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A Locational Analysis Model of the COVID-19 Vaccine Distribution

Luluk Lusiantoro
Centre for Logistics and Supply Chain Management, Department of Management,
Faculty of Economics and Business,
Universitas Gadjah Mada, Yogyakarta, Indonesia
Email: luluk.lusiantoro@ugm.ac.id *(Corresponding Author)*

Setyo Tri Windras Mara
Department of Mechanical and Industrial Engineering, Faculty of Engineering,
Universitas Gadjah Mada, Yogyakarta, Indonesia
Email: setyotriw@ugm.ac.id

Achmad Pratama Rifai
Department of Mechanical and Industrial Engineering, Faculty of Engineering,
Universitas Gadjah Mada, Yogyakarta, Indonesia
Email: achmad.p.rifai@ugm.ac.id

ABSTRACT

Even and equitable distribution of the COVID-19 vaccine becomes one of key strategies to reduce the number of positive cases and virus transmissions all over the world. This paper aims to introduce and demonstrate a mathematical model based on a maximal covering location problem (MCLP) to optimise the coverage of the COVID-19 vaccine distribution. A mathematical model is proposed and demonstrated using an illustrative case study of healthcare facilities and location coordinates of villages in Yogyakarta, Indonesia. A numerical computer experiment is conducted to obtain optimal results of the locational analysis. The results show that the proposed model provides an efficient coverage of vaccination by minimising the distances travelled by the target population. It also reveals an interesting insight that prioritising vaccination for areas with high COVID-19 cases results in a less efficient coverage. The novel location-allocation model for COVID-19 vaccination facilities proposed in this paper particularly applies in a developing country. The model could be used as an alternative way to increase the vaccination coverage and priority whilst minimising the potential risks of the virus transmissions and transport costs.

Keywords: *vaccine distribution, facility location problem, pandemic, COVID-19, healthcare logistics*

1. INTRODUCTION

The COVID-19 pandemic is not over yet. As of 23rd March 2022, the total number of confirmed cases since the beginning of the outbreak has reached over 470 million, with over 12 million new cases reported in a week and over 6 million deaths globally (WHO, 2022). This condition was mainly driven by the increased transmissibility of the new virus variants, increased people's mobility, reduced appropriate use of public health and social measures beyond lockdowns, and the challenging problem of uneven and inequitable vaccine distribution around the world (WHO, 2021). In fact, as of 23rd March 2022, only 57.05% of the world's population have been fully vaccinated by then (WHO, 2022).

The COVID-19 vaccine distribution is the greatest challenge in a lifetime (Busch, 2020). The complexity of the logistics stems not only from the cold chain facility requirements, but also from the readiness of the supply chain actors involved in the vaccine distribution processes (Busch, 2020; Swann, 2020; Smith, 2020). On top of that, vaccination coverage becomes a critical problem that needs to be solved. Busch (2020) predicts that "if we want to achieve global coverage over the next two years, that means some 200,000 pallet shipments and 15,000 flights. In the final distribution we could potentially require nearly 15 million cooling boxes, with the corresponding amounts of cooling bricks or dry ice". This challenge is real particularly for some countries that do not have such capability to handle the nationwide supply chain operations.

The complexity of the COVID-19 vaccine distribution is an additional stress test for the national vaccine supply chain that has already faced some critical challenges. WHO (2014) shows that the general landscape of the vaccine supply chain has grown "inherently more complicated", with more diseases, people, doses, funding, cold storage, and transport being handled to administer different types of vaccines across countries. WHO (2014) reports that the national vaccination coverage particularly in developing countries has been hindered by the vaccine inventory unpredictability, inadequate cold chain capacity, and insufficient funding to maintain the supply chain operations. To respond to these challenges, WHO (2014) calls for the national vaccine supply chain redesign, including modelling the facility location and distribution network configuration. In other words, locational analysis becomes a critical element that needs to be considered in designing the more effective and efficient vaccine supply chain, which could potentially contribute to the increased stock availability, decreased logistics costs, and increased vaccination coverage within the country.

Despite its criticality, studies on locational analysis and its impacts on vaccination coverage particularly in the event of pandemics in developing countries remain scant and require more significant attention (Duijzer *et al*., 2018, see also Xie and Lawley, 2015). As such, important lessons learnt on the optimal supply chain facility locations to be applied in the future COVID-19 vaccine rollout in developing countries is currently limited. Whilst vaccine facility location problems have been addressed by some researchers (e.g. Ramirez-Nafarrate *et al*., 2015; McCoy and Johnson, 2014; Ekici *et al*., 2014; Lee *et al*., 2013; Lee, *et al*., 2009; Whitworth, 2006; Lee *et al*., 2006), a recent comprehensive literature review on the vaccine supply chain suggests that the extant studies in this area are concentrated into four main themes – vaccine product, production, allocation, and distribution – in which locational analysis and vaccination coverage are not well captured and explicitly linked (Duijzer *et al*., 2018).

We address this important research gap by demonstrating a novel mathematical model based on a maximal covering location problem (MCLP) to optimise the coverage of the COVID-19 vaccination process in Yogyakarta Province of Indonesia, the fourth most populous country in the world with over 200 million people (many of them in remote areas) to be administered (Kemenkes, 2021). Our numerical experiment suggests that our model could provide an efficient coverage of vaccination by minimising the distances travelled by the target population in Yogyakarta. It also reveals an interesting insight that prioritising vaccination for areas with high COVID-19 cases results in a less efficient coverage.

This paper is structured as follows. In section 2, relevant literature is reviewed. Section 3 presents the mathematical formulation of a locational problem for vaccine distribution. Section 4 presents a case study of COVID-19 vaccine distribution in Yogyakarta, Indonesia, then the numerical experiment results and discussion are discussed in Section 5. Finally, Section 6 provides a summary of this study as well as several suggestions for future research.

