Slide 1:

The Energy trilemma is a set of three competing pressures that simple algorithms can not be solved:

First, For Consumers: Electricity is expensive and bills are unpredictable. Users are penalized for using energy during peak times, even when they need it most, such as for cooking dinner or charging a car after work.

Second, For The Grid: Demand is "peaky". The 6 PM spike in demand stresses the entire system, risking blackouts and forcing utilities to use expensive, high-emission ’peaker’ plants.

Lastly, For The Planet: We are wasting our best assets. Gigawatts of clean solar and wind energy are generated at 2 PM when demand is low, and this potential is lost forever, even as we burn fossil fuels just hours later.

Slide 2:

Hi, I'm Binh. I'm the team leader of team bearantum.

Today, I'm here to share our solution to deal with the energy trilemma using quantum optimization.

Slide 3:

To do so,

Our first step was to digitize the problem, creating a high-resolution digital twin of a home’s energy environment for a 24-hour period. Using the provided dataset, we extracted three "Given" vectors across 96 time steps (one for every 15 minutes):

• Baseline Load (Bt): it is the home’s existing, non-negotiable power consumption.
• Energy Price (Ct): The volatile 15-minute cost from the utility.
• Renewable Generation (Rt): we have the on-site ’free’ energy from solar and wind.

With the battlefield set, we defined our "Problem Space"—the controllable appliances.

These are not simple variables; they have unique, real-world constraints:

• EV Charger: Requires a 4-hour block, but can only run overnight.
• Washing Machine: Requires a 1-hour block, but only run during the day.
• Dishwasher: Requires a 1.5-hour block, only run in the evening or early morning.

Three controllable appliances with unique constraints create a massive search space of 2**101 possibilities.

as there are 101 total valid start times across all three
appliances. A simple optimizer cannot explore this space effectively.

On your righthand sides, I am showing the input dataset: baseline load, energy price, and renewable generation.

slide 4:

it's showing that the renewable energy is not always available when the demand is high.

and it's typically a problem. We want to compensate as much as possible with clean energy to reduce the peak load.

slide 5:

Now, I'm showing the objective function of the problem:

it contains three terms:
- Peak load term is to deal with the problem that I just presented above. it penalizes high simultaneous appliance usage to flatten your home's energy demand profile.

- cost term literally represents the money we'll pay for electricity. We want to minimize it as much as possible.

- constraint term makes sure every appliance runs once and only once because Users need these tasks done daily; we're only deciding the optimal timing.

finally, we need to input a hyperparameter set, these ratios define the trade-off between electricity cost, grid impact, and solution feasibility.

And We chose like it. This hyperparameter prioritization ensures appliances always run exactly once while aggressively shaving peaks, treating cost savings as a secondary benefit.

Slide 6:

In order to run on quantum computers, we need to map into QUBO equation.

Our goal is to minimizing this energy in order to get the optimal schedule.

To do so, we need to go through 3 steps:

First, digitizing choices we translate the amounts of starting times into binary variables.

Second, setting the hyperparameter set: 0.5, 3, 100.000 respectively. We'll show later how we obtained this set.

Finally, we build QUBO matrix with more than 2300 interactions.

Slide 7:

We used  the D-Wave Simulated Annealing Sampler to explore the QUBO landscape.

The hyperparameter set was not chosen randomly, we obtained by testing 27 combinations to find the statistically A,B,C settings.

The raw outputs were presented below: with energy, total  cost, and peak load.

The lowest energy was well found at 0.5, 3.0 and 100.000

Slide 8:

Since we just use our local machine, we can not calculate more combinations. thus we use interpolation method to fill this 3D space based on our data.

The results are below. In here, we would like to highlight that
Minimum energy and minimum cost do not occur at the same time.

Slide 9:

with this optimal set

We got the lowest the energy state with the total cost of 55.57 dollars.

Our result is shown on your right hand side.

It shows that  Our model (in blue) intelligently avoids the baseline peak
 (in grey) and aligns with renewable generation (in green), creating a stable, low-cost net load (in red).

The optimal schedule is presented below. We see that every appliance runs only one  and all constraint perfectly satisfied.

Slide 10:

Further, in order to prove the QUBO's power,  we built a naive "greedy" algorithm that solves three independent problems instead of one connected system.

It means the peak term is removed.

Our results are showing on this figure and the table below.

We obtain cheaper total cost with greedy method but a created massive 8.44 kW surge. The grid disaster.

With QUBO, we obtain 73 % of peak reduction.

Slide 11:

To summarize, we didn’t just find the cheapest answer; we found the best, smartest, and most stable answer. We solved the trilemma

During the hackathon, we also tried QAOA with pennylane but we got much higher total cost, our constraint was violated because we can not use higher value of C parameter as used with Dwave for constraint due to the computer limit.

It is not a failure. This demonstrates the central challenge of quantum optimization