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D-Wave Implementation of Quantum Annealing for Optimal Resource Allocation in Disaster Response Operation of Marikina City

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ABSTRACT

Quantum computing shows a positive approach for addressing optimization challenges in NP-hard problems such as the vehicle routing problem (VRP). This study focuses on improving the efficiency of disaster response operations by localizing the application of D-wave quantum annealing in Marikina City. This study uses the Solution Partitioning Solver (SPS) and the Quadratic Unconstrained Binary Optimization (QUBO) formulation to convert the VRP into an equation that can be solved using quantum annealing. The study demonstrates that quantum computing effectively distributes resources during emergency response operations and improves overall operational efficiency. In determining the most effective route for each vehicle, the D-wave Leap API and QUBO representation compute the distances traveled by each vehicle. These findings contribute to the practical applications of quantum computing to revolutionize various fields, including disaster management. Implementing D-wave quantum annealing in Marikina City shows relevance for future advancements in optimizing resource allocation and improving disaster response operations.

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1. INTRODUCTION

Quantum computing offers a novel approach to optimization challenges such as the vehicle routing problem. Localizing the application of quantum mechanics in the Philippines could transform how the government allocates and best uses resources for disaster response. This innovative methodology [1] can overcome the limitations of classical computing, paving the way for more effective and optimal vehicle routing solutions that can ultimately lead to improved cost savings, reduced emissions, and enhanced overall operational efficiency in various sectors relying on logistics.

The current state of resource allocation in Marikina City involves complex decision-making processes that use traditional approaches to handle disaster response scenarios. Heavy typhoons and flooding harm the city since the location of the Marikina River is in a low-lying place. After the flooding, the Marikina City Disaster Risk Reduction Management Office (CDRRMO) usually requests an additional workforce to assist affected areas in the fast and efficient delivery of resource aid [2]. Quantum annealing (QA) presents a remarkably parallelized method for optimization problems by using a strategy that involves converting it into a QUBO problem [3]. In another study [4], D-Wave utilizes QA to find the global minimum of an objective function via a quantum annealing algorithm to solve a problem similar to the vehicle routing problem.

The initial focus of this study is to provide and explain the variables and symbols used, aiming to enhance the readers' understanding. Then, it created a solution for the vehicle routing problem (VRP). Con-

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verting the VRP into a Quadratic Unconstrained Binary Optimization (QUBO) formulation is essential in using the proposed algorithm. The study further delves into utilizing the D-Wave quantum annealing service to address the optimization problem. The research team successfully computed the total distance covered, measured in meters, and determined the optimal path for each vehicle.

Although quantum annealing is a successful optimization solution for vehicle routing problems, there needs to be more quantum computing applications in the Philippines that could help disaster response operations. Therefore, the researchers aim to improve resource allocation by localizing the application of the D-Wave system's quantum annealing to increase efficiency, minimize response time, and maximize asset utilization after calamities in Marikina. Researchers hypothesize that the quantum annealer will provide the shortest path from distribution to evacuation centers.

2. LITERATURE REVIEW

Efficiently managing and allocating resources during disaster response operations holds immense significance in ensuring prompt and practical aid to affected areas. The emergence of quantum computing has paved the way for novel approaches to tackle the intricate optimization problems inherent in resource allocation. This literature review delves into the practical application of D-Wave quantum annealing, an increasingly promising technique in quantum computing, specifically within the context of disaster response operations in Marikina City. The review centers around three key components: quantum annealing, quadratic unconstrained binary optimization (QUBO), and the vehicle routing problem (VRP). By thoroughly examining existing literature on these subjects, the researcher aims to glean valuable insights into the potential of quantum annealing and QUBO in overcoming the challenges associated with resource allocation and route optimization during disaster response endeavors. Moreover, the review sheds light on the obstacles and considerations that emerge when implementing quantum annealing-based optimization methods in practical, real-world scenarios.

