



UNIVERSITY *of*
DENVER



Zero, One, and Everything in Between

Role of Quantum Computing in Shaping the Future Electric Grid

Amin Khodaei, Ph.D.

IEEE PES General Meeting, Denver, CO
July 2022

KLab

ENVISIONING THE GRID OF THE FUTURE

Dr. Khodaei's lab (called KLab) focuses on the design, planning, and operation of the electric grid of the future. The growing penetration of distributed energy resources, urgent need to shift towards more renewable and sustainable generation, and the ever-increasing consumers' expectations in receiving premium power, have motivated global efforts in converting legacy electric grids into more reliable, resilient, cost-effective, and green grids of the future. We study, conduct research, and architect novel models on how emerging technologies can be leveraged to achieve this goal.



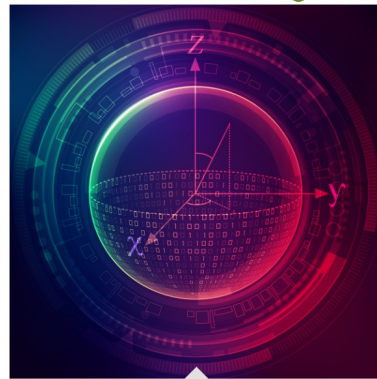
Our Focus

Research on Microgrids: Launched in 2012. Contributed to the research, development, and implementation of the first cluster microgrid in the US (BCM-ICM)

Research



Microgrids



Quantum Computing



Artificial Intelligence

Research on QC: Launched in 2019. Sponsored by electric utilities and the State of Colorado. Aimed at discovery, modeling, and simulation of practical electric power grid use cases

Research on AI: Launched in 2015. Focused on AI applications in grid resilience and advanced distribution management



