YQuantum Hackathon 2025: TaHoe Challenge Response

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Abstract

Wildfires demand rapid and strategic deployment of limited firefighting resources to save lives and minimize ecological damage and economic losses. This project aims to tackle the challenge of optimally allocating fire crews and equipment to multiple simultaneous wildfires in emergency situations. Our system evaluates each wildfire's threat level based on the fire's intensity, size and chance of spread then matches it to the nearest available fire response team with sufficient resources to contain the fire. To solve this complex allocation problem, we employ quantum computing techniques that mimic natural optimization processes – namely how physical systems settle into low-energy states. This results in an ideal assignment strategy that balances response time, firefighting ability and scale of emergency.

Introduction

Resource allocation problem statement: A fire is rapidly spreading within an area and firemen, along with their resources, must be allocated to the fires while ensuring that adequate manpower is at each fire at a reasonable time.

The Fire Intensity and Team Ability Metrics are classified below.

Fire severity model:

1. Fire intensity rated qualitatively from low to high.
2. Fire size in acres.
3. Wildfire susceptibility of current and nearby regions rated on a scale of 0 - 1.

Team ability:

1. The ratio of active personnel to total personnel.
2. The resources available to a team, ranked based on size of team from 1-4 (e.g. a volunteer fire department with only one fire truck might be ranked 1, while, a large federal fire department would be ranked 3)

Model

Inputs to the model take in parameters to assess the fire severity and assign teams based on location and severity. It uses quantum annealment to determine the most optimal arrangement of teams for the fires. The problem Hamiltonian represents this optimal solution. Using quantum annealment, the particles reaching their minimum energy as a classical system coincides with the correct result has been determined.

QUBO:

Objective Term - We want to minimize the “cost” where

$$Cost_{ij} = 7 \times Distance_{ij} \times (2 \times Ability_i / Severity_j)$$

Penalty Term - Penalties are proportional to the “fire constraints” and “team constraints”

Creating a cost function for minimization using a for loop of the teams and fires under assessment

$$H = \sum(matrix_{distance} \times (scores_{severity}[j] / \ scores_{availability}[i]) \times x[(i,\ j)]$$

To establish constraints for QUBO function the model focuses on the fire and the team constraints. These are calculated for each fire and each team then a Hamiltonian with fixed indentation is used to relate the two constraints.

$$H = H_{old} + \ 100 \times fire_{constraints} \ + \ 5 \times team_{constraints}$$

The Quantum Annealing Optimization step compiles the Hamiltonian, converts to a QUBO and solves the simulated annealing step.

Below we see an example of the model output as a list of teams mapping it to fires while detailing the distance between the two locations and the severity of the fire.

Ideal Team Assignments:
Team0 → Fire17 (Distance: 7.20 km, Severity: 1.72)
Team0 → Fire7 (Distance: 4.38 km, Severity: 0.41)
Team1 → Fire8 (Distance: 2.34 km, Severity: 1.33)
Team2 → Fire11 (Distance: 5.89 km, Severity: 1.13)
Team3 → Fire15 (Distance: 5.21 km, Severity: 1.36)
Team3 → Fire19 (Distance: 13.45 km, Severity: 1.19)
Team3 → Fire5 (Distance: 12.24 km, Severity: 1.01)
Team4 → Fire1 (Distance: 4.13 km, Severity: 1.21)
Team4 → Fire2 (Distance: 16.22 km, Severity: 0.87)
Team5 → Fire18 (Distance: 3.22 km, Severity: 1.51)
Team5 → Fire3 (Distance: 8.88 km, Severity: 1.63)
Team5 → Fire9 (Distance: 31.98 km, Severity: 0.92)
Team6 → Fire10 (Distance: 18.26 km, Severity: 0.82)
Team6 → Fire12 (Distance: 16.38 km, Severity: 0.26)
Team7 → Fire16 (Distance: 11.26 km, Severity: 0.83)
Team7 → Fire4 (Distance: 14.50 km, Severity: 1.58)
Team7 → Fire6 (Distance: 28.50 km, Severity: 1.27)
Team8 → Fire13 (Distance: 4.55 km, Severity: 1.74)
Team9 → Fire0 (Distance: 8.43 km, Severity: 0.76)
Team9 → Fire14 (Distance: 4.07 km, Severity: 1.79)

