QuEra Computing Inc.

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

Tackling the Maximum Power Section Problem for Enhanced Electricity Grid Management

1. Context and Relevance

Managing energy grids effectively and reliably is emerging as a critical global challenge. With the rapid expansion of electric vehicles, digital infrastructure, and electrified industry, electricity demand is expected to rise by around 60% by 2050, putting significant strain on existing power systems and creating risks for stable grid operation. A central challenge in ensuring grid reliability is the so-called Maximum Power Section problem, which arises in electrical power distribution and microgrids. The problem can be phrased as splitting a network of generators and loads connected by transmission lines into disjoint parts while maximizing the amount of load (demand) that can still be served by the available generation, while respecting operational limits such as power flow, line capacities, and balance constraints. Solving this problem is highly relevant for blackout prevention and resilience planning.

The Maximum Power Section problem is directly related to the graph problem called weighted MaxCut, which is known to be NP-hard, implying that the best known classical algorithms require exponentially more computational resources as the system size increases. The in-principle exponential growth of computational resources is expected to hold both for classical as well as quantum computing solutions. However, as is the case with almost any optimization problem, in practice approximations of the optimal solutions are good enough to work with, hence approximate optimization algorithms and heuristics become interesting. Traditional classical solution methods, such as Mixed-Integer Linear Programming (MILP) or the Goemans–Williamson algorithm, are widely applied to MaxCut problems but face significant scalability challenges when extended to large power systems, particularly under the added complexity and uncertainty of renewable integration. Quantum computing has emerged as a potential pathway to overcome these limitations and the hope is that quantum approaches could enable more scalable and responsive optimization frameworks tailored to the needs of modern electricity grids.

2. Challenge Overview

In this hackathon challenge, participants are tasked with developing a working prototype of a

computational workflow that generates near-optimal solutions to the Maximum Power Section problem in electrical grids, using its reduction to a weighted MaxCut instance as a baseline. Building on this formulation, the focus is on implementing and testing quantum optimization methods – particularly on neutral-atom devices, which are naturally suited for solving graph problems such as MaxCut – to tackle the problem efficiently. Participants should apply their approaches to openly available benchmark datasets, such as the IEEE Bus Power System test cases, and demonstrate how their workflow can be used to produce solutions that can be meaningfully compared with classical benchmarks in terms of quality and scalability.
Participants are encouraged to:

- Start with a simple model that outputs solutions for very small graphs, before moving on to a more complicated model. You may start with the weighted 5-node graph used as an example below.
- Make use of open source databases such as, for instance, the IEEE Bus Power System test data and benchmark their solution against known results for the same data sets with traditional computational approaches (IEEE Bus Power System data as well as other data sets linked below under Resources).
- Incorporate classical pre- or post-processing steps and justify them, e.g. the calculation of the weights in the weighted graph based on the test case data for electrical grids.
- Clearly document their workflow to ensure reproducibility and extensibility
- Demonstrate a compelling path toward a potential quantum advantage, with a clear articulation of the challenges that must be overcome.

3. Detailed Problem Description

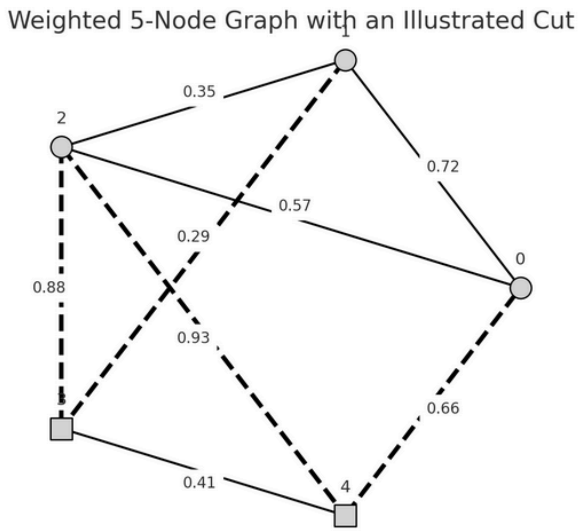
a. Mathematical Problem / Model Description

Weighted MaxCut:
Let G = (V,E,w) be an undirected weighted graph, that is, V = {0,1,2,...,n-1} is the set of vertices (=nodes), $E \subseteq V \times V$ is the set of edges, and $w: E \rightarrow R_{\geq 0}$ assigns a non-negative weight w(i,j) = w_{ij} to each edge (i,j) ∈ E.

A cut of the graph G is a partition of of the vertex set V into two disjoint subsets S and its complement S^{-} = V \ S. The weight of the cut is defined as the sum of the weights of the edges crossing the cut, i.e.

$$\mathrm{Cut}(S) = \sum_{\substack{(i,j)\in E \\ i\in S, j\in \bar{S}}} w_{ij}.$$

For example, consider the 5-node weighted graph shown below, where S = {0,1,2}, nodes shown as circles (hence $\bar{S}$ = {3,4}, nodes shown as squares). The dashed lines are the cut edges and we find Cut(S) = 0.88+0.29+0.93+0.66 = 2.76.