U.S. DEPARTMENT OF ENERGY



comedSM

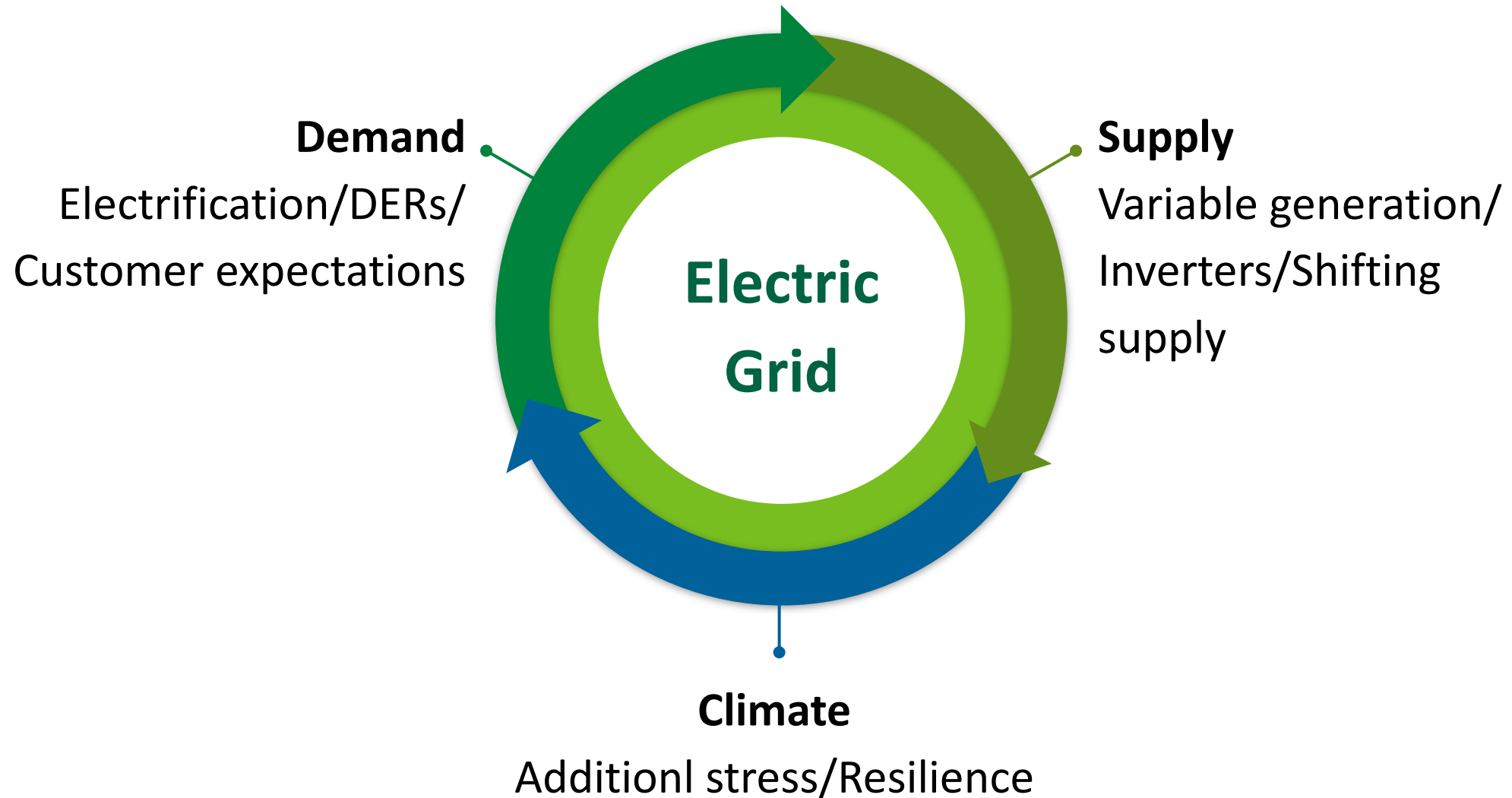
AN EXELON COMPANY



COLORADO
Office of Economic Development
& International Trade

Future Electric Grid

Electric grid is challenged



Reimagining the grid

Grid is being reimagined

Need to evolve planning and operations
Need to rethink technological capabilities



Call for improved capabilities

Existing analytical and computational capabilities may fail to address these needs, hence slowing down the pace of grid modernization



New analytics and computation

Needed to equip utilities to continue providing safe, reliable, resilient, affordable, and clean electricity to customers

“

The computational tools must be designed to formally ensure that the analytics is capable of comprehensively simulating the physical phenomena

US Department of Energy conference on Computational Needs for the Next Generation Electric Grid, 2011

The future grid will rely on integrating advanced computation and massive data to create a better understanding that supports decision making

Analytic Research Foundations for the Next-Generation Electric Grid, National Academies, 2016

More public-private partnerships are needed to advance quantum information science to the point where it can optimize the U.S. power grid

DOE's commercialization executive, 2022

“

In the News



yahoo!finance Search for news, symbols or companies [Sign in](#) [Mail](#)

guru focus


Exelon: ComEd Embraces Quantum Computing to Navigate Power Grid Disruption

GreenBiz Analysis Events Webcasts Videos Food Energy Transportation Circular [Twitter](#) [Facebook](#) [Instagram](#) [LinkedIn](#) [RSS](#)

How quantum computing is poised to support sustainable power grids

Dispatching field workers is not rocket science, but it is Quantum Physics

Published on February 24, 2021

 **Antonio Cammisecra**
Head of Enel Global Infrastructure and Networks Division presso Enel Group

13 articles [+ Follow](#)

SMART UTILITY > DATA ANALYTICS

Quantum Computing for the Future Grid

July 19, 2021

We need a robust computational foundation that can convert all this collected big data into actionable information.

Who is investing?

Company	Sector	Application	Quantum platform
NASA	Aerospace	Battery scheduling	Google, D-Wave
German Aerospace	Aerospace	Battery and fuel cell design	IBM
Mitsubishi	Automotive	Battery design	IBM
Daimler AG	Automotive	Autonomous vehicle design	Google, IBM
Volkswagen	Automotive	Traffic and travel management	D-Wave
Hyundai	Automotive	Battery chemistry design	IonQ
Samsung	Electronics	Battery performance improvement	Honeywell
ExxonMobil	Energy	Fleet management of merchant ships	IBM
JPMorgan Chase	Finance	Financial modeling	IBM
Japan's Railway	Transportation	Optimizing train operations	Hitachi
ENEL	Utility	Optimizing crew mobilization	D-Wave
E.ON	Utility	DER coordination	IBM

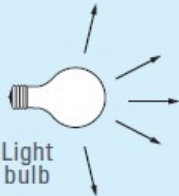
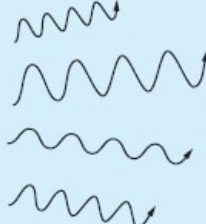
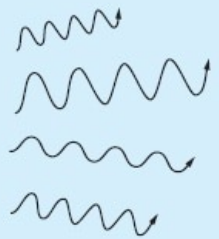
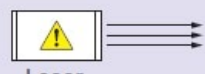
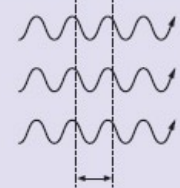
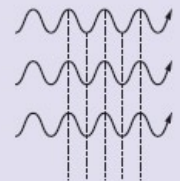
Quantum Computing

Quantum Computers

A quantum computer is a machine that performs calculations based on the laws of quantum mechanics, which is the behavior of particles at the sub-atomic level.

a fundamentally different paradigm for **processing information**, that can potentially outperform classical computers for **specific classes of problems**.

