QA vs QAOA

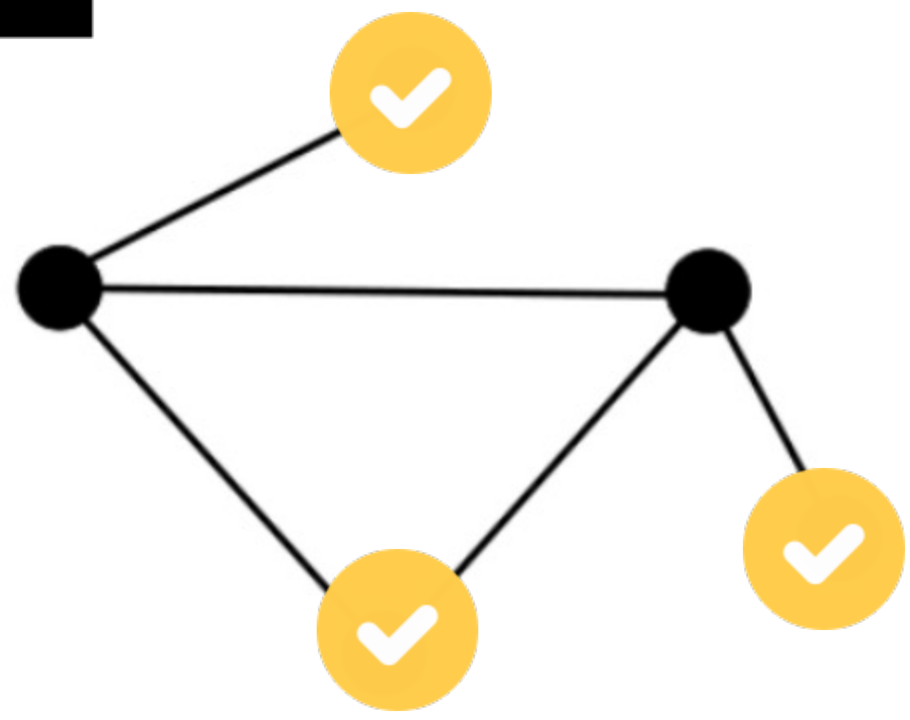
김예림(고려대),장재권(고려대),양승진(고려대)

Content

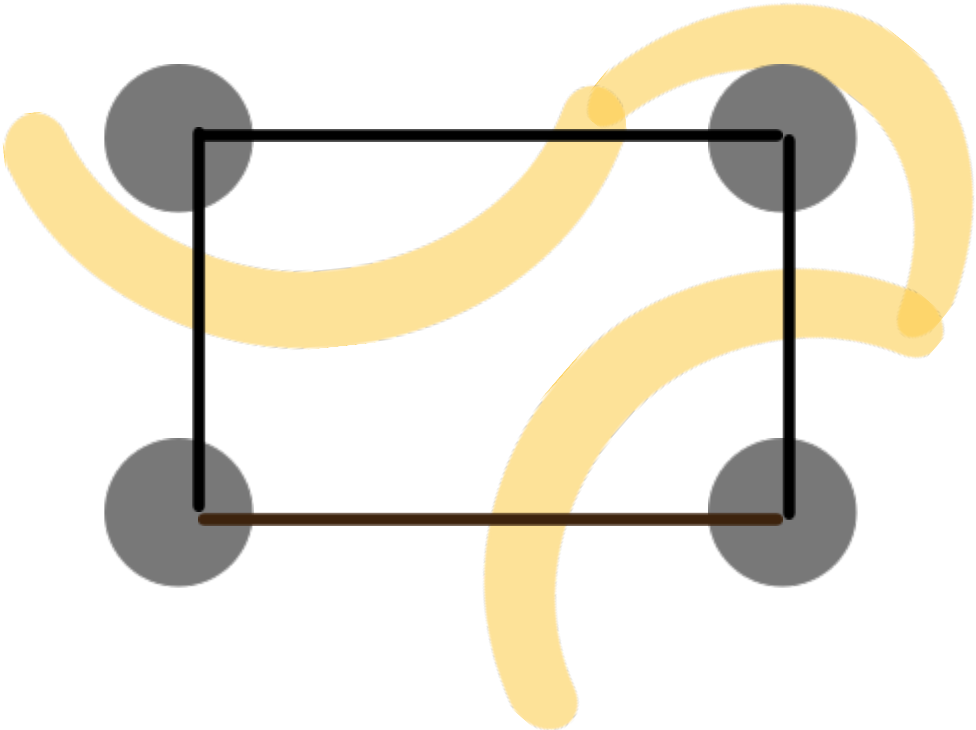
1. Research Object

Background

NP - hard



MIS



MaxCut

" QAOA can solve Combinatorial Optimization Problems "

Cost Hamiltonian : Ising Model Hamiltonian

Background

QAOA는 근본적으로 Ising model Hamiltonian 문제를 다루는 VQA 인데
이 문제들을 굳이 Gate-based quatum simulation 로 풀 필요가 있을까?

QAOA Ansatz의 motivation인 Adiabatic Theorem을 이용하여
즉 QA(Quantum Anealing)으로 풀면 되지 않을까?

Research Object

QAOA 가 푸는 문제들을 굳이 Gate-based quatum simulation 을 해야 할 필요가 있을까?

애초에 Adiabatic Quantum Optimization
즉 QA(Quantum Anealing)으로 풀면 되지 않을까?

①

Combinatorial Problem(MaxCut)을
QA와 QAOA를 통해 풀어보고 수행능력을 비교해고자 한다.

②

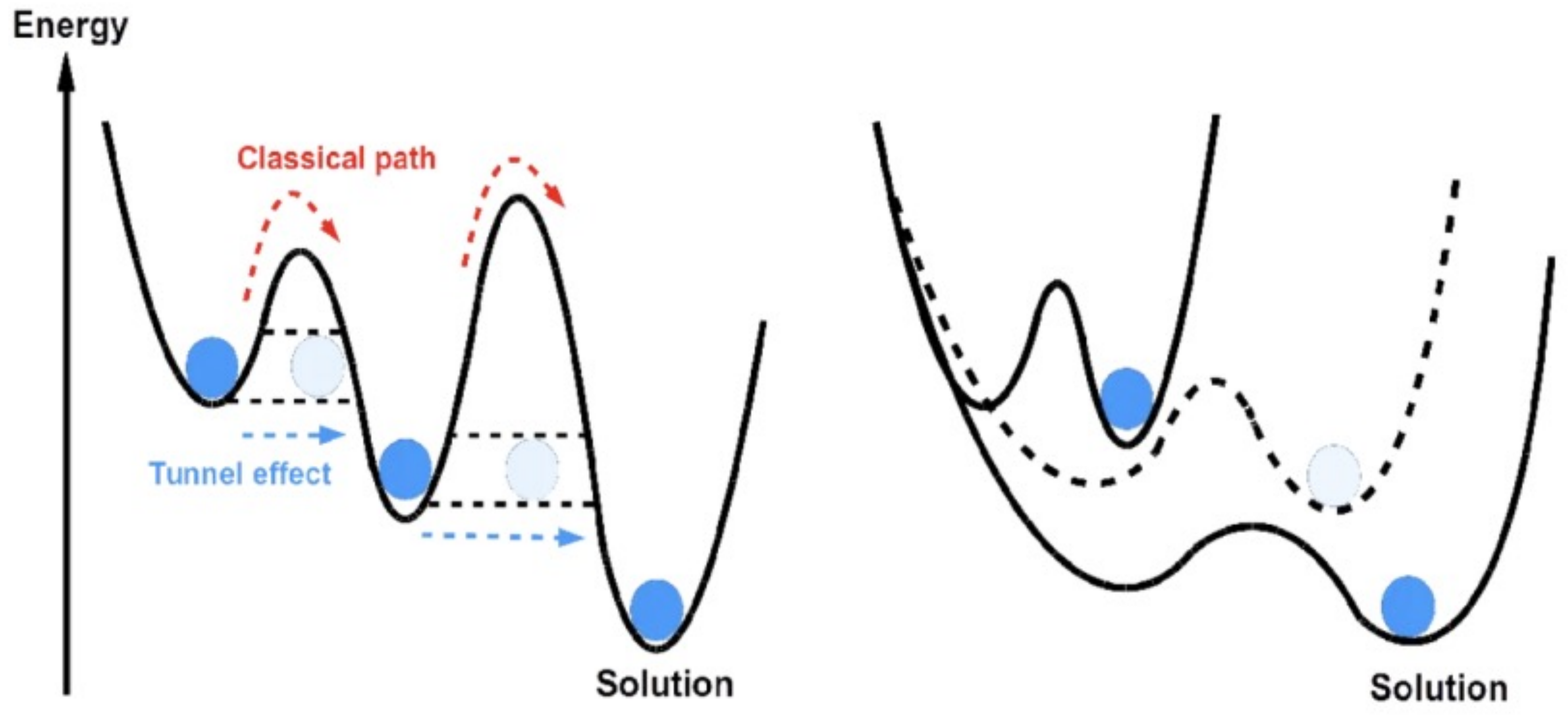
QA와 QAOA의 차이점 분석 후,
각각의 개선방향 및 발전 방향성
또한 제시하고자 한다.

2. Theory

What is QA ?

Quantum Annealing

Quantum computation which uses quantum fluctuations(quantum tunneling), in order to search for the ground state of a user programmed Hamiltonian.



