TATA CONSULTANCY SERVICES

Building on belief

Optimising Power Distribution Network

TCS Quantum Computing Challenge

Challenge Sponsor: ***EDF Energy***

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Problem Statement Overview

The energy distribution industry is essential for delivering electricity and other forms of energy to homes, businesses, and other facilities. As part of electric power distribution, it does both - delivers the electric power to every user on the grid, and once delivered, it also moderates power to safe customer-usable levels. The basic principle is having a major line of distribution (usually pipelines) and small substations for processing and delivery to the final customers. However, distribution grid networks are often inefficient, with significant energy loss occurring during distribution and step-down power for customer usage. The energy loss can be caused by a variety of factors, including transmission and distribution losses, inefficiencies in energy storage and conversion, and inefficient routing of energy through the network.

Business Value & Motivation

Why is this problem important for the industry?

The optimisation of energy distribution networks is important for the energy industry due to the immense potential to help reduce energy loss and improve efficiency, which can lead to significant cost savings and environmental benefits.

By optimising the routing of energy through distribution networks, it is possible to minimise energy loss and improve efficiency. This can lead to cost savings for energy companies, as they can reduce the amount of energy they need to produce and distribute. It can also lead to environmental benefits, as the reduction in energy loss can help to reduce greenhouse gas emissions and other forms of pollution.

Moreover, the optimisation of energy distribution networks can help to ensure a reliable supply of energy to customers. By ensuring that energy is routed through the network efficiently, it is possible to avoid overloading certain nodes in the network, which can lead to power outages and other disruptions.

Why is this a good problem for exploring a Quantum solution? What metrics are sought to be improved (speed, accuracy, training time, etc.)?

The problem of optimising energy transmission networks involves finding the optimal routing of energy through the network to minimise energy loss while ensuring that the energy demand of customers is met. This is a complex problem that requires the consideration of many factors, such as the energy demand of different customers, the capacity of different nodes in the network, and the transmission and distribution losses. The number of variables involved in this problem can grow exponentially with the size of the network, making it difficult for classical computers to solve the problem efficiently.

Quantum computing is particularly well-suited for solving combinatorial optimisation problems, and it has the potential to significantly outperform classical computer for certain types of optimisation problems.

The main metric to be improved for this case is the immediate reduction of energy loss and the planning for energy demand.

Current Solution

How is the problem currently being addressed?

This problem is currently being addressed through classical computing methods, such as linear programming, and heuristic algorithms. These methods can be effective for small and moderately sized networks but are not scalable for larger networks due to their computational complexity.

Another approach for optimising energy transmission/distribution networks is the use of machine learning techniques, reinforcement learning. Machine learning can be used to develop predictive models of energy demand and network behaviour, which can help to take informed optimisation decisions. However, machine learning techniques are limited by the amount of data available and may not be effective for optimising all aspects of the energy network thereby not assuring an optimal solution.

What are the results of the current solution?

The results depend on the specific optimisation method used and the complexity of the network being optimised.

Linear programming can be effective for smaller and less complex networks, providing optimal or near-optimal solutions in a reasonable amount of time. However, as the size and complexity of the network increase, the computational time required for linear programming can become impractical.