Laser vs. Lightbulb!

	Directivity (light waves travel in straight line)	Monochromaticity	Coherence
Ordinary light	 <p>Light bulb</p>	 <p>Many different wavelengths</p>	
Laser beam	 <p>Laser</p>	 <p>Single wavelength</p>	 <p>Peaks and troughs align</p>

History

Richard Feynman proposed the idea of creating machines based on the laws of quantum mechanics instead of classical physics.

Peter Shor came up with a quantum algorithm to factor very large numbers in polynomial time. Shor's algorithm could theoretically break many of the cryptosystems in use today.

First working 7-qubit NMR computer demonstrated at IBM's Almaden Research Center (First execution of Shor's algorithm).

IBM and Google reached **65 qubits**. IonQ reached **32 perfect qubits**. D-Wave reached **5000 qubits**.

1982

1985

1994

1998

2001

2011

2020

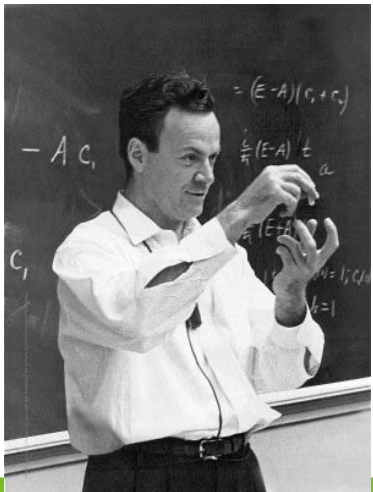
2023

David Deutsch developed the quantum Turing machine, showing that quantum circuits are universal.

First working 2-qubit NMR (nuclear magnetic resonance) computer demonstrated at University of California, Berkeley.

D-Wave Systems announced D-Wave One, described as "the world's first commercially available quantum computer", operating on a 128-qubit chipset using quantum annealing.

IBM is expected to build a 1000-qubit machine.



Quantum vs. Classical

BITS

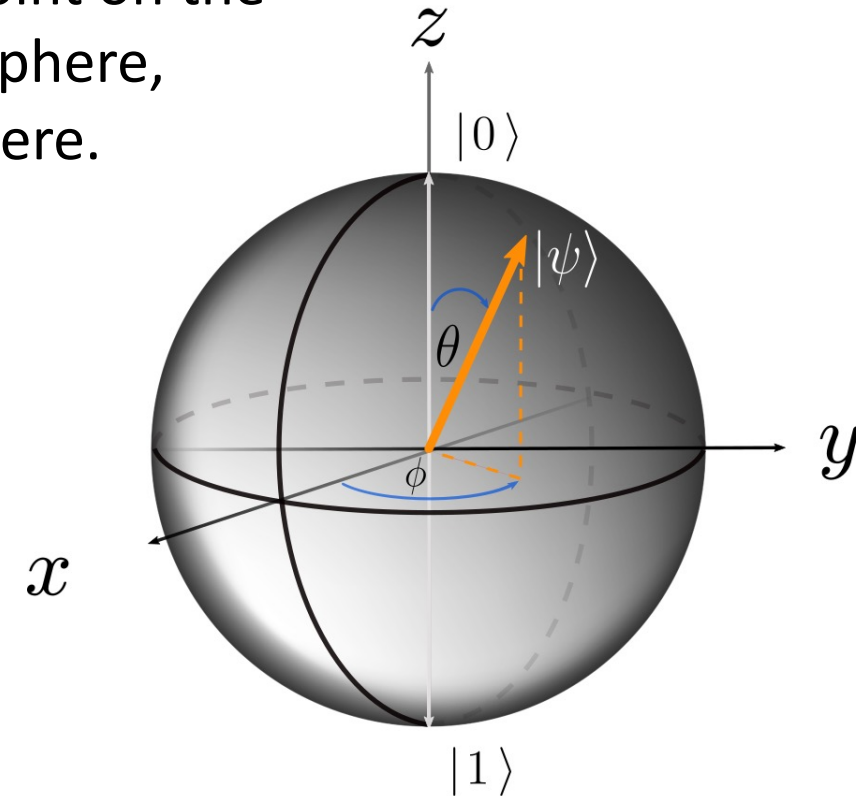
The fundamental difference between a classical computer and a quantum computer is on **how they process information:**
bit vs qubit

QUBITS

The qubit state can be mapped onto a point on the surface of a unit sphere, called a Bloch sphere.

