Facility Location Problem to Identify The Optimal Allocation of Near-Expired COVID-19 Vaccines

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***Abstract*—*Coronavirus 2019, popularly known as COVID-19 and declared a pandemic by the World Health Organization (WHO) in 2020, has affected billions of people and claimed millions of lives. Leaders and corporations worldwide have worked feverishly to develop a vaccine to combat the virus. After numerous tests and trials, COVID-19 vaccines were developed. Given the magnitude of the need for vaccination, these vaccines should not go to waste due to expiration from slow-paced rollouts or oversupply. This study aims to maximize near-expired COVID-19 vaccines in cases of oversupply by distributing them in neighbouring facilities at a low delivery cost and by utilizing P-median modelling. All gathered data were loaded into and run through the AMPL simulation model, with varying P-values or the number of facilities to be located to act as suppliers to the remaining demand nodes. Following the model simulation, it was observed that the P-value is inversely proportional to the cost; therefore, the cost of delivering near-expired COVID-19 vaccines to the demand clusters decreases as the P-value increases. Through the simulation model, the researchers determined which node facilities, if opened, would incur the lowest delivery cost.*

***Keywords*—*Supply Chain, P-median, COVID-19 vaccine, AMPL, Gurobi*

I. Introduction

On December 31, 2019, the Chinese authorities had notified the World Health Organization (WHO) about the encountered pneumonia cases with an unknown etiology in Wuhan, China. It was then identified as a novel coronavirus by the Chinese authorities in January 2020 and was temporarily named 2019-nCoV, a new strain of Coronavirus that has never previously infected people. No country was spared; even first-world nations were caught aback when millions became infected and perished due to it, and the people's response was to create an anti-viral vaccine for it [1].

On January 30, 2020, the Philippines' Department of Health (DOH) verified the country's first confirmed case of COVID-19. It was just a matter of days before the first death from COVID-19 was reported on February 2, 2020 ("DOH REPORTS," 2020) [2]. By January 1, 2021, the country had reported 474,064 COVID-19 cases, 439,796 recoveries, and 9,244 fatalities [3]. The COVID-19 vaccines were just developed in the final quarter of 2020. These vaccines are in high demand throughout the world, including the Philippines, to help reduce the risk of severe COVID-19 infections. These pharmaceutical corporations and the governments of each country work together to scale up production and meet the growing demand for vaccinations [1].

As the Philippines' procurement for COVID-19 vaccines began to arrive, additional batches were supplied by the country's business sector and select international governments ("Number of coronavirus COVID-19 vaccine," 2021) [4]. As with every vaccination developed for a specific disease, COVID-19 vaccines have their storage and handling restrictions, as well as an expiration date. African nations destroyed 450,000 doses of expired COVID-19 vaccinations in July 2021. According to WHO, the factors are a lack of financial resources, a poor pace of rollout, and, most significantly, vaccine hesitancy among their populations. In this situation, the vaccinations may have been transported to nearby storage facilities outside the region, where supplies rapidly decreased due to increased demand [5].

Separate news articles by Cinco [3] and Parrocha [6] discussed that, while the Philippines has not yet encountered the same issue, vaccine reluctance remains widespread due to misinformation. On June 30, 2021, at least 1.5 million dosages of donated vaccines would have expired, and the remainder would have expired on July 31, 2021 due to slow rollout. This scenario created concern among Filipinos, who feared being handed of expired immunizations. While this batch was dispersed successfully, a good back-up plan, or distribution model could have been deployed to ensure its efficiency and to avoid public panic caused by these incidents.

As vaccine rollouts are being conducted in the Philippines, especially in the National Capital Region, many vaccination sites and facilities are being opened to increase the daily average of vaccinated people. However, as large quantities of COVID-19 vaccinations became available, Cinco [3] observed that vaccination sites became overwhelmed and unable to maintain abreast with the volume of vaccines arriving and individuals being vaccinated, resulting in a significant number of vaccines facing the possibility of expiring without being used. Developing a model that would serve as the strategic plan for these near-expired vaccines would be beneficial as it will prevent these vaccines from being wasted. Therefore, this study aims to create a model to efficiently utilize near-expired COVID-19 vaccines by distributing these to nearby facilities with diminishing supplies at a low cost.

