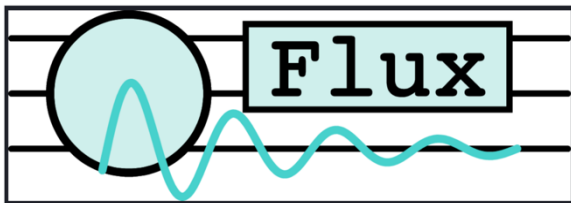
- Walsh + Gray code → NISQ-optimal



# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## PART A — STATE PREPARATION

- **Input:**  $|00 \dots 0\rangle = |0\rangle^{\otimes n} = \underbrace{\begin{pmatrix} 1 \\ 0 \end{pmatrix} \otimes \begin{pmatrix} 1 \\ 0 \end{pmatrix} \otimes \dots \otimes \begin{pmatrix} 1 \\ 0 \end{pmatrix}}_{n \text{ qubits}} = (1, 0, \dots, 0)^{\top}$
- **Target:**  $|\psi\rangle = \sum_{k_1, k_2, \dots, k_n \in \{0, 1\}} c_{k_1 k_2 \dots k_n} |k_1 k_2 \dots k_n\rangle$   
 $|\psi\rangle = (c_1, c_2, \dots, c_{2^n})^{\top}$
- **Goal:** deterministic, exact preparation
- **Strategy:** *disentangle qubits one by one*

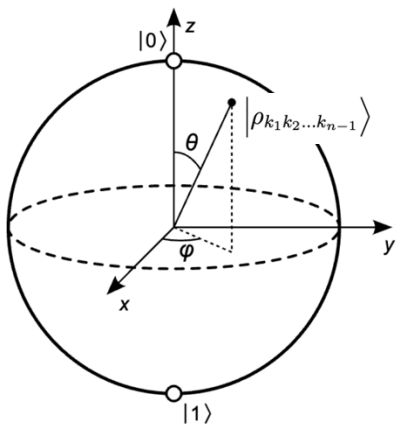


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## PART A — STATE PREPARATION

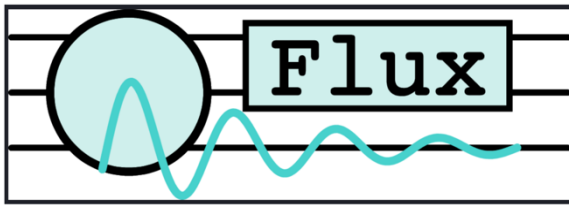
$$|\psi\rangle = \sum_{k_1, k_2, \dots, k_n \in \{0,1\}} c_{k_1 k_2 \dots k_n} |k_1 k_2 \dots k_n\rangle$$

$$|\psi\rangle = \sum_{k_1, k_2, \dots, k_{n-1} \in \{0,1\}} |k_1 k_2 \dots k_{n-1}\rangle \otimes \underbrace{\left[ c_{k_1 k_2 \dots k_{n-1} 0} |0\rangle + c_{k_1 k_2 \dots k_{n-1} 1} |1\rangle \right]}$$



$$|\rho_{k_1 k_2 \dots k_{n-1}}\rangle = c_{k_1 k_2 \dots k_{n-1} 0} |0\rangle + c_{k_1 k_2 \dots k_{n-1} 1} |1\rangle$$

$$R_y(-\theta_{k_1 k_2 \dots k_{n-1}}) R_z(-\varphi_{k_1 k_2 \dots k_{n-1}}) |\rho_{k_1 k_2 \dots k_{n-1}}\rangle = r_{k_1 k_2 \dots k_{n-1}} e^{it_{k_1 k_2 \dots k_{n-1}}} |0\rangle$$



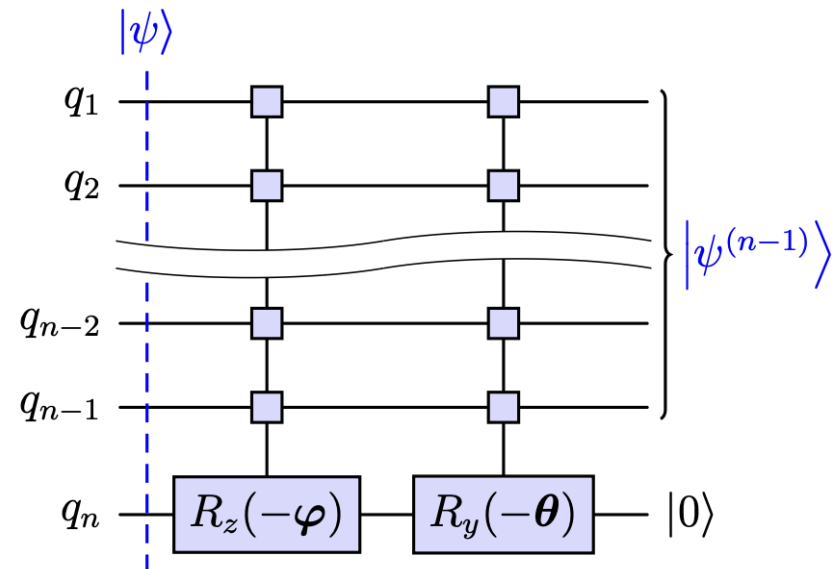
# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

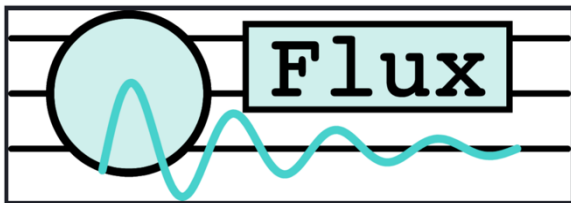
## Multiplexor Intuition

$$R^{(n)} = \bigoplus_{k_1, \dots, k_{n-1} \in \{0,1\}} R_y(-\theta_{k_1 k_2 \dots k_{n-1}}) R_z(-\varphi_{k_1 k_2 \dots k_{n-1}})$$

$$R^{(n)} |\psi\rangle = |\psi^{(n-1)}\rangle \otimes |0\rangle$$

- Group amplitudes by last qubit
- Each conditional single-qubit state lies on Bloch sphere
- Rotate each to  $|0\rangle$  using conditional rotations
- Remove entanglement one qubit at a time





# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## What Is a Multiplexor?

