Data.ON

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

Energy networks

Customer solutions

Over 70.000 employees

1.6m Km energy networks

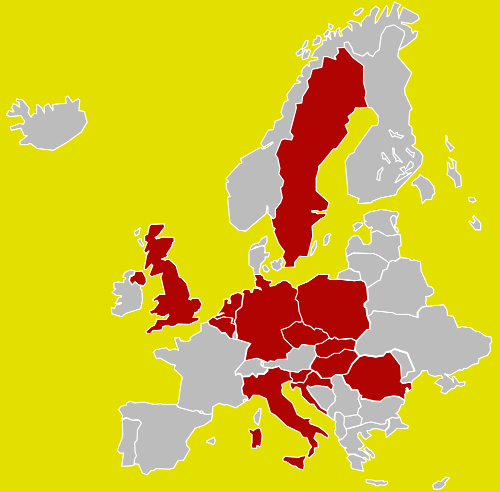
> 800.000 connected assets

Over 50 M customers

> 32.000 managed industrial sites

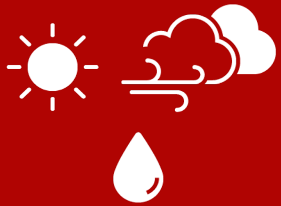
> 350 heating networks

Operating in 15 countries

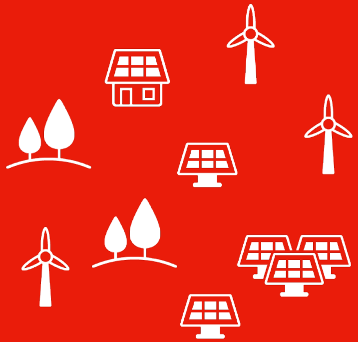




Decarbonization



Decentralization



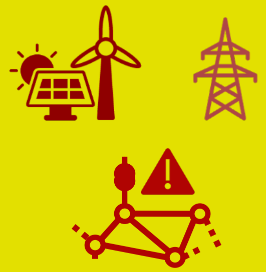
Digitalization

increasingly complex and interlinked, requiring higher levels of coordination

Smart, decentralized and flexible grids

Congestion management

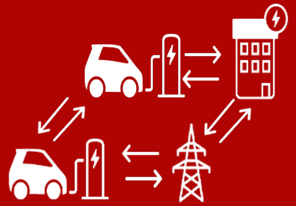
When is the energy fed into the grid going to be de-stabilizing it?



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?