While the P-median model was utilized in the study to aid with facility location, other methods that may be used are not discussed. Furthermore, the origin or sources of the vaccines, manner of vaccine rollout in the City of Manila and the vaccine brand names as well as the storage specifications for each vaccine brand are not covered in this study.

This paper is structured as follows: Chapter II includes a review of the literature on the application of P-median. Chapter III discusses P-median modeling. Results were extensively analyzed in Chapter IV. Finally, Chapter V summarizes and concludes the study with a suggestion for future research.

II. Related Works And Literature

The following related literature examples helped the researcher comprehend the p-Median model and its use in real-life situations and have guided the researchers through correct data collection, preparation, and calculation. The literature also inspired the researchers of the computing tool employed in this study.

A. *Vaccine Prioritization*

Given the vaccine's scarcity, it is crucial to maximizing its usage. Based on the established scientific report of Grauer et al [7], the optimum vaccination deployment is contingent on the individual-level parameters (e.g., who receives the vaccine first) and the spatiotemporal distribution (e.g., where to provide vaccines first). According to their results, by successively focusing on spatial places (e.g., cities) with the most significant local bilinear incidence rates or new cases, the proposed "focusing strategy" dramatically reduces death rates when compared to the usual practice of demographically distributing vaccines. However, the distribution question remains: Whom are we to distribute? According to Noh et al [8], who conducted a systematic review to determine which groups should be vaccinated first, discussed that the Health Care Workers should be prioritized because their work environment makes them susceptible to infection and easily transmit the virus to others. They ultimately contribute to society's sustainability.

This topic was included in this paper, although this study does not adapt group prioritization nor prioritize locations with the highest new COVID-19 cases. The purpose is to gain insight into the aspects to consider when determining vaccination prioritization. Additionally, through the related literature examples, the researchers recognized another limitation of this study: the concept and application of vaccine prioritization.

B. *Facility Location Problem*

The journal article of (Saravanakumar et al., 2017) [9], regarding location of organ procurement organizations in India motivated this study's conceptualization. The P-median model was used in their study, which takes the weighted distance between organ recipients into account. The model determines the demand for organs or the population density of organ recipients in a given location. The most effective organ procurement organizations (OPO's) are then selected and located.

(Benati and Garcia, 2012) [10] have introduced an adaptation of the P-median problem and its application to clustering in their work on the P-median Problem with Distance Selection. The distance/dissimilarity function between units is defined as the summation of the distances of the "q" essential variables. Since these variables are picked from a pool of m elements, a new combinatorial feature, which we refer to as the p-median model with distance selection, has been introduced into the issue. This issue stems from cluster analysis, which is frequently used in sociological surveys. Prior to executing the clustering algorithm, it is customary for researchers to select the q statistical variables they believe will be most helpful in differentiating the statistical units.

C. *Data Pre-processing*

Han et al [11] have discussed data pre-processing techniques in Chapter 3 - Data Preprocessing of their book, Data Mining Concepts and Techniques (3rd Edition). According to them, considering today's real-world databases are often massive and possibly derived from a variety of divergent sources, these are incredibly susceptible to noisy, incomplete, and inaccurate data. Inadequate data quality will result in ineffective mining results. "How can data be pre-processed to aid in improving the quality of the data and, thus, the mining results?", "How can data be pre-processed to increase the efficiency and ease of use of the mining process?" Numerous data pre-processing techniques were discussed in the book, including the cleansing, integration, reduction, transformation of data, and obscurity of data.

D. *Programming Tool and Solver for P-median problem*

It is vital to identify a tool that will facilitate and expedite the task at hand in computing. Saravanakumar et al [9] have used the AMPL, an algebraic modeling language, to develop a P-median model in their study. At the same time, CPLEX is used as the solver to compute the objective function and locate target facilities to be opened.

