Personal Protective Equipment Optimization Validation

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Research Facilitation Laboratory
Army Analytics Group
Office of the Deputy Under Secretary of the Army

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Personal Protective Equipment Optimization Validation (PPOEV)

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13. ABSTRACT (maximum 200 words) The Research Facilitation Laboratory (RFL) Investigated the logistical benefit to the COVID-19 pandemic using a specialized optimization HW platform known as a Digital Annealer manufactured by the Fujitsu Corporation. The goal of using the DA is to show that highly computationally and combinatorically complex problems are solvable in a fraction of the time on standard CPU's and also capable of generating near-theoretically optimal solutions. This particular problem involved the logistics of transferring PPE supply to PPE demand areas that minimized the mileage traveled while also meeting the demand need as close to full as possible given supplies.			
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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviation (Acronym)	Definition
AAG	Army Analytics Group
ACR	Army Central Registry
AFMS	Active Federal Military Service
AIC	Akaike information criterion
ANOVA	Analysis of variance
b	Unstandardized b (regression coefficient)
CA	Civil Affairs
CI	Confidence Interval
CRADA	Cooperative Research and Development Agreement
DA	Digital Annealer
DoD	Department of Defense
EA	Evolutionary Algorithm
ES	Executive Summary
F	The value of the F statistical test
GAT	Global Assessment Tool
GPF	General Purpose Force
IHME	Institute for Health Metrics and Evaluation
M1	Survival Analysis Model 1
M2	Survival Analysis Model 2
M	Mean
PPEOV	Personal Protective Equipment Optimization Validation
QUBO	Quadratic Unconstrained Binary Optimization
Std	Standard Deviation

Executive Summary

Background

In the first quarter of 2020, a novel, highly contagious, and deadly coronavirus emanating from the vicinity of Wuhan, China, was belatedly discovered as it spread throughout the world, infecting (by the time of this report) hundreds of millions of people and killing millions. In the United States alone, millions have been infected with what has been labeled “COVID-19”, and 200,000 have died while infected. As the spread and consequences of COVID-19 mushroomed, the United States Army was called to assist civil authorities in response.

Under the direction of the office of the Secretary of the Army, the Army Analytics Group (AAG) immediately began working with a wide range of potential sources of emerging technologies that might be employed to defeat the disease caused by the virus. In April 2020, the director of the AAG, Mr. Dan Jensen, became aware of a no-cost offer of assistance by Entanglement, Inc., and its teaming partner, Fujitsu America, Inc., to provide the Army with novel, groundbreaking proprietary technology and computational services. The Entanglement-Fujitsu team offered its services to assist the Army in determining (rapidly and repeatedly) the optimal allocation and distribution of COVID-19 supplies to medical providers and civil authorities as circumstances developed.

In May 2020, AAG and Entanglement entered into a Cooperative Research and Development Agreement (CRADA) entitled “COVID-19 Resource Allocation Optimization.” Entanglement, teamed with Fujitsu, worked for the next several weeks with the AAG’s Research Facilitation Laboratory led by Dr. Clay Stanek.

Technical Approach

Below is a key list of data elements necessary to analyze COVID-19 logistics. The analysis involved correlating data from publicly available information to model demand data in a manner that assured a known degree of confidence.

We followed the below sequence of steps to create the solution:

1. Defined different resource categories (PPEs) for which we would like to perform distribution optimization (Gloves, Gowns, Masks, Respirators, Ventilators).
2. Built a demand model based upon collected demand data for the PPEs from Johns Hopkins and forecast the demand for 2 weeks into the future in accordance with the usage guidelines for PPE published on the JHU portal.
3. Created cost functions and other constraints. Some examples include available modes of transportation, power requirements for ventilators, and the utilization of existing staging centers or TCH.
4. Performed clustering on the demand regions to identify the staging centers where we can host the PPEs for distribution.
5. Performed resource allocation optimization from inventory centers to the staging centers by creating and solving a QUBO problem.
6. Performed routing optimization to route the allocated resources from inventory centers to the staging centers and subsequently from staging centers to the regions of demand
7. Computed efficiency metrics, focusing the use case on the state of Florida

Key Findings, Implications, and Recommendations

The work under the CRADA culminated in the validated capability to solve complex combinatorial optimization problems (in this case routing and resource allocation) faster than traditional methods, and with better performance as measured by Key Performance Parameters (KPP's). The KPP's covered metrics related to total distances traveled, equitable resource allocation, and computational performance. With additional variables or larger datasets, the Entanglement/Fujitsu capability offers greater efficiency than traditional methods and can solve otherwise intractable problems at scale.

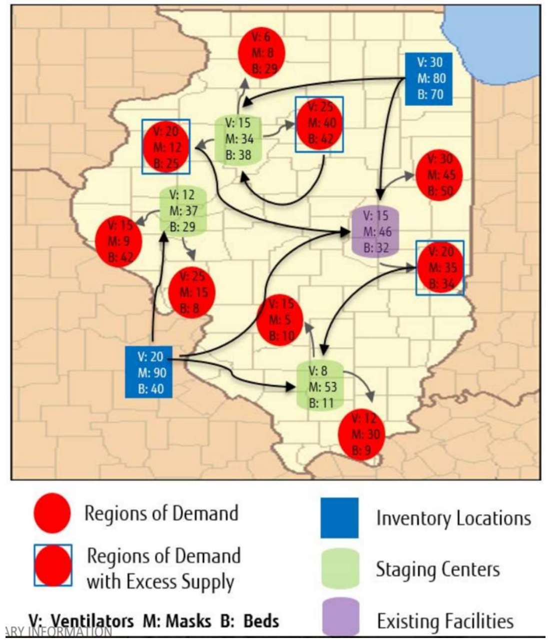


Figure 1 Supply and Demand Flow Example

The core technology is proprietary SW and HW forming a DA, a purpose-built digital circuit design with high degrees of parallelism for solving classes of problems that can be expressed as Quadratic Unconstrained Binary Optimization (QUBO) problems. Previous efforts show the DA and advanced model solves complex combinatorial optimization problems faster than CPU's with better performance (38-50% improvement) [20] across a wide domain of NP-hard problems compared to CPU's, reaching the limits of Moore's law.

The validation case was constructed from data of Hospital Locations, Army PPE Locations (as well as PPE type), COVID hospitalization/population related demand information from open sources such as JHU and the IMHE. The calculated output demonstrated for the state of Florida, with 10 secondary distribution centers, that the DA solution was extremely efficient in determining transportation routing, able to make highly uniform supply-to-demand allocation ratios in a situation where demand strongly exceeded supply, and finally was able to do the entire calculation (including round trip time) in approximately 30 seconds.

Introduction

Background

The COVID-19 pandemic has highlighted a particular class of problems, combinatorial optimization problems, as critical to the ability to construct optimal supply routing along with efficient demand-to-supply coupling across the United States. The last couple years has shown that limits of Moore's Law for standard CPU's can be observed when addressing this class of algorithms. In an attempt to drastically speed up the logistical component of the COVID-19 pandemic, the Personal Protective Equipment Optimization Validation (PPEOV) has studied and tested the application of a new generation of HW-specific solutions aimed at this NP-hard combinatorial optimization problem called the Digital Annealer (DA). Problems in this category can be thought of, for example, as the traveling salesman problem. What is the most efficient route that the salesman can travel to visit all N locations? We worked with COVID-19 infection models, demand signals from hospitals and simulated supply data from the US Army to determine the benefits of using a DA over traditional CPU's.