2. LITERATURE REVIEW

2.1 Location-allocation problems in healthcare

Location-allocation decision of special facilities in healthcare is an emergent topic that is gaining noticeable attention especially in developing countries (ElKady and Abdelsalam, 2016). In healthcare, determining the optimal facility locations is an important task since the location has a direct effect on healthcare coverage, which in turn will affect the mortality and morbidity. Various models have been developed for healthcare facility problems under different environments. Mestre *et al*., (2015) developed a two location-allocation model for the strategic planning of hospital networks with handling uncertainty. The model considers two objectives, improving healthcare access for the population and minimising cost which often are conflicting. Shariff *et al.* (2012) studied a public health service location-allocation problem in Malaysia with an objective to maximise the population covered by the facilities. Kim and Kim (2013) studied a location problem in which there are two types of patients, low-income patients and middle- and high-income patients. These two types of patients have distinct characteristics, in which the former can only use public facilities while the later can use public and private facilities. Later, Afshari and Peng (2014) outlined the challenge for determining the healthcare facility location to ensure an optimal solution, such as difficulties to cover all patients' healthcare needs within a specified number of healthcare facilities, dealing with uncertainties, and varying demand for healthcare facilities.

Ye and Kim (2016) proposed a network-based covering location problem (Net-CLP) building on traditional location problems. The Net-CLP incorporates two sub-models: a network-based maximal covering location problem and a network-based location set covering problem. Recently, Taymaz *et al*. (2020) concerned on the location problem for a multi-disease, multi-service environment under risk aversion. In accordance with the problem explored, several approaches have also been proposed to solve the problem. Kim and Kim (2013) presented an integer programming formulation for the problem and developed a heuristic algorithm based on Lagrangian relaxation and sub gradient optimization methods. Recently, metaheuristics are also gaining research interest for solving the problem, such as Particle Swarm Optimization for solving capacitated maximal covering location problem in healthcare systems (ElKady and Abdelsalam, 2016), and Artificial Bee Colony Algorithm for healthcare waste disposal facility location problems (Gergin *et al*., 2019).

Although extensive studies have been done in the context of healthcare facility location-allocation problems, the development of models to determine the facilities for COVID-19 vaccination is still in infancy. Specifically, the COVID-19 vaccination requires the development of further models due to its characteristics such as its massive scale, the requirement for more advanced networks, and the importance of considering the environments of each country. In this study, we propose a novel location-allocation model for vaccination facilities in a developing country with a case study of Yogyakarta Province of Indonesia.

2.2 Locational analysis

In this study, we discuss the locational analysis for establishing vaccination facilities. In the context of logistics, locational analysis especially involves the tasks of (i) selecting which facilities to be opened from a set of candidates in order to serve spatially distributed customer demands and (ii) assigning the customers to the selected facilities, with respect to the objective function and a number of constraints (Melo *et al*., 2009). Until now, several reviews are available on this topic, such as Francis *et al.* (1983), Klose and Drexl (2005), ReVelle *et al*. (2008), and Melo *et al*. (2009).

The analysis of facility location also finds its relevance in healthcare logistics and becomes a fruitful research stream on its own. El Mokrini *et al*. (2019), for example, addressed facility location problems using a case of the public healthcare sector in Morocco, showing that the strategic decision on the facility locations should consider demand dispersion and road infrastructure in the country. Ahmadi-Javid *et al.* (2017) recently provided a comprehensive review on the implementation of locational analysis techniques to aid the planning task in healthcare logistics, along with the review of mathematical models employed in this domain. The implementation ranges from analysis of location of hospitals (e.g. Mitropoulos *et al.* 2006), blood banks (e.g. Elalouf *et al*., 2015), organ transplant centres (e.g. Zahiri *et al*., 2014), ambulance stations (e.g. Doerner *et al*., 2005), trauma centres (e.g. Côté *et al*., 2007), to point of dispensing (POD) facilities (e.g. Lee *et al*., 2006; Ramirez-Nafarrate *et al*., 2015). They discussed how any incorrect decision in healthcare facility location planning can lead to a serious impact on the community and may trigger the rising number of morbidity and mortality. Further, with regards to the topic of vaccine distribution process, Ahmadi-Javid *et al.* (2017) also emphasised the importance of integrating the decision criteria of humanitarian logistics and the incorporation of multiple criteria on the locational analysis for locating POD facilities.

Among the most important branches in locational analysis is the covering problem. Two surveys have been conducted on this stream of research by Schilling *et al.* (1993) and Farahani *et al*. (2012). In general, Schilling *et al*. (1993) categorised the covering problem into two classes: (i) set covering problem (SCP) and (ii) maximal covering location problem (MCLP) (Church and ReVelle, 1974). The SCP deals with the case where covering all demand nodes is required, with the general goal to minimise the total cost or total number of facilities. On the other hand, the MCLP models the situation where the aim is to maximise the coverage demands and some demand nodes may not be covered or just be partially covered (Farahani *et al*., 2012).

Here, we decide to focus on the MCLP model. This decision is highly motivated by the assumption of SCP where all demand nodes must be covered, which is quite inapplicable in the context of vaccination, along with the work of Ahmadi-Javid *et al.* (2017) who observed the applicability of MCLP-based model in healthcare facility location (e.g. Plastria and Vanhaverbeke, 2009; Davari *et al.*, 2015; Aboolian *et al*., 2016). To this end, we find only one previous work from Lim *et al.* (2016) who modelled vaccination tasks using MCLP paradigm. The authors introduced four distinct mathematical models to optimise the coverage of the vaccination process by locating one or multiple outreach centres, which is the critical final link in the vaccination effort and is necessary to the vaccination of remote areas. Generally, they presented the models as follows. The first model is the basic binary MCLP model. The second model is the variable single coverage model where the coverage of demand nodes (villages) is modelled as a stepwise decreasing function of distance from the nodes to the outreach centre, allowing a partial coverage of a given demand node by a single outreach centre. The third model extends the second model by allowing a single demand node to be partially covered by more than one outreach centre. Lastly, the fourth model is the generalisation of the cooperative cover location model (Berman *et al.*, 2011), where a single target village may fall into the outreach radius of multiple immunisation health centres (IHCs), so that each village can be covered by a single outreach centre from a unique IHC.