The authors Jayakumar et al [12] used alternatively for computational efficiency. They constructed and processed the P-median model with Python 3.5.2 (PuLP 1.6.1) as the programming language and with CBC as the default library. It took less than one second to find the optimal solution and result. However, according to the study of (Lars M. Hvattum et al., 2012), GUROBI is the fastest MIP solver and outperforms CPLEX. CPLEX rapidly determines the optimal solution in comparison to GUROBI. With full regard for all of this literature, the researchers chose to use AMPL for programming and GUROBI software for solving [13].

III. Methodology

This study aims to deliver near-expired COVID-19 vaccines to nearby facilities, and it is essential to collect details or information of target facilities or hospitals.

A. Data gathering and Data Pre-processing

The district hospitals specified on the interim plan for the deployment of COVID-19 vaccines in the Philippines serve as the storage facilities in this study ("The Interim Plan," 2021) [14]. The hospital locations and coordinates are gathered from Google Maps and Earth and shown in Table I. The Haversine Formula used these coordinates to calculate the distance between hospitals to create a matrix illustrating the distance density of storage facilities shown in Table II.

The population of each district in the City of Manila is based on the Census of the Philippine Statistics Authority (PSA), the country's governing body for census and statistical data, for year 2020 and is shown in Table III ("Census of Population and Housing." 2020) [15].

On September 3, 2021, the Manila Municipal Government reported via social media that the city's immunization rate has already reached 60.5% of the total population. In this sense, the unvaccinated population accounts for the remaining 39.5% of the entire population in each district. Tondo in Cluster10 has the greatest number of unvaccinated citizens, while Intramuros in Cluster3 has the lowest number. Additionally, the number of delivery trips shown in Table III is computed by dividing the unvaccinated population by the truck capacity, which is 5,000 vaccine vials per small-sized truck.

TABLE I. Latitude And Longitude Of Hospitals In Manila, Expressed In Degree (DEG)

Cluster	Hospital Name	Latitude	Longitude
C1	Justice Jose Abad Santos General Hospital	14.60	120.97
C2	Manila Doctors Hospital	14.58	120.98
C3	Seamen's Hospital	14.59	120.98
C4	Ospital Ng Maynila Medical Center	14.56	120.99
C5	The Family Clinic, Inc.	14.58	121.00
C6	Presidential Security Group Station Hospital	14.59	121.00
C7	Sta. Ana Hospital	14.58	121.02
C8	Dr. Jose Fabella Memorial Hospital	14.61	120.98
C9	Our Lady Of Lourdes Hospital Inc.	14.60	121.02
C10	Gat Andres Bonifacio Memorial Medical Center	14.60	120.97

TABLE II. Distance Of Each Hospital Per Cluster, Expressed In Kilometer (KM)

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
C1	0	2.1	1.3	4.0	3.7	3.1	5	1.6	5.5	0.9
C2	2.1	0	0.8	2.0	1.9	2.4	3.6	2.7	4.6	2.8
C3	1.3	0.8	0	2.8	2.6	2.6	4.2	2.2	4.9	2.0
C4	4.0	2.0	2.8	0	2.2	3.7	3.9	4.7	5.2	4.7
C5	3.7	1.9	2.6	2.2	0	1.7	1.9	3.5	3.1	4.5
C6	3.1	2.4	2.6	3.7	1.7	0	2	2.3	2.4	4
C7	5	3.6	4.2	3.9	1.9	2	0	4.3	1.5	5.8
C8	1.6	2.7	2.2	4.7	3.5	2.3	4.3	0	4.4	2.1
C9	5.5	4.6	4.9	5.2	3.1	2.4	1.5	4.4	0	6.3
C10	0.9	2.8	2.0	4.7	4.5	4	5.8	2.1	6.3	0

TABLE III. Unvaccinated Population Per District And Per Cluster In The City Of Manila

Cluster	**District**	**District Population**	**Unvaccinated Population**	**Number of Delivery Trips**
C1	Binondo	20491	8094	2
C2	Ermita	19189	7580	2
C3	Intramuros	6103	2411	1
C4	Malate	99257	39207	8
C5	Sampaloc	388305	153380	31
C6	San Miguel	18599	7347	2
C7	Santa Ana	203598	80421	16
C8	Santa Cruz	126735	50060	10
C9	Santa Mesa	110073	43479	9
C10	Tondo	654220	258417	52

Table IV estimates the initial cost of transporting the vaccines in each cluster by multiplying the number of delivery trips in Table III to P2,500.00, which is the minimum rate for renting a small-sized truck. The purpose of all the calculated or pre-processed data here is to ease the researchers' input in the AMPL model. It would be easier to understand and debug the program should there be errors during the model trial.