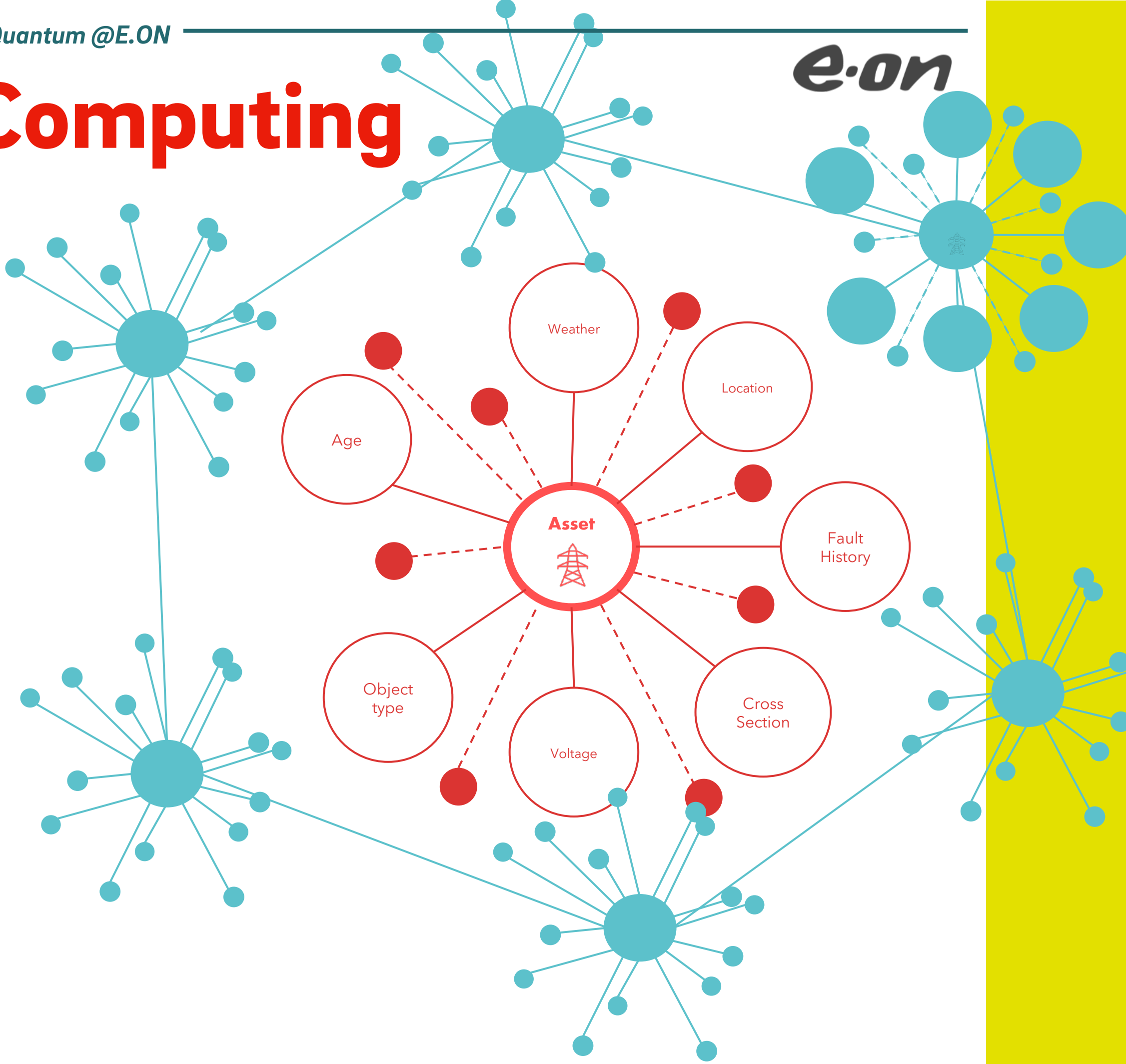
Local Energy Systems

How can we enable a Peer-to-Peer energy trading market?

Can a local energy system work completely off-grid?

e·on Quantum Computing

- 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 qGAN3 for power plant option pricing

[1] Quantum Machine Learning; [2] Quantum Amplitude Estimation; [3] Quantum Generative Adversarial Networks

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Flexibility services

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Smart asset and predictive maintenance