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

$$|\alpha|^2 + |\beta|^2 = 1$$

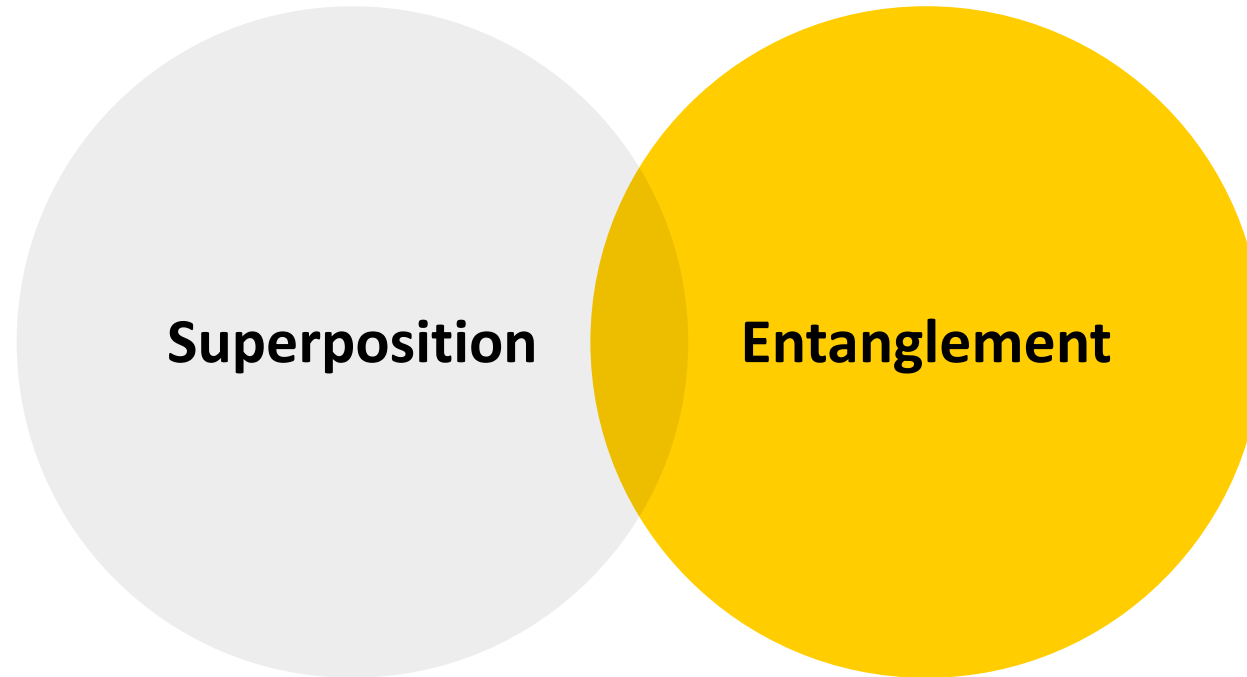


Fundamentals

A single qubit can be forced into a Superposition of the two states denoted by the addition of the state vectors:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