2.1 Quantum Annealing

Quantum annealing, a subfield of quantum computing, has gained attention as a promising approach for solving optimization problems by leveraging quantum bits, or qubits, to explore solution spaces and find optimal configurations. Studies have applied quantum annealing, mainly using systems like the D-Wave, to efficiently solve large-scale combinatorial optimization problems and explore complex solution landscapes for resource allocation [3], [5]. Study [3] examines the benefits of quantum annealing systems compared to classical computing systems and delves into the formulation and discussion of a simulator for multitasking in a quantum annealer (QAMT). This integration of classical optimization algorithms and problem-specific heuristics has significantly improved the performance and scalability of quantum annealing. Nevertheless, determining the suitability of quantum annealing requires a careful analysis of factors such as problem size, connectivity requirements, and noise. It is essential to identify the limitations and trade-offs involved. By thoroughly understanding the existing research on quantum annealing, one can effectively assess its feasibility and potential in optimizing resource allocation specifically for the disaster response operation of Marikina City.

2.2 Quadratic Unconstrained Binary Optimization (QUBO)

The mathematical framework, Quadratic Unconstrained Binary Optimization (QUBO), falls under the umbrella of quantum computing and is designed to address optimization problems. Its relevance extends to resource allocation in disaster response operations, aligning seamlessly with the objective of this research focused on implementing D-Wave quantum annealing for achieving optimal resource allocation in Marikina City. QUBO effectively formulates problems by expressing them as quadratic objective functions involving binary variables, thus accommodating diverse constraints. Extensive studies have displayed the versatility of QUBO across domains such as logistics, scheduling, and network design, demonstrating its potential for facilitating efficient resource allocation in dynamic and evolving environments. Integrating QUBO with quantum annealing, particularly leveraging the capabilities of the D-Wave system, enables the exploration of vast solution spaces and the identification of near-optimal solutions. Nevertheless, challenges surrounding scalability, the trade-off between solution quality and computational resources, and selecting appropriate parameters require careful consideration.

There are multiple studies regarding the optimization problem of NP-hard problems using QUBO. Other research also shows that quantum computers can solve these types of problems. One example of this is the use of adiabatic quantum computers. The [6] D-Wave 2000Q, an adiabatic quantum computer, can approximately solve the NP-Hard QUBO problem and has demonstrated superior performance to classical computers in several instances. According to research, NP-Hard problems are situations that modern computers cannot solve efficiently. The [7] applies QUBO problems on Adiabatic computers. Adiabatic quantum computers are quantum computing equipment that use the quantum annealing method to perform computations. Through [8], researchers delve into quantum computing to examine its potential in addressing routing problems. The ongoing advancements in quantum computing hardware, coupled with the recent breakthroughs in quantum algorithms for mathematical programming, have piqued the interest of researchers in exploring the use of quantum devices for decision-making in routing problems. This avenue of research holds significant promise and warrants further investigation [8].

2.3 Vehicle Routing Problem (VRP)

Combinatorial optimization widely recognizes the Vehicle Routing Problem (VRP), which is pivotal in managing resource allocation and logistics. Particularly in disaster response operations, the VRP takes on heightened importance as it focuses on efficiently directing vehicles to deliver essential resources to affected areas. The objective of the VRP is to minimize either the total distance covered by the vehicles or the number of vehicles required while simultaneously adhering to various constraints such as vehicle capacity, time windows, and customer demands. Conventional methodologies employed to tackle the VRP encompass heuristic technique, metaheuristic, exact method, and mathematical programming strategies. These approaches provide efficient algorithms to identify feasible and near-optimal solutions to VRP. However, the unique challenges encountered in disaster response operations [9], [10], [11], including dynamic demand, time constraints, and uncertain conditions, necessitate specific adaptations and refinements to conventional VRP algorithms. The study [9] employs a modified artificial bee colony algorithm to address issues related to time windows in vehicle routing. Another study [10] combines heuristics and dynamic programming techniques, utilizing Solomon test sets to explore the Vehicle Routing Problem with Time Windows (VRPTW). Furthermore, this investigation introduces a method to decompose the VRPTW into smaller sub-problems based on time windows, offering an efficient approach for effectively handling more significant instances of the problem [11].

Optimization techniques for the VRP have witnessed significant advancements in recent years [12], [13]. One study modifies the vehicle routing problem by altering the mathematical model and employing a heuristic approach to minimize overall costs [12]. Meanwhile, [13] adopts a two-phase optimization strategy that integrates an artificial immune system with the sweep method to address the VRP within a logistics network. Hybrid approaches combining metaheuristics with mathematical programming, integrating real-time data, and applying machine learning methodologies have exhibited promising outcomes in enhancing the efficiency and effectiveness of VRP solutions. Detailed case studies and illustrative examples demonstrate the successful utilization of VRP models and algorithms to optimize resource allocation, vehicle routing, and scheduling during emergencies. Evaluating and comparing the performance of diverse VRP solutions, rigorous benchmarking studies, and applying performance metrics furnish valuable insights into the caliber and efficacy of VRP approaches in disaster response scenarios. Developing a comprehensive understanding of the VRP and its advancements is of utmost importance in guiding the implementation of D-Wave quantum annealing for achieving optimal resource allocation in Marikina City's disaster response operations.