Finally, in this study, we develop a bi-objective MCLP under the presence of capacity constraint and partial coverage to locate P vaccination facilities within a certain area. The development of this model is inspired by the third model of Lim *et al.* (2016), in which we consider the situation where a single demand node may be partially assigned to multiple vaccination facilities. The partial coverage is an important extension of MCLP to relax the "all-or-nothing" assumption (Karasakal and Karasakal, 2004) and is also known as the gradual covering problem (Drezner *et al*., 2004). Further, we also incorporate multiple objectives in the model to capture the multicriteria nature of humanitarian aid decisions (Gralla *et al*., 2014; Gutjahr and Nolz, 2016).

3. MODEL FORMULATION

This section provides a formal description of the model developed in this study. First, let us introduce $i = [1, \dots, I]$ as the demand node and $j = [1, \dots, J]$ as the candidate location for establishing the vaccination facility. This study aims to capture the situation where decision-makers (e.g. government, healthcare service regulator) need to establish at most P vaccination facilities from J available candidate locations in order to distribute the vaccines to I demand nodes. The candidate locations for vaccination facilities are hospitals, while the demand nodes are represented by villages. Each demand node i has its corresponding non-negative vaccine demand N_i that needs to be covered by the decision-maker and it is assumed that the vaccine recipients will pick up the vaccines in their target facilities within a systematic schedule, which resembles the common practice in developing countries. Therefore, the considered situation can be modelled as a MCLP (Church and ReVelle, 1974) in a graph $G = (I \cup J, A)$, where A is the set of arcs $(i, j) \in I \cup J$.

In our proposed covering model, the decision required to be made is to select the optimal location(s) to establish the vaccination facility among the set of candidate locations. For this purpose, let $y_j \in \{0,1\}$ as a binary variable that takes the value of 1 if only a facility is established in location j and $x_{ij} \in [0,1]$ as a continuous variable to indicate whether demand node i is assigned to facility j. In this study, we aim to relax the classical 'all-or-nothing' assumption in the covering problem and open the chance for a partial coverage (Karasakal and Karasakal, 2004), in which a given demand node can be served by multiple vaccination facilities. We believe this partial coverage assumption is more realistic, especially in the case of vaccine distribution where the 'all-or-nothing' assumption may result in a single area that does not receive any vaccine at all. Then, in order to decide whether a given demand node can be covered, each candidate location j has its predefined coverage area S_j and the capacity of vaccination Q_j.

We formulate the proposed model as a simple bi-objective linear programming in Equation (1)-(9). The model consists of two objective functions in a lexicographic way, these are to maximise the covered demand population while minimising the total distance travelled by vaccine recipients to pick up the vaccines. These objectives constitute to the most important criteria of humanitarian aid operations: effectiveness and efficiency (see Gralla *et al*., 2014), that can be translated as the effort to deliver as many goods as possible within a shortest time frame. Then, we can mathematically represent these objectives in Objectives (1) and (2). Objective (1) aims to maximise the coverage population of vaccine recipients, while Objective (2) is set to minimise the weighted distance travelled by the recipients to pick up the vaccines in the vaccination facilities where d_{ij} is the distance travelled by recipients in area i to pick up vaccine in location j.

$$\max f_1 = \sum_{i \in I} \sum_{j \in J} N_i x_{ij} \tag{1}$$

$$\min f_2 = \sum_{i \in I} \sum_{j \in J} d_{ij} x_{ij} \tag{2}$$

subject to:

$$\sum_{j \in J} x_{ij} \leq 1 \qquad \forall\, i \in I \tag{3}$$

$$\sum_{j \in J} y_j \leq P \tag{4}$$

$$\sum_{i \in I} N_i x_{ij} \leq Q_j \qquad \forall\, j \in J \tag{5}$$

$$y_j \geq x_{ij} \qquad \forall\, i \in I, j \in J \tag{6}$$

$$a_{ij} \geq x_{ij} \qquad \forall\, i \in I, j \in J \tag{7}$$

$$x_{ij} \leq 1 \qquad \forall\, i \in I, j \in J \tag{8}$$

$$y_j \in \{0,1\} \qquad \forall\, j \in J \tag{9}$$

These objectives are subjected to a set of constraints as follows. Constraint (3) is the assignment constraint to guarantee that the total covered demand of a single node i is not more than its corresponding demand N_i. Constraint (4) is the budget constraint to ensure that the number of facilities is not violated the maximum number of establishments allowed. Note that if the establishment cost data is available, we can convert the Constraint (4) with a more straightforward budget constraint in Equation (10), where C_j stands for the capital cost required to establish vaccination facility in location j and TB is the total budget available. However, as the establishment cost is not available, we do not use the budget constraint in our model.

$$\sum_{j \in J} C_j y_j \leq TB \tag{10}$$

Constraint (5) is the capacity constraint to ensure that total demand assigned to j does not violate the capacity of j. Constraints (6) and (7) are the relationship constraints to guarantee that a given demand node i is only assigned to facility j if the facility j is established and their distance is within the maximum coverage S_j. For clarity, $a_{ij} \in \{0,1\}$ is a binary variable to decide whether area i can be covered by location j or not. The value of a_{ij} is 1 if $d_{ij} \leq S_j$ and 0 otherwise. Finally, Constraints (8) and (9) regulate the value of the decision variables.