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Flexibility services

Smart asset and predictive maintenance

Risk and portfolio management

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Future of the Energy Sector

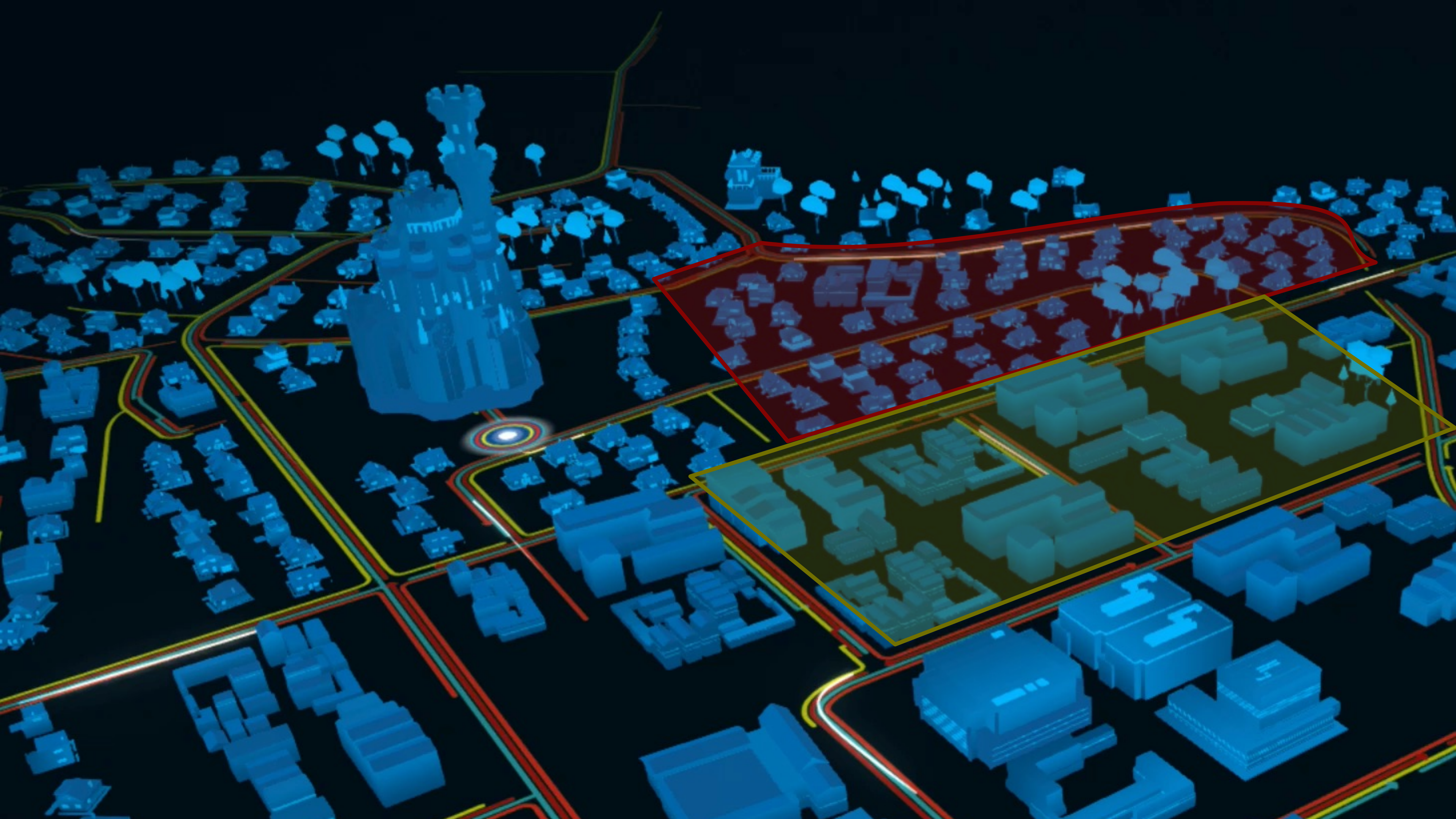
Goal — *EU requires to achieve 40% renewable generation by 2030 (Fit for 55).*

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

Community Detection in Grids

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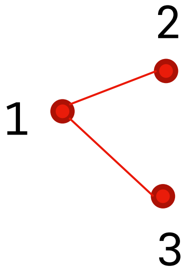

$$A = \begin{vmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{vmatrix}$$

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

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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