Quantum Tunnelling

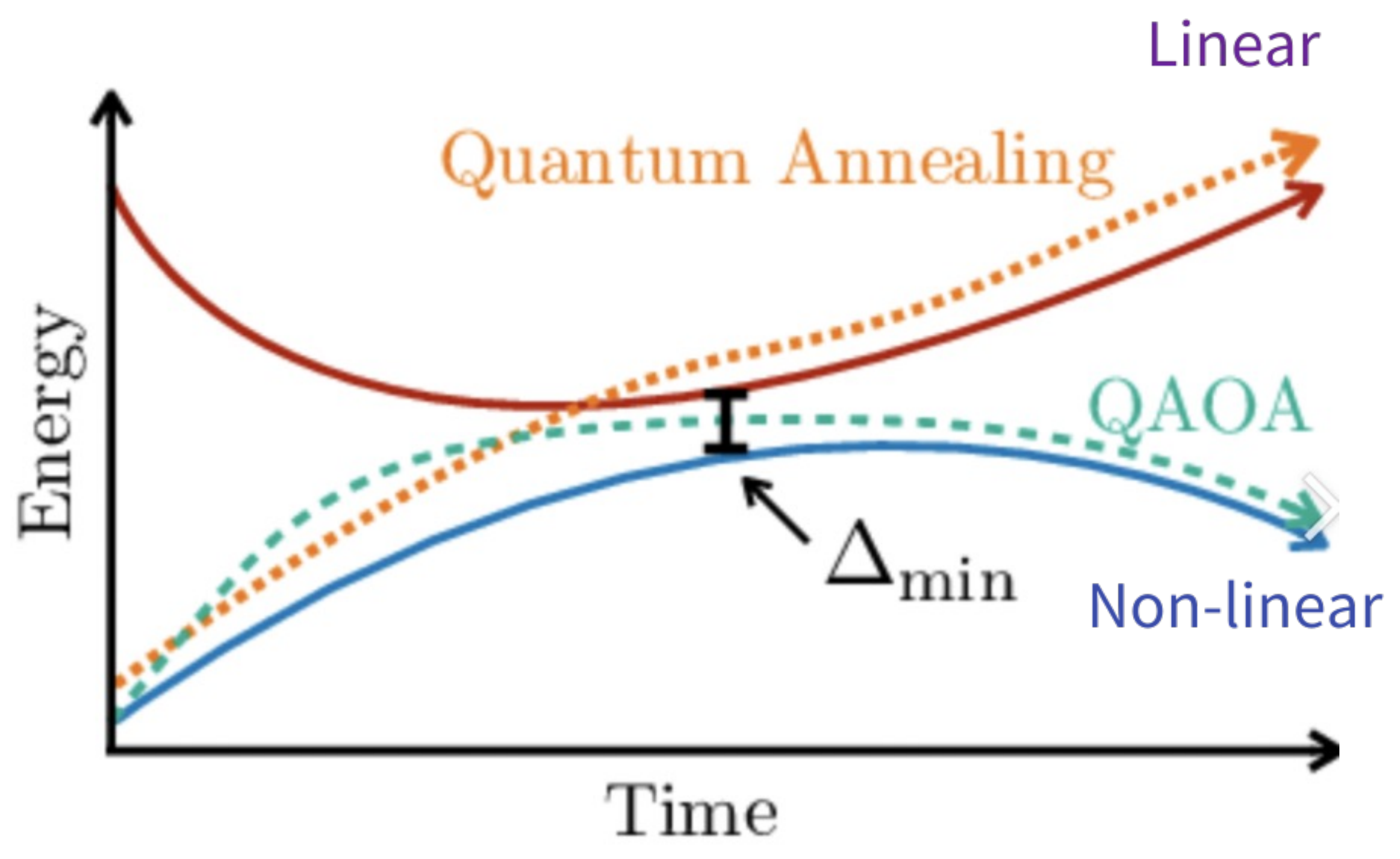
Adiabatic evolution

QA vs QAOA

	QA	QAOA
Aspect of Progress	Continuous (Analog)	Discrete (Digital)
Annealing Path	$H_{\mathrm{QA}}(s) = -[sH_C + (1-s)H_B],$ $s = t/T,$	$H_{\mathrm{QAOA}}(t) = -[f(t)H_C + (1-f(t))H_B],$ $f\left(t_i = \sum_{j=1}^{i}(\lvert\gamma_j^*\rvert + \lvert\beta_j^*\rvert) - \frac{1}{2}(\lvert\gamma_i^*\rvert + \lvert\beta_i^*\rvert)\right) = \frac{\gamma_i^*}{\lvert\gamma_i^*\rvert + \lvert\beta_i^*\rvert}$
Time To Solution (TTS)	$\mathrm{TTS}_{\mathrm{QA}}(T) = T\frac{\ln(1-p_d)}{\ln[1-p_{\mathrm{GS}}(T)]}$ $\mathrm{TTS}_{\mathrm{QA}}^{\mathrm{opt}} = \min_{T>0}\mathrm{TTS}_{\mathrm{QA}}(T).$	$\mathrm{TTS}_{\mathrm{QAOA}}(p) = T_p\frac{\ln(1-p_d)}{\ln[1-p_{\mathrm{GS}}(p)]}$ $\mathrm{TTS}_{\mathrm{QAOA}}^{\mathrm{opt}} = \min_{p>0}\mathrm{TTS}_{\mathrm{QAOA}}(p),$
Annealing Time	T	$T_p = \sum_{i=1}^{p}(\lvert\gamma_i^*\rvert + \lvert\beta_i^*\rvert)$

QA vs QAOA

Aspect of Progress	C (
Annealing Path	$H_{QA}(s) = -$
Time To Solution (TTS)	$\mathrm{TTS}_{QA}(T$ TTS^{op}_{Q}
Annealing Time	



$T_p = \sum_{i=1}(|\gamma_i| + |\beta_i|)$

QA vs QAOA

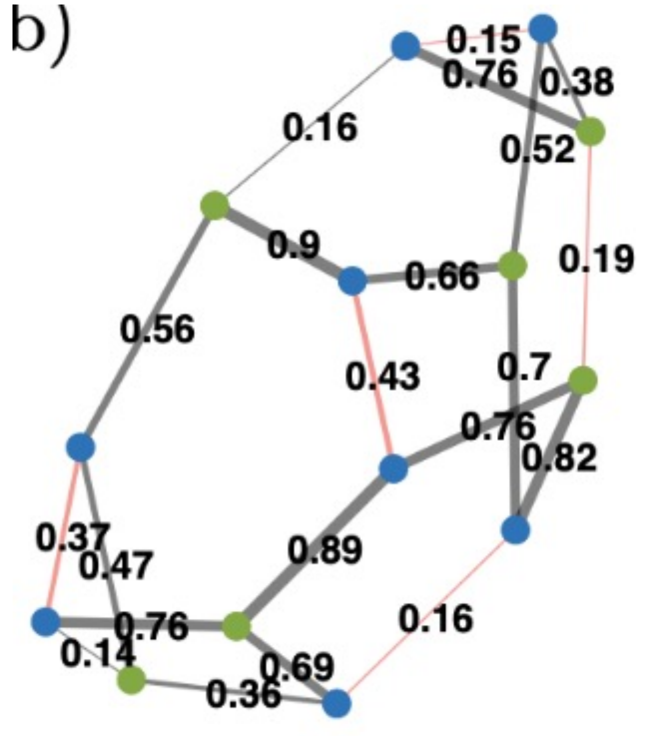
	QA	QAOA
Aspect of Progress	C(	
Annealing Path	$H_{\mathrm{QA}}(s) = -$ s	
Time To Solution (TTS)	$\mathrm{TTS}_{\mathrm{QA}}(T$ $\mathrm{TTS}^{\mathrm{opt}}_{\mathrm{QA}}$	
Annealing Time		

Landau-Zener formula $\ln\left(1 - p_{GS}(T)\right) \propto T{\Delta_{min}}^2$

$$\therefore \mathrm{TTS}_{QA} \propto \frac{1}{{\Delta_{min}}^2}\ (independent\ of\ T)$$

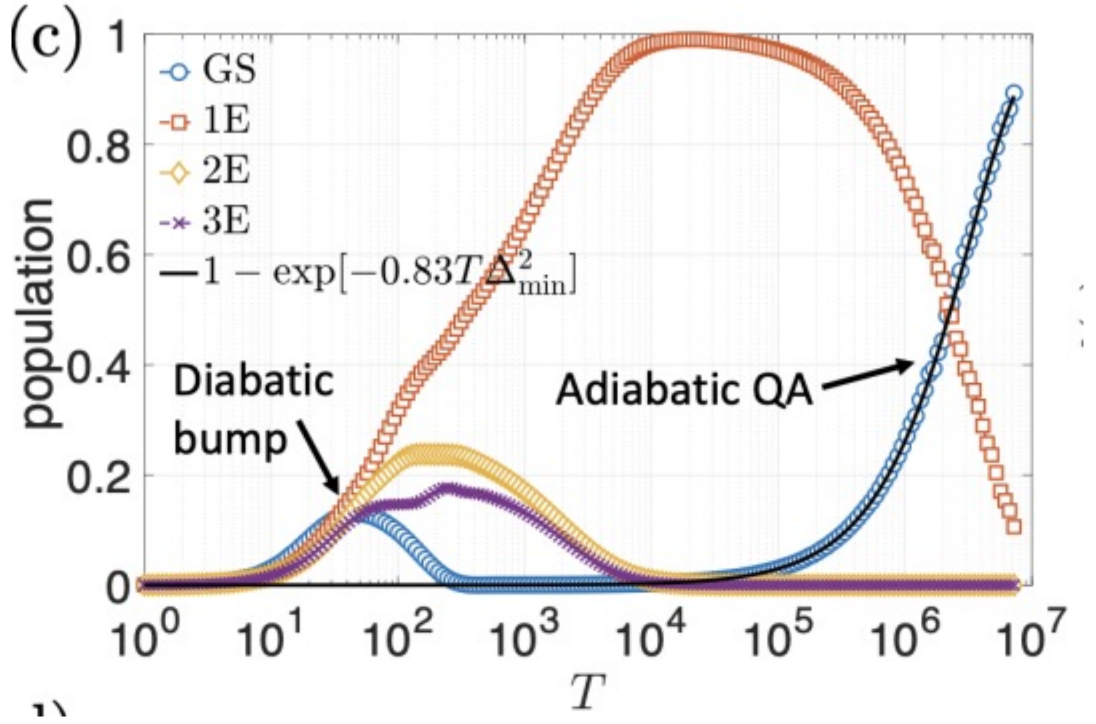
< QA-Hard instance>

b)



$\Delta_{\min} < 10^{-3}$.

(c)