*For each bitstring of the control qubits, apply a different  $R_y$ – $R_z$  pair to the target*

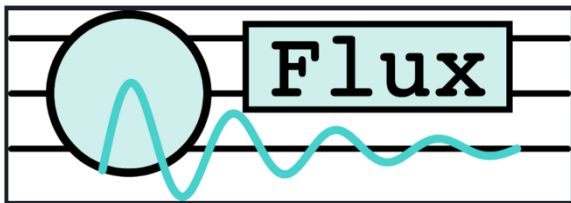
- A gate that applies different single-qubit rotations depending on controls
- Block-diagonal structure:
  - One rotation per control configuration
- Acts as “conditional disentangler”

▶

```
1 from scipy.linalg import block_diag
2
3 def multiplexor_matrix(n, vector, bit=0):
4     bit = int(bool(bit))
5     multiplexor = None
6     for i in np.arange(0, 2**n, 2):
7         c0, c1 = vector[i], vector[i+1]
8         theta, phi = compute_bloch_angles(c0, c1)
9         r = ry_matrix(bit*np.pi - theta) @ rz_matrix(-phi)
10        multiplexor = block_diag(multiplexor, r) if multiplexor is not None else r
11    return multiplexor
```

**Script S.1.3:** [Part III.ipynb](#)





# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## Recursive Disentanglement Algorithm

- Step 1: rotate last qubit  $\rightarrow |0\rangle$
- Step 2: recurse on remaining  $n-1$  qubits
- Reverse the sequence to prepare  $|\psi\rangle$
- Cost:  $\sim 2^n$  CNOTs

**Script S.1.5:** [Part III.ipynb](#)

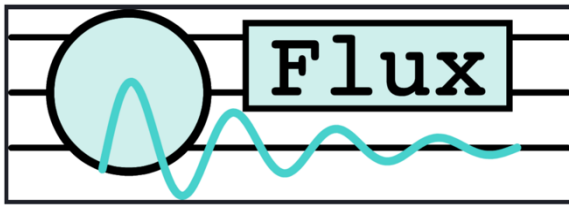
**Example: Three-Qubit State Preparation**

**Script S.1.6:** [Part III.ipynb](#)

**Example: Coherent Wavepacket State Preparation on a 6-Qubit System**

### Script S.1.5: Example: Three-Qubit State Preparation

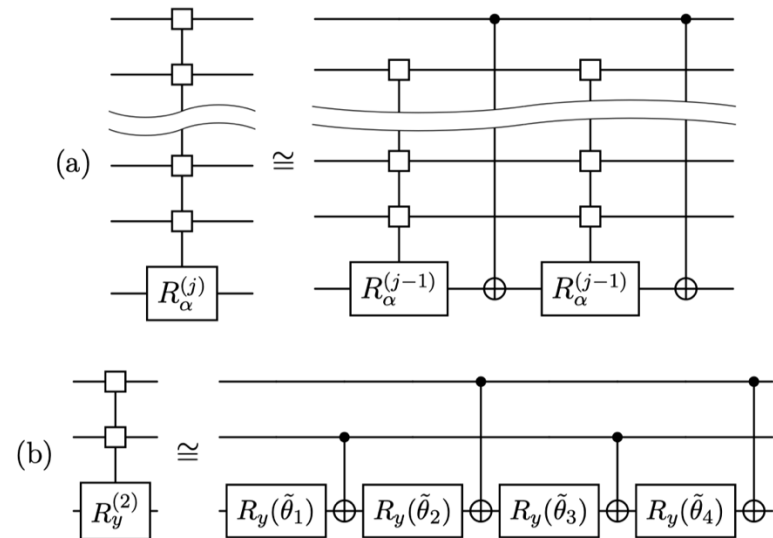
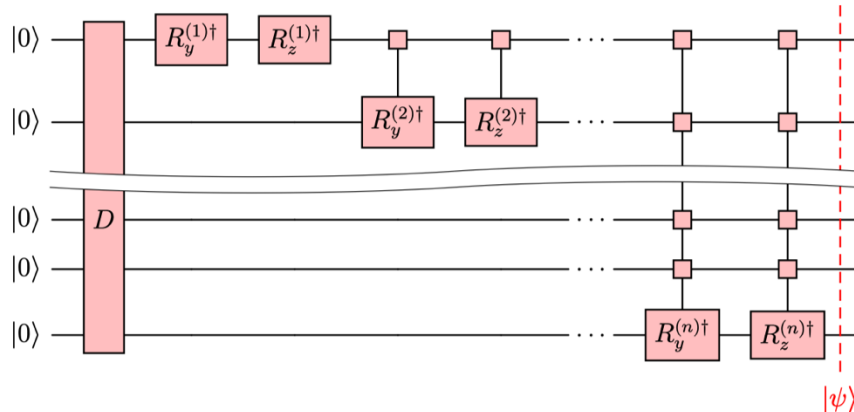
```
1 from numpy import linalg as LA
2 #np.random.seed(42)
3 nq = 4
4 ndim = 2**nq
5 state_vector = (2*np.random.rand(ndim)-1) * np.exp(1j*2*np.pi*np.random.rand(ndim))
6 state_vector /= LA.norm(state_vector)
7 mrot = rotate_to_vacuum_matrix(state_vector)
8 rot_vector = mrot.dot(state_vector)
9 back_vector = np.conjugate(mrot.T).dot(rot_vector)
```