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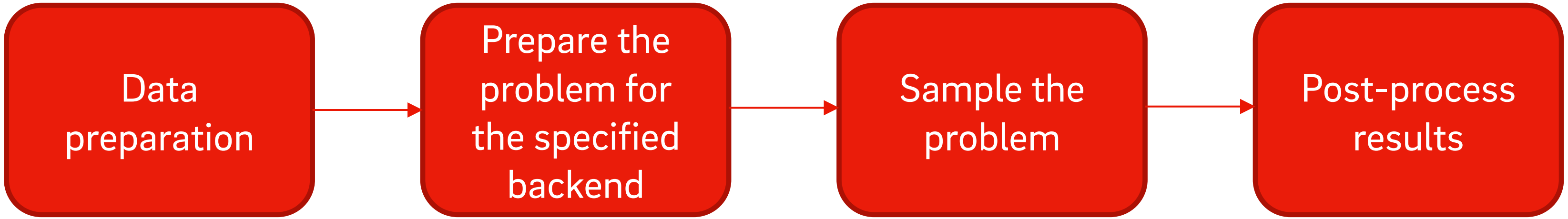
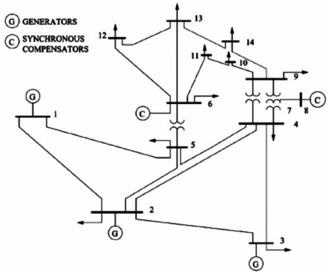
How can we partition an electrical grid maximizing electrical modularity?

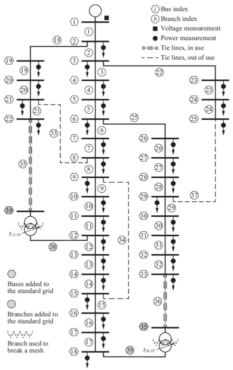
Workflow

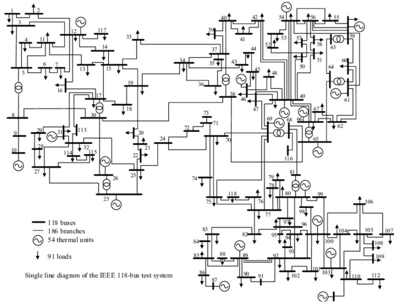

Data preparation
Prepare the problem for the specified backend
Sample the problem
Post-process results

Workflow

Data preparation







Elements	IEEE-14	IEEE-33	IEEE-118
Buses	14	33	118
Lines	15	37	173
Loads	11	32	99
Generators	4	0	53
Grid ext.	1	1	1
Trafos	6	0	13

Workflow

Creates problem

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

Binary Integer Programming (BIP) Problem

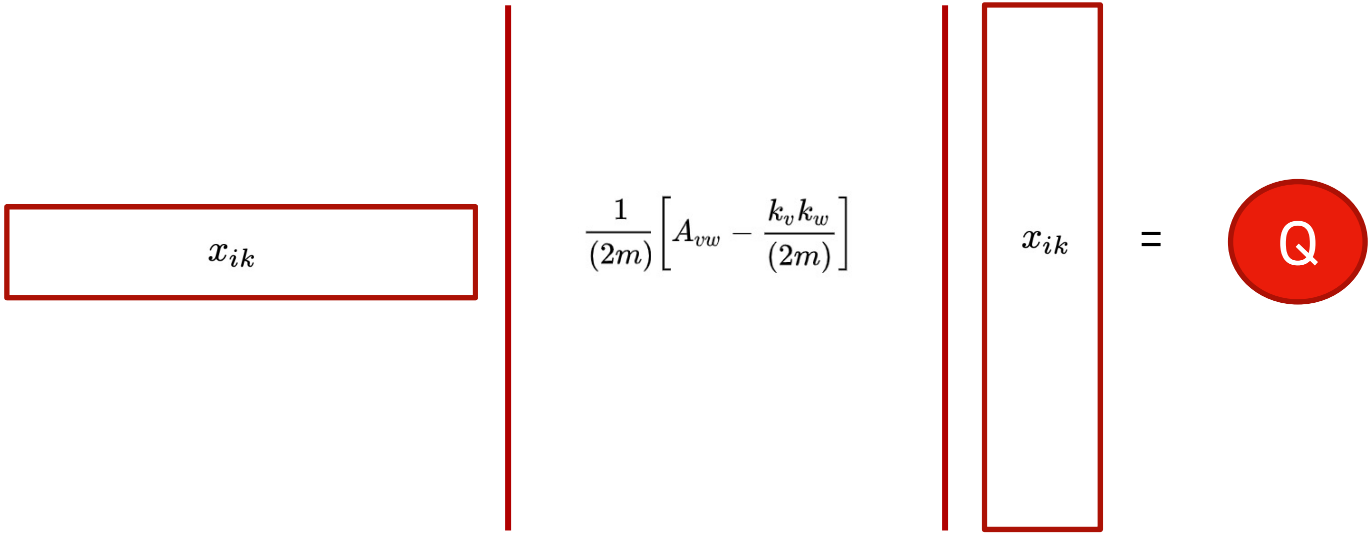
x_{ik} Binary, 1 if bus i belongs to group k