QA vs QAOA

	QA	QAOA
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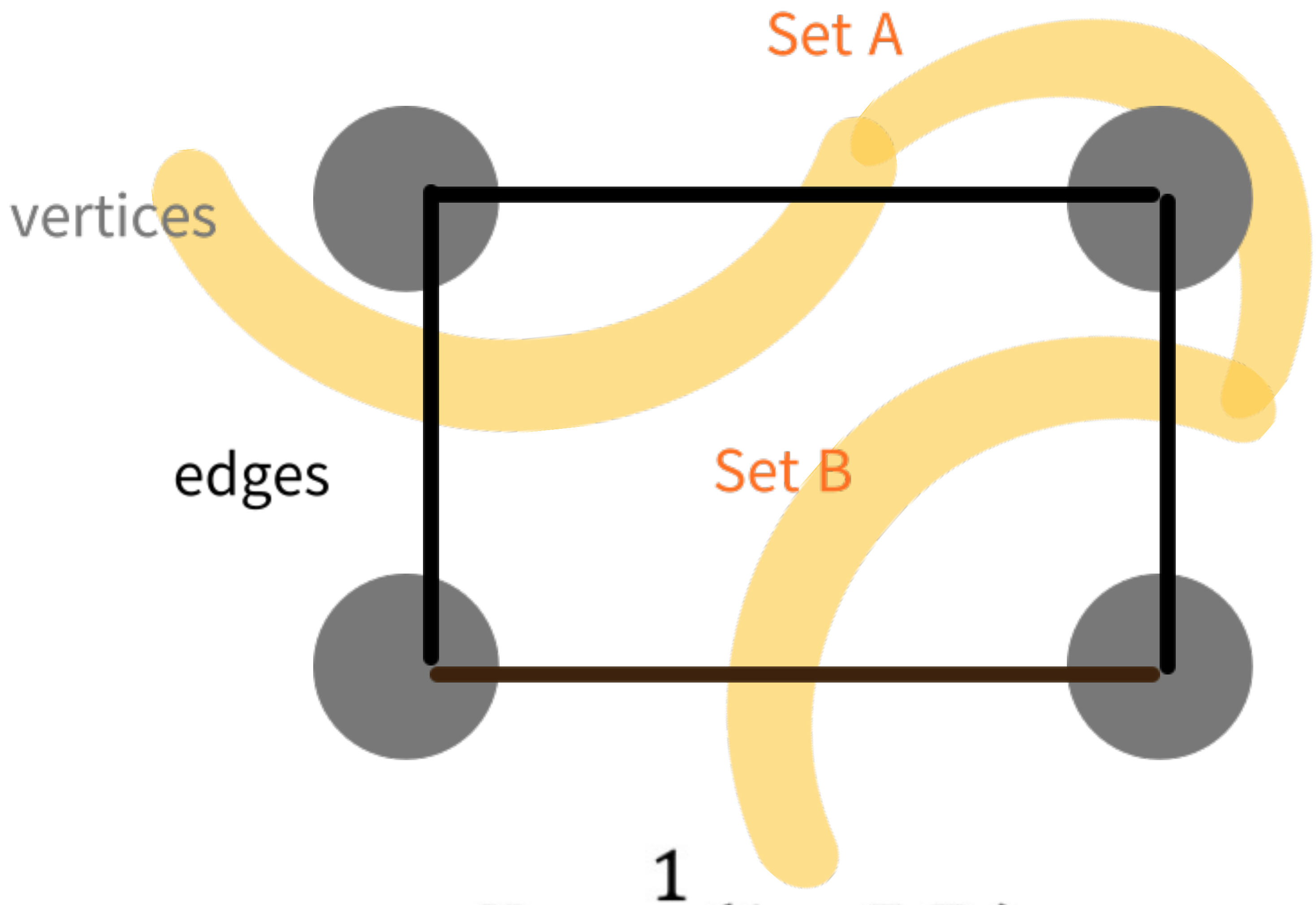
Annealing Time	T	$T_p = \sum_{i=1}^{p}(\lvert\gamma_i^*\rvert + \lvert\beta_i^*\rvert)$

Max Cut

대표적인 Combinotorial Optimization Problem
2개의 part로 vertex를 나누면서
가장 많이 egdge를 지나가야하는 문제



$$H_C = \frac{1}{2}(1 - Z_j Z_k)$$

3. Method

References

①

Quantum Annealing vs. QAOA: 127 Qubit Higher-Order Ising Problems on NISQ Computers

Elijah Pelofske*[1], Andreas Bärtschi†[1], and Stephan Eidenbenz[1]

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②

Optimization Applications as Quantum Performance Benchmarks

Thomas Lubinski,[1,2] Carleton Coffrin,[3] Catherine McGeoch,[4]
Pratik Sathe,[5,6] Joshua Apanavicius,[7,8] and David E. Bernal Neira[6,9]
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QA

③

Quantum Approximate Optimization Algorithm: Performance, Mechanism, and Implementation on Near-Term Devices

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(Dated: November 12, 2019)

유일하게 QA의 한계점이
드러난 문제 제기
Depth가 늘어난다면
QAOA의 더 나은 수행능력 예상

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Measuring Performance

1. Result Fidelity

- QAOA : Approximation ratio

$$r = \frac{F_p(\vec{\gamma}^*, \vec{\beta}^*)}{C_{\max}}.$$

$$F_p(\vec{\gamma}, \vec{\beta}) = \langle \psi_p(\vec{\gamma}, \vec{\beta}) | H_C | \psi_p(\vec{\gamma}, \vec{\beta}) \rangle,$$

- QA : Population of ground state

2. Execution Time

유일하게 QA의 한계점이
드러난 문제 제기
Depth가 늘어난다면
QAOA의 더 나은 수행능력 예상

References

1

2

3

<문제 설정>

1. QAOA에서 이론적 approximation ratio 가 있는 문제

- Circuit depth(p) 에 따른 r

- 가장 낮은 depth 인 p=1일때 r

2. QA의 Adiabatic Limitation 인 minimal sprectral gap이 작은 문제

(Dated: November 12, 2019)

Measuring Performance

1. Result Fidelity

- QAOA : Approximation ratio

$$r = \frac{F_p(\vec{\gamma}^*, \vec{\beta}^*)}{C_{\max}}.$$

$$F_p(\vec{\gamma}, \vec{\beta}) = \langle \psi_p(\vec{\gamma}, \vec{\beta}) | H_C | \psi_p(\vec{\gamma}, \vec{\beta}) \rangle,$$

- QA : Population of ground state

2. Execution Time

유일하게 QA의 한계점이 드러난 문제 제기

Depth가 늘어난다면 QAOA의 더 나은 수행능력 예상

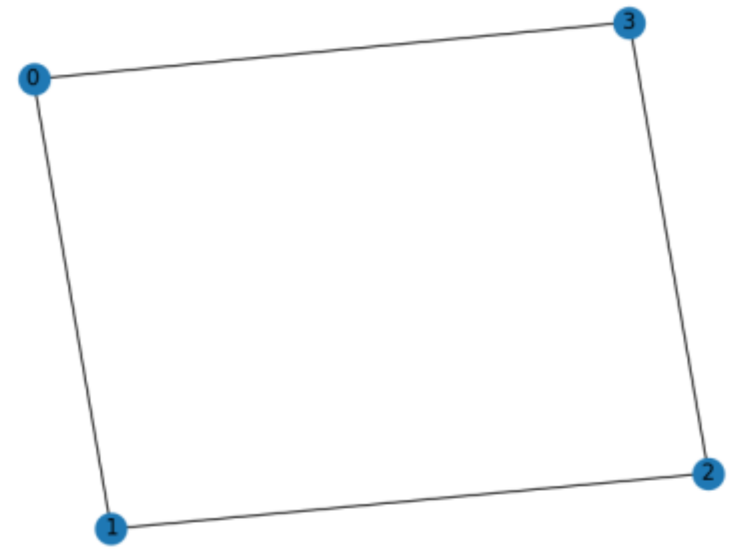
Problems

	① u2r Graph	② u3r Graph	③ w3r Graph
Object	Circuit Depth 에 따른 QAOA 수행 능력 확인 & QA와 수행능력 비교	가장 낮은 depth일때 QAOA 수행 능력 확인 & QA와 수행능력 비교	Minimal spectral gap이 작은 문제에서의 QA 수행 능력 확인 & QAOA와 수행능력 비교
Theoretical Approximation Ratio	$r \geq \frac{(2p+1)}{(2p+2)} (p < \left[\frac{N}{2}\right], p = even)$ $r \approx 1 \left(p \geq \left[\frac{N}{2}\right]\right)$	$r \geq 0.6924\ (p = 1)$	
Node	4	4, 6	14
Ciruit Depth	1,8	1	1