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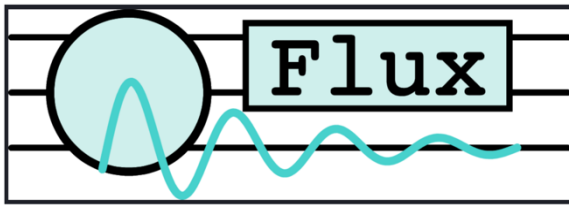
## Recursive Disentanglement Algorithm

### Script S.1.4: Recursive Quantum Multiplexor Transformation



What is the asymptotic cost? CNOT gates:  $2^{n+1} - 2n$

Single-qubit rotations:  $O(2^n)$

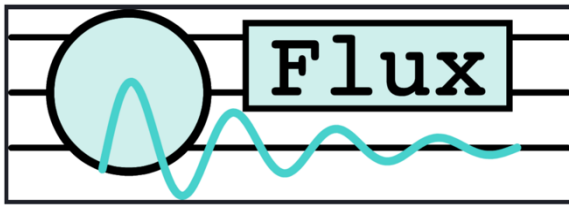


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## When to Use Multiplexors

- **Best for:**
  - Conceptual clarity
  - Debugging pipelines
  - Small  $n$
- **Tradeoff:**
  - Higher CNOT count
  - Recursive, irregular structure



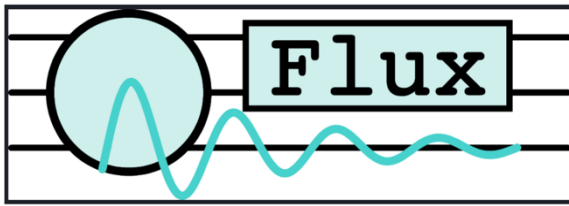
## PART B — UNIFORMLY CONTROLLED ROTATIONS (UCR)

### *Motivation for UCRs*

- Same goal: prepare arbitrary

$$|\psi\rangle = \left( |c_1|e^{i\omega_1}, |c_2|e^{i\omega_2}, \dots, |c_N|e^{i\omega_N} \right)^\top$$

- But:
  - Non-recursive
  - Regular layered structure
  - Predictable gate counts



# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## Key Idea: Separate Phase and Amplitude

*First, we make the state real and positive*

- **Step 1:** remove all relative phases with uniformly controlled z-rotations  $\mathcal{R}_z$

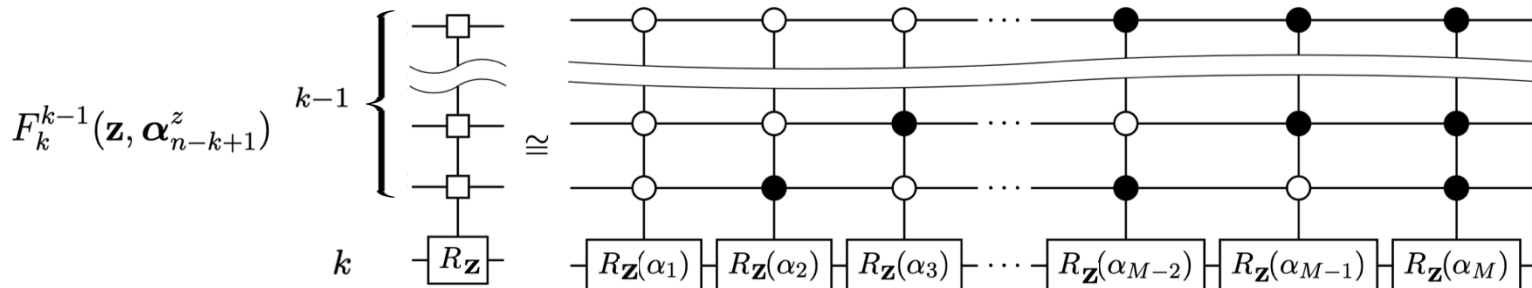
$$|\psi\rangle = \left( |c_1|e^{i\omega_1}, |c_2|e^{i\omega_2}, \dots, |c_N|e^{i\omega_N} \right)^\top$$

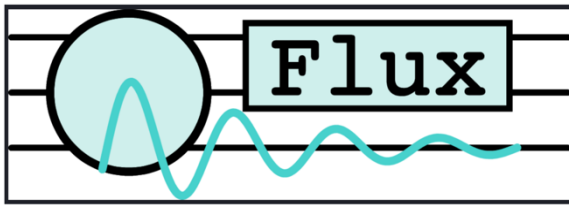
Angles for phase equalization:

$$(\alpha_j)_k^z = \sum_{l=1}^{2^{k-1}} \frac{\omega_{(2j-1)2^{k-1}+l} - \omega_{(j-1)2^k+l}}{2^{k-1}}, \quad j = 1, \dots, 2^{n-k}$$

$$\mathcal{R}_z |\psi\rangle = e^{i\Omega} (|c_1|, |c_2|, \dots, |c_N|)^\top$$

$$\mathcal{R}_z = \prod_{k=1} F_k^{k-1}(\mathbf{z}, \boldsymbol{\alpha}_{n-k+1}^z) \otimes I_{2^{n-k}}$$





# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## Key Idea: Separate Phase and Amplitude