4. ILLUSTRATIVE CASE OF YOGYAKARTA, INDONESIA

To illustrate our model, in this section we describe a case of the COVID-19 vaccine distribution in Yogyakarta Province, a special region in Indonesia, one of the biggest developing countries hit hard by the pandemic. The purpose of this case study is not to evaluate the effectiveness and efficiency of the vaccine distribution in this area, but to demonstrate how our proposed model could be used as an alternative approach to distribute the vaccine. At the beginning of July 2021, Indonesia had the highest cumulative number of COVID-19 cases (2,537,203) and deaths (66,464) among the Association of Southeast Asian Nations (ASEAN) countries and the second highest in South-East Asia after India (WHO, 2021; Tani, 2021). As of 22nd March 2022, nationally, there were 5,974.,646 cumulative cases and 154,062 deaths due to the virus (Satuan Tugas Penanganan COVID-19, 2022a). By then, 93.63% of the Indonesian population had their first dose of vaccination, whereas 74.67% and 8.46% had their second and third doses respectively (Satuan Tugas Penanganan COVID-19, 2022a).

At the same time, there were 217,549 cumulative cases, 184,856 recovered from the virus, and 5,713 people died due to the COVID-19 in Yogyakarta (Satuan Tugas Penanganan COVID-19, 2022b). Whilst these numbers are only a small part (3.6%) of the cumulative cases in Indonesia as of 21st March 2022 (Satuan Tugas Penanganan COVID-19, 2022b), Yogyakarta has been considered a critical region because it is one of the most popular tourism destinations in Indonesia and wonders of the world. With tourists being allowed to visit the region, it could potentially become a big new cluster of the virus transmission if the cases were not handled carefully. Yogyakarta Province not only consists of cities, but also rural areas, spanning across five big regencies/municipalities and 79 districts, each has its COVID-19 cases (Pemda DIY, 2021). Despite this condition, Yogyakarta was once acknowledged by the Indonesian government as the best province to handle the COVID-19 pandemic (Republika, 2020; Kontan, 2020). As such, we argue that Yogyakarta could be one of the ideal cases that could provide valuable lessons learnt for other provinces in Indonesia and other developing countries.

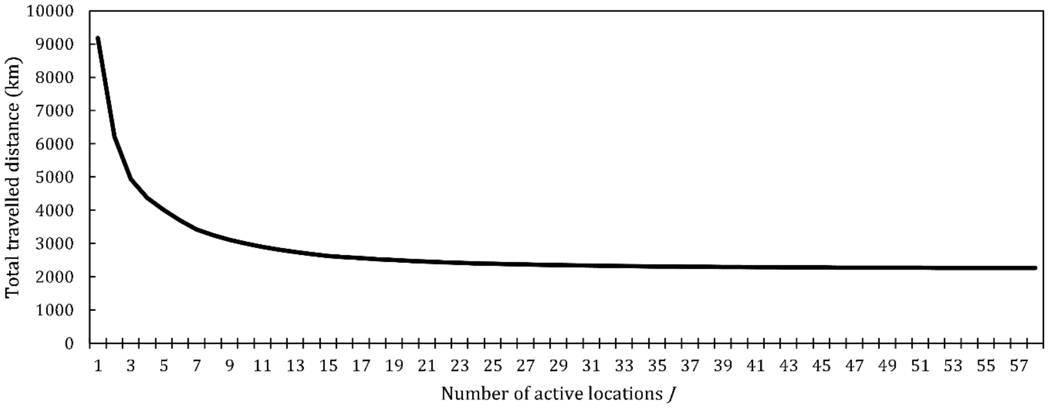
The COVID-19 vaccine distribution in Yogyakarta follows the national vaccine distribution agenda set by the Ministry of Health (Nugraheny, 2020). The vaccines are dropped in the Provincial Health Office acting as a local distribution centre. They are then distributed to the regencies/municipalities through hospitals and health centres appointed by the local government. The existing national immunisation logistics and cold chain facilities are used to deliver the vaccines. In addition, some organisations also work hand in hand in providing better access to vaccination using available facilities across different areas in the province. Whilst the effectiveness and efficiency of the existing immunisation supply chain has not been tested before, monitoring and evaluation of the COVID-19 vaccine distribution process are currently ongoing. This study is therefore timely and relevant, as it could be used as an alternative solution to the current vaccine distribution.

To demonstrate our model, we use 58 hospitals in the province as candidate locations and 438 villages to represent the demand nodes. We do not consider vaccinations in other facilities such as health centres and halls which are also used to organise mass vaccination events. We collected the location coordinate for each hospital and village (represented by the village administration office) using Google Maps. We assume that the vaccination capacity for the hospitals is dependent upon the hospital classification applied within the region. Hospital class A, B, C, and D must have a minimum of 400, 200, 100, and 50 beds in service respectively. We use this initial data to calculate the proportion of vaccination capacity for each of the hospital classes. Whilst our goals are to maximise the vaccination coverage and to minimise travel distance, we assume that there are no limitations to the number of vaccines and the number of people being vaccinated at the same time in each facility location. We also use the number of COVID-19 cases in each district as a percentage of total number of cases in Yogyakarta as a proxy for demand. We assume that villages within districts that have more confirmed COVID-19 cases should be prioritised over other villages with lower number of cases. As such, we were able to create a priority index for each village. We then compared our results with and without priority indices to see the differences.