Problems

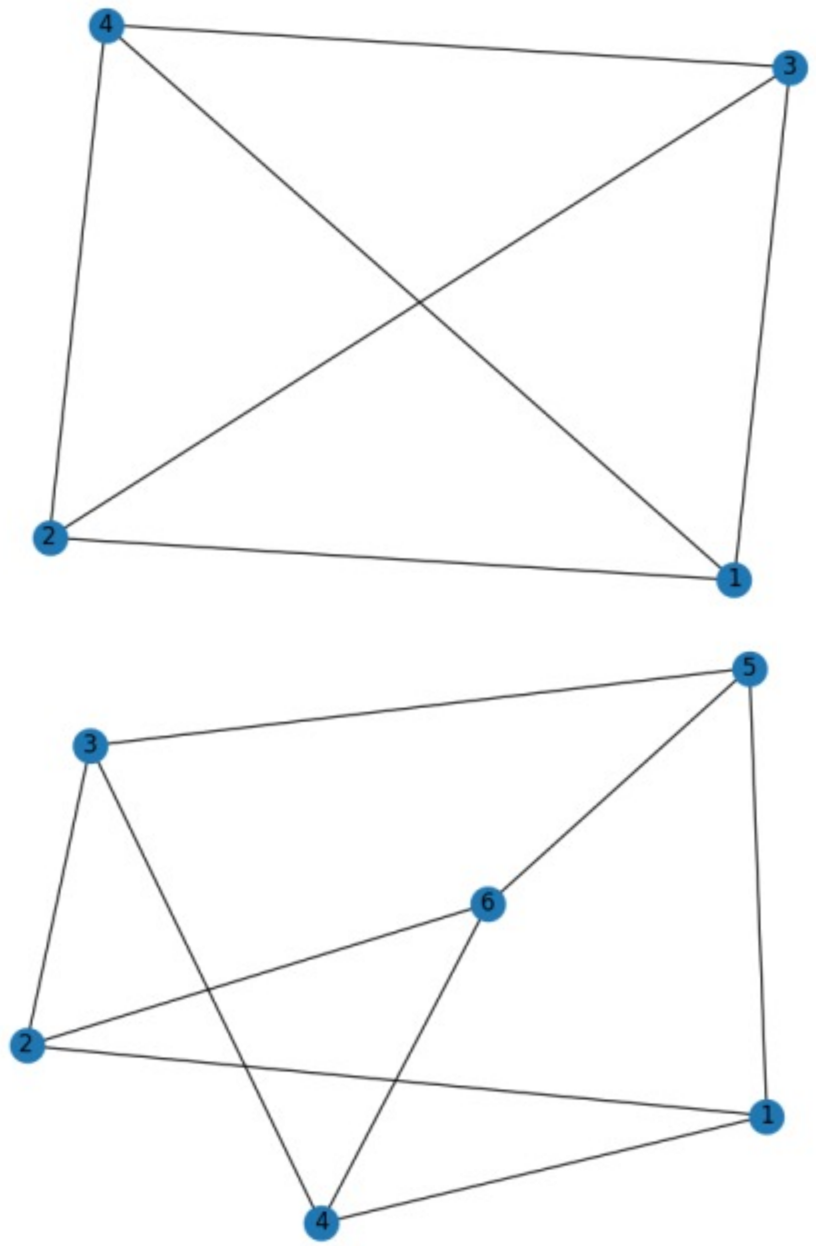
①

u2r Graph



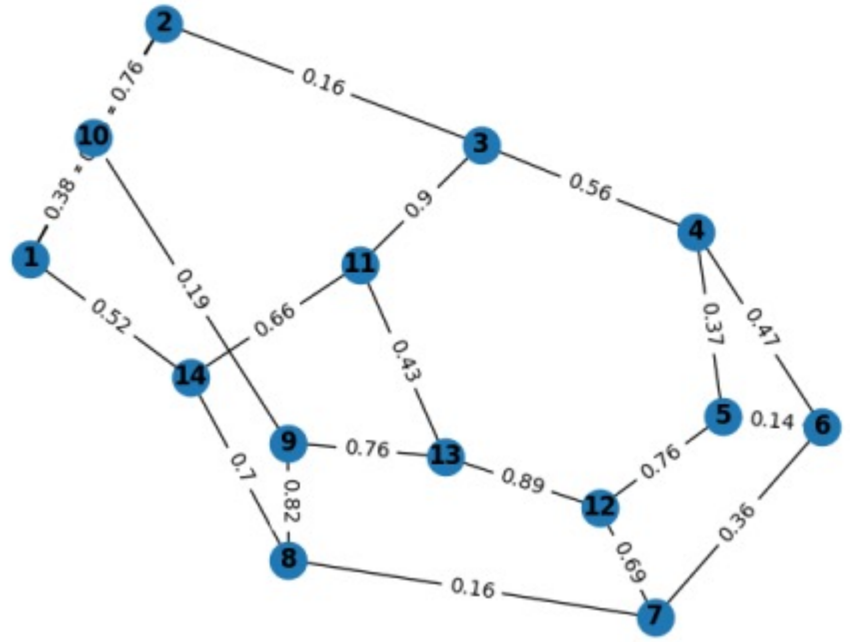
②

u3r Graph



③

w3r Graph



Object

Theoretical Approximation Ratio

Node

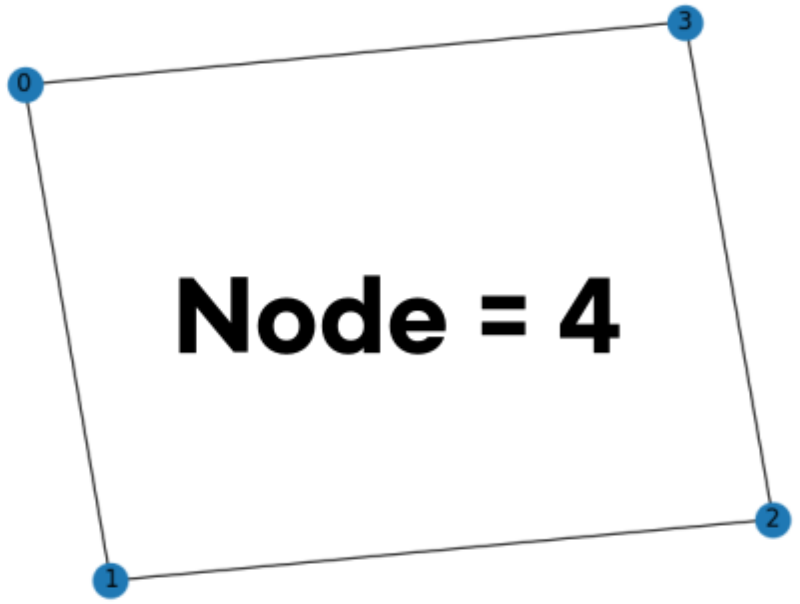
Ciruit Depth

Parameters

	QAOA	QA
Device	CPU	CPU, QPU (D-Wave Cloud)
Quantum Simulator/Sampler	pennylane의 default.qubit device # of samples : 100	sample_qubo, smaple_ising Chainstrength : 8, 2
Classical Optimizer	Adagrad Optimizer step size : 0.5 step number : 100	X

4. Results

u2r Graph

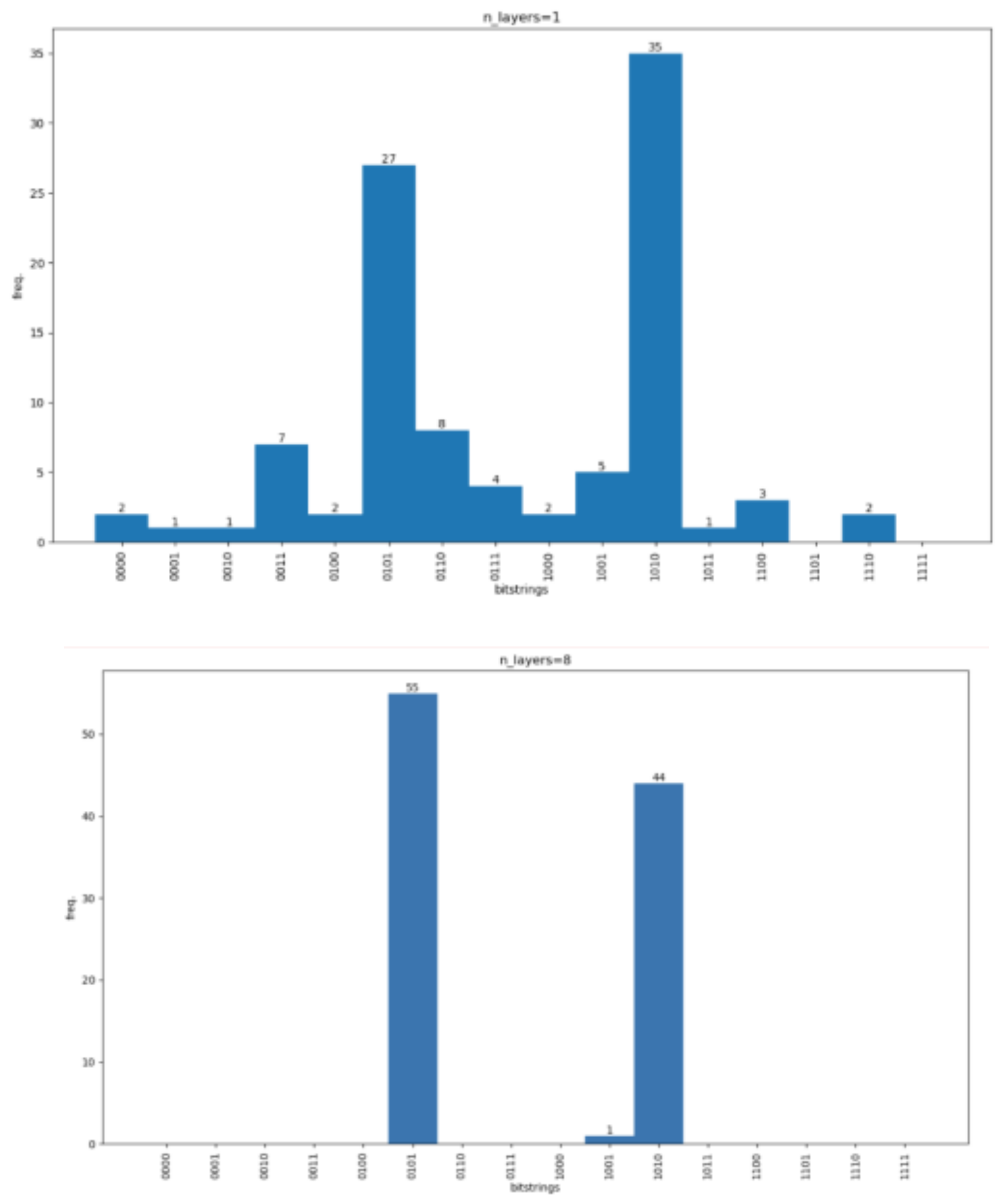


QAOA

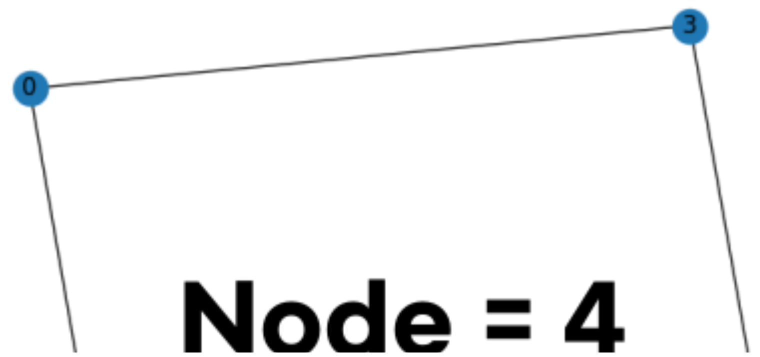
	p = 1	p = 8
Result Fidelity	0.800	0.99
Exceution Time	10 s	180
Theoretical Approximation Ratio	0.75	≈ 1

p = 1

p = 8



u2r Graph



Node = 4

Set 0	Set 1	Energy	Cut Size
[1, 3]	[2, 4]	-4.0	4
[2, 4]	[1, 3]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[2, 4]	[1, 3]	-4.0	4
[1, 3]	[2, 4]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[1, 3]	[2, 4]	-4.0	4
[2, 4]	[1, 3]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[1, 3]	[2, 4]	-4.0	4
[2, 4]	[1, 3]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[2, 4]	[1, 3]	-4.0	4
[1, 3]	[2, 4]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[1, 3]	[2, 4]	-4.0	4
[2, 4]	[1, 3]	-4.0	4
Set 0	Set 1	Energy	Cut Size
[2, 4]	[1, 3]	-4.0	4
[1, 3]	[2, 4]	-4.0	4

X 100

<100번 중 답 나온 횟수>

$Sol1\ |1010\rangle$: 100/100

$So12\ |0101\rangle$: 100/100

QA

1

1s 미만

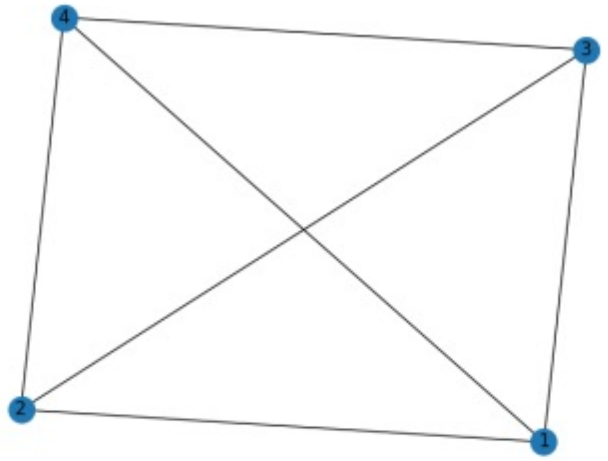
QAOA vs QA

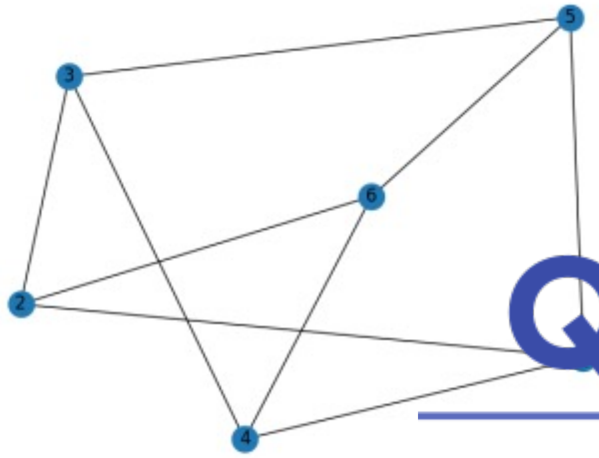
QA

QA

u3r Graph

4.