*Second, we move probability mass across basis states.*

- **Step 2:** redistribute amplitudes with uniformly controlled y-rotations  $\mathcal{R}_y$

$$\mathcal{R}_y = \prod_{k=1}^n F_k^{k-1}(\mathbf{y}, \boldsymbol{\alpha}_{n-k+1}^y) \otimes I_{2^{n-k}}$$

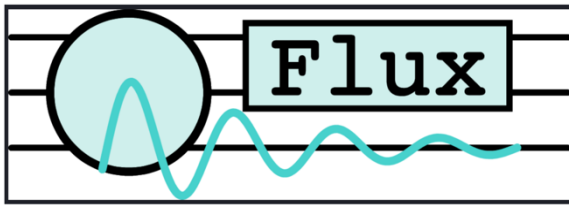
**Angles for cancelling amplitudes:** (with the least significant qubit set to 1)

$$(\alpha_j)_k^y = 2 \arcsin \left( \frac{\sqrt{\sum_{l=1}^{2^{k-1}} |c_{(2j-1)2^{k-1}+l}|^2}}{\sqrt{\sum_{l=1}^{2^k} |c_{(j-1)2^k+l}|^2}} \right) \quad \mathcal{R}_y \mathcal{R}_z |\psi\rangle = e^{i\Phi} |0 \dots 0\rangle$$

$$|\psi\rangle = \mathcal{R}_z^\dagger \mathcal{R}_y^\dagger e^{i\Phi} |0 \dots 0\rangle$$

**What is the asymptotic cost?**

CNOT gates:  $2^{n+2} - 4n - 4$ ; Single-qubit rotations:  $2^{n+2} - 5$



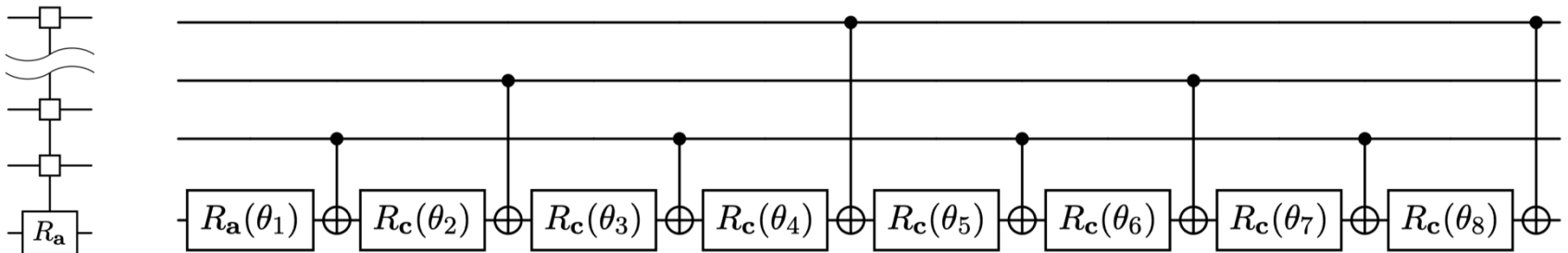
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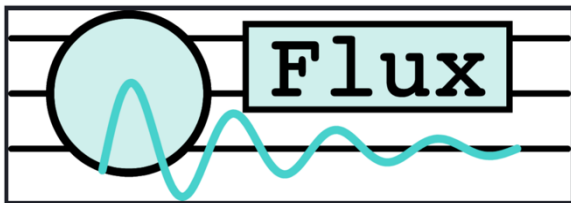
## Gray Code

$$M_{ij} = 2^{-k}(-1)^{b_{j-1} \cdot g_{i-1}}$$

- Control patterns reordered by Gray code
- Consecutive gates differ by one control bit
- Enables:
  - Minimal CNOTs
  - Systematic cancellations

$$\begin{bmatrix} \theta_1 \\ \vdots \\ \theta_{2^k} \end{bmatrix} = \mathbf{M} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_{2^k} \end{bmatrix}$$





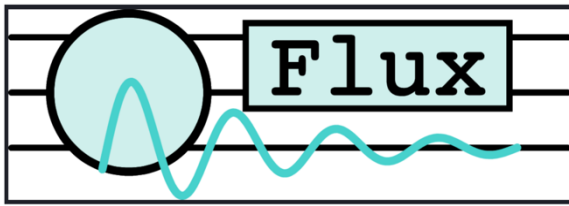
# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## When to Use UCRs

*In practice, this is your default state-preparation engine  
Clean, compact, and hardware-friendly*

- Best for:
  - Scalable synthesis
  - Automation
  - Compiler pipelines
- Cost:
  - Fewer CNOTs than multiplexors
  - Analytic angles

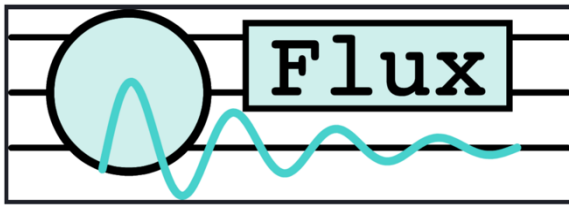




## PART C — GENERIC UNITARY DECOMPOSITION

*Problem: Arbitrary Unitary Synthesis*

- Input:  $U \in \text{SU}(2^n)$
- Goal: decompose into 1- and 2-qubit gates
- Constraint: minimize CNOT count



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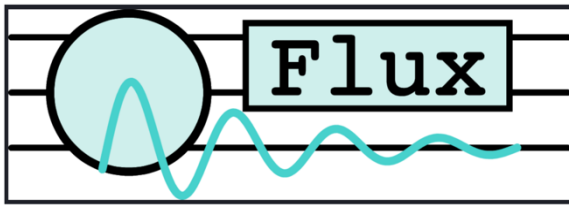
## Givens Rotations (QR Intuition)