Workflow

Creates problem

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

BIP Problem



Workflow

Creates problem

BIP Problem

$$\max \quad \sum^{K} x_k^T Q_e x_k$$

$$\text{subject to} \quad \sum^{K} x_{ik} = 1 \qquad \forall i \in B$$

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Workflow

Creates problem

BIP Problem

$$\max \quad \sum^{K} x_k^T Q_e x_k$$

$$\text{subject to} \quad \sum^{K} x_{ik} = 1 \qquad \forall i \in B$$

QUBO Problem

Quadratic Unconstrained Binary Optimization

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

$$H_{obj} = -\sum^{K} x^T Q_e x \quad \text{and}$$

$$H_{c_i} = \lambda\left(\sum^{K} x_{ik} - 1\right)^2 ,$$

Workflow

Creates problem

BIP Problem

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Workflow

Backends

Methods	IEEE-14	IEEE-33	IEEE-118
DWaveSampler	✓	-	-
LeapHybridSampler	✓	✓	-
LeapHybridDQMSampler	✓	✓	✓
Louvain	✓	✓	✓
Gurobi	✓	✓	✓

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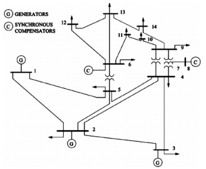
Workflow

Results



	Number of communities k				
Method	1	2	3	4	5
DWaveSampler	0,000	0,3495	**0,4646**	**0,4844**	0,4393
LeapHybrid	0,000	0,3495	0,4613	0,4613	0,4613
LeapHybridDQM	0,000	0,3495	0,4613	0,4613	0,4613
Louvain	-	-	0,4613	-	-
Gurobi (MIP)	0,000	0,3495	0,4613	0,4613	0,4613

Table 1. Modularity results for several samples and several number of communities.