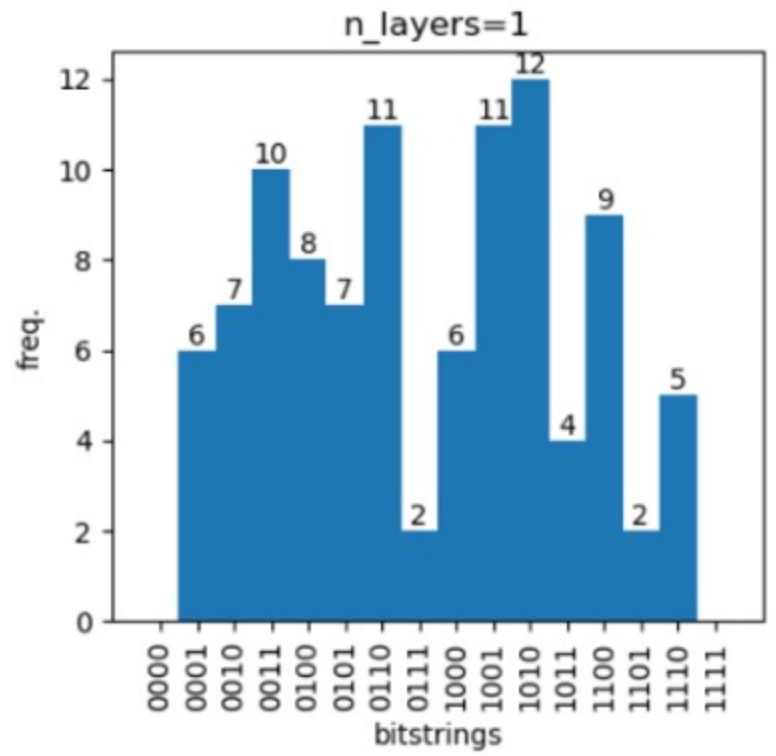


QAOA

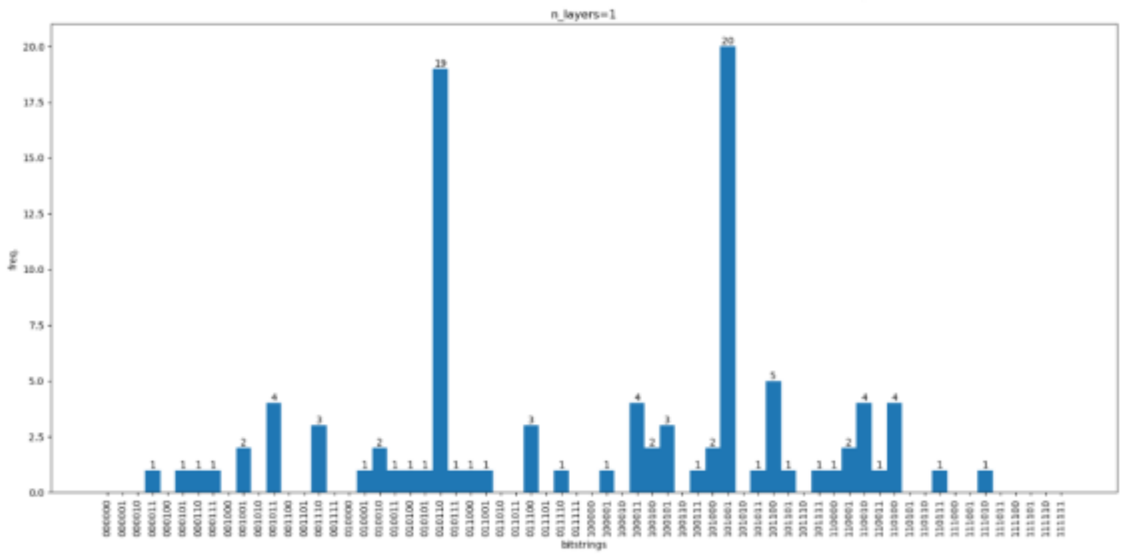
p = 1

	Node = 4	Node = 6
Result Fidelity	0.756	0.7311
Exceution Time	5s	30s
Theoretical Approximation Ratio	0.6924	0.6924

Node= 4



Node= 6



u3r Graph

4.

Node = 4

Set 0	Set 1	Energy	Cut Size
[1, 2]	[0, 3]	-2.0	4
[0, 3]	[1, 2]	-2.0	4
[0, 2]	[1, 3]	-2.0	4
[2, 3]	[0, 1]	-2.0	4
[0, 1]	[2, 3]	-2.0	4
[1, 3]	[0, 2]	-2.0	4

Set 0	Set 1	Energy	Cut Size
[0, 1]	[2, 3]	-2.0	4
[2, 3]	[0, 1]	-2.0	4
[1, 3]	[0, 2]	-2.0	4
[1, 2]	[0, 3]	-2.0	4
[0, 3]	[1, 2]	-2.0	4
[0, 2]	[1, 3]	-2.0	4
[0, 2, 3]	[1]	0.0	3

Set 0	Set 1	Energy	Cut Size
[1, 3]	[0, 2]	-2.0	4
[0, 2]	[1, 3]	-2.0	4
[0, 3]	[1, 2]	-2.0	4
[2, 3]	[0, 1]	-2.0	4
[0, 1]	[2, 3]	-2.0	4
[1, 2]	[0, 3]	-2.0	4

Set 0	Set 1	Energy	Cut Size
[1, 3]	[0, 2]	-2.0	4
[0, 2]	[1, 3]	-2.0	4
[0, 3]	[1, 2]	-2.0	4
[2, 3]	[0, 1]	-2.0	4
[0, 1]	[2, 3]	-2.0	4
[1, 2]	[0, 3]	-2.0	4
[1, 2, 3]	[0]	0.0	3

Set 0	Set 1	Energy	Cut Size
[0, 1]	[2, 3]	-2.0	4
[2, 3]	[0, 1]	-2.0	4
[1, 2]	[0, 3]	-2.0	4
[1, 3]	[0, 2]	-2.0	4
[0, 2]	[1, 3]	-2.0	4
[0, 3]	[1, 2]	-2.0	4

$Sol1\ |0011\rangle$: 100/100
$Sol2\ |1100\rangle$: 100/100
$Sol3\ |0110\rangle$: 100/100
$Sol4\ |1001\rangle$: 100/100
$Sol5\ |0101\rangle$: 100/100
$Sol6\ |1010\rangle$: 100/100

Node = 6

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[0, 2, 5]	[1, 3, 4]	-9.0	9
[1, 3, 4]	[0, 2, 5]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

Set 0	Set 1	Energy	Cut Size
[1, 3, 4]	[0, 2, 5]	-9.0	9
[0, 2, 5]	[1, 3, 4]	-9.0	9