- Classical QR  $\rightarrow$  eliminate off-diagonal entries column by column
- Quantum version:
  - Two-level rotations
  - Cancel one element at a time

$${}^i\Gamma_{j,k} = \frac{1}{\sqrt{|U_{ji}|^2 + |U_{ki}|^2}} \begin{pmatrix} U_{ki}^* & U_{ji}^* \\ -U_{ji} & U_{ki} \end{pmatrix}$$

$${}^iG_{j,k} = \begin{pmatrix} \ddots & & & & \\ & 1 & & & \\ & & \ddots & & \\ & & & U_{ki}^* & U_{ji}^* \\ & & & -U_{ji} & U_{ki} \\ & & & & \ddots & & \\ & & & & & 1 & \ddots \end{pmatrix}$$

$\leftarrow k$   
 $\leftarrow j$



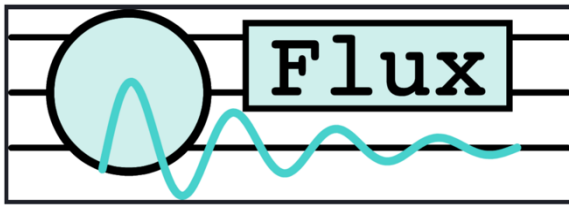
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## Givens Rotations (QR Intuition)

**Example:** [4×4] unitary matrix  $U$

$$\begin{aligned}
 U &\xrightarrow{e^{-i \arg(\det U)/4} I} \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{pmatrix} \xrightarrow{{}^1G_{4,3}} \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \\ 0 & * & * & * \end{pmatrix} \xrightarrow{{}^1G_{3,2}} \begin{pmatrix} * & * & * & * \\ * & * & * & * \\ 0 & * & * & * \\ 0 & * & * & * \end{pmatrix} \xrightarrow{{}^1G_{2,1}} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & * & * & * \\ 0 & * & * & * \\ 0 & * & * & * \end{pmatrix} \\
 &\xrightarrow{{}^2G_{4,3}} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & * & * & * \\ 0 & * & * & * \\ 0 & 0 & * & * \end{pmatrix} \xrightarrow{{}^2G_{3,2}} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & * & * \\ 0 & 0 & * & * \end{pmatrix} \xrightarrow{{}^3G_{4,3}} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}
 \end{aligned}$$

$$U = \exp[i \arg(\det U)/4] I {}^1G_{4,3}^\dagger {}^1G_{3,2}^\dagger {}^1G_{2,1}^\dagger {}^2G_{4,3}^\dagger {}^2G_{3,2}^\dagger {}^3G_{4,3}^\dagger$$



# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## Gray Code Makes It Implementable

- Reorder basis states by Gray code
- Each rotation couples states differing by one qubit
- Implemented as multi-controlled single-qubit gates

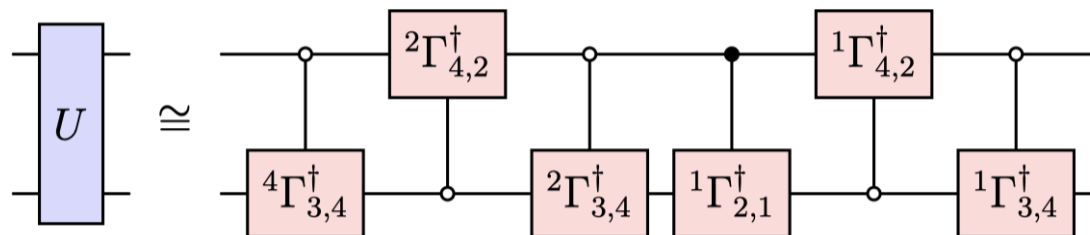
General formula:

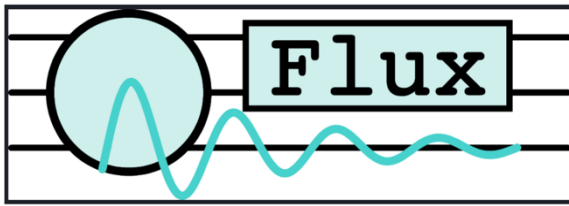
$$\left[ \prod_{i=1}^{N-1} \prod_{j=i+1}^N \gamma^{(N-i)} G_{\gamma(j), \gamma(j-1)} \right] \left( e^{-i \arg(\det U)/N} I \right) U = I$$

$\gamma(\cdot)$  = Gray-code permutation  
(i.e., the integer value of a Gray-coded bitstring)

**Example:** 2 qubit unitary

[Part III.ipynb](#) (Scripts S.2.1–S.2.4)





## Column-by-Column Decomposition (CCD)

*State preparation on every column*

- Apply reverse state preparation to each column
- Protect previously fixed columns with extra controls

$$U = \mathcal{R}_0^\dagger \mathcal{R}_1^\dagger \cdots \mathcal{R}_{2^n-2}^\dagger D^\dagger$$

$$\text{with } D = \mathcal{R}_{2^n-1}^\dagger$$

1. Rotate its first column to  $|0\rangle$  (state preparation):

$$\mathcal{R}_0 U_0 |0\rangle = |0\rangle \quad \text{with } U_0 := U$$

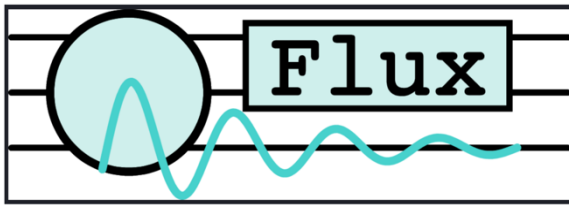
2. Rotate the second column of  $U_1 := \mathcal{R}_0 U_0$  to  $|1\rangle$  :

$$\mathcal{R}_1 U_1 |1\rangle = |1\rangle \quad \text{with } \mathcal{R}_1 |0\rangle = |0\rangle$$