$$|\alpha|^2 + |\beta|^2 = 1$$



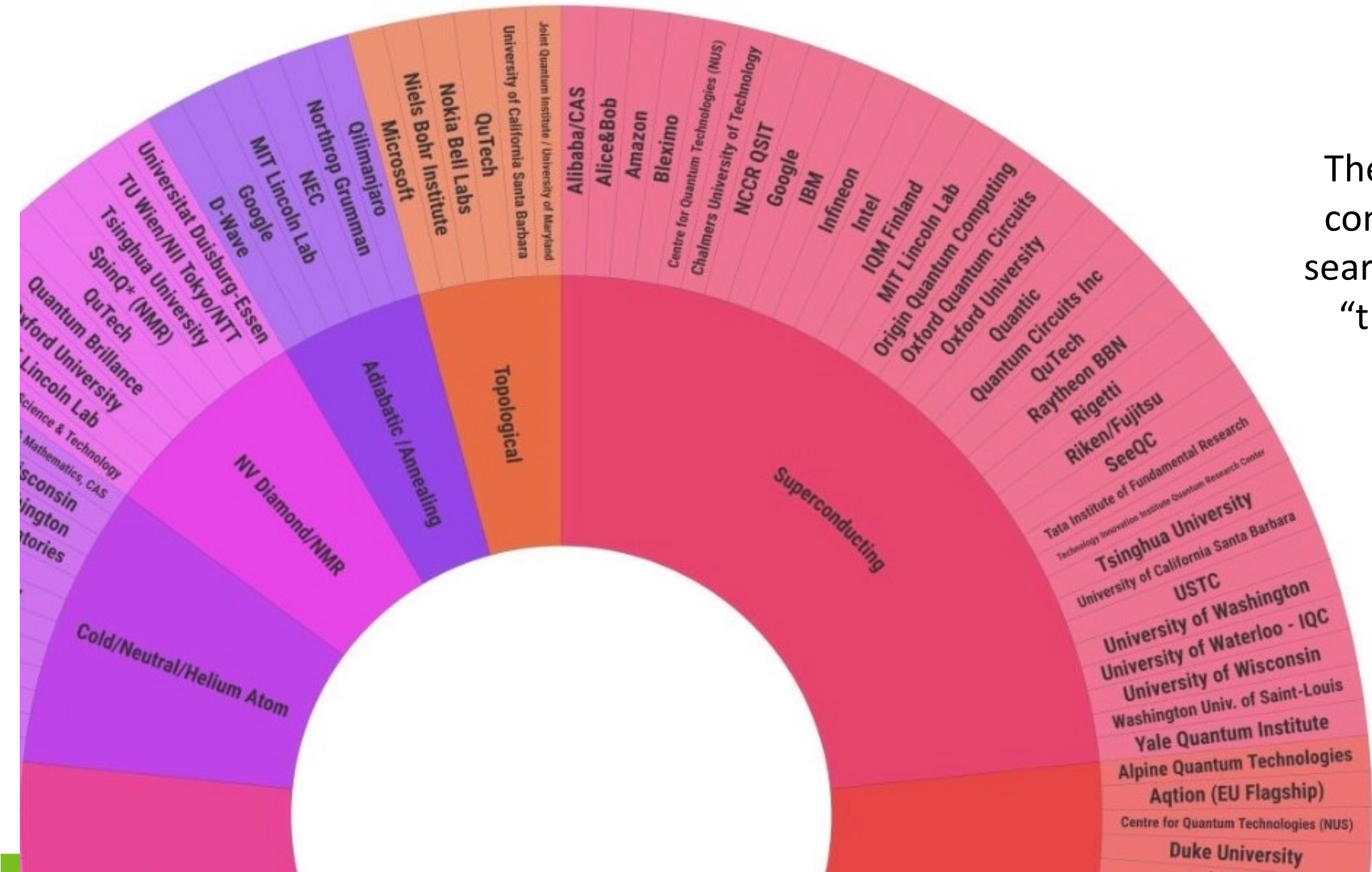
A strong correlation between quantum particles, to the point that two or more quantum particles can be inextricably linked in perfect unison, even if separated by great distances.
(spooky action at a distance!)

For N bits, there are 2^N possible classical states.

A classical computer can represent only one of these N-bit states at a time.

A quantum computer can be set into a single superposition state that may simultaneously carry aspects of all 2^N components.

The quantum community is searching for its “transistor”



Source: Michel Kurek
[Linkedin.com/in/michelkurek](https://www.linkedin.com/in/michelkurek)

Quantum algorithms and speedup

	ALGORITHM	CLASSICAL RESOURCES	QUANTUM RESOURCES	QUANTUM ADVANTAGE	LIMITATION
	Simulation (quantum chemistry)	2^N (for N atoms)	N^C	Exponential	Mapping problem to qubits
Shor's algorithm, 1994	Factoring (+ related number theoretic)	2^N (for N digits)	N^3	Exponential*	Classical runtime limit unproven
HHL algorithm, 2009	Linear systems ($Ax=b$)	2^N (for N digits)	$\sim N$	Exponential	Strict conditions, e.g. sparse matrix
	Optimization	2^N (for N items)	?	?	Empirical
Grover's algorithm, 1996	Search (unsorted/unstructured data)	N (for N entries)	\sqrt{N}	Polynomial (\sqrt{N})	Data loading

$21 = ? \times ?$

The runtime to factor a 30-digit number with a quantum computer is $30^3 = 27,000$

The runtime to factor this number with a classical computer is $2^{30} = 1,000,000,000$