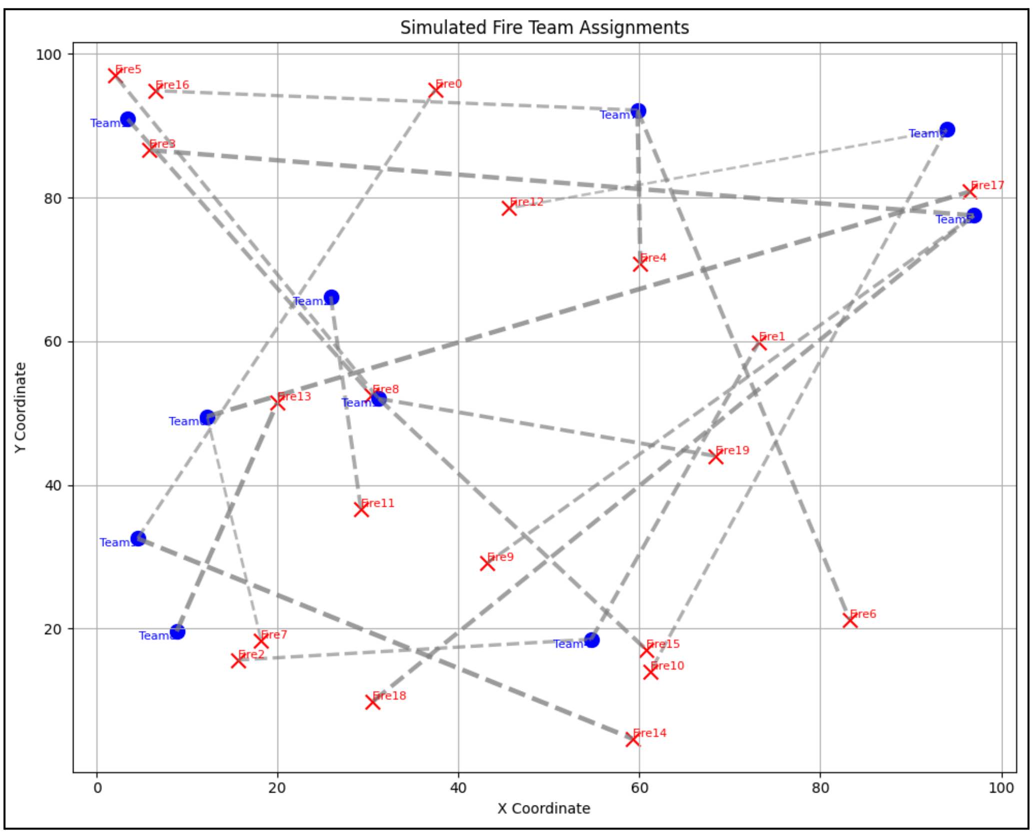

Fig 1. Visualization of the team and fire mappings after quantum processing of the system.

Process

The model maps the fires and fire departments, and the quantum implementation would give us their lowest energy state to solve the problem and generate a solution. This is the process of quantum annealment. The lowest energy state would be the best solution to the natural physics of the world. Artificial intelligence is useful in data science, data collection and presentation. The Quantum system simulates the physical problem to provide a viable lowest energy state. Quantum physics forces the quantum system to play out until it is in its lowest definitive state, no superposition. This quantum annealment runs for 20 microseconds. The use of connectors and magnetic fields allows for the probability distribution of the quantum states to be manipulated, providing the opportunity to further influence other qubits. Allowing us to create a set of qubits who simulate a real life situation, in this case, the travel of firemen and distribution of resources to particular wildfires. These qubits represent the initial Hamiltonian, as they approach their lowest energy state, they approach the problem Hamiltonian. Once reached, the optimal paths and order for the firemen is returned.

Safety Measures

We must be assured that the particles in our system are behaving in a quantum manner. The verification systems we can use for this are verification of the eigenspectrum using manipulation of annealing speed and measurement of freezeout time. The quantum particles will exhibit features that align with the Eigenspectrum if they are not classical. This is checked by doing experiments with the annealing speed and the energy levels of a particle at any given time. The other method is by restricting classical flipping by measuring the freezeout time, which should stay the same regardless of temperature change if the particles are quantum. This verification can provide confidence that the system is operating in a quantum state, and the results are accurate.

Future steps

This model is designed to assess fire department availability in relation to wildfire outbreaks within a given region. Once the quantum algorithm has run on Qbraid, the system produces numerical team-to-fire matchings and creates a visual graph for intuitive analysis. To further implement the model for physical systems, real-world data from government fire records is used as input, and team assignments are overlaid onto a geographic map of the affected area to show the relationships between resources and fire locations.

This solution is a hybrid of classical and quantum computing approaches to use the different strengths of the two approaches. Using Artificial Intelligence and Qbraid as our classical and quantum parts respectively. By integrating geographical maps of wildfire-prone areas with real-time fire department information, the model creates an interactive map that reflects optimal resource deployment.