3. Rotate subsequent columns analogously:

$$\mathcal{R}_j U_j |j\rangle = |j\rangle \quad \text{with } U_{j+1} := \mathcal{R}_j U_j$$

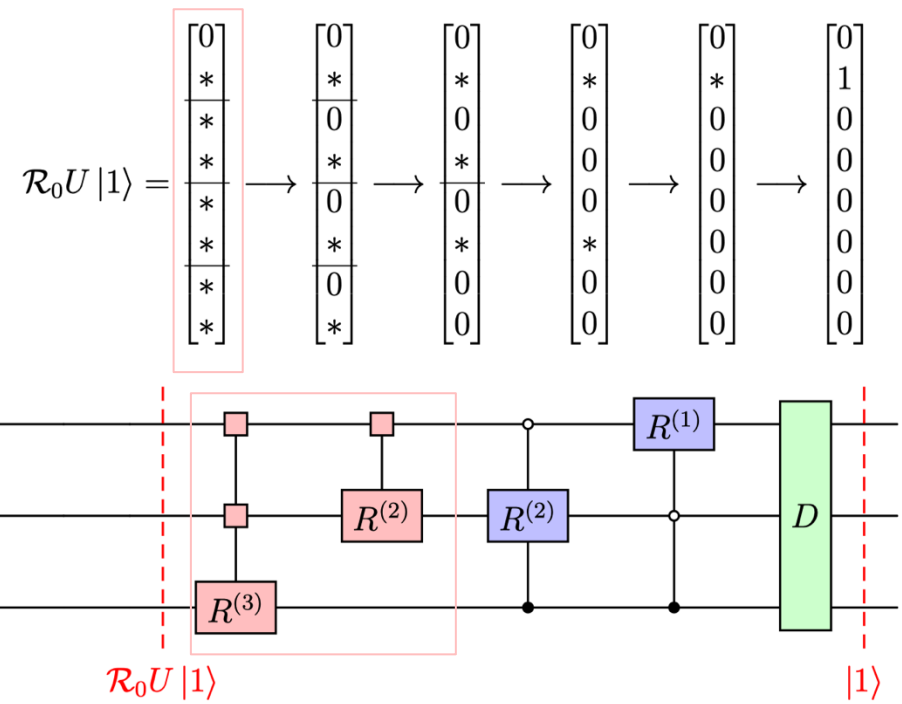
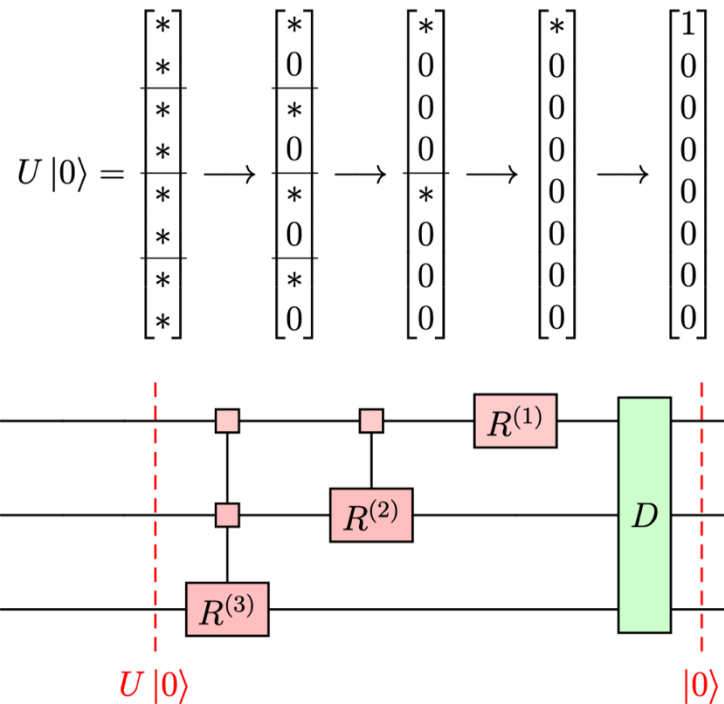
$$\mathcal{R}_j |i\rangle = |i\rangle \quad \text{for all } i < j.$$

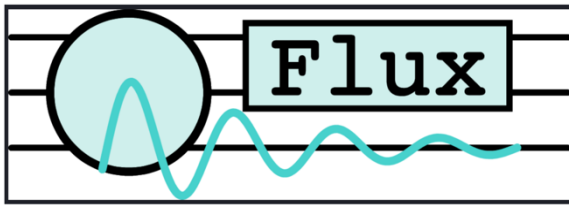


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## Column-by-Column Decomposition (CCD)

*State preparation on every column*





# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

## CSD & Quantum Shannon Decomposition

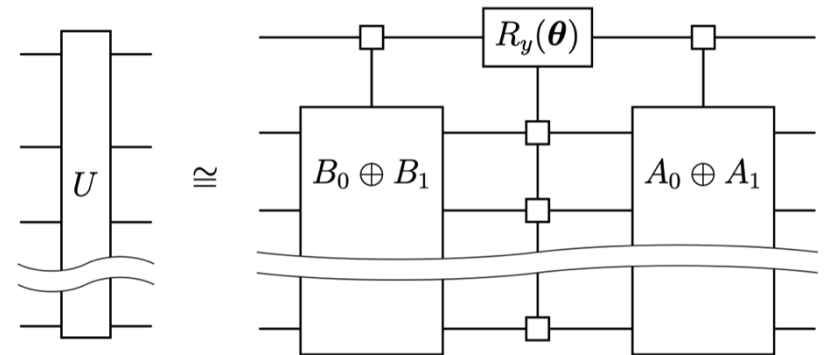
- Recursively split unitary into blocks
- Push all control into single-qubit multiplexed rotations