$Sol1\ |010110\rangle$: 100/100

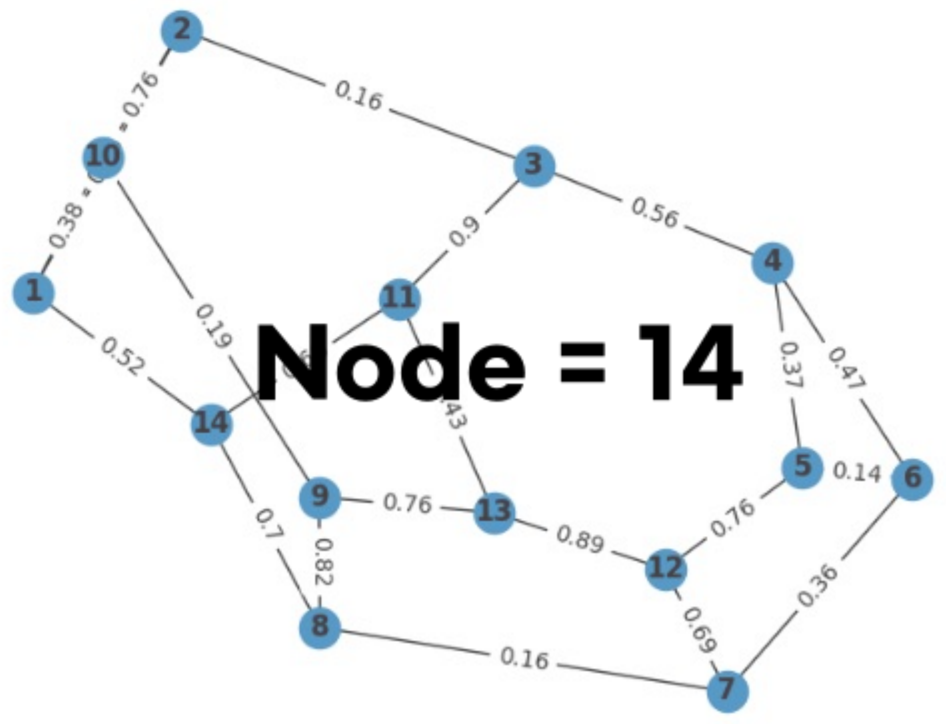
$So12\ |101001\rangle$: 100/100

QA

QAOA vs QA

de = 4	Node = 6	
1	1	QA
s 미만	1s 미만	QA

w3r Graph

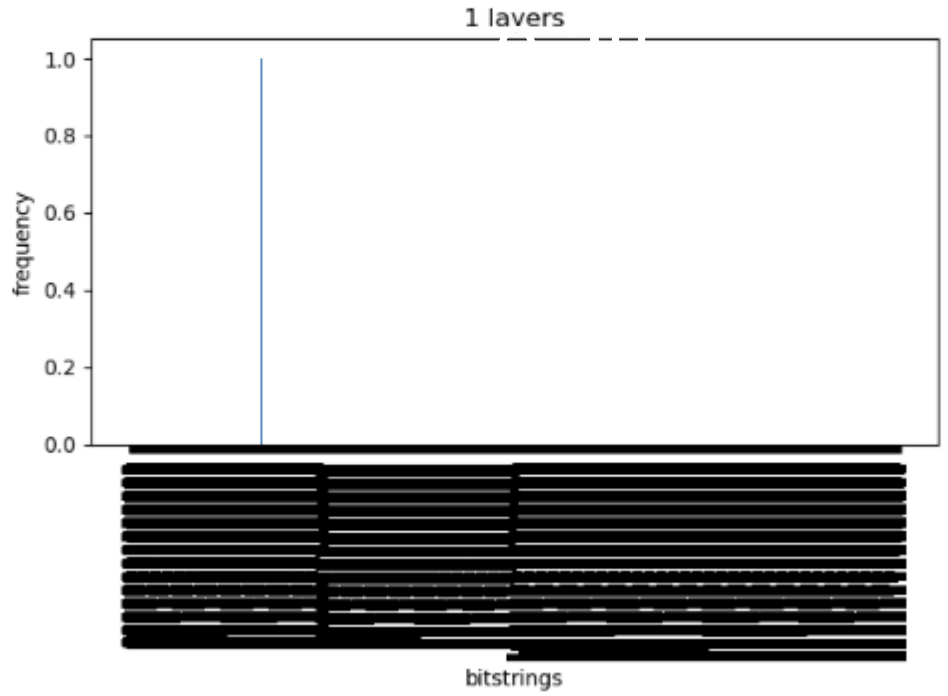


QAOA

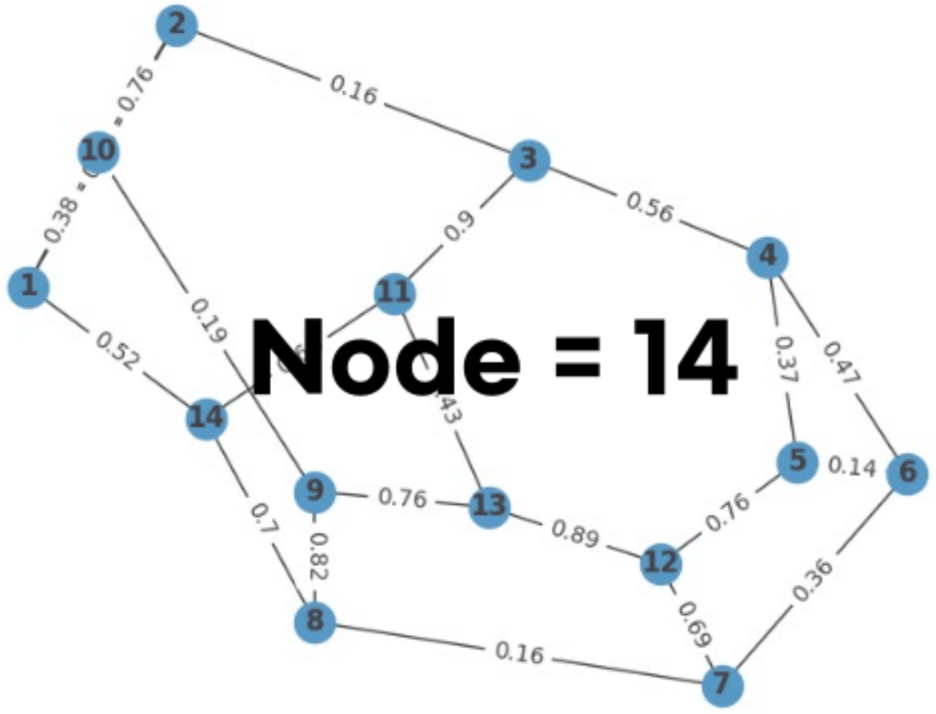
p = 1

Result Fidelity	Sorry...
Exceution Time	36900 s
Theoretical Approximation Ratio	

```
[20… optimal_params = out['x']  # This is a 1x8 array
     optimal_params_vector = optimal_params.tolist()  # Convert to a Python list if needed

     final_bitstring = get_counts(optimal_params_vector)

     binary_bit_string = ''
     for bit in decimal_to_binary(final_bitstring[2]):
         binary_bit_string += str(bit)

     print(f'The answer to our weighted maxcut is: {final_bitstring[2]} or {binary_bit_string}')

     The answer to our weighted maxcut is: 659 or 00001010010011

[22… import matplotlib.pyplot as plt

     xticks = range(0, 2**15)
     xtick_labels = list(map(lambda x: format(x, "014b"), xticks))
     bins = np.arange(0, 2**15+1) - 0.5

     plt.title(f"{num_layers} layers")
     plt.xlabel("bitstrings")
     plt.ylabel("frequency")
     plt.xticks(xticks, xtick_labels, rotation="vertical")
     plt.hist(final_bitstring[1], bins=bins)

     plt.tight_layout()
     plt.show()
```

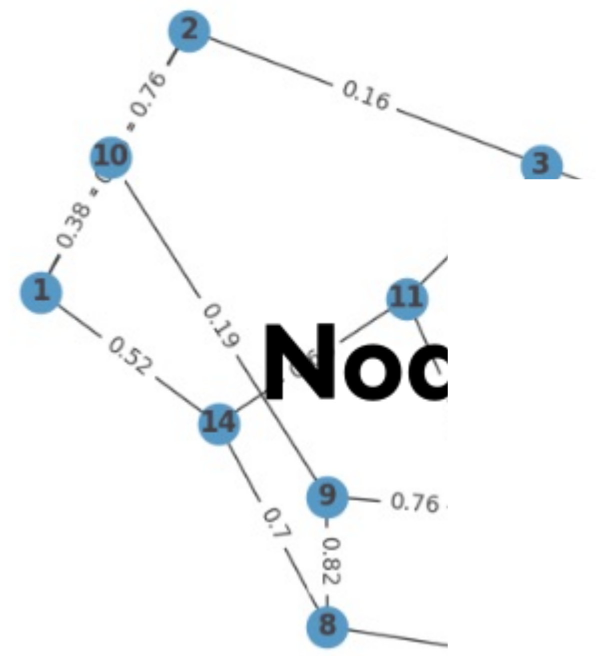


w3r Graph



	QAOA p = 1	QA	QAOA vs QA
Result Fidelity	Sorry...	0.28	QA
Exceution Time	36900 s	1.8 s	QA
Theoretical Approximation Ratio			

w3r Graph



Result Fi

Exceution

Theoreti
Approximati

$Sol1\ |11011011001101\rangle : 55/100$

$So12\ |00100100110010\rangle : 56/100$

둘 중 하나라도 나온 것 : 83/100

둘다 나온 것 : 28/100

QA

0.28

1.8 s

QAOA vs QA

QA

QA

5. Analysis

Analysis

Measuring Performance	u2r Graph		u3r Graph		w3r Graph
Node	4		4	6	14
Result Fidelity	0.800	0.995	0.756	0.7311	Sorry..
	1		1	1	0.28
Exceution Time	10s	180s	5s	30s	36900s
	1s 미만		1s 미만	1s 미만	1.8s

Analysis

Measuring Performance	u2r Graph	u3r Graph		w3r Graph
	Node = 4	Node = 4	Node = 6	Node = 14
Result Fidelity	QA	QA	QA	QA
Exceution Time	QA	QA	QA	QA

Analysis

①

Quantum Annealing vs. QAOA: 127 Qubit Higher-Order Ising Problems on NISQ Computers

Elijah Pelofske*[1], Andreas Bärtschi†[1], and Stephan Eidenbenz[1]

[1]CCS-3 Information Sciences, Los Alamos National Laboratory

②

Optimization Applications as Quantum Performance Benchmarks

Thomas Lubinski,[1,2] Carleton Coffrin,[3] Catherine McGeoch,[4]
Pratik Sathe,[5,6] Joshua Apanavicius,[7,8] and David E. Bernal Neira[6,9]
(Quantum Economic Development Consortium (QED-C) collaboration)*
[1]*Quantum Circuits Inc, 25 Science Park, New Haven, CT 06511*
[2]*QED-C Technical Advisory Committee on Standards and Performance Benchmarks*
[3]*Advanced Network Science Initiative, Los Alamos National Laboratory, USA*
[4]*D-Wave Systems, Burnaby, British Columbia, Canada, V5G 4M9, Canada*
[5]*Department of Physics and Astronomy, University of California at Los Angeles, USA*
[6]*Research Institute of Advanced Computer Science, Universities Space Research Association, Mountain View, CA, USA*
[7]*Indiana University Department of Physics, Bloomington, Indiana 47405, USA*
[8]*Indiana University Quantum Science and Engineering Center, Bloomington, Indiana 47405, USA*
[9]*Quantum Artificial Intelligence Laboratory, NASA Ames Research Center, Mountain View, CA, USA*

③

Quantum Approximate Optimization Algorithm: Performance, Mechanism, and Implementation on Near-Term Devices

Leo Zhou,[1,*] Sheng-Tao Wang,[1,†] Soonwon Choi,[1,2] Hannes Pichler,[3,1] and Mikhail D. Lukin[1]
[1]*Department of Physics, Harvard University, Cambridge, MA 02138, USA*
[2]*Department of Physics, University of California Berkeley, Berkeley, CA 94720, USA*
[3]*ITAMP, Harvard-Smithsonian Center for Astrophysics, Cambridge, MA 02138, USA*
(Dated: November 12, 2019)

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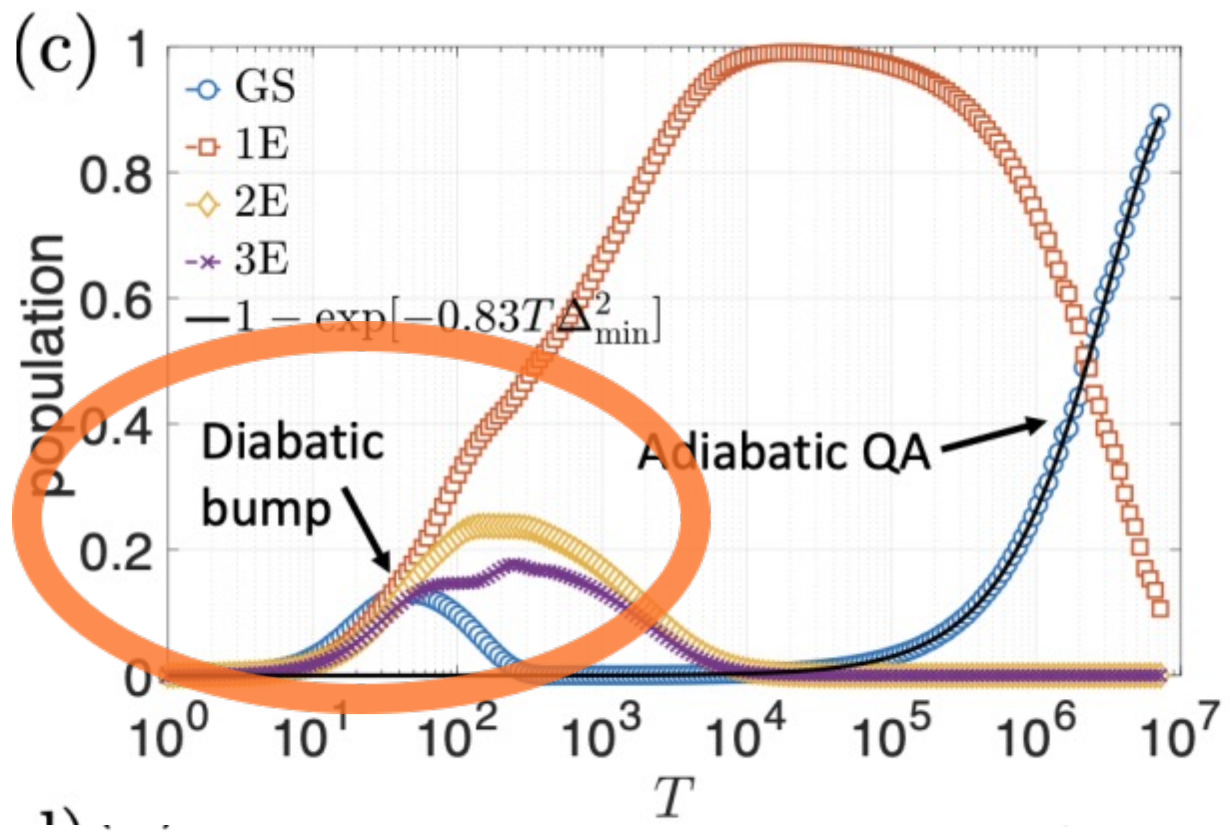
< 논문 1,2 >
수행한 문제들 모두에서
QA가 QAOA보다
더 나은performance를 보여 주었다.