Discrete optimization problems have ubiquitous applications in various fields and, in particular, many NP-hard combinatorial optimization problems can be mapped to a quadratic Ising model [1] or, equivalently, to a quadratic unconstrained binary optimization (QUBO) problem. Such problems arise naturally in many fields of research, including finance [2], chemistry [3, 4], biology [5, 6], logistics and scheduling [7, 8], and machine learning [9–12]. For this reason, there is much interest in solving these problems efficiently, both in academia and in industry.

Much of the benchmarking effort has centered on “spin glasses”, a type of constraint satisfaction problem, in part due to their being the simplest of the hard Boolean optimization problems. Furthermore, application-based benchmarks from, for example, industry tend to be structured and, therefore, systematic benchmarking is difficult. As such, spin glasses have been used extensively to benchmark algorithms on off-the shelf CPUs [13,14], novel computing technologies such as quantum annealers [15, 16, 17, 18] and recently developed application-specific CMOS hardware designed to solve fully connected QUBO problems (i.e., on complete graphs), known as the DA [19,20] as demonstrated by Fujitsu.

This effort is a traditional minimum-cost routing problem as well as most efficient demand-supply coupling where the supplies must be organized in such as manner as to minimize transportation costs while meeting as much of the demand as can be met with a given supply. In our problem, the supplies concern Personal Protective Equipment (PPE) (gloves, masks, gowns), respirators and ventilators as well as additional hospital beds. The amount of supply was a mere fraction of demand which made further constraints on the DA that have not been benchmarked in references above.

Project Aims and Guiding Questions

The project has 4 guiding questions that provide structure and clarity for the analyses:

1. **What is the fundamental logistics problem to be solved?** This problem is concerned with the COVID-19 supply chain and distribution of supplies to areas of demand with the most efficient routes possible subject to several real-world constraints.
2. **What are the key data elements necessary to analyze COVID-19 Logistics?** This project leverages existing Army data, IHME data, and JHU data. We focused on demand-producing features in analyzing the problem.

3. **How are we going to translate costs and constraints used in optimization problems into the language of the DA (Quadratic Unconstrained Binary Optimization or QUBO mathematical formulation)?**
   We address this in the section on Technical Methodology
4. **What do predictive optimization models tell us about the most efficient distribution of supply from staging centers to demand areas?**
   This question is covered in the section on Validation.

Project Roadmap

Figure 2 depicts the four key phases of this project. Phase 1 involved use case creation, core requirements, translation of requirements to mathematical model of cost function and constraints and finally the generation of a QUBO form of the problem for running on the DA.

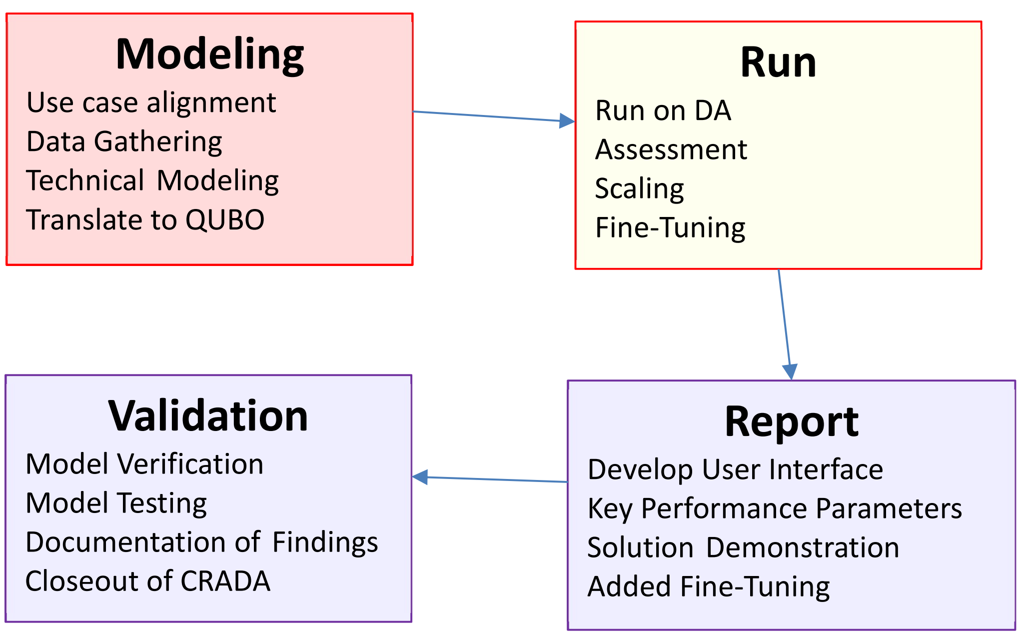


Figure 2. PPEOV Phase Activities

Modeling phase: Collect, cleanse and create a standardized demand and supply data to use as input into Modeling. Model various components (resource allocation, routing etc.) using QUBOs and the standardized data.

Run phase: Run the QUBOs created in the previous step on DA. Design and create a scalable solution that works for large dataset. Fine-tune any parameters (both business and QUBO related) to obtain the best possible solution from DA.

Report: Create a user interface demonstrating the key aspects of optimization process (parameter setting, performing optimization on DA in real-time). Define and compute Key Performance Metrics and perform any further fine-tuning of the parameters.

Validation: Validate the DA optimization solution by creating and comparing against an alternate approach based on classical algorithms. Documentation of all the findings.

Methodology

Problem Scope and Definition

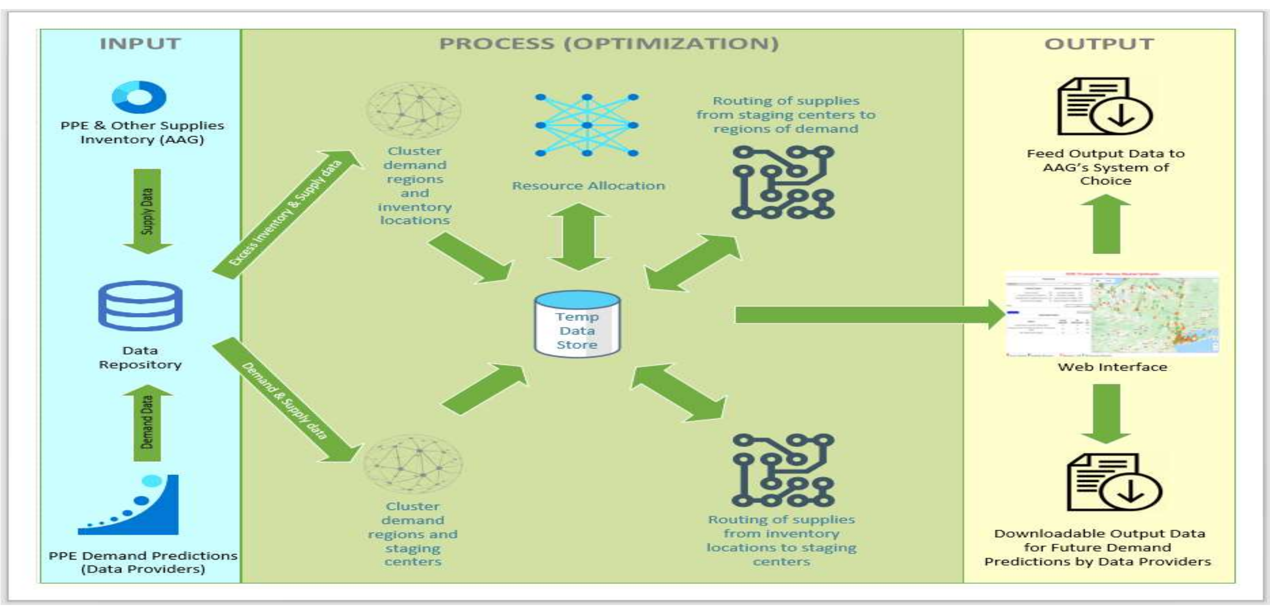


Figure 3 The Components of the PPEOV Project

The problem is divided into three components as shown in Figure 3:

1. Input: In this component the supplies and predicted demand datasets are transformed to an easily consumable form and stored in a Data Repository. For Demonstration purpose an MS Excel file is used as the Data Repository
2. Process: In this component, demand regions from selected dataset are clustered and centroids of the clusters are designated as the Staging Centers capturing consolidated demands. The resource allocation module then computes the PPE allocation from Inventory Locations to Staging Centers and the fulfilment ratios for Staging Centers. The Routing module then calculates the optimized routes from Inventory Locations to staging centers and then to regions of demand. All data interaction between modules are through a temp data store having a lifespan limited to a session.
3. Output: In this component, the web Interface displays the session data in an easily comprehensible visual display at every step. This also provides a way to download the optimization results for the session.