2.4 Challenges and Considerations for Quantum Annealing Based Optimization

While there are undoubtedly advantages to utilizing quantum annealing-based optimization through D-Wave quantum computing, it is essential to acknowledge the accompanying challenges. Quantum annealing machines possess specific architectures with limited connectivity, making it difficult to represent specific problem structures or constraints accurately. Consequently, the research team undertakes additional measures to map the problem onto the available qubits. Furthermore, the limited availability of quantum annealing machines presents constraints regarding hardware accessibility, qubit availability, and other associated limitations.

Another obstacle pertains to the susceptibility of quantum systems to noise, which can introduce inaccuracies and errors during the computational process. Additionally, the scarcity of available qubits in quantum annealers necessitates decomposing large-scale optimization problems into smaller sub-problems or implementing advanced techniques to manage scalability effectively and efficiently. Given these challenges, resolving a quantum problem and obtaining a satisfactory solution is more complex, particularly when tackling NP-hard problems like the Traveling Salesman Problem. Consider numerous constraints and complexities, which may necessitate exploring alternative solutions or subdividing the problem into more manageable components.

3. MODEL

3.1 Description of the Problem

In the face of catastrophic events, the urgent and efficient provision of practical assistance to impacted families becomes paramount. Marikina, a city in Metro Manila, is frequently subjected to the devastating consequences of typhoons and flooding, underscoring the critical necessity for timely aid. A pivotal aspect of disaster response revolves around establishing optimal vehicle routes to transport essential resources to designated evacuation centers. The primary research objective is to identify the most effective paths that enable vehicles to reach these centers in the shortest time possible while minimizing the distance traveled. Accomplishing this objective is critical to promptly and efficiently supplying vital provisions to the evacuation centers.

A systematic approach is adopted to enable the efficient planning of vehicle routes across all affected areas falling under the jurisdiction of Marikina. The research team treats the problem as a vehicle routing problem and establishes a model. The model takes inspiration from previous models in past studies [9], [10], [11].

3.2 Construction of Model

3.2.1 Model Assumptions

1. The research has identified the locations between the distribution center and each evacuation center and the routes between different evacuation centers.
2. The weight of the food packs distributed by each vehicle is the same.
3. The vehicle's load capacity is sufficient to fulfill the demand at the evacuation centers encountered along its route.
4. A single vehicle is responsible for distributing resources to each evacuation center.
5. All vehicles maintain a consistent speed of 40 km/h, as assumed during the aftermath of the disaster.
6. By substituting the shortest time with the shortest path, the objective function undergoes a transformation that prioritizes the discovery of the most efficient route. This alteration allows optimizing the path taken rather than solely considering the time factor.

3.2.2 Variables, Symbols, and Descriptions

Table 1 serves as a valuable resource for detailed explanations and representations of the variables and symbols utilized in the formula. It offers a comprehensive overview of the elements involved, ensuring clarity and understanding regarding their meanings and functions.

3.2.3 Model Establishment

Building upon the assumptions and analyses discussed previously, the researcher has constructed a series of mathematical models. These models represent the underlying principles, offering a structured framework for conducting in-depth analysis and facilitating informed decision-making. By formulating these models, the researcher can extract valuable insights and utilize them as a solid foundation for effective decision-making within the framework. They are crucial in translating abstract theoretical concepts into concrete mathematical expressions, fostering deeper comprehension, and empowering practical decision-making in various scenarios.