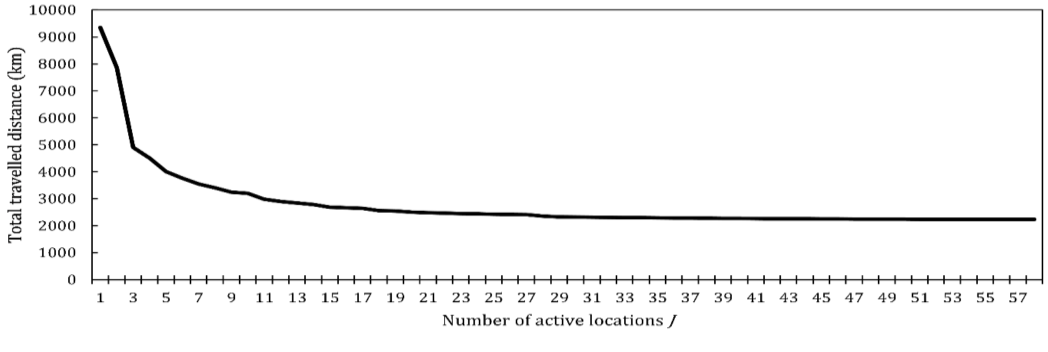
5. RESULTS AND DISCUSSION

This section describes the experiments to test and evaluate the developed model. To obtain the optimal solution, we use GUROBI 9.0.2, written and executed in Python 3.7. Experiments are carried out in a personal computer with Intel® Core^{TM} i7-10770 CPU 2.90 GHz with 32 GB of RAM and a Microsoft Windows 10 operating system. The computations are performed under two conditions, with and without considering the priority index. The priority index represents the severity of COVID-19 cases in an area, in which it is calculated as the ratio of number of cases over the total population of that area. Hence, the residents of areas with higher priority index will be prioritised to get vaccines early.

For each condition, the experiments are performed in various scenarios, depending on the number of hospitals used to distribute the vaccine, from $J = 1$ to $J = 58$. The results of the experiment for each scenario both with and without considering the priority index are presented in **Figure 1**. As the number of active locations increases, the total distance travelled to reach the hospital decreases. It is understandable because the optimization techniques will select the hospitals so that the total travelled distance of the residents is minimised.



(a)



(b)

Figure 1 Total travelled distance in each scenario (a) without priority and (b) with priority

As visualised in **Figure 1**, a similar pattern is recorded in both scenarios. The difference lies in the determination of specific hospitals used for the vaccination. Considering priority indices, the hospitals close to the area with higher priority index are generally chosen as active locations. This decision is to accommodate the vaccination for the area with severity of COVID-19 cases so that it can be performed early and the population in those areas do not need to travel long distances. Meanwhile, the computation for the cases without priority indices only considers the travel distance to be minimised. Therefore, with the same number of active locations, the total travelled distance for cases with priority indices is generally higher than those without considering priority indices. The complete results of the numerical experiment are shown in **Table 1**.