< 논문3 >
minimal spectral gap이 작은
w3r (node 14 이상)문제는
QA의 한계점을 보여준다.

Analysis



minimum spectral gap $\Delta_{\min} < 10^{-3}$

$$T \gtrsim 1/\Delta^2_{\min} \approx 10^6.$$

0.28 정도의 population을 보일 수 있었던 이유는
Diabatic bump 때문이라 생각됨

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6. Conclusions

Conclusions

그렇다면 아예 QAOA가 QA의 수행능력보다
더 나은 점을 기대해볼 수 있는 건 없을까?

QA -Hard Instance

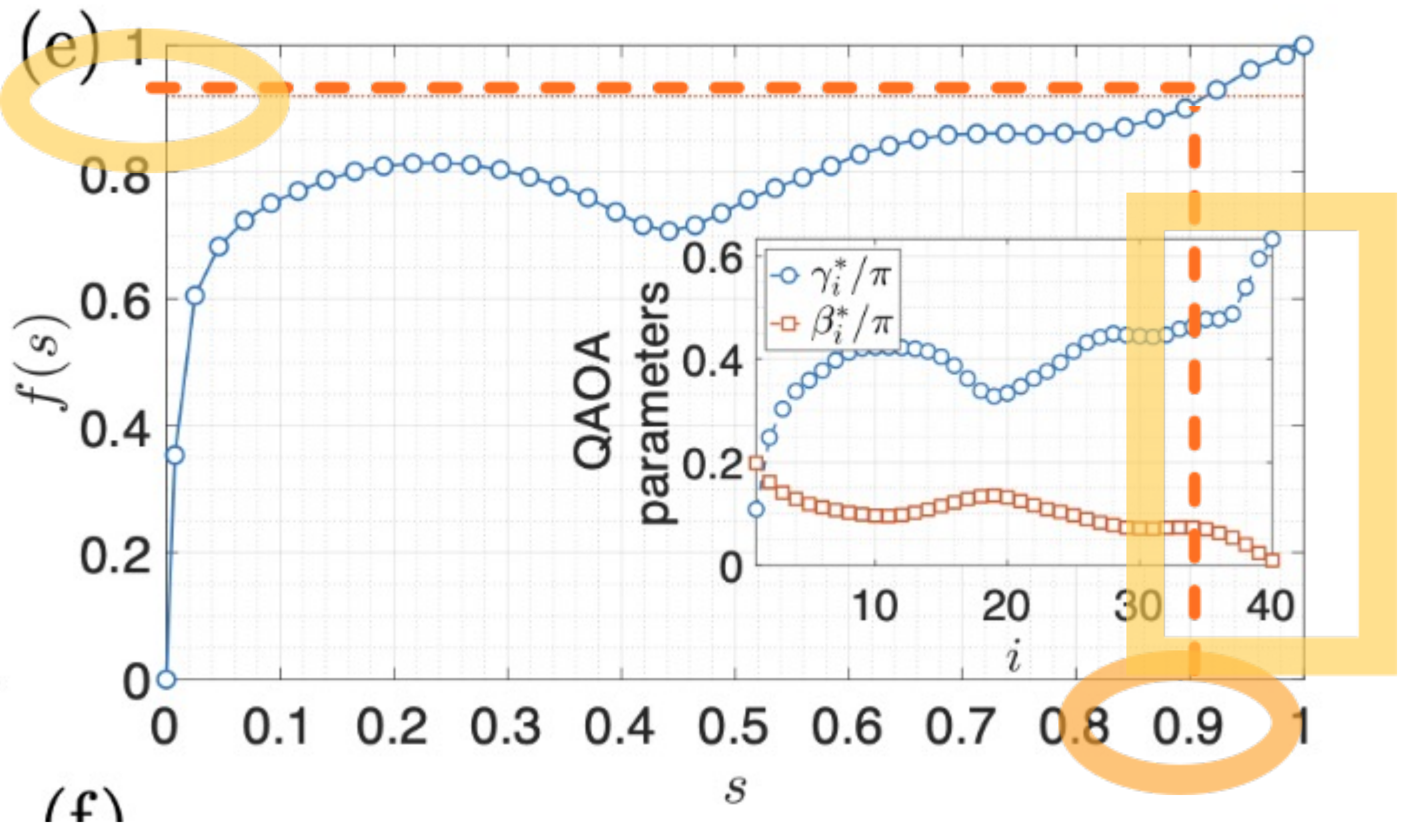
QAOA Annealing Path

$$H_{\mathrm{QAOA}}(t) = -[f(t)H_C + (1-f(t))H_B],$$

$$f\left(t_i = \sum_{j=1}^{i}(|\gamma_j^*| + |\beta_j^*|) - \frac{1}{2}(|\gamma_i^*| + |\beta_i^*|)\right) = \frac{\gamma_i^*}{|\gamma_i^*| + |\beta_i^*|}$$

circuit depth = 40 일 때 f (s) = 0.92
-> 거의 Cost Hamiltonian만 살아남음

0.92



$$s = t/T,$$

Conclusions

그렇다면 아예 QAOA가 QA의 수행능력보다
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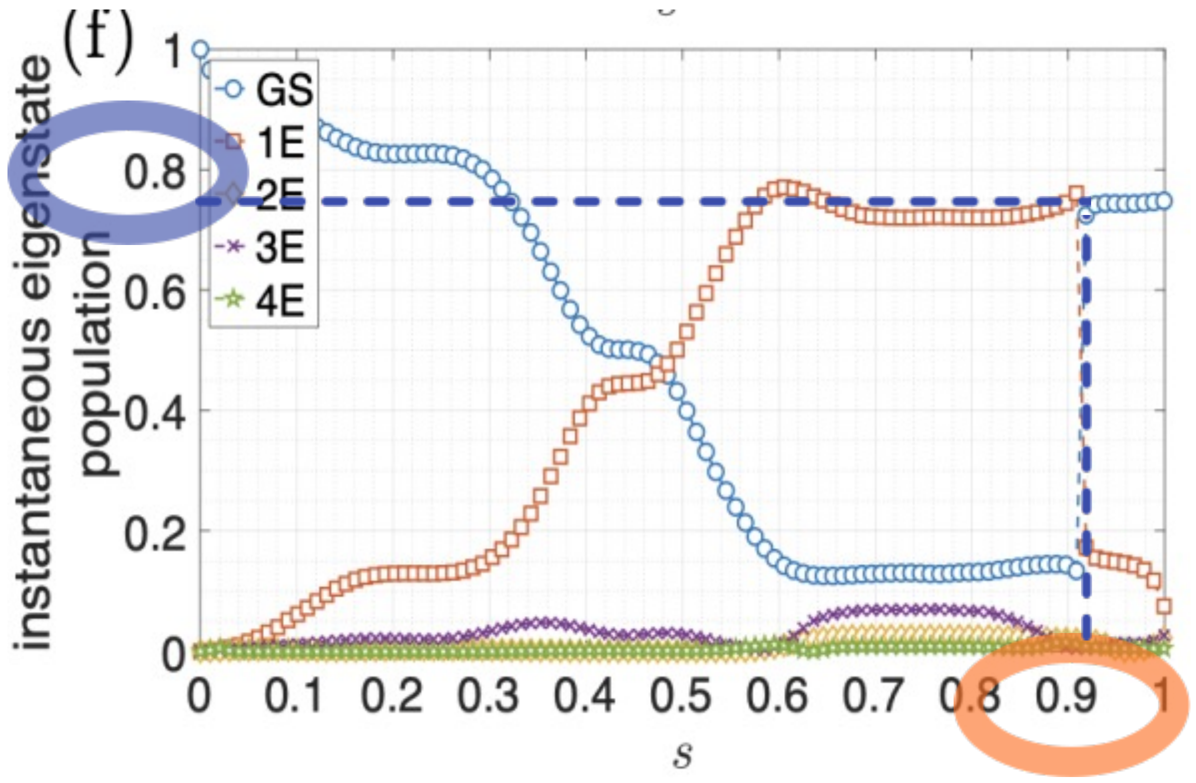
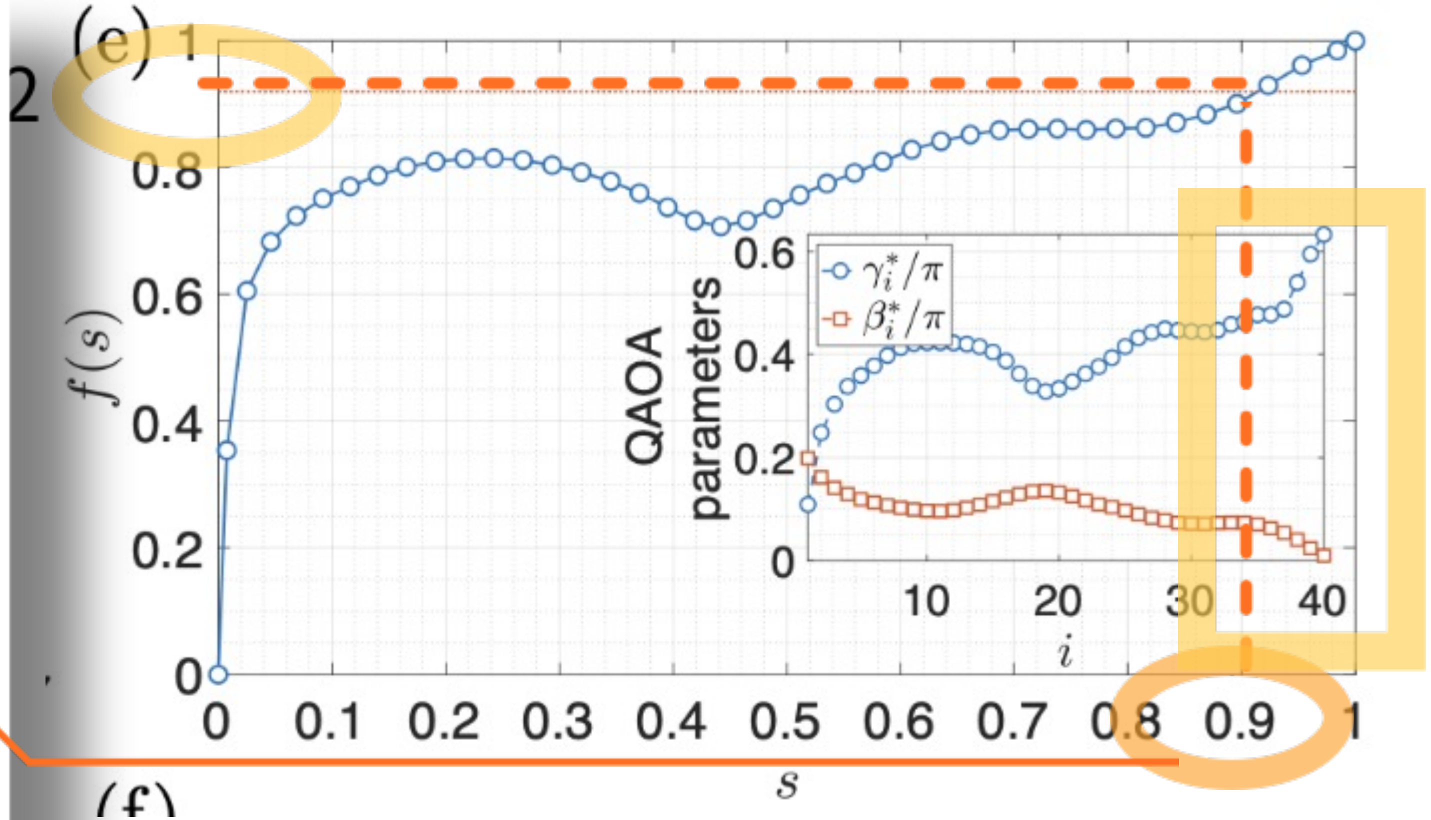