Quantum speedup for grid security

IEEE 300-bus test system

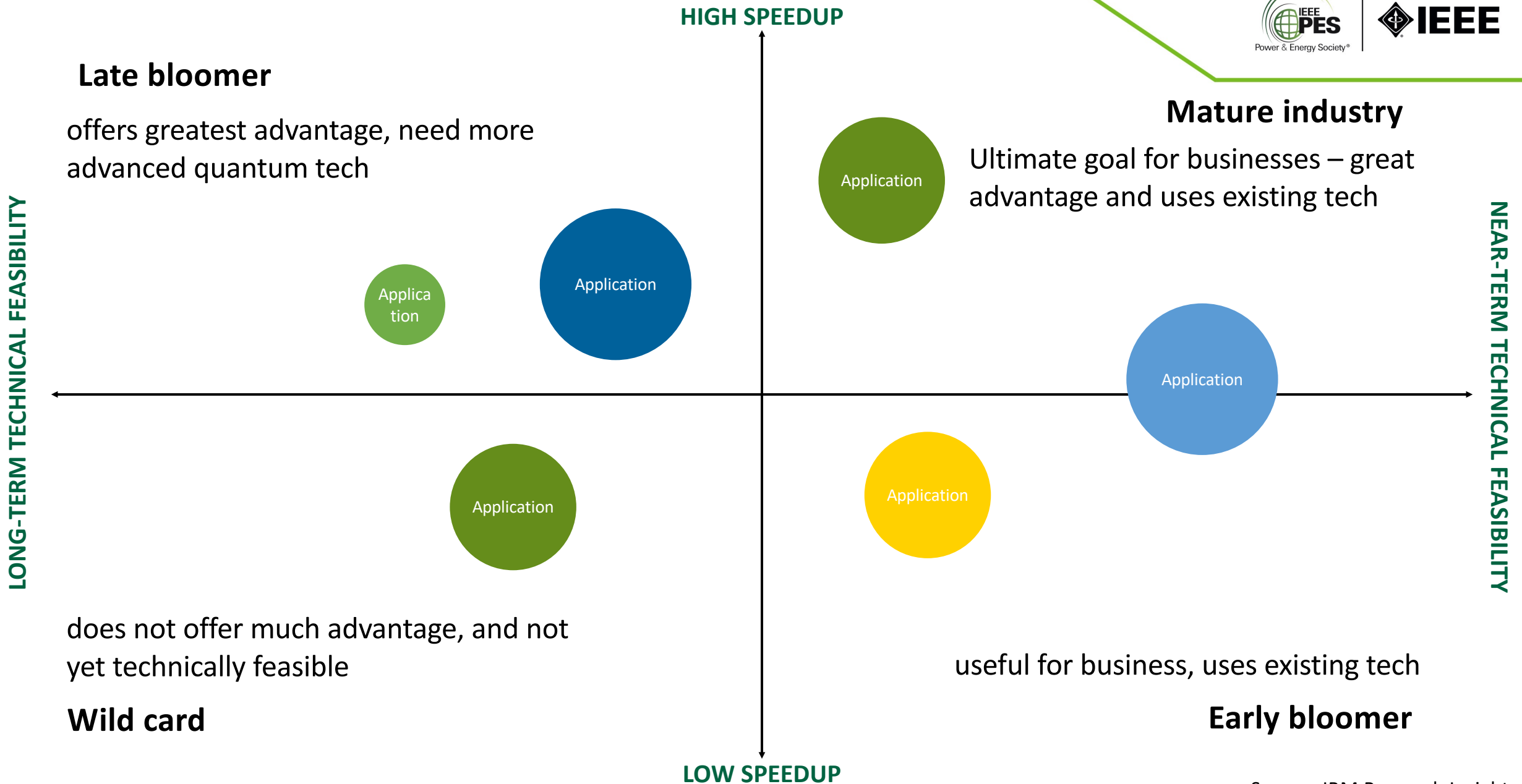
300 buses, 69 generators, 304 transmission lines

Contingency analysis – Solved using the HHL quantum algorithm

Computation time comparison (theoretical)

Contingency type	N-1	N-2	N-3
# of times to solve power flow	373	69,000	8.5 million
Computation time (classical)	37 s	2 hrs	10 days
Computation time (quantum)	0.3 s	0.5 s	0.7 s

A Practical Application



Unit commitment

Definition

Given a set of generation units with unique costs and capacities, determine the least-cost generation schedule to meet a forecasted demand

Significance



Reduced electricity costs. The system operators sacrifice the optimality for a faster, practical solution



Improved reliability. A faster UC solution can examine a large set of generation uncertainty and failure scenarios to schedule units



Lowered emission. Streamlined integration of renewable resources (large-scale and DER), resulting in environmental benefits

Unit commitment

Minimize Total generation cost
s.t. Load balance
 Unit capacity limit

How to make it quantum-compatible?