The weighted MaxCut problem is to find a cut with maximum weight, i.e. solve the following optimization problem

$$\max_{S \subseteq V} \ \mathrm{Cut}(S).$$

There is an equivalent binary variable formulation of the problem which will come in handy later. For this, assign a decision variable $x_i \in \{-1, +1\}$ to each node $i \in V$, indicating on which side of the cut the nodes lie (e.g. $x_i = -1$ if $i \in S$).
Then the problem can be rewritten as

$$\max_{x \in \{-1,+1\}^n} \sum_{(i,j) \in E} w_{ij} \cdot \frac{1 - x_i x_j}{2}.$$

The reformulation is helpful when rephrasing the problem as an energy minimization problem of an (Ising) Hamiltonian on n qubits. Let Z_i be the Pauli-Z operator on qubit i. Then the highest energy state of the following (Ising) Hamiltonian corresponds to the MaxCut of the weighted graph G,

$$H = \sum_{(i,j) \in E} \frac{w_{ij}}{2} (I - Z_i Z_j),$$

where the derivation of this result is a straight-forward consequence of the binary formulation of the MaxCut problem. Equivalently, we could be looking for the ground state of the negative of this Hamiltonian, i.e. -H.

Note that the formulation as an energy minimization of an (Ising) Hamiltonian is indifferent to whether the weights w_{ij} are non-negative. Hence, when reducing the Maximum Power Section problem to a weighted MaxCut problem, we can allow negative weights.

Maximum Power Section:
Consider an electrical power network represented as a graph G = (V,E), where V is the set of buses (nodes) partitioned into generators $V_G \subseteq V$ and loads $V_L \subseteq V$, and E is the set of transmission lines. Each load node $i \in V_L$ is associated with a power demand $d_i > 0$, and each generator node $j \in V_G$ has an available capacity $g_j > 0$. Each edge $(i,j) \in E$ has a line capacity $c_{ij} > 0$.

The Maximum Power Section problem is defined as follows: partition the set of buses V into two disjoint sections by removing a subset of edges in E, such that the total served load in the resulting sections $S \subseteq V$ and $\bar{S} = V \setminus S$ are maximised. The lost served load is accounted for by weights w_{ij} assigned to each edge. There are multiple ways for assigning these weights. Possible starting points for weights assignment could be capacity-based weights $w_{ij} = c_{ij}$, or flow-based weights $w_{ij} = |p_{ij}|$, where p_{ij} is the optimal (or approximately optimal) pre-contingency flow in the total network in line (i,j). More sophisticated strategies for weight assignments can be explored.

In summary, the Maximum Power Section problem is looking for maximizers of the objective function

$$S(x) = \sum_{i \in V_L} d_i - \sum_{(i,j) \in E} w_{ij} \frac{1 - x_i x_j}{2}$$

Where we already used the binary variable formulation. Here, the first term represents the total demand and is independent of the partitioning (hence it is irrelevant for the maximization). The second term already uses the binary formulation of the partitioning, as introduced above. Interpreting the second term as a “cut penalty” (i.e. the demand that may no longer be served) and omitting the first term (independent of the cut) we can rephrase this problem as the minimization problem:

$$\min_{x \in \{-1,+1\}^n} \sum_{(i,j) \in E} w_{ij} \frac{1 - x_i x_j}{2}$$

If one likes, this is nothing else but a “weighted MinCut” problem.

Note: Sometimes an additional constraint is imposed. One may enforce that the total demand in each section S can be supplied by the available generation within that section, i.e. that

$$\sum_{i \in S \cap V_L} d_i \leq \sum_{j \in S \cap V_G} g_j.$$

Reducing Maximum Power Section to Weighted MaxCut:
Having formulated the Maximum Power Section problem as a weighted MinCut problem already, and having understood that the Ising Hamiltonian formulation of the weighted MaxCut problem is indifferent to whether the weights are positive or negative, we can directly phrase the Maximum Power Section problem as finding the ground state energy of the Ising Hamiltonian with the corresponding weights

$$H = \sum_{(i,j) \in E} \frac{w_{ij}}{2}(I - Z_i Z_j)$$

b. Proposed Quantum Approaches

Quantum computing approaches for this challenge should take electrical grid networks as input and output a candidate solution for the Maximum Power Section Problem. The quantum approaches for this challenge are limited to what can be carried out on analogue neutral-atom quantum processors of today's generation. Aquila, the device you will have access to **cannot** solve arbitrary MaxCut instances natively, and circumventing this is where the challenge will be biggest. Aquila **can** generate solutions to maximal/maximum independent set (MIS) problems, in the particular class of unit-disk graphs, and we can use that as a starting point. Aquila, the device you will have access to cannot solve arbitrary MaxCut instances natively, and circumventing this is where the challenge will be biggest. Aquila can generate solutions to maximal/maximum independent set (MIS) problems, in the particular class of unit-disk graphs, and we can use that as a starting point. Suggested approaches include:

- Mapping MIS cost functions to MaxCut cost functions: under specific conditions these two cost functions can translate to each other. You can discover what are those conditions, determine how the problem has to be simplified or constrained so that the conditions are met, and showcase that you can natively extract solutions for the given MaxCut problem from MIS solutions from Aquila. You may draw inspiration from this work. .
- Using Aquila as a sampler for maximal independent set bitstrings, and relying on those bitstrings as seeds for a classical post-processing pipeline that generates the solution to the weighted MaxCut problem at hand. Heuristically search for which classes of maximal independent set seeds could best improve the performance of the classical post-processing pipeline. Here is another point for inspiration!