Key Performance Parameters (KPP's)

In this section we bound the use case complexity and establish the set of KPP's.

Input complexity:

1. The current version of the solution has been tested for up-to 3 states (5-10 inventory centers, 10-15 staging centers, ~500 demand regions, 5 PPE categories)

KPPs used for evaluating performance:

1. The QUBO objective function value
2. Fractions of allocated supply to demand at various staging centers
3. Mean and Standard Deviation of allocated fractions across staging centers for each of the resource categories and comparison of those values to the corresponding overall supply to demand ratios (for respective PPEs)
4. Number of staging centers with no allocation for each of the PPEs
5. How many staging centers have fractions of allocation within 90% of overall supply to demand ratio for a given resource category

6. Round-trip time taken for overall optimization (DA time + QUBO processing time + Network transit time)
7. How the statistics on fractions of allocations, optimization time change as we vary parameters such as number of staging centers, maximum number of staging centers that can be visited from any inventory location etc.
8. Average and total distances covered by trucks going from inventory to staging centers and also from staging centers to regions of demand

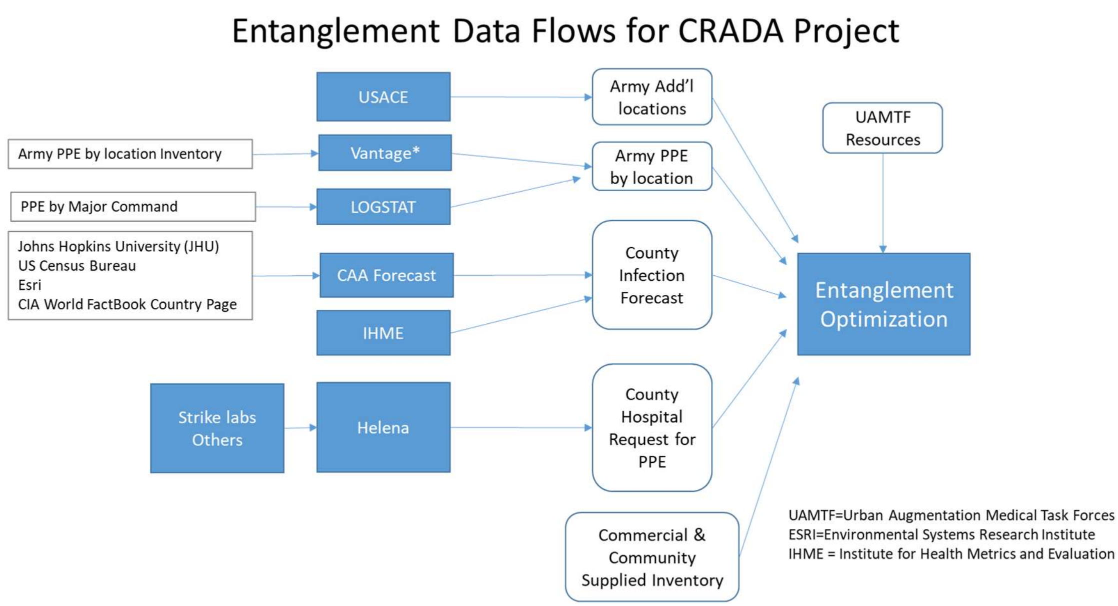


Figure 4. Datasets Used

Information Needs and Availability

Figure 4 provides a diagram for the origin of various data elements and their flow into the PPEOV test environment. We describe the data in detail below.

Demand data is structured as below:

- Resource Category: This describes the category of demand like Beds, PPEs, Ventilators
- Classification Level1: This describes the resources in demand

- Resource Details: Details about the resources, if any
- State: US State Name
- Region (County/City/Facility/etc): Name of Demand Regions
- Latitude (Region)
- Longitude (Region)
- Needed Within 2 Weeks (demand in the following 2 weeks)
  - Mean
  - 95th-Percentile
  - 99th-Percentile
- Needed Within 4 Weeks (demand in the following 4 weeks)
  - Mean
  - 95th-Percentile
  - 99th-Percentile

Supply data provided from AAG is structured as below:

- Resource Category : This describes the category of demand like Beds, PPEs, Ventilators
- Classification Level1: This describes the supply for various resources
- Resource Details: Details about the resources, if any
- State: US State Code or Country Name
- Region (County/City/Facility/etc): Name of City of Inventory Location or Country
- Latitude (Region)
- Longitude (Region)
- Stock (Amount of supply available)

Supply Data Sources:

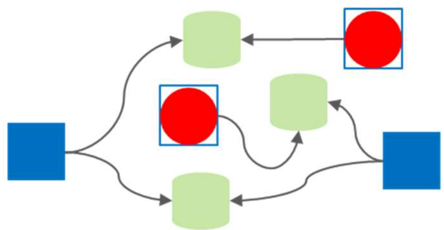
- PPE Synthetic Inventory v3.xlsx → PPE
- USACE Public Data.xlsx → Beds

Data Processing and Preparation:

1. A linear regression model has been used to forecast the demand for next two weeks which is used as demand side input for optimization.
    a. Helena.org demand model data was provided on 4 occasions between mid-July and the end of August but it had not matured in time to be used in this study. Their model has now matured enough that any future work could use their demand model. Helena's model produces predictions of epidemiology variables and PPE demand at a county level, whereas IHME's model produces estimates at a state level. Helena's model is a recurrent neural net architecture that estimates the probability density function over case growth in a future time frame. It ingests historical data including foot traffic at businesses and other locations of interest, demographic factors, and epidemiological statistics.
2. Beds are not considered for optimization
3. TCHs are included as staging centers alongside creating new ones
4. Geodesic distances are used for computing routing optimization

Technical Modeling

Mathematical Modeling for Running on DA



$\boldsymbol{x_{ijkl}}$: Binary variable denoting whether resource l in category k is allocated from i^{th} inventory (or region of excess demand) location to j^{th} staging location
y_k: Slack variables (for QUBO)
S_{ik}: Supply of resource k at inventory location i
D_{jk}: Demand of resource k at staging location j
W_k: Conversion factor between different resource categories
T_j: Demand threshold at staging location j $(0-1)$
A, B, C: QUBO multipliers

OBJECTIVE:

$$Maximize \sum_{jk} \frac{\sum_{il} x_{ijkl}}{D_{jk}} \quad \text{OR} \quad Minimize \sum_{jk} \left[\left(\sum_{il} x_{ijkl} - D_{jk} \right) W_k \right]^2 \quad \text{OR} \quad Minimize \sum_{j} \left[\left(\sum_{ikl} x_{ijkl} W_k - \sum_{k} D_{jk} W_k \right) \right]^2$$