(1) Following is the objective function:

$$\min \sum_{m=1}^{M} \sum_{p=1}^{N} \sum_{q=1}^{N} d_{pq} x_{mpq} \tag{1}$$

Table 1: *Variables and Symbols.*

	Variable	Description
Sets	N	Set of all evacuation centers, $n \in N$
	M	Set of all delivery vehicles, $m \in M$
Parameters	d_{pq}	The distance from the evacuation center $p \in N$ to evacuation center $q \in N$
	d_{0p}, d_{p0}	The distance from the distribution center to evacuation center $p \in N$
	r_n	The demand for evacuation center $n \in N$
	b_m	The carrying capacity of vehicle $m \in M$
Decision Variables	x_{mpq}	A binary variable indicating whether vehicle $m \in M$ went from evacuation center $p \in N$ to evacuation center $q \in N$. If so, the variable's value is 1 and 0 otherwise.
	v_{mp}	A binary variable indicating whether vehicle $m \in M$ delivered to evacuation center $p \in N$. If so, the variable's value is 1 and 0 otherwise.
QUBO Variables	$QUBO_{vrp}$	The general form of the QUBO equation
	C	The total cost for all the traveled route by all the vehicles
	Q	The penalty for violating the constraint of having one vehicle deliver for each of the evacuation centers
	R	The penalty for violating the constraint of having all the vehicle start and end at the distribution center
	S	The penalty for violating the constraint of having each vehicle's capacity not exceed the total capacity for the evacuation center in its route

Formula (1) outlines the objective function employed in this study. This objective function seeks to minimize the total cost of travel by all the vehicles. The distance traveled will represent the cost of this problem based on the assumption made in the previous section. Assuming that the vehicles are traveling at the same speed, substitute the shortest path for the shortest time.

(2) Following are the constraints:

$$\sum_{m=1}^{M} v_{mp} = 1, \forall p \in N \tag{2}$$

$$\sum_{q=1}^{N} x_{m0q} = \sum_{p=1}^{N} x_{mp0}, \forall m \in M \tag{3}$$

$$\sum_{n=1}^{N} r_n v_{mn} \leq b_m, \forall m \in M \tag{4}$$

$$x_{mpq} \in \{0,1\} \forall m \in M, p \in N, q \in N \tag{5}$$

$$v_{mp} \in \{0,1\} \forall m \in M, p \in N \tag{6}$$

Formula (2) imposes a crucial constraint on the transportation process, specifying that only one vehicle can transport materials to each evacuation center. This restriction is essential for maintaining efficiency and organization in the distribution of resources.

Formula (3) outlines the behavior expected from vehicles, indicating that they will depart from the distribution center, complete their assigned deliveries, and then return to the exact location. This cyclical pattern ensures the effective utilization of vehicles and facilitates proper monitoring of their activities.

Formula (4) introduces a significant consideration regarding the load capacity of distribution trucks. It states that the capacity of these trucks will exceed the demand of the evacuation center they visit. This provision guarantees a consistent and sufficient supply of materials to each center, preventing any shortages or disruptions in the delivery process.

Lastly, Formulas (5) and (6) provide guidelines for determining the acceptable range of values for each decision variable involved in the process.

The constraints used in the study follow the previous studies made in establishing models for solving vehicle routing problems [9], [10], [11]. These constraints allow the solutions returned to be viable in real-world scenarios and follow the assumptions.

4. ALGORITHM

This study aims to solve the vehicle routing problem using the Solution Partitioning Solver (SPS). However, to effectively utilize this algorithm, it is essential to transform the vehicle routing problem into a Quadratic Unconstrained Binary Optimization (QUBO) formulation. After encoding the problem as a QUBO, the next step involves utilizing the D-Wave quantum annealing service, following the optimization problem-solving workflow outlined in D-Wave's documentation [14].

QUBO Formulation

The study formulates a QUBO Model as a formal representation of the defined Vehicle Routing Problem (VRP) based on the VRP Model discussed earlier. This QUBO Model is employed to address and solve the challenges inherent in VRP.

The representation of the VRP in QUBO:

$$QUBO_{VRP} = A_1 C + A_2 Q + A_3 R + A_4 S \tag{7}$$

$$C = \sum_{m=1}^{M} \sum_{p=0}^{N} \sum_{q=0}^{N} d_{pq} x_{mpq} \tag{8}$$

$$Q = \left(\sum_{m=1}^{M} v_{mp} - 1\right)^2, \forall p \in N \tag{9}$$

$$R = \left(\sum_{p=1}^{N} x_{mp0} - \sum_{q=1}^{N} x_{m0q}\right)^2, \forall m \in M \tag{10}$$

$$S = M(1 - a_{ik}) + C a_{ik} \tag{11}$$

$$a_{ik} = \begin{cases} 1, & \text{if} \sum_{n=1}^{N} r_n v_{mn} \leq bm, \forall m \in M \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

Formula (7) provides a generalized representation of the Quantum Unconstrained Binary Optimization (QUBO) model for the Vehicle Routing Problem (VRP). This formulation builds upon the QUBO model introduced in reference [15].