We recommend using adiabatic protocols for obtaining solutions out of quantum hardware. Those should be the easiest way to get acquainted with neutral-atom analog quantum computers. High-level information about solving MIS problems on these systems can be found here. Finally, here is an extra reference for a few more perspectives or a different way to address related problems.

The participants are encouraged to also think about fault-tolerant quantum algorithms that may further enhance the computational pipeline. However, when it comes to the working prototype, a key deliverable of this hackathon challenge, NISQ algorithms will likely be the only viable option.

4. Expected Deliverables

- **Working Prototype:** A functional model that takes data as input and produces a solution to the posed challenge. We recommend a step-by-step approach, beginning with a proof-of-concept for a very simple toy model before expanding to a full model, e.g. tackling larger data sets or problem instances.
- **Technical Documentation:** A detailed report explaining the quantum algorithms used, the data model, and the rationale for choosing the specific approach. The focus should be on the clear and deliberate use of methodology and the benchmarking process, rather than solely on high-performing results. Participants should benchmark their quantum model against standard classical solutions. If more than one model was developed during the hackathon the team may also benchmark against those.
- **Classical Bottleneck Analysis and Justification for Quantum Computing Approach:** An analysis of standard approaches and their bottlenecks. This is the basis for arguing why a quantum computing approach may be beneficial for the problem at hand.
- **SDG Impact Assessment:** An assessment of the impact of your solution on the main SDG tackled by this challenge. Your arguments should be backed by references to publications and publicly available data.
  Also: What other SDGs may be impacted by your solution (both to the positive or to the negative)? List them and argue for why your solution is relevant also to those.
- **Business Case:** A concise plan outlining the commercial viability, target users, and market strategy. Think about how your solution could be commercialized, how you would approach commercialization, what would the product be, who would be the customers, how you would make money with it.
  Also: In what other fields / problems could your solution be useful?
- **Pitches & Technical Deep Dive:** At the end of the hackathon you will have the chance to present your solution in a final presentation as a 3 min pitch with slides. Please explain the solution's potential and its future roadmap, including an honest discussion

of the challenges that need to be addressed before it can be a fully realized product, all based on the above deliverables. The pitch will be followed by a 2 min Q&A with the jury for the respective challenge, which consists of 50% technical experts and 50% business experts.
In addition, you will have the chance to present your solution in a 10 min technical deep dive to the technical experts in the jury. For this, no slides are required, but a prepared code review is envisioned.

Importantly: A deeper investigation into one quantum computing approach is preferred over a superficial overview of many. The goal is not to find a single "best" model, but to demonstrate a clear understanding of the chosen approach. The solution should focus on demonstrating how the quantum approach can be applied to the problem, specifically addressing the challenge specified above. The goal is to articulate a compelling case for a future computational speed-up or greater accuracy, rather than proving an immediate advantage.

Target audience: The project should be compelling to technical professionals who are interested in exploring how quantum computing can be applied to their domain.

5. Resources

[Context] SDG 9: https://sdgs.un.org/goals/goal9

[Context] BloombergNEF's long-term energy and climate scenarios for the transition to a low-carbon economy: https://about.bnef.com/insights/clean-energy/new-energy-outlook/

[Intro] Wikipedia entry for MaxCut: https://en.wikipedia.org/wiki/Maximum_cut

[Intro] Wikipedia Max Independent Set: https://en.wikipedia.org/wiki/Maximal_independent_set

[Technical Paper, Data] MaxCut and applications to power grid optimization with QuEra neutral atoms device, incl. IEEE 9 Bus Power System test data: https://arxiv.org/pdf/2404.11440

[SDK] Bloqade SDK: https://bloqade.quera.com/latest/

[Tutorial] Bloqade for QAOA:
https://bloqade.quera.com/v0.23.0/digital/examples/qaoa/

[Data] IEEE 14+ Bus Power System test data:
https://www.researchgate.net/profile/Sajith_Nishal2/post/Is_there_any_power_flow_from_44_bu

s_to_45_bus_in_IEEE_57_bus_system/attachment/5be57ca3cfe4a7645500e52e/AS%3A691032131911684%401541766307662/download/IEEE_data.pdf

[Data] Other test data sets for power systems:
https://tweckesser.wordpress.com/power-system-data-and-test-cases/