CONSTRAINTS:

$$\sum_{jl} x_{ijkl} = S_{ik} \ \forall i, k \qquad \sum_{ikl} x_{ijkl} W_k < T_j \sum_{k} D_{jk} W_k \ \forall j$$

HAMILTONIAN (QUBO):

$$-A \sum_{jk} \frac{\sum_{il} x_{ijkl}}{D_{jk}} + B \sum_{ik} \left(\sum_{jl} x_{ijkl} - S_{ik} \right)^2 + C \sum_{j} \left(\sum_{ikl} x_{ijkl} W_k - \sum_{0 \le k \le [T_j \sum_k D_{jk} W_k]} y_k \right)^2$$

Figure 5 Resource Allocation Modelling

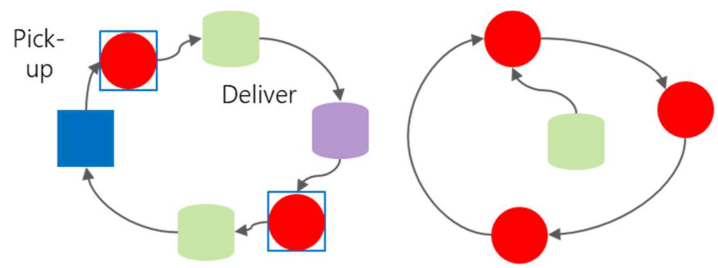
This section defines the two QUBO relations that are solved by the DA and attempts to provide an English translation of the mathematical expressions. We first consider the supply-demand allocation QUBO in Figure 5.

Objective: Minimize the total sum (across all staging centers and PPEs) of squared differences/ratio between number of resources allocated to a staging center for a PPE, and the actual demand for that PPE at that staging center

Constraints:

1. All supply available for every PPE must be distributed to one or the other staging center
2. Total allocation of PPEs to every staging center must not exceed a certain threshold (defined by T)

Hamiltonian: The energy function that is minimized by DA. It encodes the objective and constraints into one function. The equality constraint (supply allocation) becomes a quadratic term to account for the deviations of variables to either side of the target value. The inequality constraint (demand threshold) also becomes a quadratic term but encoded with the help of slack variables



y_{ij}: Binary variable denoting selection of edge i, j in the optimal path
C_{ij}: Cost of traversing edge i, j
u_i, z_{ijk}: Slack variables to ensure there are no subtours
A, B, C: QUBO multipliers
m: Number of vertices in the graph

OBJECTIVE: $Minimize \sum_{ij} y_{ij} c_{ij}$

CONSTRAINTS: $\sum_i y_{ij} = 1$ $\quad \sum_j y_{ij} = 1$ $\quad u_i - u_j + m y_{ij} \leq m - 1; i \neq j$, $u_i, u_j \in \{0..m-1\}$

HAMILTONIAN (QUBO):

$$A \sum_{ij} y_{ij} c_{ij} + B \sum_j \left(\sum_i y_{ij} - 1\right)^2 + C \sum_i \left(\sum_j y_{ij} - 1\right)^2 + D \sum_{ij} \left(u_i - u_j + m y_{ij} - \sum_{k<m-1} z_{ijk}\right)^2$$

Figure 6 Routing Optimization

The second QUBO in Figure 6 is described below and is a modified traveling salesman problem.

Objective: Minimize the total cost of traveling from a given inventory center (or staging center), visiting all the necessary staging centers (or demand regions) exactly once and returning back to the source (inventory center / staging center)

Constraints:

1. Visit a place (staging center / demand region) exactly once in the traversed path (in graph theory terms, every node needs to have exactly one incoming edge and one outgoing edge)

2. The optimal paths cannot have sub-tours (a closed loop between a subset of nodes in the graph)

Hamiltonian: As with the previous Hamiltonian, the objective is directly encoded as the linear term, equality constraint is encoded as the quadratic term, inequality constraint is encoded as another quadratic term with slack variables. Minimizing the Hamiltonian will result in the optimal path (decoded using variables y) for the Traveling Salesman Problem

User Interface

Figure 7 is a snapshot of the GUI with red dots denoting demand centers and 3 blue dots denoting inventory supply depots existing in Florida. Note the global allocation statistics on right side.

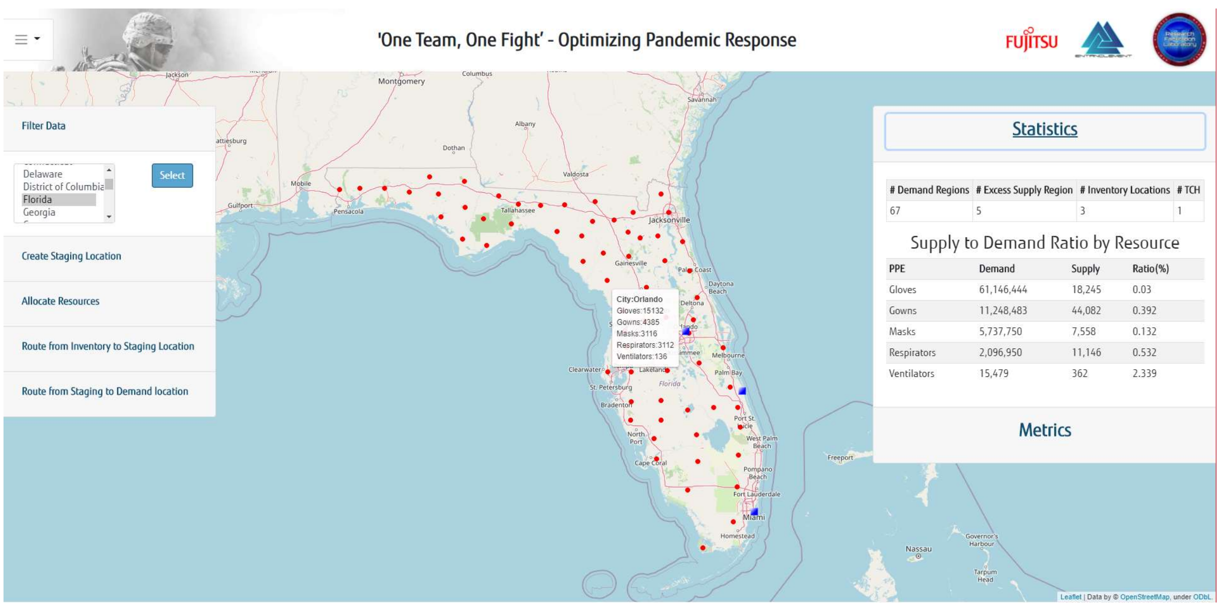


Figure 7 PPE Demand Regions and Inventory Locations shown with statistics for Florida

Figure 8 denotes optimal staging locations (PPE distribution centers each with unique color) have been identified and multiple demand regions attached to each staging locations (matching color, smaller dot).