In Formula (8), the total cost, denoted as C, of the travel of all vehicles.

Formulas (9), (10), and (11) present the QUBO representation of the various constraints applicable to the VRP, which adds a penalty to solutions that violate the constraints. Formula (9) is the QUBO formulation of the constraint of having only one vehicle delivered to an evacuation center. Formula (10) adds a penalty if the route does not start and end in the distribution center. Formula (11) adds a penalty if the total demand for all the evacuation centers in a vehicle's route exceeds the vehicle's total capacity. These constraints define the limitations and requirements that must be satisfied in the optimization process.

Formula (12) introduces an auxiliary variable to support constraint fulfilment (11). The formulation of these constraints draws inspiration from the principles outlined in the reference [16].

SPS Algorithm and D-Wave Implementation

In this study, the research team utilizes the Solution Partitioning Solver (SPS), an algorithm designed to partition the Traveling Salesman Problem (TSP) solution generated by another algorithm into sequential intervals, which subsequently serve as solutions for the Vehicle Routing Problem (VRP) [15]. The SPS algorithm uses a quantum solver for the other algorithm. The solver chosen for this paper is the D-Wave's hybrid solver.

The D-wave hybrid solver is among the many solvers offered in the Ocean SDK. It combines quantum and classical resources for its approach.

Four branches, referred to as solvers, execute in parallel. A classical tabu search solver, interruptible when one of the other three solvers finishes executing, constitutes one of the branches. The other three branches are a sampler, a composer, and a decomposer [17].

The team compared the results from the SPS algorithm to various classical algorithms. The team ran the classical algorithms using the same test case with Google OR Tools. Google OR Tools allows users to represent a vehicle routing problem as a routing model. The library's built-in solution can solve the routing model. Two parameters are changed to find better solutions to different problems: the first solution and local search strategies. Different combinations of the first solution and local search strategies may yield different results. OR tools have five search strategies or algorithms and 13 first solution strategies. [18]

In this study, the team used an Energy Impact Decomposer with a size of 30 as the decomposer. The team employed a QPU Subproblem Auto Embedding Sampler as the sampler and a Splat composer as the composer. Both the sampler and composer utilize the default parameters. The team based the implementation code in this paper on the code available at the GitHub Repository of [15]. This Python script developed using the D-Wave Ocean SDK provides access to D-Wave's Quantum Solver. The team used a free developer plan on D-Wave Leap to conduct our experiments as our execution platform.

The platform encountered limitations during its use. The D-Wave's Solver limits the execution time to an hour of total execution but renews it every month. Lastly, access to the platform was blocked for the Philippines, requiring a VPN to sign in.

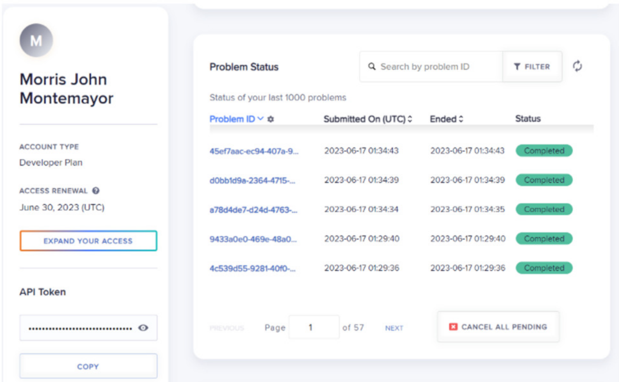

Fig.1: *Quantum Leap Web Interface.*

Fig. 1 displays a screenshot of the Quantum Leap Web interface, the platform for obtaining the necessary API key to connect with D-Wave's Quantum Computing services.