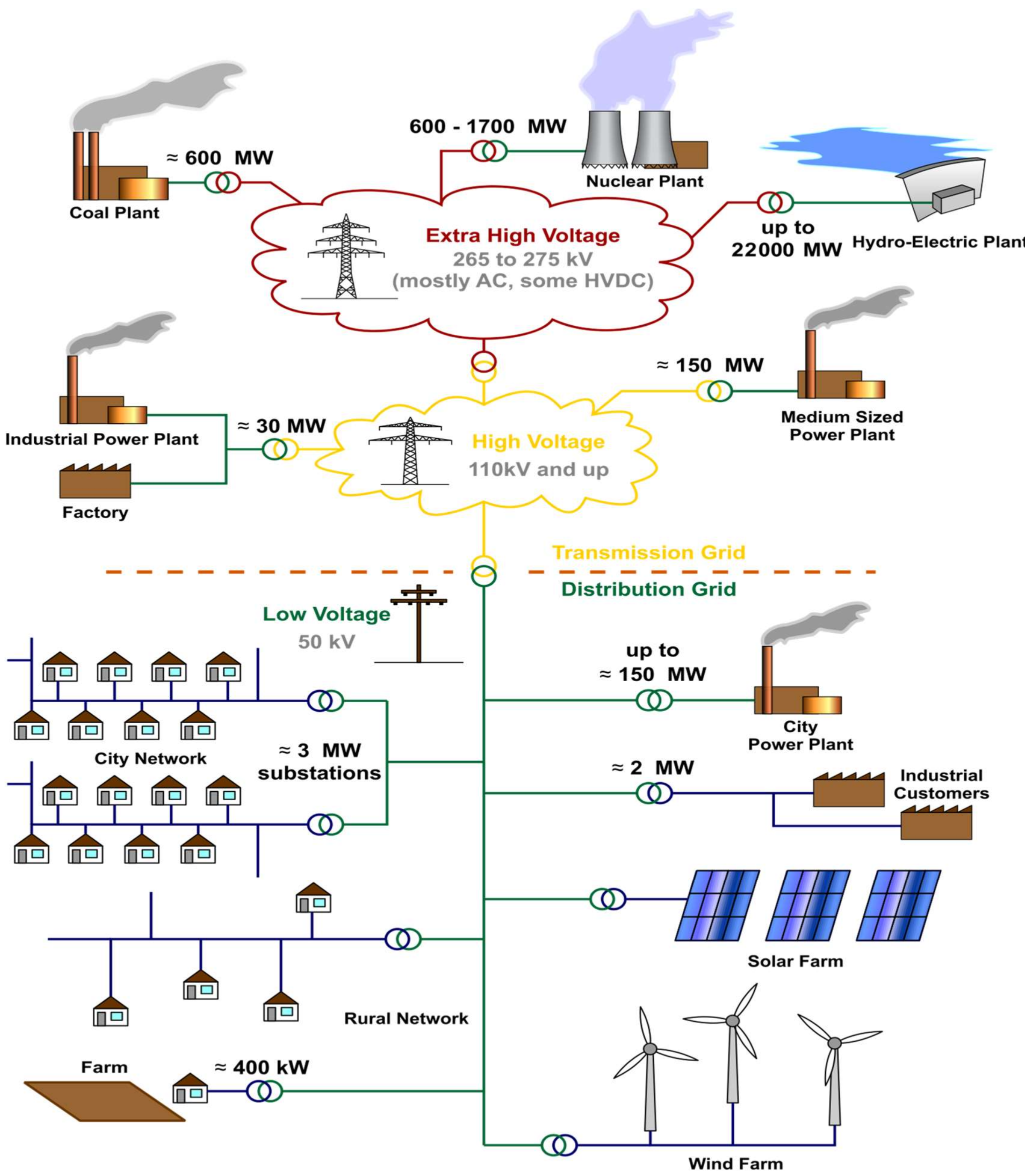
Heuristic algorithms can be used for larger and more complex networks but may not provide optimal solutions [3]. These algorithms can be effective at finding near-optimal solutions that are practical and useful, but the quality of the solution can vary depending on the specific algorithm and problem instance.

Machine learning techniques can be useful for predicting energy demand and network behaviour, which can help to take informed optimization decisions. However, the accuracy of these predictions is limited by the amount and quality of data available.

Problem Definition for the Quantum Challenge

Redefined scope of the problem for the purpose of the Challenge

Electricity is generated at power plants and moves through a complex system, sometimes called the grid, of electricity substations, transformers, and power lines that connect electricity producers and consumers. Most local grids are interconnected for reliability and commercial purposes, forming larger, more dependable networks that enhance the coordination and planning of electricity supply.



High-voltage transmission lines, such as those that hang between tall metal towers, carry electricity over long distances to meet customer needs. Higher voltage electricity is more efficient and less expensive for long-distance electricity transmission. Lower voltage electricity is safer for use in homes and businesses. Transformers at substations increase (step up) or reduce (step down) voltages from the power plant, on long-distance transmission lines, to distribution lines. Additionally, they adjust the voltage depending on the usage in homes and businesses.