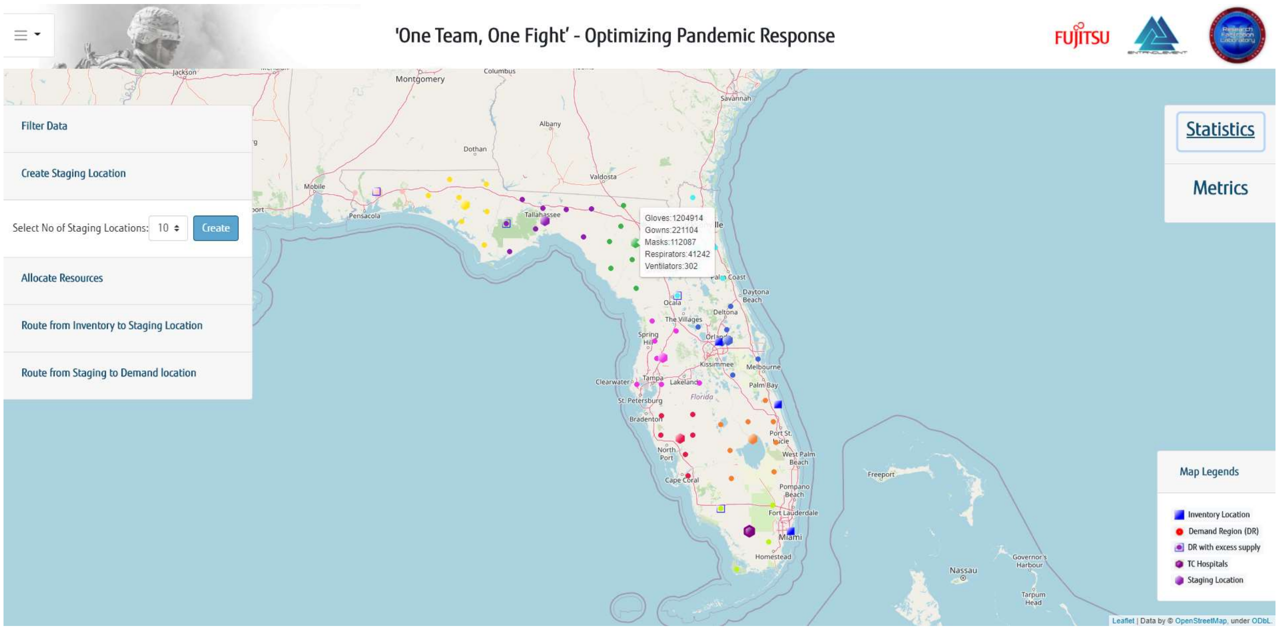


Figure 8 Secondary staging locations from clustering (10 large dots) and associated demand locations (color-coded)

Route optimization for transporting PPEs from Inventory Locations to Staging Centers completed, with multiple options to display the routes is shown in Figure 9. Figure 10 and Figure 11 provide examples of all the possible analytic plots available in the GUI.

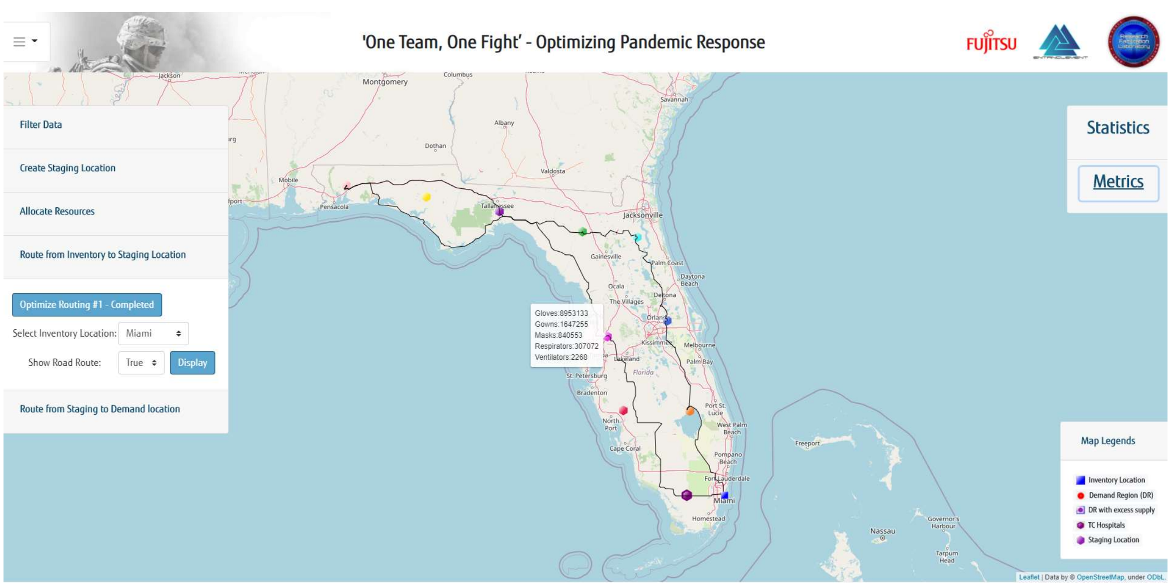


Figure 9 Routing optimization visualization

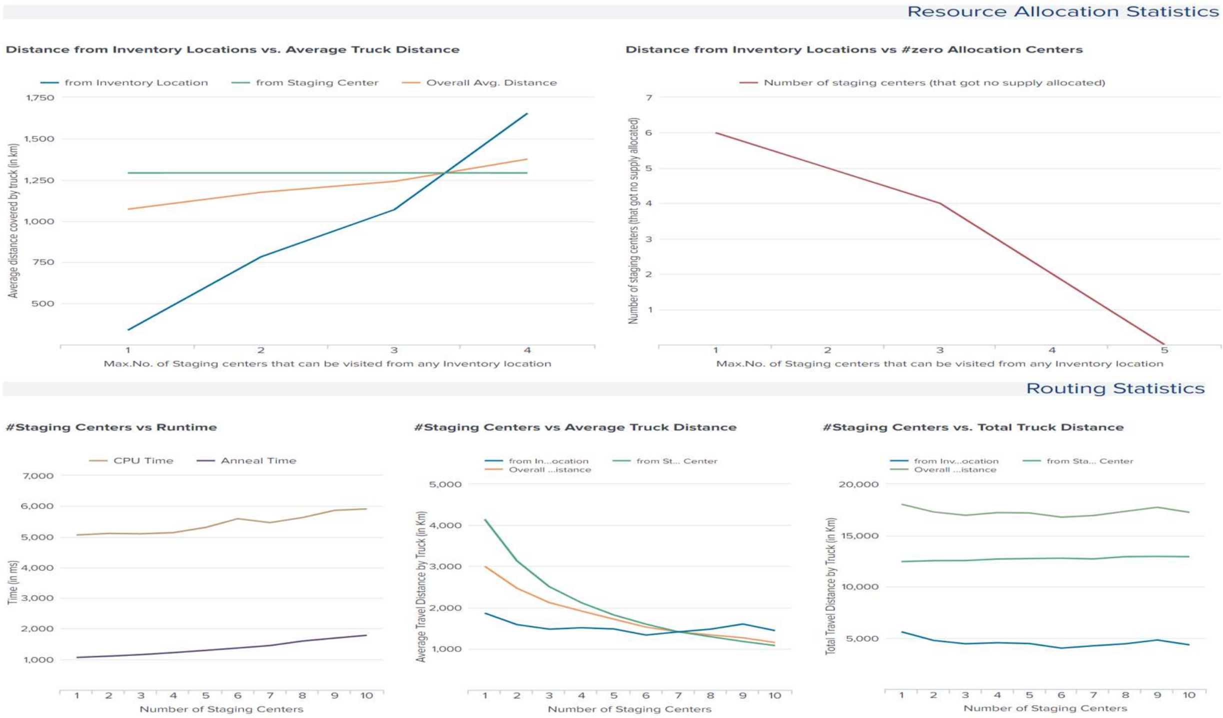


Figure 10 Machine Performance and Analysis Dashboard

Figure 11 Machine Performance Analysis II

Validation Results

Analytic Strategy

We chose to implement a software-based Evolutionary Algorithm (EA) for comparison with the DA. This provides more realistic results for comparisons than the Greedy method.

