Organ Donation QuAllocation Quantum Approximate Optimization Algorithm for Organ Donor and Patient Matching

Alma Alex¹, Annli Zhu¹, Shannen Espinosa², and Siona Tagare¹

Yale University, New Haven, CT

Northeastern University, Boston, MA

I. Background

After becoming an established form of treatment in the 70s and 80s, organ transplantation is now acknowledged as the best and very often only life-saving therapy for several serious and life-threatening congenital, inherited, and acquired diseases and injuries. Despite this, progress in organ transplantation is slow, with slower rates of intervention and decreased donation activity globally. The United States witnessed a record 46,000+ transplants in 2023. However, there remains an increasing trend of now-approximately 1 in 5 kidneys recovered for transplant needlessly discarded. Currently, more than 100,000 Americans, primarily in need of kidneys, are awaiting organ transplants and an estimated 17 people lose their lives daily while on the organ transplant waiting list.

Setting	Intervention	2015	2019
Low-income Countries	Dialysis	27%	35%
	Kidney Transplant	5%	5%
Lower middle-income Countries	Dialysis	40%	47%
	Kidney Transplant	18%	13%
Upper middle-income	Dialysis	58%	82%
Countries	Kidney Transplant	36%	40%

The current technologies behind the organ donation and transplant system needs modernization with its aged software, system failures, and overreliance on manual input of data. The antiquated systems lack transparency in deciding how to weigh considerations for transplant eligibility, perpetuating racial, regional, and other socioeconomic disparities. In response to these challenges, we designed and built QuAllocation -- a cloud-based, quantum-powered, healthcare-facing application that seeks to modernize and optimize the matching allocation process between organ donors and patients using quantum approximate optimization algorithms (QAOA).

II. Technical Configurations

QuAllocation was integrated with IBM's open-source quantum computing framework, Qiskit. We interfaced directly through the IBM Quantum Lab, executing our computations in a real-world quantum computing environment with IBM's quantum processors. The backend infrastructure was hosted on the IBM Cloud Platform for scalability through parallel processing in handling larger datasets and configurations of patient-donor pairs as among our future directions. We aimed for a flexible and adaptable architecture that could facilitate secure communication across broader organ donation systems nationally to truly optimize organ donor-patient matching.

We then created a mobile application using Apple's XCode Swift interface to match patient-donor pages in a user friendly manner. Given a little more time in the future, this application can be connected to IBM Quantum Lab through Google's database – Firebase (unfortunately, Firebase interfacing could not match XCode requirements as of last night; however, given more time to investigate deprecated package dependencies the connection has been done and is possible).

III. Dataset Features

We start with an initial dataset of people, who may be patients or donors, have an identified blood type, and their respective organ of interest for donation. Further features are their name, gender, age, location, and general metric of health. Such health metric quantifies each person's respective medical history and lifestyle as 1 for extremely unhealthy or up to 5 for healthy. After filtering the database into patients and donors, the acuity of the patient is added to represent 1 for non-urgent and 5 for emergency.

IV. Compatibility

The classical compatibility algorithm evaluates the suitability between organ donors and patient recipients for successful organ transplantation. It weighs together patient-donor pairs by measuring shared features of their blood type, gender, age, overall health, and geographic distance, as well as taking into account the emergent nature of the patient.

Blood Type

On the surface of red blood cells are antigens that trigger an immune response that produces particular antibodies and categorizes our blood into four types: A, B, AB, and O. This classification is based on the presence or absence of A and B surface antigens. A person with type A blood will make antibodies against the B antigen, but not against the A antigen.

We assigned a compatibility score based on the preference of a perfect match at 1.0, 0.7-0.9 to account for variability between different yet compatible blood types, and 0.0 for incompatible matches.

Recipient	Donor	
Α	A, O	
В	B, 0	
AB	A, B, O	<pre># universal acceptor</pre>
0	0	# universal donor

Gender Matching

If the biological gender of the organ donor and patient recipient do not match, there is a notable decrease in organ survival rate. A score of 1.0 is for identical genders, with a small penalty to a score of 0.5 for opposing genders to account for objective studies and variations.

Age Matching

We calculate the age matching score by assessing the age difference between the patient and donor. This score ranges from 0.0 for significantly disparate ages to 1.0 for perfectly matched ages, ensuring that age-related considerations are factored into the compatibility assessment.

Health Matching

To ensure a safe and healthy transplantation process, we prioritize healthy donors, scored at 1.0. Extremely unhealthy individuals are at 0.0. Those in between will have a range of overall health that optimizes for both the likelihood of successful outcomes and the minimization of discarded organs.