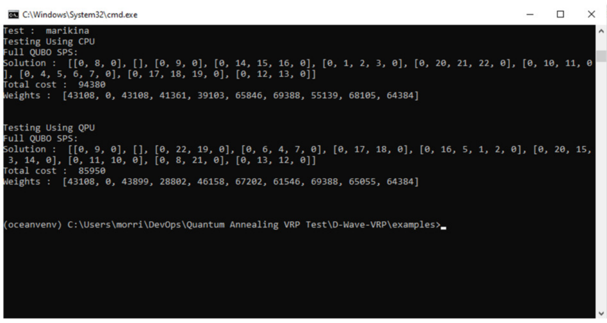

Fig.2: *Results of the Code.*

Fig. 2 is a screenshot of the results of the code. The program returns a list of routes for the solution, the total distance traveled by the vehicle, and the weights each vehicle needs to carry.

5. CASE ANALYSIS

Table 2: *Location and Distance.*

	Distance (meters)																						
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
A	0	2300	2800	2100	1500	3500	1100	1100	2400	2200	5400	5500	3900	5600	1300	18600	1700	850	1200	3500	2200	2700	200
B	2800	0	500	4800	1900	2800	1900	1900	4100	4100	7300	7400	6000	6900	5100	20300	1300	2800	3200	3100	4600	4400	3200
C	1800	600	0	4400	1400	3300	1400	1400	3700	3600	6700	6900	5500	6400	4700	19800	850	2300	2800	2700	4300	4000	2700
D	2000	3800	4600	0	4600	3500	2700	2700	5000	4600	8200	8300	6700	7300	1000	16800	4000	2600	1700	1800	4800	4400	1900
E	1500	1000	1500	3300	0	2200	400	400	2600	2400	5400	5800	4300	5000	2700	18600	550	1300	1700	1600	4800	2900	1500
F	3500	2800	2900	3300	2400	0	2400	2400	4400	4600	7500	7800	6300	7400	3800	20400	1600	3500	3800	5600	5100	5000	5700
G	1100	1000	1500	3300	400	2200	0	0	2600	2100	5300	5400	4000	4900	2300	18600	550	900	1400	1300	2900	2600	1200
H	1100	950	1500	3300	350	2200	0	0	2300	2100	5300	4400	2800	3300	2600	18600	550	900	1400	1300	2700	2600	1200
I	2700	3200	3700	5500	2600	4400	2300	2300	0	1100	4300	4200	2800	3300	3900	18100	2800	2100	2300	3500	1600	1200	2700
J	2200	3000	3500	5300	2400	4200	2100	2100	950	0	5100	5200	3800	4200	3300	17800	2600	1500	1800	2300	2600	2100	2200
K	5400	6200	9700	7300	5700	11000	5300	5300	3900	5200	0	850	3100	2100	6800	20100	5800	5400	5600	5600	4000	2700	5500
L	5500	6300	9800	7300	5800	11100	5400	5400	3800	5300	850	0	2600	2800	6900	20200	5900	5800	5700	5600	3600	2800	5200
M	4400	5000	8700	6300	4500	9100	4100	4100	3000	4000	3100	3200	0	1400	5200	17800	4600	3800	3700	4600	1800	1700	4000
N	5600	6400	9800	7500	5800	10800	5400	5400	4800	5200	3300	3000	1400	0	7100	19300	5900	5400	5300	5800	4000	2800	6000
O	1600	4300	5100	900	2600	4400	2200	2200	4500	4100	6300	7500	5500	6300	0	14900	2800	2200	2400	1000	3900	4000	1100
P	18600	19100	19900	15700	19100	18600	18800	18800	20200	18900	21900	22000	18700	19400	15700	0	19200	16400	16700	16800	16800	17400	18000
Q	1700	400	1300	3600	550	1600	550	550	2900	2700	5800	59000	4600	5500	4000	19200	0	1400	1900	1800	3500	3100	1700
R	850	2300	2800	2700	1500	3300	1300	1300	2100	2300	4800	49000	3800	4800	2200	16400	1700	0	200	1200	1800	1700	1100
S	1200	2000	2500	2800	1400	3200	1100	1100	2000	1800	5500	49000	3300	5100	2500	16700	1600	300	0	1500	2100	2000	1400
T	350	2300	2800	1900	1700	4800	1300	1300	3200	3500	5800	6700	4300	4900	1000	15700	1800	1100	1300	0	2900	3000	99
U	2000	3500	4000	4500	2800	7400	2400	2400	1500	2400	3700	3800	2200	3000	3500	17300	3000	1500	1400	2400	0	600	2300
V	2700	3500	4000	4500	2900	4700	3200	3200	1500	2500	3300	2800	1800	2300	4000	17400	3100	2500	2400	2900	450	0	2800
W	230	2200	2700	2000	1600	4900	1200	1200	3100	2700	5700	5800	4200	4900	1200	16900	1700	1100	1300	100	2800	2900	0

Table 2 presents letter A as the distribution facility at Marikina Sports Center, while letters B through L indicates the Marikina City evacuation centers. This table provides information on the distances between each of the locations.