1. This should be converted into **Quadratic Unconstrained Binary Optimization (QUBO)**:

Minimize Total generation cost + A*Unit capacity limit + B*Load balance

where A and B are penalty coefficients

2. Continuous variables must be handled (cannot be included in the QUBO model)

Approach 1

Approach 1: Discretizing continuous variables. Considering N segments with similar sizes

- Each segment will have a size of $(\text{MaxCapacity} - \text{MinCapacity})/N$
- One binary variable will be assigned to each segment

Example: $\text{MinCapacity} = 0$, $\text{MaxCapacity} = 100$

$$N=2 \rightarrow p = 50*z_1 + 100*z_2$$

$$N=4 \rightarrow p = 25*z_1 + 50*z_2 + 75*z_3 + 100*z_4$$

$$N=8 \rightarrow p = 12.5*z_1 + 25*z_2 + 37.5*z_3 + \dots + 100*z_8$$

- This formulation gives very accurate results, if N is large. However,
- A large N increases both the number of segments and the number of binary variables, z
- As N increases, computation time significantly increases

Approach 2

Approach 2: Discretizing continuous variables, using the Power of 2

- $n = \log_2(N)$, where n is the number of binary variables. N must be an exponent of 2
- Each segment will have a size of $(2^{(i-1)}) * (\text{MaxCapacity} - \text{MinCapacity}) / (N-1)$, $i=1, \dots, n$
- One binary variable will be assigned to each segment

Example: MinCapacity = 0, MaxCapacity = 100

$$N=2 \rightarrow p = 100 * z_1$$

$$N=4 \rightarrow p = 33.3 * z_1 + 66.6 * z_2$$

$$N=8 \rightarrow p = 14.28 * z_1 + 28.57 * z_2 + 57.14 * z_3$$

- Multiple segments and binary variables can be active at once, reducing the need for as many variables as in the first formulation
- Results in significant reduction in computation time

Comparison

Approach 1

N	Units										Total	No. Binary Variables	Time (s)
	1	2	3	4	5	6	7	8	9	10			
2	455	455	130	130	162	80	85	0	0	0	1497	30	6.79
4	455	455	102.5	130	162	80	85	0	0	32.5	1502	50	16.05
8	378.75	455	116.25	116.25	144.87	57.5	55	55	39.375	55	1473	90	43.84
16	435.94	455	123.125	116.25	93.5	76.3	62.5	32.5	43.75	43.75	1483	170	131.586
32	450.59	357.18	112.81	123.13	149.16	80	81.25	36.72	49.38	40.98	1481	330	425.443
Target	455	455	130	130	162	80	25	43	10	10	1500	-	-

Approach 2

N	Units										Total	No. Binary Variables	Time (s)
	1	2	3	4	5	6	7	8	9	10			
2	455	455	110	110	137	60	60	45	45	0	1477	20	3.69
4	455	455	110	110	162	40	40	30	30	30	1462	30	7
8	455	455	94.28	94.28	162	51.42	76.42	25.71	25.71	25.71	1466	40	10.99
16	455	455	88	88	152.86	68	73	24	24	24	1452	50	13.83
32	445.16	445.16	99.35	105.16	148.74	66.45	71.45	23.22	23.22	23.22	1451	60	17.3
Target	455	455	130	130	162	80	25	43	10	10	1500	-	-

Observations

There is always a level of inaccuracy in the results

- Since constraints are converted into penalty terms and added to the objective
- It can be resolved by fine tuning the penalty coefficients