DA Output Examination

First, we examine in Figure 12 the total number of staging locations to be used in order to reach the 67 individual demand locations shown in the Florida data.

Route-Staging - 1	Route-Staging - 2	Route-Staging - 3	Route-Staging - 4	Route-Staging - 5	Route-Staging - 6	Route-Staging - 7	Route-Staging - 8	Route-Staging - 9	Route-Staging - 10
Staging - 1	Staging - 2	Staging - 3	Staging - 4	Staging - 5	Staging - 6	Staging - 7	Staging - 8	Staging - 9	Staging - 10
Sarasota, Florida	Gilchrist, Florida	Washington, Florida	Brevard, Florida	Okeechobee, Florida	Taylor, Florida	Clay, Florida	Pasco, Florida	Collier, Florida	Escambia, Florida
Manatee, Florida	Dixie, Florida	Holmes, Florida	Osceola, Florida	Indian River, Florida	Madison, Florida	Bradford, Florida	Pinellas, Florida	Broward, Florida	Santa Rosa, Florida
Hardee, Florida	Levy, Florida	Walton, Florida	Orange, Florida	St. Lucie, Florida	Jefferson, Florida	Nassau, Florida	Hillsborough, Florida	Miami-Dade, Florida	Okaloosa, Florida
DeSoto, Florida	Alachua, Florida	Bay, Florida	Lake, Florida	Martin, Florida	Leon, Florida	Duval, Florida	Polk, Florida	Monroe, Florida	Staging - 10
Lee, Florida	Union, Florida	Gulf, Florida	Volusia, Florida	Palm Beach, Florida	Gadsden, Florida	St. Johns, Florida	Sumter, Florida	Staging - 9	
Charlotte, Florida	Baker, Florida	Calhoun, Florida	Seminole, Florida	Hendry, Florida	Liberty, Florida	Flagler, Florida	Citrus, Florida		
Staging - 1	Columbia, Florida	Jackson, Florida	Staging - 4	Glades, Florida	Franklin, Florida	Marion, Florida	Hernando, Florida		
	Hamilton, Florida	Staging - 3		Highlands, Florida	Wakulla, Florida	Putnam, Florida	Staging - 8		
	Suwannee, Florida			Staging - 5	Staging - 6	Staging - 7			
	Lafayette, Florida								
	Staging - 2								

Figure 12 Route Staging to Demand Areas for Staging Locations

Supply Snapshot							
Resource Category	Classification Level1	Resource Details	State	Region(County/City/Facility/etc)	Latitude (Region)	Longitude(Region)	Stock
PPE	Respirators		FL	Miami	25.7742658	-80.1936589	1842
PPE	Respirators		FL	Orlando	28.5421109	-81.3790304	3112
PPE	Respirators		FL	Vero Beach	27.6387163	-80.3975399	2741
Ventilator	Ventilators		FL	Miami	25.7742658	-80.1936589	153
Ventilator	Ventilators		FL	Orlando	28.5421109	-81.3790304	136
Ventilator	Ventilators		FL	Vero Beach	27.6387163	-80.3975399	72
PPE	Masks		FL	Miami	25.7742658	-80.1936589	1785
PPE	Masks		FL	Orlando	28.5421109	-81.3790304	3116
PPE	Masks		FL	Vero Beach	27.6387163	-80.3975399	2657
PPE	Gowns		FL	Miami	25.7742658	-80.1936589	6947
PPE	Gowns		FL	Orlando	28.5421109	-81.3790304	4385
PPE	Gowns		FL	Vero Beach	27.6387163	-80.3975399	10125
PPE	Gloves		FL	Miami	25.7742658	-80.1936589	1289
PPE	Gloves		FL	Orlando	28.5421109	-81.3790304	15132
PPE	Gloves		FL	Vero Beach	27.6387163	-80.3975399	1824
Bed	NonICU		FL	Miami	25.7742658	-80.1936589	450

Figure 13 Supply Stock for Florida

Second, in Figure 13 we note a sample of the Army supplies available at the 3 original supply centers in Miami, Orlando and Vero Beach. This data was synthesized from actual supply data but was permutated to a level that actual supply levels at actual locations cannot be inferred.

Figure 14 provides a detailed snapshot of demand for PPE type of gloves at many of the 67 demand locations that were part of this optimization. Figure 15, Figure 15 , and Figure

16 show the demand allocation for the secondary staging centers from each of the primary inventory hubs at Miami, Orlando, and Vero Beach.

Resource Category	Classification Level1	Resource Deta	State	Region(County/City/Facility/etc	Latitude (Region)	Longitude(Region)	Needed Within 2 Weeks			Needed Within 4 Weeks		
							mean	95th-Percentile	99th-Percentile	mean	95th-Percentile	99th-Percentile
PPE	Gloves	12001	Florida	Alachua	29.67866525	-82.35928158	449173	456937	463475	556129	567366	576764
PPE	Gloves	12003	Florida	Baker	30.33060121	-82.28467476	44867	49055	52426	58045	65072	70078
PPE	Gloves	12005	Florida	Bay	30.26548745	-85.62122584	459900	536720	600975	604755	716410	809677
PPE	Gloves	12007	Florida	Bradford	29.95079741	-82.16611613	38942	49770	58862	50077	66809	79987
PPE	Gloves	12009	Florida	Brevard	28.29409504	-80.73091022	714571	745320	770960	884863	929504	966791
PPE	Gloves	12011	Florida	Broward	26.15184651	-80.48725556	7314270	7633707	7900535	9226502	9690590	10078369
PPE	Gloves	12013	Florida	Calhoun	30.40666734	-85.19394153	37614	43028	47625	48136	56002	63540
PPE	Gloves	12015	Florida	Charlotte	26.90131002	-81.92949121	236385	250789	262741	289301	310141	327609
PPE	Gloves	12017	Florida	Citrus	28.84804315	-82.47614748	158748	177646	193480	202266	229745	252628
PPE	Gloves	12019	Florida	Clay	29.98319144	-81.85609986	378584	401467	420570	481250	514552	542338
PPE	Gloves	12021	Florida	Collier	26.11091986	-81.34687065	1204402	1273868	1331891	1458154	1559083	1643463
PPE	Gloves	12023	Florida	Columbia	30.22509788	-82.62160164	323523	425065	510057	429457	577071	700474
PPE	Gloves	12027	Florida	DeSoto	27.18677893	-81.80941373	160484	174480	186125	192152	212481	229439
PPE	Gloves	12029	Florida	Dixie	29.60631086	-83.15724673	32711	38738	43743	42109	50792	58045
PPE	Gloves	12031	Florida	Duval	30.33225875	-81.66976468	2864415	3091607	3281410	3587159	3917322	4193038
PPE	Gloves	12033	Florida	Escambia	30.67652764	-87.37284571	1051579	1118899	1175186	1335160	1433024	1514646
PPE	Gloves	12035	Florida	Flagler	29.45933576	-81.31508595	112370	120133	126569	139543	150780	160076
PPE	Gloves	12037	Florida	Franklin	29.83791238	-84.82731662	14731	17387	19635	19941	23823	27092
PPE	Gloves	12039	Florida	Gadsden	30.57796289	-84.61915825	168452	202674	231175	214013	263661	305135
PPE	Gloves	12041	Florida	Gilchrist	29.72856978	-82.79880657	44765	56410	67217	57330	75287	89487
PPE	Gloves	12043	Florida	Glades	26.95635849	-81.18996211	47012	62110	73857	58249	79782	96842
PPE	Gloves	12045	Florida	Gulf	29.93543004	-85.2427099	40372	50281	58453	54163	69465	81417
PPE	Gloves	12047	Florida	Hamilton	30.49673973	-82.94998918	69362	73755	77433	80702	87035	92449
PPE	Gloves	12049	Florida	Hardee	27.49293939	-81.80956574	102461	104197	105627	121563	124117	126160
PPE	Gloves	12051	Florida	Hendry	26.55386945	-81.16469006	194706	199201	202981	226374	232912	238428
PPE	Gloves	12053	Florida	Hernando	28.55364461	-82.42700204	221062	229439	236487	281435	293694	303909
PPE	Gloves	12055	Florida	Highlands	27.34254618	-81.34071957	148737	174888	196749	187862	225966	257736
PPE	Gloves	12057	Florida	Hillsborough	27.9276559	-82.32013172	3811082	4065038	4277213	4677353	5046335	5354536
PPE	Gloves	12059	Florida	Holmes	30.86747479	-85.81319222	50281	58147	65685	62825	74266	83868
PPE	Gloves	12061	Florida	Indian River	27.69308961	-80.60556721	285113	303909	319641	356519	383794	406677