Table 1 Experiment results of the two scenarios

Number of Facilities	Model without priority			Model with priority			$\Delta f1$ (%)	$\Delta f2$ (%)	$\Delta\sigma$ (%)
	Total Covered Demand $f1$(person)	Total Distance $f2$ (km)	Max - Min Distance Travelled σ (km)	Total Covered Demand $f1$ (person)	Total Distance $f2$ (km)	Max - Min Distance Travelled σ (km)			
1	3,656,922	9,175.81	58.91	3,654,883	9,349.04	62.95	-0.06%	1.89%	6.85%
2	3,656,922	6,215.34	32.24	3,654,883	7,857.19	62.26	-0.06%	26.42%	93.13%
3	3,656,922	4,932.09	29.78	3,654,883	4,903.69	31.39	-0.06%	-0.58%	5.43%
4	3,656,922	4,371.07	29.62	3,654,883	4,508.88	31.39	-0.06%	3.15%	6.00%
5	3,656,922	4,012.41	29.78	3,654,883	4,008.67	31.39	-0.06%	-0.09%	5.43%
6	3,656,922	3,697.58	26.79	3,654,883	3,768.10	31.39	-0.06%	1.91%	17.19%
7	3,656,922	3,424.14	26.79	3,654,883	3,548.81	29.78	-0.06%	3.64%	11.15%
8	3,656,922	3,253.85	26.79	3,654,883	3,409.29	29.78	-0.06%	4.78%	11.15%
9	3,656,922	3,108.65	26.79	3,654,883	3,241.76	29.78	-0.06%	4.28%	11.15%
10	3,656,922	3,001.02	26.79	3,654,883	3,199.74	29.78	-0.06%	6.62%	11.15%
11	3,656,922	2,897.03	26.71	3,654,883	2,981.88	26.79	-0.06%	2.93%	0.29%
12	3,656,922	2,816.34	26.71	3,654,883	2,900.04	26.79	-0.06%	2.97%	0.29%
13	3,656,922	2,742.64	26.58	3,654,883	2,846.27	26.79	-0.06%	3.78%	0.80%
14	3,656,922	2,681.59	26.71	3,654,883	2,789.07	26.79	-0.06%	4.01%	0.29%
15	3,656,922	2,628.42	26.71	3,654,883	2,689.68	26.79	-0.06%	2.33%	0.29%
16	3,656,922	2,592.44	26.71	3,654,883	2,666.10	26.79	-0.06%	2.84%	0.29%
17	3,656,922	2,560.73	26.55	3,654,883	2,643.92	26.65	-0.06%	3.25%	0.39%
18	3,656,922	2,530.58	26.55	3,654,883	2,558.85	26.65	-0.06%	1.12%	0.39%
19	3,656,922	2,505.42	26.55	3,654,883	2,548.16	26.65	-0.06%	1.71%	0.39%
20	3,656,922	2,480.75	26.55	3,654,883	2,505.04	26.65	-0.06%	0.98%	0.39%
21	3,656,922	2,457.42	26.55	3,654,883	2,481.71	26.65	-0.06%	0.99%	0.39%
22	3,656,922	2,434.66	26.55	3,654,883	2,470.98	26.79	-0.06%	1.49%	0.90%
23	3,656,922	2,418.51	26.55	3,654,883	2,447.65	26.79	-0.06%	1.20%	0.90%
24	3,656,922	2,402.25	26.55	3,654,883	2,439.17	26.79	-0.06%	1.54%	0.90%
25	3,656,922	2,390.66	26.55	3,654,883	2,429.81	26.79	-0.06%	1.64%	0.90%
26	3,656,922	2,379.37	26.71	3,654,883	2,418.50	26.79	-0.06%	1.64%	0.29%
27	3,656,922	2,369.22	26.71	3,654,883	2,411.09	26.79	-0.06%	1.77%	0.29%
28	3,656,922	2,359.47	26.71	3,654,883	2,360.57	26.71	-0.06%	0.05%	0.00%
29	3,656,922	2,349.95	26.71	3,654,883	2,326.76	26.71	-0.06%	-0.99%	0.00%
30	3,656,922	2,342.43	26.71	3,654,883	2,319.00	26.71	-0.06%	-1.00%	0.00%
31	3,656,922	2,335.29	26.71	3,654,883	2,314.91	26.71	-0.06%	-0.87%	0.00%
32	3,656,922	2,329.05	26.71	3,654,883	2,310.55	26.71	-0.06%	-0.79%	0.00%
33	3,656,922	2,322.86	26.71	3,654,883	2,304.36	26.71	-0.06%	-0.80%	0.00%
34	3,656,922	2,317.10	26.71	3,654,883	2,300.90	26.71	-0.06%	-0.70%	0.00%
35	3,656,922	2,311.46	26.71	3,654,883	2,291.39	26.71	-0.06%	-0.87%	0.00%
36	3,656,922	2,306.71	26.71	3,654,883	2,288.17	26.71	-0.06%	-0.80%	0.00%
37	3,656,922	2,302.74	26.71	3,654,883	2,285.98	26.71	-0.06%	-0.73%	0.00%
38	3,656,922	2,298.78	26.71	3,654,883	2,282.29	26.71	-0.06%	-0.72%	0.00%
39	3,656,922	2,295.09	26.71	3,654,883	2,276.06	26.71	-0.06%	-0.83%	0.00%
40	3,656,922	2,291.64	26.71	3,654,883	2,273.02	26.71	-0.06%	-0.81%	0.00%
41	3,656,922	2,288.54	26.71	3,654,883	2,265.64	26.71	-0.06%	-1.00%	0.00%
42	3,656,922	2,285.51	26.71	3,654,883	2,260.89	26.71	-0.06%	-1.08%	0.00%
43	3,656,922	2,282.83	26.71	3,654,883	2,258.47	26.71	-0.06%	-1.07%	0.00%
44	3,656,922	2,280.41	26.71	3,654,883	2,256.80	26.71	-0.06%	-1.04%	0.00%
45	3,656,922	2,278.22	26.71	3,654,883	2,251.03	26.71	-0.06%	-1.19%	0.00%
46	3,656,922	2,276.27	26.71	3,654,883	2,249.09	26.71	-0.06%	-1.19%	0.00%
47	3,656,922	2,274.48	26.71	3,654,883	2,245.12	26.71	-0.06%	-1.29%	0.00%
48	3,656,922	2,273.26	26.71	3,654,883	2,243.77	26.71	-0.06%	-1.30%	0.00%

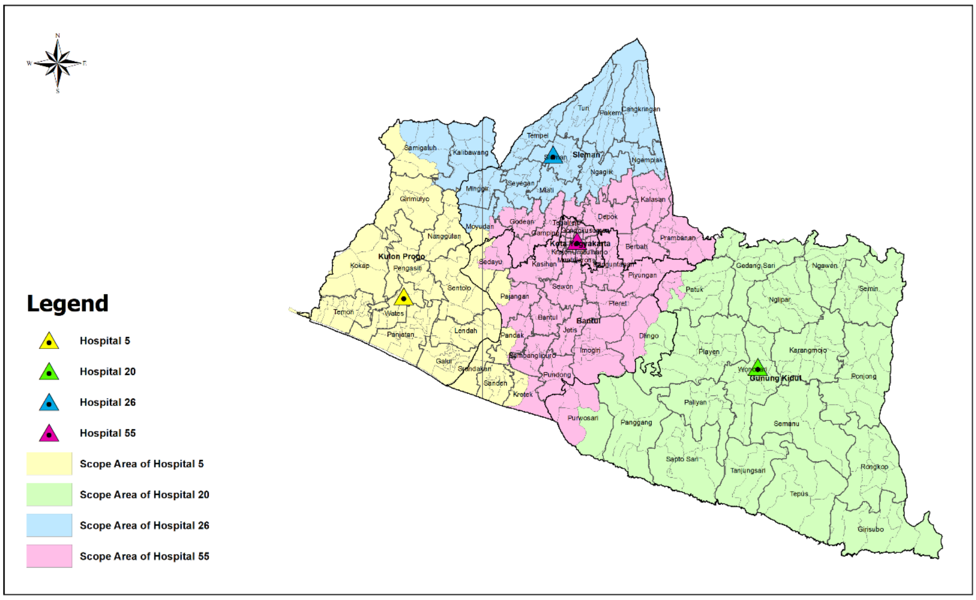
Table 1 Experiment results of the two scenarios (Con't)