A - Distribution Center / Marikina Sports Center
B - Barangka Elementary School
C - Barangka National High School
D - Kalumpang Elementary School
E - Kalumpang National High School
F - Industrial Valley Elementary School
G - Jesus Dela Peña National High School
H - Leodegario Victorino Elementary School
I - Malanday Elementary School
J - Malanday National High School
K - Nangka Elementary School
L - Nangka High School
M - Parang Elementary School
N - Parang High School
O - San Roque Elementary School
P - San Roque National High School
Q - Tañong High School
R - Sto. Nino Elementary School
S - Sto. Niño National High School
T - Marikina Elementary School
U - Marikina High School
V - Concepcion Integrated School
W - Sta. Elena High School

Table 3: *Package.*

Resource	Weight(kg)	Quantity	Total Weight(kg)
Canned Goods	0.155	8	1.24
Instant Noodles	0.06	8	0.36
Coffee	0.05	6	0.3
Rice	-	-	6

Table 3 details the resource package assigned to each family, including the weight of the entire bundle. The team recorded the total weight of the bundle as

7.9 kilograms, approximately rounded to 8 kilograms, and used this information to calculate the demand per evacuation center.

Table 4: *Population and Demand.*

Barangay	School	Population (2020)	Population per Evacuation Center	Demand (kg)
Barangka	Barangka Elementary School	16639	8319	13310.4
	Barangka National High School		8320	13312
Kalumpang	Kalumpang Elementary School	15602	7801	12481.6
	Kalumpang National High School		7801	12481.6
Industrial Valley	Industrial Valley Elementary School	16461	16461	26337.6
Jesus de La Peña	Jesus Dela Peña National High School	10201	5100	8160
	Leodegario Victorino Elementary School		5101	8161.6
Malanday	Malanday Elementary School	53886	26943	43108.8
	Malanday National High School		26943	43108.8
Nangka	Nangka Elementary School	43368	21684	34694.4
	Nangka High School		21684	34694.4
Parang	Parang Elementary School	40240	20120	32192
	Parang High School		20120	32192
San Roque	San Roque Elementary School	16949	8474	13558.4
	San Roque National High School		8475	13560
Tañong	Tañong High School	8902	8902	14243.2
Santo Niño	Sto. Nino Elementary School	28849	14424	23078.4
	Sto. Niño National High School		14425	23080
Santa Elena and Tumana	Marikina Elementary School	54871	13717	21947.2
	Marikina High School		13717	21947.2
	Concepcion Integrated School		13717	21947.2
	Sta. Elena High School		13720	21952

Table 4 presents detailed information regarding the population and resource demand in each barangay of Marikina City.
The expression "(population/a) x b" is the equation calculating the demand. In this equation, the variable 'a' signifies the average family size, assumed to be five members, while 'b' represents the total weight of the resource package. This table offers valuable insights into the population distribution and the corresponding resource demand in each barangay, facilitating a comprehensive understanding of the resource allocation requirements within the evacuation centers in Marikina City.

Table 5: *Vehicle and Capacity.*

Vehicle No.	Capacity (kg)
1	50000
2	50000
3	50000
4	50000
5	50000
6	70000
7	70000
8	70000
9	70000
10	70000

Table 5 provides information regarding the numbers of vehicles and their corresponding carrying capacities, measured in kilograms, utilized for resource allocation during disaster response operations in Marikina City.

Table 6 contains the best result from running the SPS algorithm 100 times on D-Wave's QPU. The table also shows the outcomes produced by the classical algorithms. These figures came from executing every possible combination of the first solution and local search strategies, repeated 100 times, with the best result selected for each combination. The SPS algorithm produced a slightly worse result than the best

Table 6: *Simulations Result.*

Algorithm	Result
Guided Local Search with Savings	83250
Simulated Annealing with First Unbound Min Value	83730
Greedy Descent with Best Insertion	83800
Tabu Search with Best Insertion	83800
Generic Tabu Search with Best Insertion	83800
SPS Algorithm	84650

results from the classical algorithms. However, the SPS algorithms' result is close to the results achieved by the classical algorithms. Quant-based algorithms like the SPS algorithm, even in its early stages, are promising and worthy of further exploration.