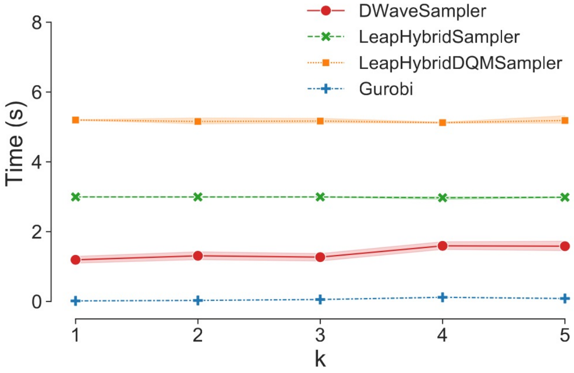
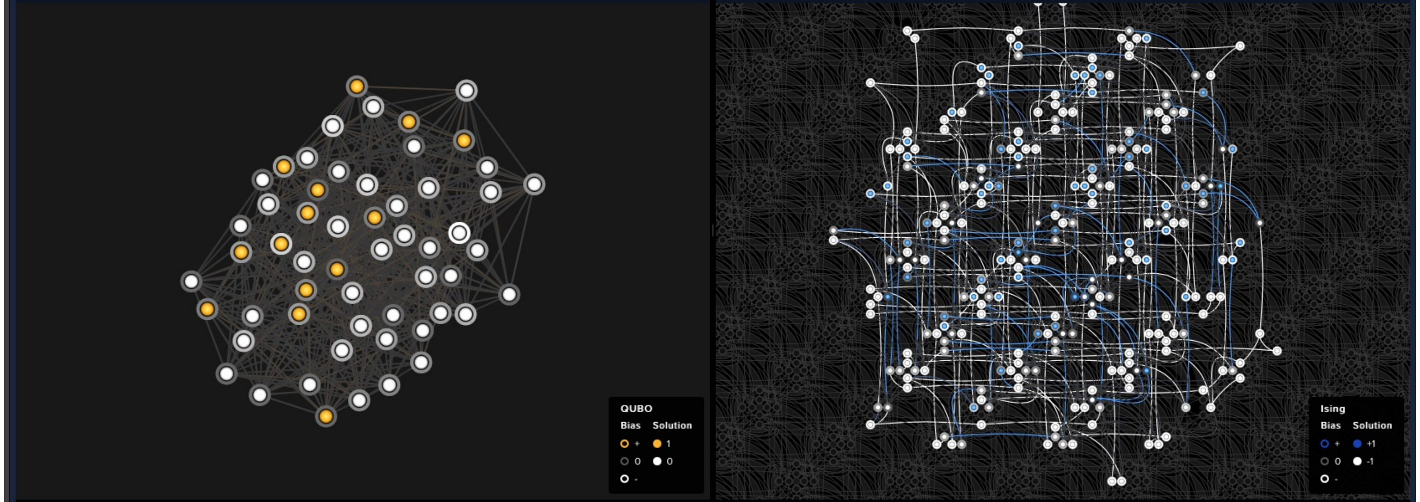


Fig. 1. Average run time performance in seconds for each partition and tested method in the IEEE 14-bus test case

Workflow

Results



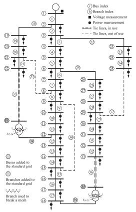
Console 1 — 2 OF 2

All Warning Types | Show warnings for selected sample only

Type	Description	Sample	Source	Target
Chain Strength Warning	Some quadratic biases are stronger than the given chain strength	N/A	N/A	N/A
Chain Length Warning	Chain length greater than 7	N/A	44	3591, 3592, 3590, 1443, 1442, 1353, 3622, 3637

Workflow

Results



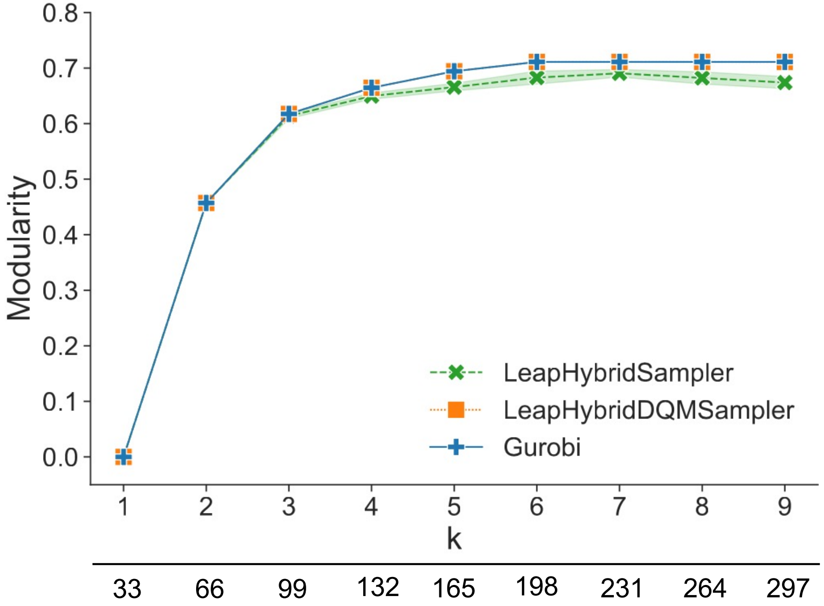


Fig. 2. Modularity versus number of partitions plots for each tested method in the IEEE 33-bus test case.