Figure 14 Example of Glove Demand for 28 locations in Florida

Staging Center	Gloves	Gowns	Masks	Respirators	Ventilators
Staging - 1	0	0	0	0	0
Staging - 2	395	463	162	166	7
Staging - 3	0	0	0	0	0
Staging - 4	0	0	0	0	8
Staging - 5	0	2330	821	835	33
Staging - 6	0	0	0	0	6
Staging - 7	0	1827	170	234	30
Staging - 8	894	0	383	354	58
Staging - 9	0	2327	0	0	0
Staging - 10	0	0	249	253	11

Figure 15 PPE Allocation for Miami

Staging Center	Gloves	Gowns	Masks	Respirators	Ventilators
Staging - 1	0	0	0	0	0
Staging - 2	0	0	0	0	0
Staging - 3	330	0	136	139	6
Staging - 4	2479	0	0	0	0
Staging - 5	1981	0	0	0	6
Staging - 6	326	0	0	0	0
Staging - 7	1553	0	473	421	0
Staging - 8	0	0	0	0	0
Staging - 9	7862	4385	2507	2552	124
Staging - 10	601	0	0	0	0

Figure 16 PPE Allocation for Orlando

Staging Center	Gloves	Gowns	Masks	Respirators	Ventilators
Staging - 1	1445	1699	598	609	28
Staging - 2	0	0	0	0	0
Staging - 3	0	388	0	0	0
Staging - 4	154	3097	1091	1110	44
Staging - 5	0	0	0	0	0
Staging - 6	0	382	134	137	0
Staging - 7	0	0	0	0	0
Staging - 8	225	3456	834	885	0
Staging - 9	0	396	0	0	0
Staging - 10	0	707	0	0	0

Figure 17 PPE Allocation for Vero Beach

Key Performance Parameter Comparison

Digital Annealer Output Examination

We have a handful of performance metrics available to us for comparison. These include:

- **The fractional allocation of PPE type across all staging centers**. Fractional allocations across staging centers such that the fraction of allocated supply to demand for each staging center / resource category is given. From this, various statistics can be computed such as averages, std. dev.'s, other moments looking column wise. This is depicted in Figure 18.
- **Overall and fractional allocations**: A comparison of overall supply to demand ratio, to the average / std. dev. of allocated supply to demand ratios for each of the resource categories. This is depicted in Figure 19.
- **Allocation within 90%:** Number of staging centers with allocations within 90-110% of the overall supply to demand ratios is depicted in Figure 20
- **Zero Allocations:** Fractions of number of zero allocations (of various resources to the staging centers) to the overall allocations w.r.t individual inventory locations, and also across all inventory locations combined
- **The DA runtime statistics**, round trip times, average and total distances covered (from inventory to staging centers, staging centers to demand regions and total

distance) for different numbers of staging centers (6,8,10,12). See Figure 21 and Figure 22.

Staging Center	Gloves	Gowns	Masks	Respirators	Ventilators
Staging - 1	0.000328	0.002097	0.001447	0.004033	0.02518
Staging - 2	0.000328	0.002094	0.001445	0.004025	0.023179
Staging - 3	0.000328	0.002098	0.001448	0.00403	0.023715
Staging - 4	0.000328	0.002098	0.001448	0.004033	0.025578
Staging - 5	0.000328	0.002098	0.001449	0.004032	0.025524
Staging - 6	0.000328	0.002094	0.001449	0.004026	0.024291
Staging - 7	0.000328	0.002098	0.001448	0.004035	0.025042
Staging - 8	0.000125	0.002098	0.001448	0.004035	0.025573
Staging - 9	0.000328	0.001613	0.001115	0.003106	0.020412
Staging - 10	0.000328	0.002097	0.001447	0.004025	0.023758

Figure 18 Fractional Allocation of PPE Type Across All Staging Centers

	Overall Supply to Demand Ratio	Average Supply to Demand Ratio	Std. Dev. Supply to Demand Ratio
Gloves	0.000298	0.000308	0.000064
Gowns	0.001908	0.002048	0.000153
Masks	0.001317	0.001414	0.000105
Respirators	0.00367	0.003938	0.000292
Ventilators	0.023322	0.024225	0.0016

Figure 19 Overall Supply to Demand Ratio Averaged Across 10 Staging Centers

	Fraction of staging centers with allocated supply/demand between 90% and 110% of overall supply/demand
Gloves	0.9
Gowns	0.9
Masks	0.9
Respirators	0.9
Ventilators	0.9

Figure 20 Fraction of Staging Centers within 90-110% of Overall Supply/Demand

		DA Runtime Stats		Average Distance			Total Distance		
#taging Centers	total round trip time (sec.)	anneal time (ms)	cpu time (ms)	mean dist (inv to stag)	mean dist (stag to demand)	overall mean dist	total dist (inv to stag)	total dist (stag to demand)	overall total dist
6	38	30241	2191	1,781	607	998	5,342	3,640	8,983
8	33	23497	2114	1,703	459	798	5,110	3,669	8,779
10	35	22521	2552	1,990	382	753	5,970	3,824	9,793
12	52	34073	3559	1,960	320	648	5,880	3,835	9,716

Figure 21 Timing Analysis for Use of DA Varying with Number of Staging Centers

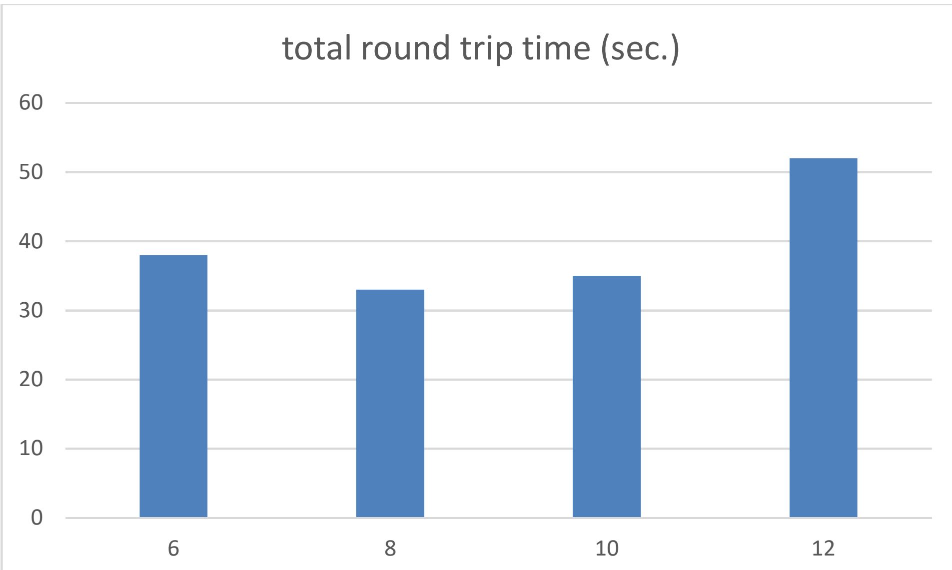


Figure 22 Total Staging Centers versus Total HW Runtime

Evolutionary Algorithm Output Examination

For the Evolutionary Algorithm implementation, similar metrics were measured, namely:

- **The fractional allocation of PPE type across all staging centers**. Figure 18. provided the DA results. The EA method is shown in Figure 23. The results from the DA are overall smoother, in the range of 80-90% more.
- **Overall and fractional allocations**: Figure 19 was the DA results and the EA results are in Figure 24. The DA results are better when looking at standard deviation by roughly a factor of 5.
- **Allocation within 90%:** Figure 20 was the DA results and Figure 25 has the EA results. The DA outperformed the EA by the largest margin for this metric—nearly 900% better.

- **The EA runtime statistics**, which include the wall time and CPU time for the algorithm to converge are shown for comparison in Figure 22 for the DA and Figure 26 for the EA. The EA approach was 5 times slower.
- **The Total moved inventory,** which displays how much of the total inventory was allocated to staging centers. For the DA, all inventory was allocated, as shown in Figure 27, 97% of inventory was allocated with the EA method.

Staging Centers	Gloves	Gowns	Masks	Respirators	Ventilators
Staging - 1	0.000165	0.00160982	0.00176854	0.00603311	0.02248201
Staging - 2	0.001341	0.00703289	0.00837742	0.02104651	0.32119205
Staging - 3	0.000929	0.01657808	0.00506766	0.05557972	0.13833992
Staging - 4	0.000833	0.00100041	0.00066369	0.00201658	0.00344319
Staging - 5	0.000182	0.00087501	0.00240697	0.00155012	0
Staging - 6	0.001304	0.01289838	0.01210876	0.02915246	0.61538462
Staging - 7	0.000161	0.00078201	0.00133269	0.00370831	0.00417362
Staging - 8	0.000113	0.00126574	0.00050324	0.00201256	0
Staging - 9	3.39E-05	0.000611	0.00017207	0.00047954	0.00065844
Staging - 10	0.001288	0.01399323	0.00509166	0.00692102	0.07775378

Figure 23 - Fractional Allocation of PPE Type Across All Staging Centers

PPE	Overall Supply to Demand Ratio	Average Supply to Demand Ratio	Std. Dev. Supply to Demand Ratio
Gloves	0.000282976	0.000635026	0.000556028
Gowns	0.001858384	0.005664659	0.006433717
Masks	0.001291098	0.003749271	0.003933613
Respirators	0.003630511	0.012849992	0.017762332
Ventilators	0.02332192	0.118342763	0.202081171

Figure 24 - Overall Supply to Demand Ratio Averaged Across 10 Staging Centers

PPE	Fraction of staging centers with allocated supply/demand between 90% and 110% of overall supply/demand
Gloves	0
Gowns	0
Masks	0.1
Respirators	0.1
Ventilators	0.1

Figure 25 - Fraction of Staging Centers within 90-110% of Overall Supply/Demand

	Wall	CPU
Time in Seconds	152.4859	152.0625

Figure 26 - Time to Compute

	Amount of Inventory Moved	Amount of Inventory	Percentage
Total	53589	55316	0.968779

Figure 27 - Total Moved Inventory

Conclusion

Key Findings & Implications

The DA model solved the COVID-19 allocation optimization faster than traditional methods with better performance. With additional variables or larger datasets, it increases exponentially greater efficiency, compared to conventional computing and can solve otherwise intractable problems. The DA to Evolutionary Algorithm quantitative specifics are:

- While the EA compared to the DA have comparable metrics, the overall supply allocation was 100% for the DA compared to 97% for the Evolutionary Algorithm.
- The overall equability of demand to supply as shown Figure 18 for the DA exceeds that of the Evolutionary Algorithm by 90%.
- Finally, the total compute time for 10 staging centers was roughly 32 seconds for the DA and about 150 seconds for the Evolutionary Algorithm.

It should be noted that the Florida use case for comparison was not very stressful for the DA and did not allow for it to show its scalability. This is due to the fact only 67 total demand centers existed in the state of Florida compared to the many thousand that would be put into the problem if doing allocation across the entire United States. The factor of 5 difference in performance time would have been significantly higher with more states.

Recommendations

Given that the problem of vaccine distribution requires consideration of cost and constraints across the entire US as well as added constraints not needed for allocation, the DA would make a good platform for use in programs such as Warp Speed.

Prior to the COVID-19 use case, the DA and its unique quantum-inspired optimization have proven to be of great value across diverse industry use-cases such as supply chain logistics, transport / mobility (vehicle routing problems), manufacturing (paint shop scheduling), finance (portfolio optimization), computational fluid dynamics (design optimization) etc. This highlights the world-class services support of the technical staff.

There are several areas of improvement in the current use-case:

1. First and foremost, the datasets can be further refined to mimic reality such as coming up with a better demand prediction model such as Helena's.
2. In the creation of staging centers, more types of already available locations can be leveraged (other than TCHs)
3. More PPE categories can be added to the optimization (such as Beds)
4. As per the current implementation, as we extend the staging center creation to other states, the already-created centers could potentially move which may be impractical. A way to create consolidated staging center locations needs to be figured out even when scaling the solution to multiple states
5. Also, sometimes the staging locations could end up in the middle of highways, inside the lakes etc. which needs to be accounted for by the approach. Additional constraints and datasets to disallow this need to be incorporated
6. Account for the minimum period for which a staging center needs to be static
7. Take capacities of staging centers into account
8. The definition of equitable allocation could be refined by adding more parameters such as patient's demographics etc.
9. Prioritize distribution based on urgency of need

10. In routing, taking the maximum number of trucks / drivers available, truck capacities, positioning of trucks into account
11. Combine the resource allocation and routing problems into a single QUBO formulation so we can optimally allocate resources by also simultaneously optimizing for the truck distance covered, thereby the fuel costs
12. Incorporate more efficiency metrics to evaluate the performance

Limitations

While the extensive capabilities of Entanglement and Fujitsu in the solutions of combinatorial optimization were made quite clear to RFL during the project, if an organization wanted to implement QUBO solutions without Entanglement/Fujitsu technical support, a significant investment in technical knowledge would be necessary for that organization unless it could obtain a license to the underlying intellectual property.

Additional Pathways

The type of computation, modeling and optimization performed for the CRADA PPE Optimization can be applied to many U.S. Government agencies for:

1) UAV positioning and coverage
2) Command and Control
3) Optimal ship positioning & routing
4) Cyber – network analysis
5) Air Traffic Control
6) Air & Fluid dynamics
7) Predictive parts failure for mission-critical platforms and logistics of the supporting supply chain
8) Port(s) logistics and scheduling
9) Satellite Constellation Optimization – optimal orbits to assure best network and communication performance
10) Power grid & resiliency optimization for the optimal distribution of power, power re-routing, and black-out mitigation

11) Emergency services and rapid disaster response

12) Optimization of multiple national stockpiles

13) Analysis of location information and network optimization

14) Artificial Intelligence: data optimization

15) Various types of tomography

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