TABLE IV. Initial Cost Of Transporting Vaccines Per Cluster Using Small-Sized Truck, Expressed In Thousand Philippine Peso

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
C1	0	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
C2	2.5	0	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
C3	2.5	2.5	0	2.5	2.5	2.5	2.5	2.5	2.5	2.5
C4	2.5	2.5	2.5	0	2.5	2.5	2.5	2.5	2.5	2.5
C5	2.5	2.5	2.5	2.5	0	2.5	2.5	2.5	2.5	2.5
C6	2.5	2.5	2.5	2.5	2.5	0	2.5	2.5	2.5	2.5
C7	2.5	2.5	2.5	2.5	2.5	2.5	0	2.5	2.5	2.5
C8	2.5	2.5	2.5	2.5	2.5	2.5	2.5	0	2.5	2.5
C9	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	0	2.5
C10	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	0

B. Mathematical Notation

The "p-median" problem is a distance-based optimization problem in which p facilities must be located and assigned to demand points such that each demand point is mapped to a single facility and the sum of all demand points and corresponding facilities is minimized [16]. P–median modeling is employed to determine the objective function, which AMPL and Gurobi then process. Mathematical notation of the P-median model's objective function and constraints is used to make the model more understandable:

Indices:

I=set of demand; J=set of facility

Input parameter:

P = count of facility to be located

h_i = demand at node i ϵ i, divided by truck capacity.

(Note: "h_i" also represents the count of delivery trips calculated by dividing the unvaccinated population by 5,000 vaccine vials, which is the capacity of a small-sized truck)

d_{ij} = distance density of storage facilities

c_{ij} = cost per trip

Decision variable based from model:

X_j = 1, if facility was assigned as supplier; 0 if otherwise

Y_{ij} = 1, condition if selected receiver was covered by the assigned supplier; 0, otherwise

The objective function of this study is expressed in (1), which is to minimize delivery cost while considering the distance density and count of delivery trips required to cover the demand nodes. The constraints in this model are defined in (2) to (4), whereas the integrality constraints in (5) to (6). Equation (2) indicates that each demand node must be covered by at least one of the selected or opened storage facilities in the AMPL program. Equation (3) stipulates that demand nodes must be covered by only those storage facilities that have been opened. Equation (4) sets the number of P facilities to be selected or opened, which will serve as suppliers to the remaining demand nodes. Equations (5) and (6) are utilized to activate the binary mode of the decision variables X_j and Y_{ij}.

Objective function:

$$\text{Equation 1: Minimize } \sum i \sum j \ h_i \, d_{ij} \, c_{ij} \, X_j \, Y_{ij} \tag{1}$$

Constraints:

$$\text{Equation 2: } \sum j \ Y_{ij} = 1 \ \ \forall i \epsilon i \tag{2}$$

$$\text{Equation 3: } Y_{ij} - X_j \le 0 \ \forall i \epsilon i , \forall j \epsilon j \tag{3}$$

$$\text{Equation 4: } \sum j \ X_j = P \tag{4}$$

$$\text{Equation 5: } X_j \epsilon \{0, 1\} \ \ \forall i \epsilon i \tag{5}$$

$$\text{Equation 6: } Y_{ij} \epsilon \{0, 1\} \ \forall i \epsilon i \tag{6}$$

C. Manner of Data Analysis

All gathered and pre-processed data were inputted in AMPL to calculate optimum cost based on the desired number of "P" facilities to be located to serve as a supplier to other remaining demand nodes. In this study, however, the researchers computed the cost using all "P" values to visualize the trend of Objective Function while increasing P-value from 1 to 10. The results are then tabulated and will be discussed in succeeding Chapter IV. From the results, a Conclusion will be generated and will be discussed in Chapter V.