Table 7: *Optimal Route.*

Vehicle No.	Route
1	A, V, S, B
2	
3	A, J, A
4	A, G, C, D, A
5	A, N, O, E, A
6	A, F, P, D, H, A
7	A, L, K, A
8	A, M, L, A
9	A, U, S, R, A
10	A, I, T, A

Table 7 demonstrates that the optimal path is as follows: A-V-S-B, A-J-A, A-G-C-D-A, A-N-O-E-A, A-F-P-D-H-A, A-L-K-A, A-M-L-A, A-U-S-R-A, A-I-T-A. Moreover, the length of the route that takes the smallest amount of time is 84650 meters. The solver tries to find a solution that minimizes the number of vehicles used. The solution did not assign a route to vehicle no. 2. Since vehicles 1 through 5 all have the same capacity, any of these vehicles can be unused. The emergency response team can follow this route to ensure their total distance traveled is lower than mindlessly assigning routes for each vehicle. It can help lower the team's response time.

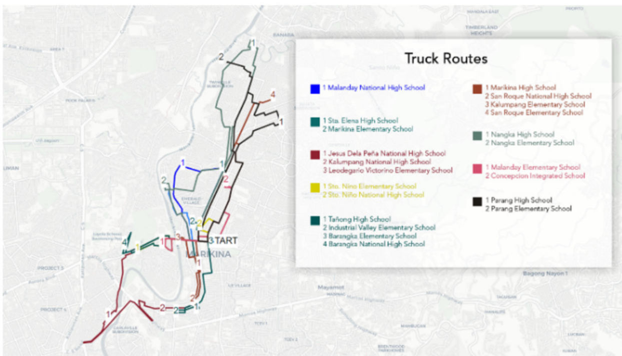

Fig.3: *Optimal Route Map.*

The truck's resulting routes, representing different trucks, are plotted on a map in Fig. 3. Each route has a distinct color, and the numbers on the map indicate the order in which the truck visits the evacuation center at each location. The START mark is the location of the distribution center, and the team used Python and OpenStreetMap to create this plot.

6. CONCLUSION

This study explores the implementation of D-Wave quantum annealing using the D-Wave Leap API as a cloud service and QUBO to provide a formula representation of the VRP for optimal resource allocation in Marikina City disaster response operations. It successfully demonstrates the effectiveness of quantum computing in solving the complex problem of resource allocation during disaster response.

The research team determined the total distance, in meters, covered by all the participating vehicles by using the D-Wave quantum computer. It is then compared to the results of different classical-based algorithms gathered using Google OR Tools. Even though the result is slightly worse, the study shows that quantum annealing offers valuable insights into the best route for each vehicle.

The D-Wave implementation highlighted in this research shows relevance for future advancements in optimizing resource allocation strategies during critical events. This study adds to the body of knowledge on the real-world uses of quantum computing and its potential to transform various industries, including disaster management and response.

7. RECOMMENDATIONS

This study showed the successful implementation of D-Wave quantum annealing for optimal resource allocation in Marikina City disaster response operations. Future researchers should conduct programs and field testing in collaboration with local government agencies and disaster response organizations to further enhance this research and capitalize on the potential of quantum computing. Specifically, the research team worked with the Marikina City Disaster Risk Reduction Management Office (CDRRMO) to integrate quantum computing solutions into their resource allocation processes. Thus, it will validate the effectiveness and practicality of quantum computing in real-world scenarios. These programs can help gather empirical data, evaluate the scalability of quantum algorithms, and assess the feasibility of implementing quantum computing solutions on a larger scale.

Furthermore, the researchers should explore opportunities to extend the utilization of quantum annealing to optimize fleet management, route planning, and scheduling in industries such as transportation and delivery services. With these, future researchers can contribute to the practical implementation of quantum computing solutions in disaster response operations, support the growth of quantum computing infrastructure in the Philippines, and pave the way for further advancements in optimizing resource allocation strategies during critical events.

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