QAOA의 Circuit Depth = 40 이면
0.8정도의 population



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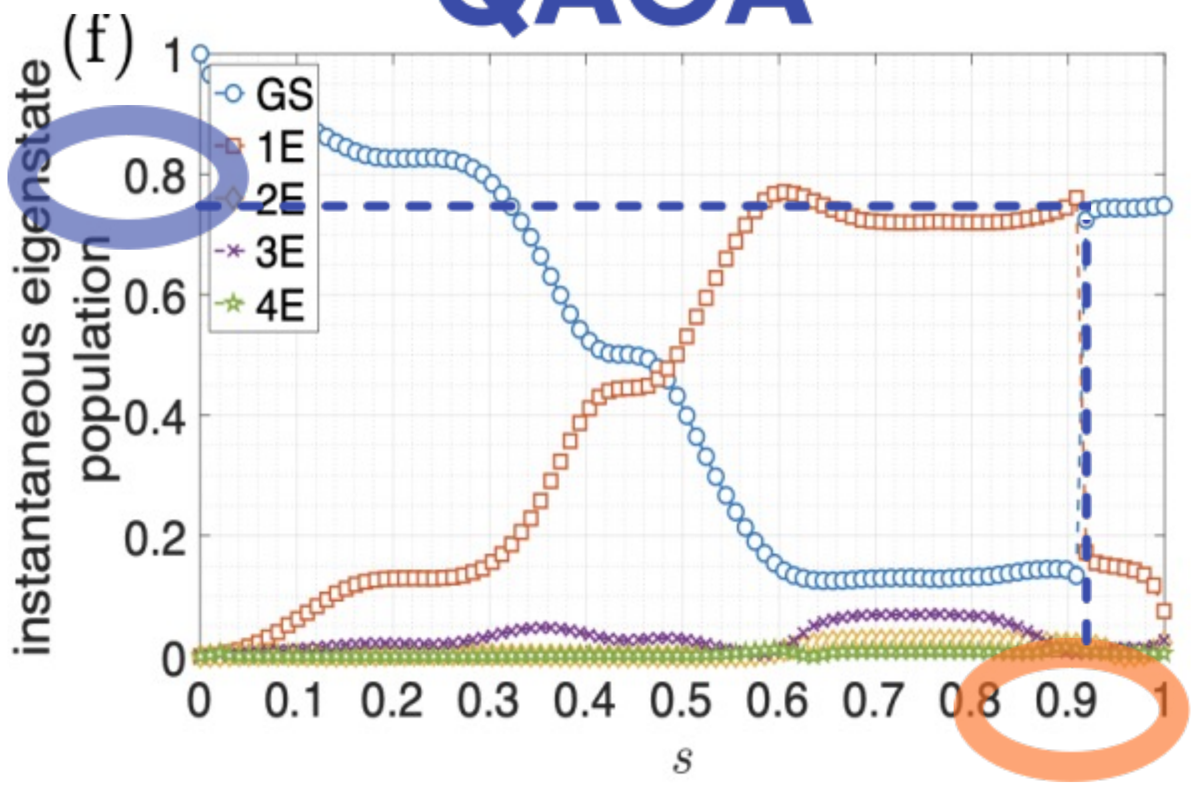
QA -Hard Instance

QAOA



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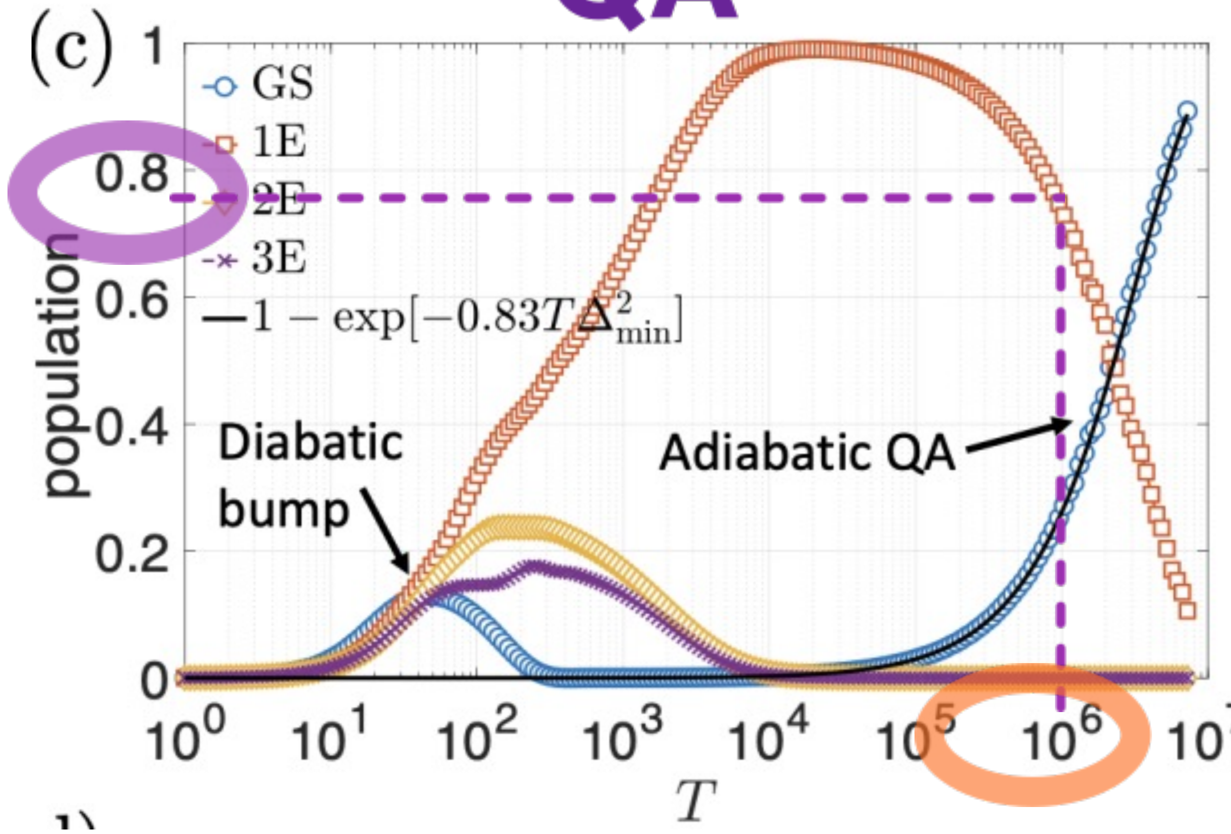


QA가 같은 정도의 population를 가지려면
Annealing time = 10^6 microsec =1s

Further Research..

QAOA

Circuit Depth = 40 인 연산을
1초 안에 구현할 것이냐

VS

QA

1초동안 Adiabatic Process를
유지할 수 있느냐

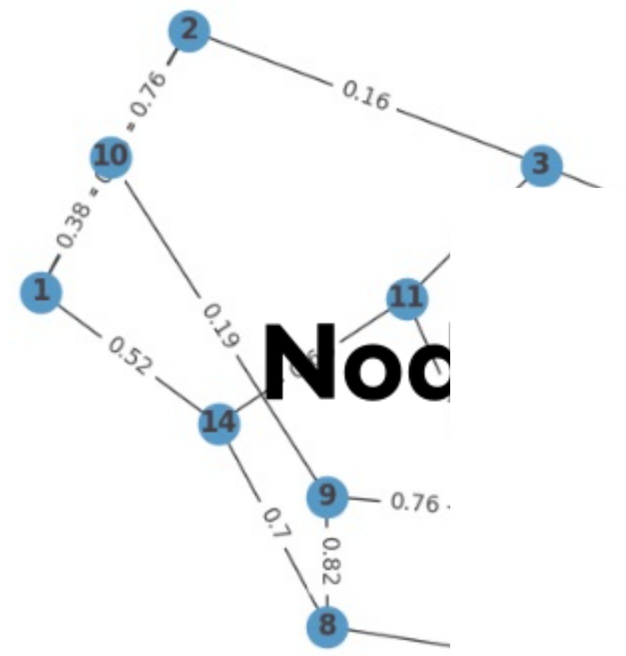
Reference

[1]Leo Zhou, Sheng-Tao Wang, Soonwon Choi, Hannes Pichler,and Mikhail D. Lukin, Quantum Approximate Optimization Algorithm: Performance, Mechanism, and Implementation on Near-Term Devices, ,9Nov2019,https://arxiv.org/pdf/1812.01041.pdf

[2]Elijah Pelofske, Andreas Bärtsch, and Stephan Eidenbenz,Quantum Annealing vs. QAOA: 127 Qubit Higher-Order Ising Problems on NISQ Computers,18MArch2023,https://arxiv.org/pdf/2301.00520.pdf

[3]Thomas Lubinski, Carleton Coffrin,Catherine McGeoch, Pratik Sathe,Joshua Apanavicius, and David E. Bernal Neira,Optimization Applications as Quantum Performance Benchmark,5Feb2023,https://arxiv.org/pdf/2302.02278.pdf

w3r Graph



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