Continuous variables cannot be directly considered

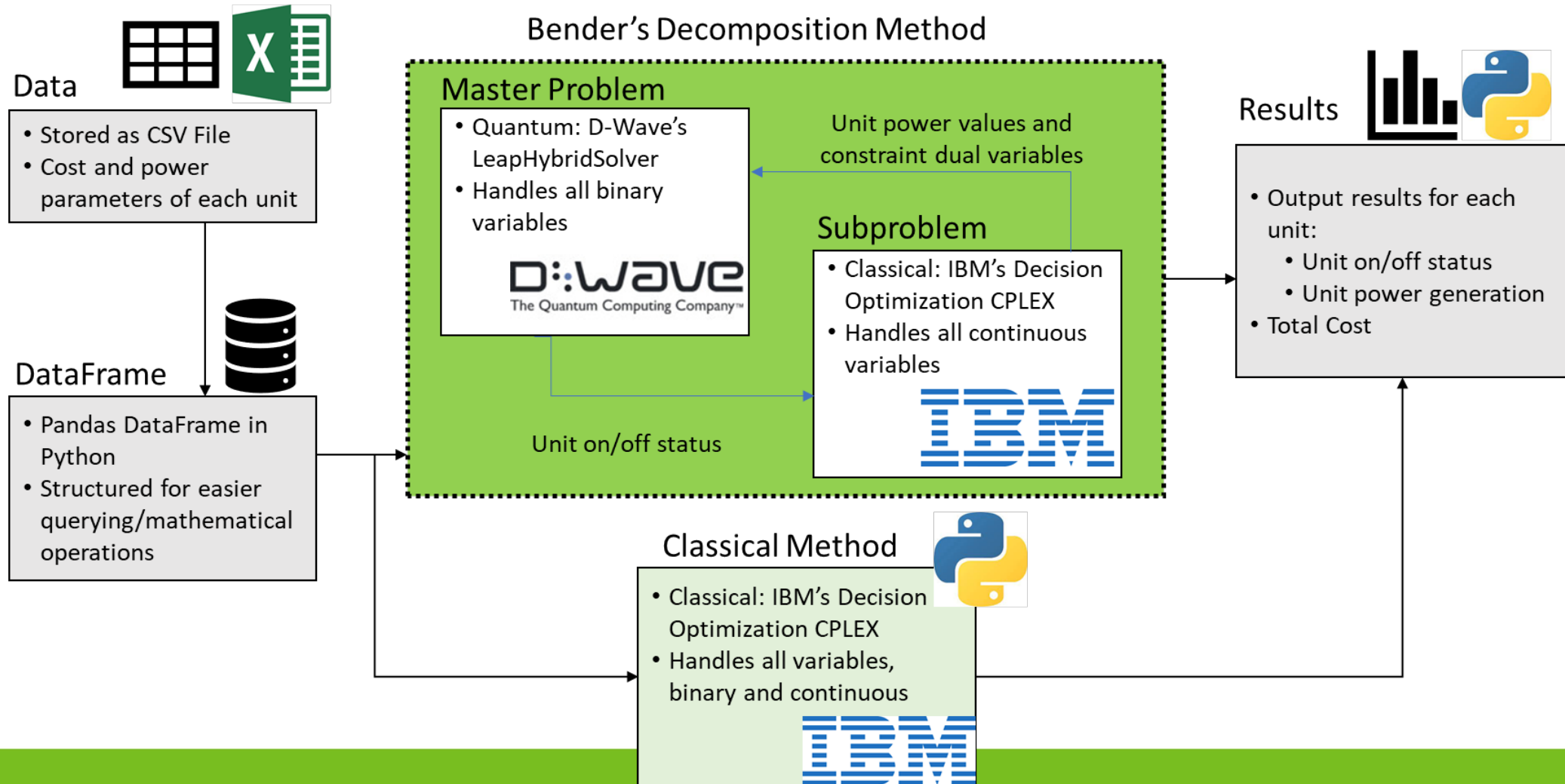
- Should be converted into binary variables
- Significantly increases the computation time (adding many additional binary variables)

If the problem can be efficiently modeled as BQM, it could potentially outperform classical solutions

- Very effective in binary optimization

Approach 3

Hybrid quantum-classical solution



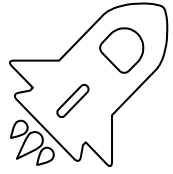
Approach 3

Decomposes the original problem into several problems (BQM and LP/NLP)

BQM is solved by D-Wave (as it only has binary variables), and LP/NLP are solved by a classical solver (as they only have continuous variables). Solution found iteratively.

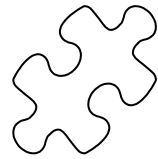
Units	Quantum Comp Time	MINLP Comp Time	Absolute Relative Error %
10	3.012	0.025	1.01E-08
20	3.003	0.077	3.564
30	3.006	0.048	4.217
40	3.002	0.071	5.299
50	3.005	0.097	5.301
60	3.004	0.129	9.523
70	3.005	0.126	10.676
80	3.007	0.178	9.660
90	3.007	0.157	12.742
100	3.008	0.361	12.511
150	3.003	24.478	13.407
200	3.008	75.990	16.299
250	3.056	276.916	17.330
300	3.025	8927.573	16.504

Takeaways



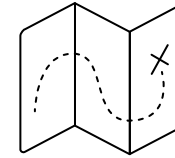
Grid is changing, so should its decision-making

Electric power grid is facing unprecedented challenges and is undergoing major transformation. Enhanced analytics and computation are of paramount importance.



Legacy solutions may not work anymore

Applying the same mathematics on more powerful computers may not provide the answers we are looking for. The historically-common simplifications and approximations may fail to support grid management.



Quantum computing is here to stay

Although a few years away from error-corrected large-scale quantum computers, now is the time to investigate quantum applications, especially for the power sector.

Questions?

amin.khodaei@du.edu