Grid operators are responsible for ensuring that a secure supply of electricity is provided everywhere, at all the times, and that systems are designed to be both reliable and resilient. Nowadays, significant amounts of distributed generation (DG) and distributed energy resources (DER), such as solar, wind, or natural gas microturbines have been added to the networks. However, because of the variability of wind and solar, these networks may experience severe fluctuations in generation which in turn may cause losses if network configuration is static in nature. This makes the task of controlling existing grids difficult, forcing grid operators to reconfigure the network using operations such as line switching, bus splitting, and changing the generation dispatch.

Switching equipment such as Circuit Breakers (CBs) and isolators are usually installed in substations to allow for flexible network topology and emergency intervention. Under certain CB configurations, the substation bus can become electrically disconnected, commonly termed as "bus splitting" or "bus split." Figure 1 shows bus-split event in the bus-branch model depicting 3 buses i, j, and k. Bus i is split into two different buses, i and i'. Both generator and load can be reconnected to the new bus i'.

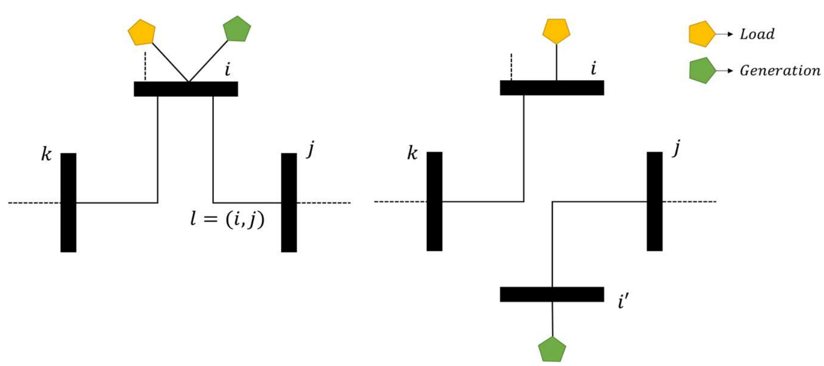


Figure 1: (Left) Original bus-branch model and (Right) model with a bus split at bus i

As bus i' is only connected to bus j, it can be removed from the system by moving its connected injection directly to bus j. The resultant model is mathematically equivalent to a power transfer between bus i and bus j. The three possible power transfer cases in the post-split system are depicted in Figure 2. Similarly, for line (i,j), bus-split can also happen at bus j instead of bus i.

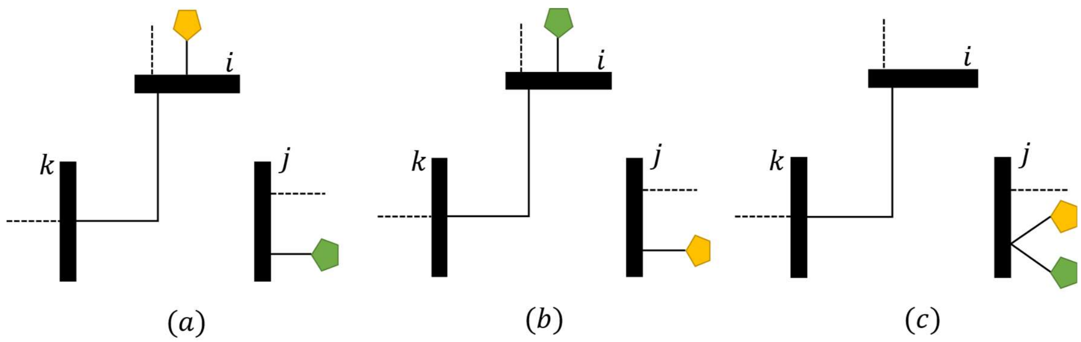


Figure 2: Power-transfer cases from bus i to bus j, namely, (a) generation only, (b) load only, and (c) both load and generation

Complexity

The problem of reconfiguring the network is combinatorial in nature. As the size of the network increases, so does the possible number of configurations. Current classical solutions can find optimal topology for smaller networks quite efficiently but doing the same for larger networks (>500 nodes) has proven to be challenging. This is where quantum computing can come into the picture. Although current NISQ-era quantum processors are still not advanced enough to tackle these larger network problems, developing novel algorithms and benchmarking for smaller networks is possible.