Number of Facilities	Model without priority			Model with priority			$\Delta f1$ (%)	$\Delta f2$ (%)	$\Delta\sigma$ (%)
	Total Covered Demand $f1$(person)	Total Distance $f2$ (km)	Max - Min Distance Travelled σ (km)	Total Covered Demand $f1$ (person)	Total Distance $f2$ (km)	Max - Min Distance Travelled σ (km)			
49	3,656,922	2,272.05	26.71	3,654,883	2,243.00	26.71	-0.06%	-1.28%	0.00%
50	3,656,922	2,271.22	26.71	3,654,883	2,241.79	26.71	-0.06%	-1.30%	0.00%
51	3,656,922	2,270.45	26.71	3,654,883	2,241.02	26.71	-0.06%	-1.30%	0.00%
52	3,656,922	2,269.68	26.71	3,654,883	2,240.19	26.71	-0.06%	-1.30%	0.00%
53	3,656,922	2,269.20	26.71	3,654,883	2,239.71	26.71	-0.06%	-1.30%	0.00%
54	3,656,922	2,268.88	26.71	3,654,883	2,239.39	26.71	-0.06%	-1.30%	0.00%
55	3,656,922	2,268.88	26.71	3,654,883	2,239.39	26.71	-0.06%	-1.30%	0.00%
56	3,656,922	2,268.88	26.71	3,654,883	2,239.39	26.71	-0.06%	-1.30%	0.00%
57	3,656,922	2,268.88	26.71	3,654,883	2,239.39	26.71	-0.06%	-1.30%	0.00%
58	3,656,922	2,268.88	26.71	3,654,883	2,239.39	26.71	-0.06%	-1.30%	0.00%

The results indicate that generally the number of active facilities does not affect the total covered demand. Instead, it will have a significant impact on the pace of the vaccination process. Adding more active locations means increasing the pace of the vaccination process, in which more people can be vaccinated within a shorter period. In fact, each hospital usually has a limit on how many vaccinations can be performed daily, influenced by the capacity of the equipment, such as refrigerators, and the number of medical staff. Therefore, the decision to select the number of active locations could also consider the number of available vaccines and the number of allocated vaccines for the cities or provinces. Further, it is reported that there is no significant difference in the total covered demand criteria between both with and without priority models in all scenarios of the number of active facilities.

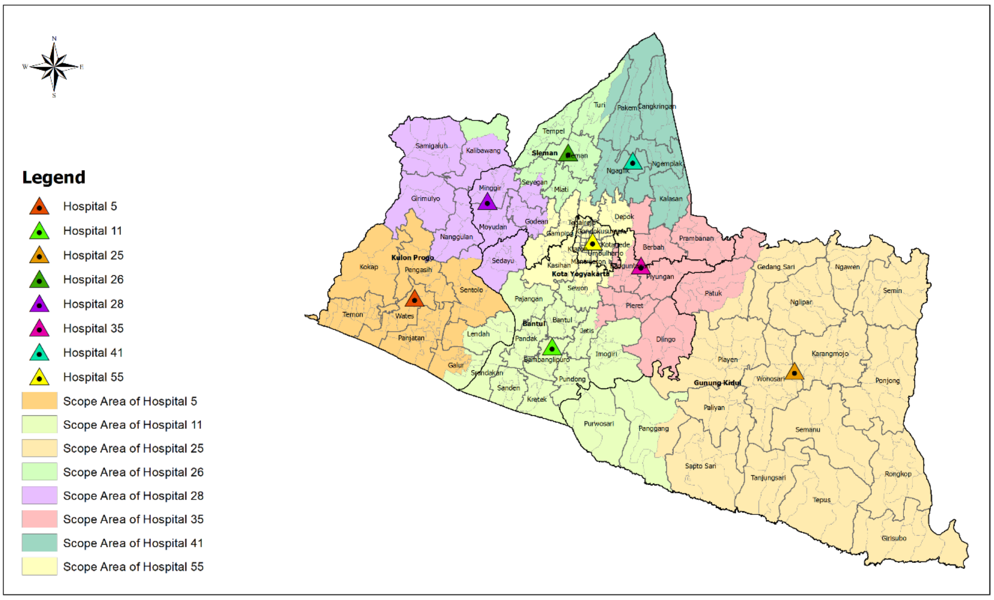
In terms of the total travelled distance, the difference in this criterion between the model with and without priority is significant when the number of facilities used for vaccination is small. The results also indicate that after a certain number of active locations are selected, adding more active locations does not significantly decrease the total travelled distance. The same trend is also observed for the max-min distance travelled. As the number of facilities increased, the difference between models with and without priority in max-min distance travelled $\Delta\sigma$ decreases, and at some point, there is no more difference between both models.

Further, **Figure 2** presents the illustrations of population assignment to hospitals when the numbers of active locations are $J = 4$ and $J = 8$. Each colour represents an area that is assigned to a hospital. Each hospital can be allocated with the same number of populations so that the same pace of vaccination process can be performed. Therefore, the hospital assigned to an area with higher population density will cover a smaller area than the hospital assigned to areas with lower population density. The latter case leads to a smaller average travelled distance of the residents.



Map Source:
Peta Badan Informasi Geospasial Indonesia

(a)



Map Source:
Peta Badan Informasi Geospasial Indonesia

(b)

Figure 2 Population assignment to the hospital with number of active locations (a) $J = 4$ and (b) $J = 8$

Whilst our model focuses on the vaccination coverage to minimise the total distance travelled by the population, in reality, vaccination in Yogyakarta has been conducted in many locations without pre-allocation of where people have to go to get vaccinated. In other words, people can be vaccinated in any available location (not only hospitals and health centres) with prior registration and subject to vaccine availability. In addition, the real vaccination capacity in each available location is not always consistent. Whilst some big hospitals could vaccinate up to hundreds of people per day, in some locations outside the hospitals, thousands of people can be vaccinated in a short period of time. Although this has accelerated the vaccination process and helped the government achieve the vaccination target, such an irregular pattern does not limit people's mobility across different areas with different numbers of cases. Some might argue that strict health protocols could minimise the transmission of COVID-19 virus amongst people in the crowded vaccination facilities. However, a potential risk of getting infected is still there if screenings are not accurately conducted for those who particularly have COVID-19 but showing no symptoms or those who are not honest with their COVID-19 related health conditions. In fact, there are already cases showing that the vaccines do not automatically protect people from getting the virus. Some people still get the virus even if they have been fully vaccinated (having two doses of vaccines). Whilst our proposed model does not cover such irregular patterns of vaccination in the field, it could be used as an alternative to minimise such risks by containing the mobility of people from high-risk areas to vaccination facilities. Selecting facilities with shorter travel distances could also help people reduce transport costs and make it easier for those who have disabilities or health conditions to access the facilities.