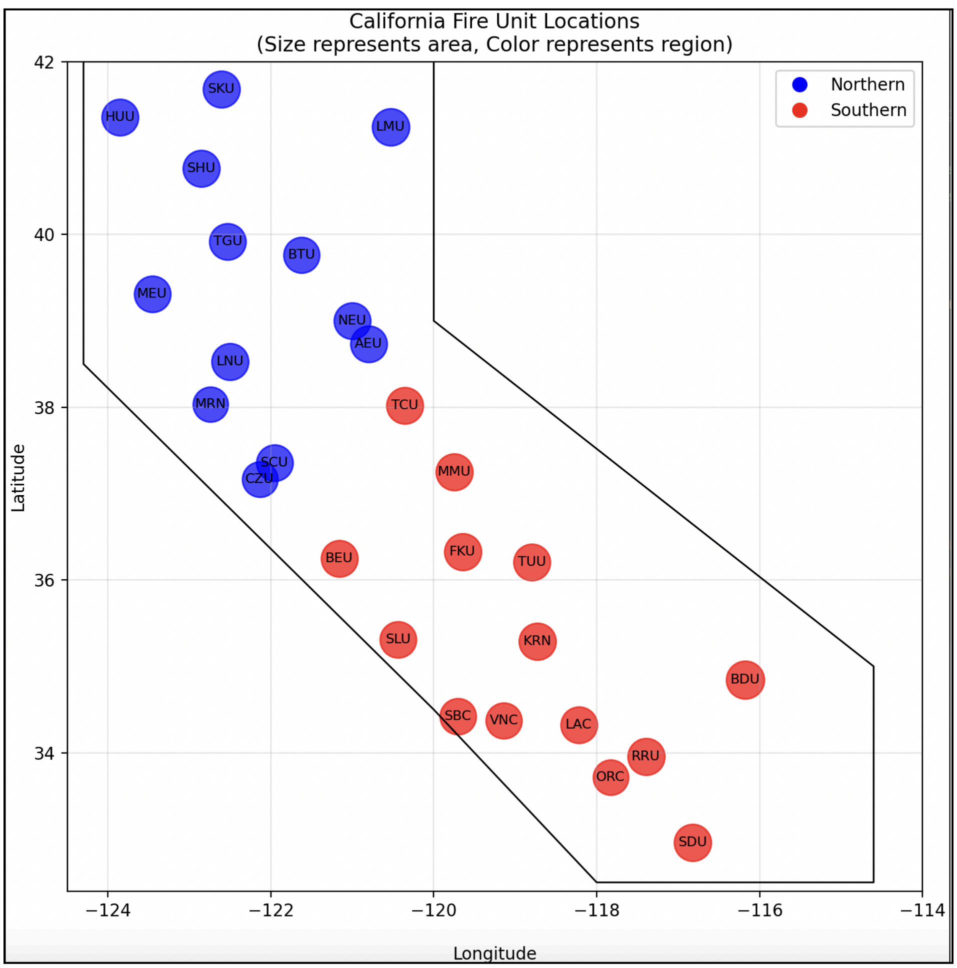

Fig 2. Map depicting the location, latitude and longitude, of the fire departments in California in 2023.

References

1. Quantum Computing | D-Wave. https://www.dwavequantum.com/learn/quantum-computing/
2. O'Brien, Jeremy L. "Optical Quantum Computing." Science, vol. 318, no. 5856, Dec. 2007, pp. 1567–70. DOI.org (Crossref) https://doi.org/10.1126/science.1142892
3. Santoro, Giuseppe E., and Erio Tosatti. "Optimization Using Quantum Mechanics: Quantum Annealing through Adiabatic Evolution." Journal of Physics A: Mathematical and General, vol. 39, no. 36, Sept. 2006, pp. R393–431. DOI.org (Crossref) https://doi.org/10.1088/0305-4470/39/36/R01.
4. Petrovic, Nada, et al. "Dynamic Resource Allocation in Disaster Response: Tradeoffs in Wildfire Suppression." PLoS ONE, edited by Renaud Lambiotte, vol. 7, no. 4, Apr. 2012, p. e33285. DOI.org (Crossref) https://doi.org/10.1371/journal.pone.0033285.
5. Rosmanis, Ansis. "Hybrid Quantum-Classical Search Algorithms." ACM Transactions on Quantum Computing, vol. 5, no. 2, June 2024, pp. 1–18. DOI.org (Crossref), https://doi.org/10.1145/3648573.