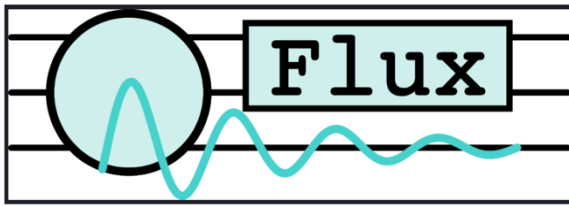
**Cosine-Sine Decomposition (CSD):** 
$$U = \begin{pmatrix} U_{00} & U_{01} \\ U_{10} & U_{11} \end{pmatrix} = \underbrace{\begin{pmatrix} A_0 & 0 \\ 0 & A_1 \end{pmatrix}}_{A_0 \oplus A_1} \underbrace{\begin{pmatrix} C & -S \\ S & C \end{pmatrix}}_{\text{cos-sin block}} \underbrace{\begin{pmatrix} B_0 & 0 \\ 0 & B_1 \end{pmatrix}}_{B_0 \oplus B_1},$$

$$C = \text{diag}(\cos \frac{\theta_1}{2}, \dots, \cos \frac{\theta_{2n-1}}{2})$$

$$S = \text{diag}(\sin \frac{\theta_1}{2}, \dots, \sin \frac{\theta_{2n-1}}{2})$$

*Applying CSD recursively to  $A_0 \oplus A_1$  and  $B_0 \oplus B_1$*





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## CSD & Quantum Shannon Decomposition

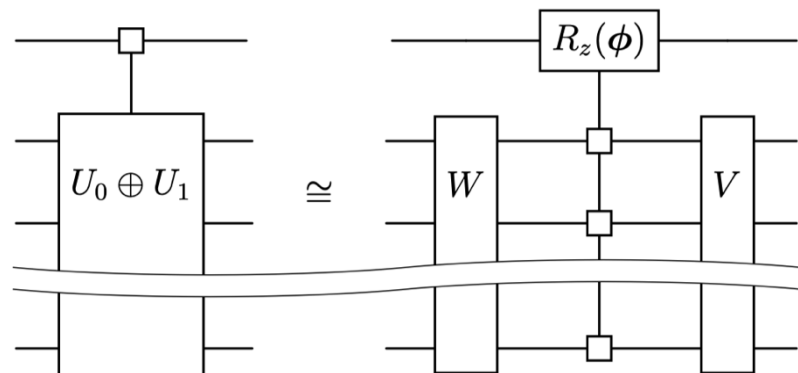
- Recursively split unitary into blocks
- Push all control into single-qubit multiplexed rotations

**Quantum Shannon Decomposition (QSD):**

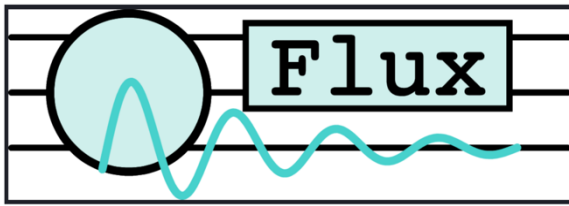
$$U = \begin{pmatrix} V & 0 \\ 0 & V \end{pmatrix} \begin{pmatrix} D & 0 \\ 0 & D^\dagger \end{pmatrix} \begin{pmatrix} W & 0 \\ 0 & W \end{pmatrix}, \quad W = DV^\dagger U_1$$

$$U = \begin{pmatrix} U_0 & 0 \\ 0 & U_1 \end{pmatrix}$$

*The middle block  $D \oplus D^\dagger$  is a diagonal multiplexor and maps to a single multiplexed  $R_z(\phi)$  on the most significant qubit*



