Community Detection in Electrical Grids Using Quantum Annealing

E.ON: Optimizing the Renewable Electric Grid

Marina Fernández Fernández-Campoamor, Corey O’Meara, Giorgio Cortiana, Vedran Peric, Juan Bernabe-Moreno

https://arxiv.org/abs/2112.08300
Over 70,000 employees

Energy networks

Customer solutions

Operating in 15 countries

1.6m Km energy networks

Over 50 M customers

> 32,000 managed industrial sites

> 800,000 connected assets

> 32,000 managed industrial sites

> 350 heating networks

Over 50 M customers

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Decarbonization, Decentralization, Digitalization increasingly complex and interlinked, requiring higher levels of coordination.
Smart, decentralized and flexible grids

Congestion management
When is the energy fed into the grid going to be de-stabilizing it?

Optimization and energy storage
What is the optimal charging schedule for a fleet of e-vehicles?
How can e-Mobility be exploited to improve building energy efficiency and grid-stability?

Local Energy Systems
How can we enable a Peer-to-Peer energy trading market?
Can a local energy system work completely off-grid?
Started Quantum Program in 2019

DWave and IBM Q Partner

Team of fulltime Quantum Engineers plus supervision of additional M.Sc./Ph.D students through academic alliances

Focus on real world use-cases which have potential to deliver business value
Use-Cases We’ve Explored

- Optimization: Community Detection in Electrical Grids/Peer-to-Peer
- Optimization: Vehicle-to-Grid Optimizing Bi-Directional Assets
- QML\(^1\): Power Plant Anomaly Detection via Hybrid Neural Networks
- QML: Clustering-based Anomaly Detection for Grid Assets
- QML/QAE\(^2\): Optimized qGAN\(^3\) for power plant option pricing

\(^1\) Quantum Machine Learning; \(^2\) Quantum Amplitude Estimation; \(^3\) Quantum Generative Adversarial Networks
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Optimization: Vehicle-to-Grid Optimizing Bi-Directional Assets

QML¹: Power Plant Anomaly Detection via Hybrid Neural Networks

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Future of the Energy Sector

**Goal**

EU requires to achieve 40% renewable generation by 2030 (Fit for 55).

**Role**

Households’ role changes from consumers to prosumers.

**Opportunities**

New energy markets at the distribution system level are gaining strength.

**Challenges**

Congestion, role of DSO, accommodate new market players...
The future grid is complex, decentralized and bidirectional
Community Detection in Grids

Question
How can we optimally detect communities taking into account technical characteristics of the electrical grid?

Couple market and infrastructure
Simplify power analysis
Reduce power losses in transactions
Community Detection in Grids

Modularity (complex network theory)

“Fraction of the edges that fall within the given group minus the expected fraction if edges were distributed at random.”
Community Detection in Grids

Modularity (complex network theory)

“Fraction of the edges that fall within the given group minus the expected fraction if edges were distributed at random.”

$$Q = \frac{1}{(2m)} \sum_{vw} \left[ A_{vw} - \frac{k_v k_w}{(2m)} \right] \delta(c_v, c_w)$$

$Q =$ modularity
$m =$ total number of edges in a graph
$A_{vw} =$ coeff. for the $v, w$ th elem. of the adjacency matrix
$k_v =$ the degree of bus $v$
$\delta(C_v, C_w) = 1$ if $v$ and $w$ are in same partition, 0 otherwise
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Community Detection in Grids

Electrical Modularity

Modularity applied to a graph in which edges are given a weight based on two electrical measures:

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- Composite weight
  - Line resistance
  - Sensitivity of the line
Community Detection in Grids

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Composite weight

- Line resistance
- Sensitivity of the line

How can we partition an electrical grid maximizing electrical modularity?
Workflow

Data preparation → Prepare the problem for the specified backend → Sample the problem → Post-process results
# Workflow

## Data preparation

<table>
<thead>
<tr>
<th>Elements</th>
<th>IEEE-14</th>
<th>IEEE-33</th>
<th>IEEE-118</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buses</td>
<td>14</td>
<td>33</td>
<td>118</td>
</tr>
<tr>
<td>Lines</td>
<td>15</td>
<td>37</td>
<td>173</td>
</tr>
<tr>
<td>Loads</td>
<td>11</td>
<td>32</td>
<td>99</td>
</tr>
<tr>
<td>Generators</td>
<td>4</td>
<td>0</td>
<td>53</td>
</tr>
<tr>
<td>Grid ext.</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Trafos</td>
<td>6</td>
<td>0</td>
<td>13</td>
</tr>
</tbody>
</table>
Workflow

Creates problem

Binary Integer Programming (BIP) Problem

\[ Q = \frac{1}{(2m)} \sum_{vw} \left[ A_{vw} - \frac{k_v k_w}{(2m)} \right] \delta(c_v, c_w) \]

\( x_{ik} \) Binary, 1 if bus \( i \) belongs to group \( k \)
Workflow

BIP Problem

\[ Q = \frac{1}{(2m)} \sum_{vw} \left[ A_{vw} - \frac{k_v k_w}{(2m)} \right] \delta(c_v, c_w) \]
Workflow