6. CONCLUSION

In this article, we address an important issue on the COVID-19 vaccine logistics by developing a mathematical model based on the concept of MCLP. The purpose of this model is to select the optimal location(s) to establish the vaccination facility among the set of candidate locations, so that these facilities can provide vaccination services to a set of demand nodes. Our proposed model comprises two objective functions: to maximise the coverage of vaccination effort and to minimise the total distance travelled by the recipients to get vaccinated. We also consider the partial coverage situation, in which a single demand node may be partially assigned to multiple vaccination facilities. To illustrate the effectiveness of our model, we execute our model using an illustrative case of COVID-19 vaccine distribution in Yogyakarta Province of Indonesia and provide our analysis based on the results. Our model shows an efficient coverage of vaccination by minimising the distances travelled by the target population in Yogyakarta. It also suggests that prioritising vaccination for areas with high COVID-19 cases results in a less efficient coverage.

Our novelty and therefore contributions are twofold. First, we demonstrate for the first time a model to determine the facilities for COVID-19 vaccination, which is unprecedented in nature. Our research could therefore serve as a lesson learnt for similar cases particularly in developing countries like Indonesia. Second, we model COVID-19 vaccination tasks using the MCLP paradigm that has been rarely adopted in the vaccination literature. Based on our results, we believe that MCLP could offer a flexible assignment of demand nodes to multiple vaccination facilities. Such flexibility is required and to some extent has been proven to be successful in speeding up the vaccination process in Indonesia particularly for the first and second doses of the COVID-19 vaccines.

Our research has several limitations. First, we use an illustrative case which might not fully represent what happens in the field. Second, we do not evaluate our model against the current practices of vaccine distribution in Yogyakarta so that direct comparison between the approaches is not possible. In other words, we treat our model as an alternative approach rather than a replacement of the existing practices. Future research could address these limitations and develop a more comprehensive and empirically validated model. This research can still be extended in various interesting and useful directions. First, the vaccination effort is typically done in a long planning horizon, in which the demand for vaccines might fluctuate from one period to the other. In this regard, extending our proposed model to consider multiple periods or stochastic demand may produce a more robust model. Second, future research should consider the integration of the routing aspect into our FLP model, which may result in a more comprehensive model for the last-mile distribution of COVID-19 vaccines. Third, one of the biggest challenges in the COVID-19 vaccine distribution is the requirement of cold-chain infrastructure to transport the vaccines (see Sujaree and Samattapapong, 2021; Hassan *et al*., 2021). Therefore, future research which considers the routing aspect of vaccine distribution should also take the cold-chain management into account. Finally, future research could also consider limitations to the number of vaccines and the number of people being vaccinated at the same time in each facility location as additional constraints to the model.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available upon reasonable request.

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Luluk Lusiantoro is a Lecturer within the Department of Management, Faculty of Economics and Business, Universitas Gadjah Mada. He received his MSc and Doctorate degree in Logistics and Supply Chain Management from Cranfield School of Management, Cranfield University, UK. His research focusses on operations, logistics, and supply chain sustainability, reliability, and resilience in various contexts including healthcare supply chains, humanitarian logistics, and supply chain for perishable products. In 2015, his project in the blood supply chain with National Health Service Blood and Transplant (NHSBT) won an MSc Dissertation of the Year from the Chartered Institute of Logistics and Transport, UK. He has published his works in reputable international journals including International Journal of Operations & Production Management, International Journal of Physical Distribution & Logistics Management, and Journal of Small Business and Enterprise Development.

Setyo Tri Windras Mara is a PhD student in The University of New South Wales (UNSW) at Australian Defence Force Academy, Canberra, Australia. He received his M.Sc and MBA degrees from a joint-degree program in Universitas Gadjah Mada and National Taiwan University of Science and Technology. His broad research interests include operational research, mathematical optimization, heuristics, and transportation science.

Achmad Pratama Rifai is currently a lecturer in the Department of Mechanical and Industrial Engineering, Universitas Gadjah Mada (UGM), Indonesia and is affiliated with the Production Process and System Laboratory. He completed his Ph.D. in integrated design engineering at Keio University, Japan in 2019. Earlier, he received his B.Eng. in industrial engineering from Universitas Gadjah Mada in 2011, and M.Eng. in manufacturing engineering from the University of Malaya, Malaysia in 2014. His research interests include manufacturing and production system, combinatorial optimization, and metaheuristics. Much of his work has been on the development of optimization methods for manufacturing system scheduling, plant layout, and routing problems. In addition, he also has interests in artificial intelligence, deep learning, computer vision, and pattern recognition, in particular for their application in manufacturing. He was involved in some research projects in Indonesia, Malaysia, and Japan in both manufacturing system and inspection domains. He has participated in international conferences and has published several articles in reputable journals indexed in Web of Science and Scopus in the field of computing, operation research, and manufacturing, such as Computers and Industrial Engineering, Multimedia Tools and Applications, Expert System with Applications, Journal of Industrial and Production Engineering, Applied Soft Computing, The International Journal of Advanced Manufacturing Technology, PLOS One, ASEAN Engineering Journal, and Measurement. He is active as a reviewer in various reputable international journals and conferences.