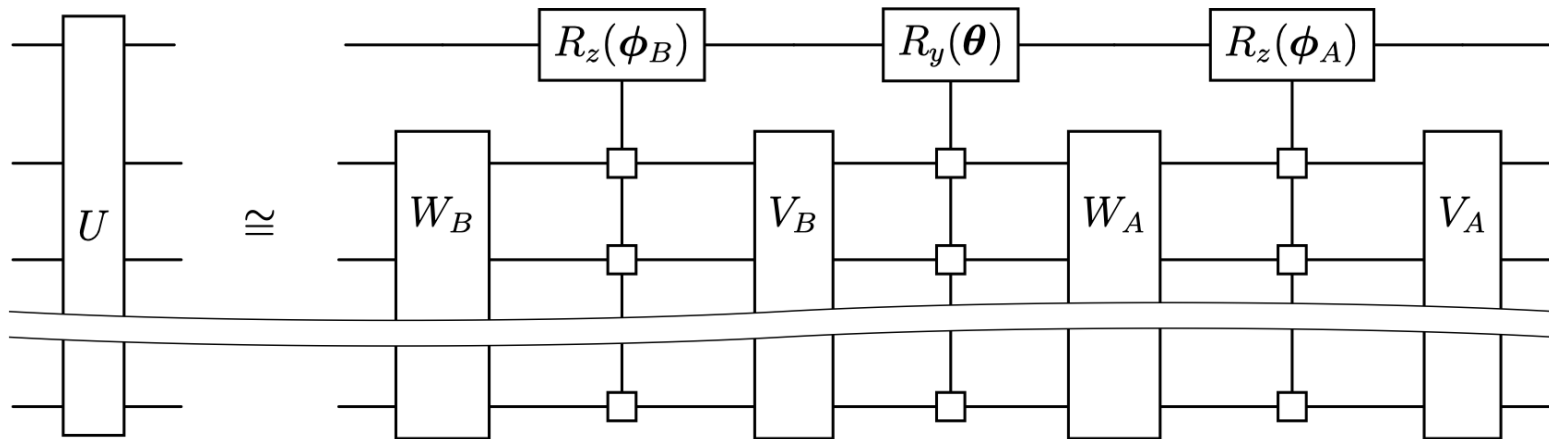




# QFlux: An Open-Source Python Package for Quantum Dynamics Simulations

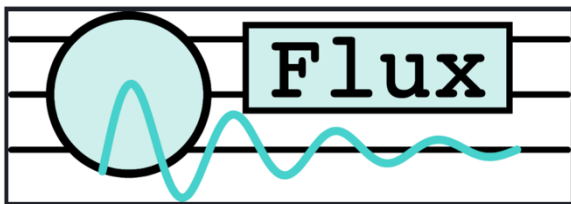
## CSD + Quantum Shannon Decomposition

- Recursively split unitary into blocks
- Push all control into single-qubit multiplexed rotations



**What is the asymptotic cost?** CNOT gates: CSD:  $O(4^n)$  (smaller constants)

Optimized QSD:  $\frac{23}{48}4^n - \frac{3}{2}2^n + O(1)$



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## PART D — DIAGONAL UNITARIES

### *Special Case: Diagonal Operators*

- Arise in:

- $e^{-iHt}$

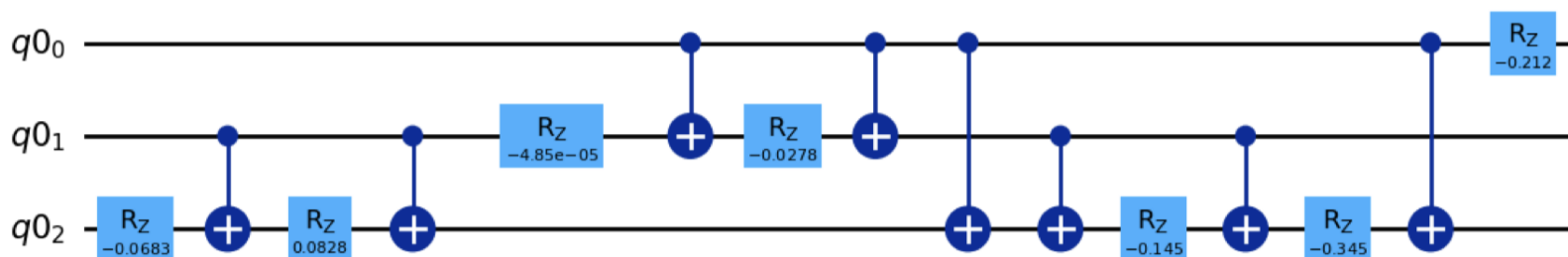
- Phase oracles

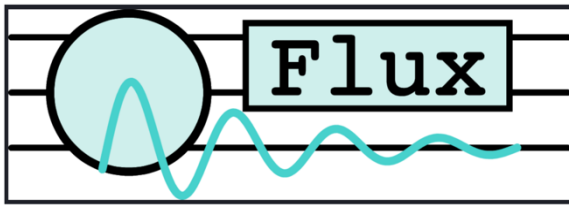
- Lindblad dilation

**Best method:** Walsh decomposition

[Part III.ipynb](#) **Section S.3.6:** Walsh Synthesis of  $e^{-iV(x_j)t}$  for a unitary of a Double-Well Potential

**Scripts S.3.1-5:**  $U = \text{diag}(e^{if_k})$





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## Walsh + Gray Code = NISQ-Optimal

- Expand diagonal operator in Walsh basis
- Order terms by Gray code
- Systematic CNOT cancellation
- Cost:  $O(2^n)$  entangling gates

$$U = \prod_{j=0}^{2^n-1} e^{ia_j w_j}$$

*Each factor  $e^{ia_j w_j}$  is efficiently realized with one single-qubit Z-rotation and at most  $2n$  CNOTs  
Ordering terms by a Gray code cut two-qubit cost from naive  $O(n2^n)$  to roughly  $O(2^n)$  in practice*

$$U = e^{iF}$$

$$F = \text{diag}(f_0, \dots, f_{2^n-1}) \quad \text{real}$$

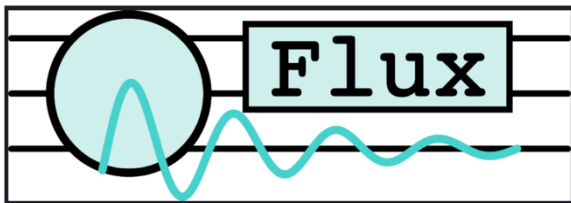
$$F = \sum_{j=0}^{2^n-1} a_j w_j$$

$$w_j := Z_1^{j_1} \otimes Z_2^{j_2} \otimes \dots \otimes Z_n^{j_n}$$

$$a_j = 2^{-n} \text{Tr}(w_j F)$$

$j = (j_1 \dots j_n)_2$  is the *binary* label

$$j = \sum_{l=1}^n j_l 2^{n-l}$$



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## Take-Home Messages

- State prep and unitary synthesis are the backbone of all simulations
- Operator structure determines optimal circuits
- QFlux provides:
  - Transparent algorithms
  - Predictable scaling
  - Reusable infrastructure