Creates problem

BIP Problem

\[
\begin{align*}
\max & \quad \sum_{k}^{K} x_k^T Q_e x_k \\
\text{subject to} & \quad \sum_{k}^{K} x_{ik} = 1 \quad \forall i \in B
\end{align*}
\]
Workflow

BIP Problem

\[
\text{max } \sum_{k=1}^{K} x_k^T Q_e x_k
\]

subject to \( \sum_{k=1}^{K} x_{ik} = 1 \quad \forall i \in B \)

QUBO Problem

Quadratic Unconstrained Binary Optimization

\[
H = H_{obj} + \sum_{i=1}^{B} H_{ci} \quad \text{where}
\]

\[
H_{obj} = -\sum_{k=1}^{K} x^T Q_e x \quad \text{and}
\]

\[
H_{ci} = \lambda (\sum_{k=1}^{K} x_{ik} - 1)^2 ,
\]
**Workflow**

BIP Problem

\[
\begin{align*}
\text{max} & \quad \sum_{k=1}^{K} x_k^T Q_e x_k \\
\text{subject to} & \quad \sum_{k=1}^{K} x_{ik} = 1 \quad \forall i \in B
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\]

QUBO Problem

**Quadratic Unconstrained Binary Optimization**

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\]
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H_{obj} = -\sum_{k=1}^{K} x^T Q_e x \quad \text{and}
\]
\[
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\]
Workflow

**BIP Problem**

\[
\text{max } \sum_{k=1}^{K} x_k^T Q_e x_k \\
\text{subject to } \sum_{k=1}^{K} x_{ik} = 1 \quad \forall i \in B
\]

**QUBO Problem**

Quadratic Unconstrained Binary Optimization

\[
H = H_{obj} + \sum_{i=1}^{B} H_{c_i} \quad \text{where}
\]

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H_{obj} = -\sum_{k=1}^{K} x_k^T Q_e x \
H_{c_i} = \lambda \left( \sum_{k=1}^{K} x_{ik} - 1 \right)^2,
\]
# Workflow

## Backends

<table>
<thead>
<tr>
<th>Methods</th>
<th>IEEE-14</th>
<th>IEEE-33</th>
<th>IEEE-118</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWaveSampler</td>
<td>✓</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>LeapHybridSampler</td>
<td>✓</td>
<td>✓</td>
<td>-</td>
</tr>
<tr>
<td>LeapHybridDQMSampler</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Louvain</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Gurobi</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
### Table 1. Modularity results for several samples and several number of communities.

<table>
<thead>
<tr>
<th>Method</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWaveSampler</td>
<td>0.000</td>
<td>0.3495</td>
<td><strong>0.4646</strong></td>
<td><strong>0.4844</strong></td>
<td>0.4393</td>
</tr>
<tr>
<td>LeapHybrid</td>
<td>0.000</td>
<td>0.3495</td>
<td>0.4613</td>
<td>0.4613</td>
<td>0.4613</td>
</tr>
<tr>
<td>LeapHybridDQM</td>
<td>0.000</td>
<td>0.3495</td>
<td>0.4613</td>
<td>0.4613</td>
<td>0.4613</td>
</tr>
<tr>
<td>Louvain</td>
<td>-</td>
<td>-</td>
<td>0.4613</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Gurobi (MIP)</td>
<td>0.000</td>
<td>0.3495</td>
<td>0.4613</td>
<td>0.4613</td>
<td>0.4613</td>
</tr>
</tbody>
</table>

Fig. 1. Average run time performance in seconds for each partition and tested method in the IEEE 14-bus test case.
Workflow

Results

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Sample</th>
<th>Source</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chain Strength Warning</td>
<td>Some quadratic biases are stronger than the given chain strength</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Chain Length Warning</td>
<td>Chain length greater than 7</td>
<td>N/A</td>
<td>44</td>
<td>3591, 3592, 3590, 1443, 1442, 1353, 3622, 3637</td>
</tr>
</tbody>
</table>
Workflow

Fig. 2. Modularity versus number of partitions plots for each tested method in the IEEE 33-bus test case.
Fig. 4. Average run time performance for each partition and tested method in IEEE 33-bus test case.
Workflow

Results

Table 2. Modularity and run time for IEEE 118 bus partitioned into 9 communities.

<table>
<thead>
<tr>
<th>Method</th>
<th>Modularity</th>
<th>Running time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LeapHybridDQMSampler</td>
<td>0.7444</td>
<td>6.2</td>
</tr>
<tr>
<td>Gurobi</td>
<td>0.7448</td>
<td>3600 (*)</td>
</tr>
</tbody>
</table>

Fig. 5. Partition of network IEEE 118-bus test case
Conclusions

• Quadratic objective functions create a perfect candidate to use quantum annealing.

• Hybrid samplers bridge the gap between current quantum hardware and scalable applications.

• Modularity optimization can be applied to electrical grids and serves as a flexible tool to account for other information.

• Partnership with D-Wave has proven invaluable in the development of the project.
Ongoing work

- Incorporate live data and weight analysis
- Further analysis on relevant applications in the E.ON context
- Cloud architecture deployment for q-software in production
- Further exploration of hybrid architectures for performance improvement
- Hyperparameter tuning
Quantum Computing @E.ON

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Quantum Lead

Dr. Giorgio Cortiana
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Dr. Kumar Ghosh
Quantum Engineer

Arthur Kosmala
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