IV. Results And Discussion

Tables V and VI summarize the results of running the program in AMPL. The cells containing 1's in Table V represent the facilities that have been selected as the supplier and opened based on the P-value. If P=3, the following facilities will be identified and chosen as suppliers of COVID-19 vaccines to nearby facilities with depleting vaccine supplies: Sampaloc in Cluster5, Sta. Ana in Cluster7, and Tondo in Cluster10. The total cost of delivery would be Php 156,000. While if P=5, Malate and Santa Cruz will join the three previously assigned facilities, resulting in a lower delivery cost of Php 60,000. The P-value indicates the number of facilities specified as suppliers in the model. As the number of P increases, the number of suppliers also increases. If the P-value is increased to the maximum value, all ten nodes will become suppliers. However, in Table VI, we can also observe that starting P=4, there are facilities assigned as suppliers but no receiver to supply to.

TABLE V. 1'S INDICATE THE ASSIGNED SUPPLIER PER P-VALUE

Cluster	**P values**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
C1	1								1	1
C2							1	1	1	1
C3										1
C4					1	1	1	1	1	1
C5		1	1	1	1	1	1	1	1	1
C6								1	1	1
C7			1	1	1	1	1	1	1	1
C8				1	1	1	1	1	1	1
C9						1	1	1	1	1
C10		1	1	1	1	1	1	1	1	1

TABLE VI. 1'S INDICATE THE SELECTED RECEIVER PER P-VALUE

Receiver	**Suppliers**											
	P=3			**P=4**				**P=5**				
	C5	C7	C10	C5	C7	C8	C10	C4	C5	C7	C8	C10
C1			1				1					1
C2	1			1					1			1
C3			1				1					
C4	1			1				1				
C5												
C6	1			1					1			
C7												
C8			1			1					1	
C9		1			1					1		
C10												1

The number of optimal solutions and the objective function as determined by Gurobi 9.1.2 are listed in Table VII. It can be seen that the delivery cost is highest at P=1. It is observed that when the P-value increases, the objective function decreases. A P-value of 5 or 6 can be selected since these have lower objective functions or delivery costs.

TABLE VII. DERIVED OBJECTIVE FUNCTION, EXPRESSED IN PHILIPPINE PESO

P-value	Optimal Solution	Objective Function
1	--	868,475
2	36	267,525
3	37	156,000
4	30	103,000
5	30	60,000
6	29	27,375
7	29	14,875
8	26	6,325
9	22	2,025
10	--	0

However, this study aims to maximize the use of near-expired COVID-19 vaccinations. As observed in Table VI, starting P=4, there are supplier nodes with no corresponding receiver. Therefore, a P-value of 3 is selected as the suggested solution to be used in practice since, at P=3, all of the assigned supplier nodes have corresponding receiver nodes. Each supplier node is utilized.

V. CONCLUSION AND RECOMMENDATION

With the use of the P-median model, this study was able to locate facilities that will supply the near-expired COVID-19 vaccines at a low delivery cost. Additionally, based on the simulation results, it can be concluded that the P-value is inversely proportional to the objective function. The higher the number of P-values set by the researchers, the lower the cost. The P-value determines how many nodes from the storage facilities pool are assigned as suppliers. Therefore, a higher P-value is recommended to minimize cost. However, it is crucial to verify that all selected facilities have corresponding receivers to ensure all vaccines from opened supplier nodes are used.

This study could assist during the vaccination rollout's planning and decision-making stages. This study may serve as a tool in human life conservation as near-expired COVID-19 vaccines have the potential to save human lives if used as intended. For future research, it is strongly recommended to conduct analyses on a much broader geographical scale, such as regional or national, to accommodate additional facilities with a depleting supply of COVID-19 vaccines. Second, collaboration with Local Government Units is recommended to obtain real-time vaccine demand data from their system. Third, it is advisable to have a range of delivery truck sizes and capacities to provide a more diverse rental cost option. Finally, the research should be undertaken over a sufficient period to examine the intended purpose and associated challenges adequately.

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