Possible Scenarios

This challenge aims to test the potential of quantum computing to address this important real-world problem. A transmission network is provided in the data set that must be reconfigured under two possible scenarios. More specifically:

- **Scenario 1:** For the given network, finding the optimal topology and configuration to reduce the generation cost while ensuring all components of the network operate within the specified limits.
- **Scenario 2:** After network changes (such as the addition of load or reduction in generation at a particular node, breaking of a certain transmission line, a faulty bus, and so on), finding the corrective topology with the least generation cost that ensures efficient power transmission to all parts of the network and that all the components operate within the specified limits.

The scope of the problem is to leverage quantum computing to create an efficient optimisation algorithm that, given any power network, searches through the combination of possible operations such as line switching, bus splitting, and generation re-dispatching to handle the above-mentioned scenarios.

Description of the data/datasets provided

Given is a power network graph, with substations (nodes), some containing consumers (load) or production (generation) or both, and interconnecting power lines (edges).

Specifically, the IEEE 14-bus system is provided which consists of 14 buses (nodes), 20 distribution lines, and 5 generators.

Dataset link:
(IEEE 14-Bus System) **https://icseg.iti.illinois.edu/ieee-14-bus-system/**

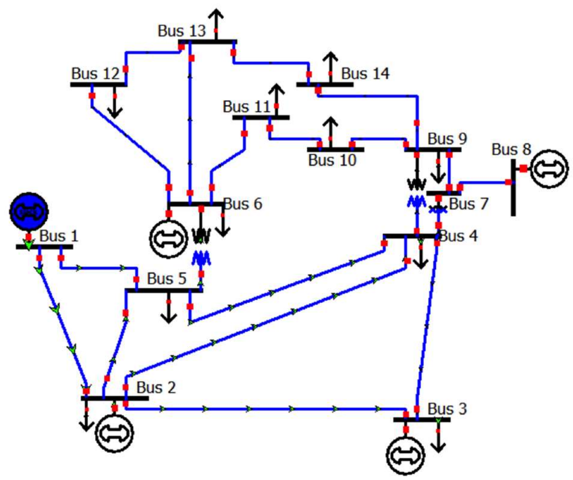


Figure 2: IEEE 14-Bus System

Representative dataset

Table 1: Line data

Line number	From bus	To bus	Line Impedance ($p.u.$)		Half-line charging susceptance ($p.u.$)	MVA rating
			Resistance	Reactance		
1	1	2	0.01938	0.05917	0.0264	120
2	1	5	0.05403	0.22304	0.0219	65
3	2	3	0.04699	0.19797	0.0187	36
4	2	4	0.05811	0.17632	0.0246	65
5	2	5	0.05695	0.17388	0.017	50
6	3	4	0.06701	0.17103	0.0173	65
7	4	5	0.01335	0.04211	0.0064	45

Table 2: Generator data

Generator number	Bus	g_i^{min}	g_i^{max}	a_i	b_i	c_i
G1	1	10	160	0.005	2.45	105
G2	2	20	80	0.005	3.51	44.1
G3	3	20	50	0.005	3.89	40.6

Table 3: Bus data

Bus number	Bus voltage		Generation		Load		Reactive power limits	
	Magnitude $(p.u.)$	Phase angle $(degree)$	Real power (MW)	Reactive power $(MVAR)$	Real power (MW)	Reactive power $(MVAR)$	Q_{min} $(MVAR)$	Q_{max} $(MVAR)$
1	1.06	0	114.17	-16.9	0	0	0	10
2	1.045	-4.9826	40	0	21.7	12.7	-42	50
3	1.01	-12.725	0	0	94.2	19.1	23.4	40
4	1.01767	-10.3128	0	0	47.8	-3.9	0	0
5	1.01951	-8.7738	0	0	7.6	1.6	0	0

Suggestions or pointers to the participants for attempting the solution

Objective Function

1) Minimising total generation cost
2) Minimising cost of corrective actions (line switching + bus-splitting + generation re-dispatching)