Workflow

Results

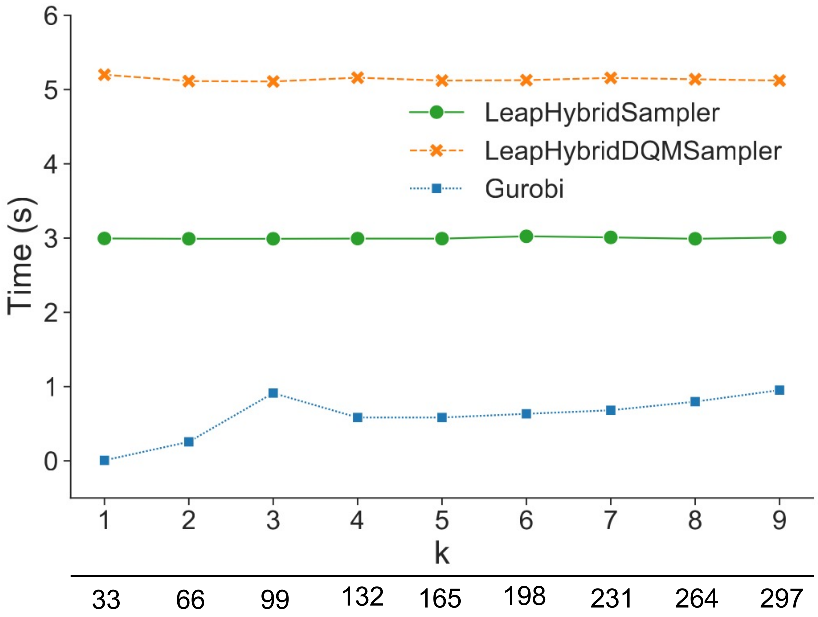
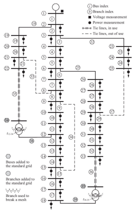


Fig. 4. Average run time performance for each partition and tested method in IEEE 33-bus test case.



Workflow

Results

Method	Modularity	Running time (s)
LeapHybridDQMSampler	0,7444	6,2
Gurobi	0,7448	3600 (*)

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

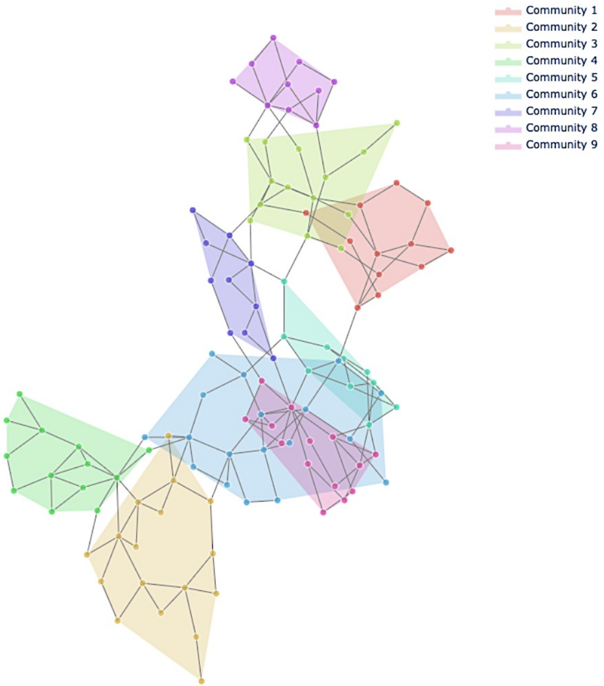


Fig. 5. Partition of network IEEE 118-bus test case

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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