Distance Matching

Distance is represented as a 50 x 50 grid. The locations of both donors and patients are represented as (x, y) coordinates and the algorithm computes the Euclidean distance between the patient and donor. As max_distance calculates for the maximum possible distance between two points, after the distance is normalized, the score returned is either the maximum distance of 0 or the same location of 1.

Acuity Score Integration

As acuity is only a unit of a patient set, it is integrated into the overall compatibility score directly after computing the above. Where 1 is for non-urgent cases and 5 is for emergency cases, the algorithm can prioritize urgent matches and expedite transplantation for those who need it.

V. Interface

In order for patients and donors to be easily matched, we created a mobile app with interfaces for both donor centers and patients/hospital centers. Donor centers have the ability to add new donor information to the app while patients/hospitals can input their own information to request a donor. In theory, once a donor is added their data will be stored in Google Firebase, an online realtime database, and then processed through IBM's backend to find a match. Once a match is found, the patient-donor pair would be updated in Firebase and a notification would be sent to the patient informing them of the match. We were able to connect IBM's backend to Firebase and update information; however, interfacing XCode proved troublesome as their newest updates have deprecated Firebase dependencies without

documentation. In the future, this pathway will be easier to construct once more documentation is released as Firebase and XCode have interfaced well in the past. By creating an accessible user friendly application, we hope to foster greater transparency and efficiency in the organ matching process.

VI. Optimization

In order to optimize the pairs of donors and patients, we used the quantum approximate optimization algorithm (QAOA). Essentially, we used the application of this algorithm on maximum cut situations. We recursively partitioned the bipartite graph (with patients and donors) into pairs in order to maximize compatibility.

We created a weight matrix w that had the compatibility numbers between the donors and patients. We also used the equation 10MN for the combinations of donor-donor or patient-patient connections in the map in order to decrease the chances of the algorithm pairing these people together. We also defined the weight of the donor-patient connections to be

$$\mathbf{w}_{ij} = 1 - C_{ij}$$

in which C represents the compatibility between the donor and patient.

Next, we found a Hamiltonian cost function that would work with our graph for each pair.

$$H_{ij} = w_{ij} Z_i Z_{j}$$

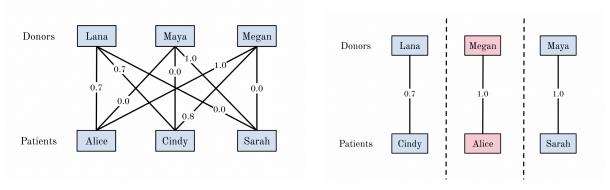
After summing all of them together, we get the function

$$\mathbf{H} = \sum_{i=1}^{M} \sum_{j=1}^{M} H_{ij}$$

We decided to use Maximum Cut for the QAOA algorithm because other processes would have to use many more qubits (by assigning the qubits to the edges of the graph instead of the vertices). Because of this, the circuit wouldn't be as efficient and wouldn't create an optimal graph for more than 3 pairs since current quantum computers don't have as many qubits. Additionally, as you increase the number of qubits, the noise increases greatly.

VII. Results

The output of the function lists all of the possible partitions where 0 represents one group and 1 represents the other. The most optimal partition is the one with the largest probability. Due to really long wait times on actual quantum computers, we mainly tested our algorithm on the ibm_qasm_simulator backend. We then tested our code on a set of 3 patients and 3 donors. For each cut, we ran the circuit on the quantum computer for 1000 cuts so that we would have a proper sample. The algorithm was able to properly match up patients and donors with the maximum compatibility as shown in the graphs below.



VIII. Future

We are excited for future directions of this project.

For the compatibility function, we seek to make it more thorough and extensive to truly take advantage of every aspect of quantum circuitry. We want to include tissue typing, greater details of health history, environmental factors, and even making a special interface specifically for children.

For greater functionality, we hope to shed more transparency towards how much time it would take to get the organ to the patient in emergency situations, like tracking in real time the travel of the organ using Google Maps API.

We would also like to use an actual quantum computer instead of a simulator to run the circuit. Hopefully in the future, with larger and less noisy quantum computers, we would be able to run this algorithm for a really large database of donors and recipients.

Given more time, we would connect the application front end to the quantum processing backends through online databases – at this moment we are able to store data in Google Firebase through IBM Quantum Labs but are unable to access this data through the app due to deprecated Firebase dependencies that have not been documented. However, with an impending Firebase update these problems are easily addressed and there is a clear pathway for the application to interface with the quantum computer, allowing for real time interaction between patients and donors.

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