Parameters

- $N := \{1, \dots \dots, n\}$; Set of n buses (Nodes)
- $L := \{(i, j)\} \subset N \times N$; Set of m transmission lines (Edges)
- v_i^{min} / v_i^{max} ; Max/min voltage magnitude for each node
- $\theta_i^{min} / \theta_i^{max}$; Max/min voltage phase angle for each node
- g_i^{min} / g_i^{max} ; Max/min generation limits for each node *
- g_i^{up} / g_i^{down} ; Ramp up/down rate for generators at each node.
- f_l^{min} / f_l^{max} ; Max/min power flow limits for each line.
- $\boldsymbol{Y} \in \mathbb{C}^{n \times n}$; Admittance nodal matrix containing admittance for each transmission line $(i, j) \in L$
- $\boldsymbol{A} \in \mathbb{Z}^{n \times m}$; Incidence matrix of underlying graph (N, L)
- a_i, b_i, c_i ; Quadratic cost coefficients for each generator i *

*Only relevant when generator i is being committed.

Decision Variables

- $v_i \in \mathbb{R}^n$; Voltage magnitude at bus i
- $\theta_i \in \mathbb{R}^n$; Voltage phase angle at bus i
- $g_i \in \mathbb{R}^n$; Power generated at generator i
- $f_l \in \mathbb{R}^m$; Power flow in line l
- $z_l \in \{0,1\}$; Status of Line l (1: Closed, 0: Open)
- $\boldsymbol{w}_{l,i} \in \{0,1\}^3$; Vector for selecting one of three power transfer scenarios for line $l = (i, j)$ in case of split at bus i

- $\boldsymbol{w}_{l,j} \in \{0,1\}^3$; Vector for selecting one of three power transfer scenarios for line $l = (i, j)$ in case of split at bus j
- $r_i \in \{0,1\}$; Re-dispatch status of Generator i (1: Ramping up or down, 0: Static)

Constraints

i. Voltage limits at each node
ii. Generation limits at each node
iii. Generation redispatch ramp up/down limit at each node
iv. Power flow limit for each transmission line
v. Power flow equations (either simplified DC power flow or AC power flow)
vi. Bus splitting constraints
vii. Limiting number of open lines
viii. Generator dispatch constraints

Challenge Evaluation Criteria

The entries will be evaluated by a Jury panel consisting of experts from the Industry and Academia. A representative list of criteria that would be considered by the Jury while evaluating the Phase-I and Phase-II submissions is given below. Please note that there are no specific weightages assigned to any of the criteria, and this should not be interpreted as a comprehensive list. The criteria listed below are indicative, and the Jury panel would be free to use their expertise, experience, and judgement to evaluate the entries.

Phase I:

- **Background work done:** Quality of background work done to understand the use case and the state of the art.
- **Innovation Quotient:** The overall innovation quotient in terms of originality and novelty seen in the approach, concept, and the algorithm.
- **Comprehensiveness:** Level of detail, coverage of the tasks towards the targeted goal of the challenge.
- **Promise:** As reflected through the results from any early experimentation done. Promise of the planned approach for Phase II.
- **Technical soundness:** Ability of the team to defend their work during presentation/ interaction with the Jury. Capability of the team to carry forward the work.

Phase II:

- **Innovation Quotient:** The overall innovation quotient in terms of originality and novelty seen in the approach, concept, and the algorithm.
- **Comprehensiveness:** Level of detail, coverage of the tasks towards the targeted goal of the challenge.

- **Technical completeness:** Quality and completeness of the code/solution and its ability to execute and produce results as documented.
- **Comparison with internal benchmarks:** How well does the solution compare with any benchmark results that may have been achieved by the organisers.
- **Impact:** Value impact of the solution on current quantum hardware (any benefits shown in terms of improved optimisation, speed, accuracy etc. vis-à-vis classical approaches).
- **Extensibility:** Ease of adapting/modifying the solution to address variants of the use case (especially additional complexities).
- **Resource requirements & Scalability:** Any resource estimation provided for the solution to indicate the potential future scaling of the solution.
- **Technical soundness:** Ability of the team to defend their work during presentation/ interaction with the Jury. Capability of the team to carry forward the work.
- **Pitch:** Clarity, demonstration, and structure of the overall pitch.

Solution KPI

Solution is expected to work for any topology (variable number of buses, lines, and generators).

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