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Optimizing the Distribution and Allocation of COVID-19 Vaccines Using Mathematical Programming Approach: A Case Study in Indonesia

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A B S T R A C T

Effective distribution of COVID-19 vaccines is crucial for pandemic control. This study utilized a multi-product mixed-integer nonlinear programming (MINLP) model to optimize the distribution of five vaccine types across (AstraZeneca, Sinopharm, Moderna, Pfizer, and Sinovac). The population, segmented into five age groups (12-18 years, 19-30 years, 31-45 years, 46-59 years and over 60 years), accesses vaccines through 59 healthcare facilities in one of the large cities in Indonesia. With a budget of IDR 150 billion, the model procured five vaccine a total of 574,748 vaccine doses, distributed as follows: 112,954 of type 1, 115,733 of type 2, 115,649 of type 3, 112,171 of type 4, and 118,241 of type 5 vaccines. The model successfully optimized the distribution, achieving a delivery-to-demand ratio of 0.049, which reflects the proportion of vaccine demand met under various scenarios, particularly in scenario 4, which represents actual conditions. Decision-makers can further enhance vaccine allocation by adjusting the total budget; for instance, an additional IDR 10 billion would enable the distribution of 123,474 more doses, increasing the delivery-to-demand ratio to 0.056. This ratio of 0.056 was obtained by adjusting the total budget allocated for vaccine distribution in scenario 5, based on the results from AMPL and Gurobi software. A significant contribution of this study is the development of a MINLP model that ensures equitable distribution tailored to age-specific pandemic requirements. Validation using real-world data enhances the existing literature on vaccine distribution strategies. This study provides valuable insights for policymakers and managers aiming to optimize resource allocation and distribution strategies for COVID-19 vaccination programs, thereby improving overall pandemic management efficiency.

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1. INTRODUCTION

Mass vaccination is the main and most effective strategy in reducing the spread of COVID-19 (Shiri et al., 2022). As of January 19, 2022, approximately nine billion vaccine doses have been administered globally, which is an important milestone in the fight against the pandemic (World Health Organization, 2022). A universally implemented vaccination initiative could offer a long-term solution to the COVID-19 crisis (Deroo et al., 2020). The success of such a programme depends on various factors, including vaccine potency, efficient administration, equitable accessibility, and distribution (Su, McDonnell et al., 2021).

The pivotal phase of the mass vaccination effort lies in the production and dissemination of the COVID-19 vaccine. Such an endeavor demands meticulous planning and execution to meet the staggering demands. Public institutions must adeptly navigate and surmount all conceivable obstacles, including challenges in distribution and allocation. Hence, optimizing vaccine distribution emerges as a pivotal concern to bolster the global success of COVID-19 vaccination programs (Davahli et al., 2021).

Indonesia's healthcare facilities were under immense pressure due to the COVID-19 pandemic, especially at the height of the Delta variant in mid-2021. This unprecedented health crisis resulted in a surge of cases, causing hospitalization rates to increase significantly and overwhelming health facilities nationwide. The Indonesian government launched a mass vaccination initiative in January 2021, prioritizing healthcare workers and high-risk groups to mitigate the impact of the virus. By the end of 2022, more than 70% of the population had received at least one dose of the vaccine, thanks to coordinated efforts between central and local governments, as well as support from the private sector (Alam et al., 2021). Balikpapan City, one of the largest cities in Indonesia, was particularly hard hit during the height of the surge. According to the Kementerian Kesehatan Republik Indonesia Direktorat Jenderal Pencegahan dan Pengendalian Penyakit (2021), the increased vaccination coverage significantly contributed to a decrease in hospitalizations and deaths from COVID-19 in the region.

Several prior studies explored mathematical programming as a prevalent approach in modeling vaccine distribution. Notable research efforts include those by Abbasi et al. (2020), Bluth et al. (2022), Ma et al. (2021), Marie (2021), Matrajt (2020), and Shim (2021) have focused on COVID-19 vaccine distribution. Additionally Enayati & Özaltın (2020), Kim & Jung (2019), and Rastegar et al. (2021) have also contributed to this research. These authors proposed mathematical models for vaccine distribution, emphasizing population group prioritization (based on age or susceptibility) and optimal allocation strategies across various locations. Additional research by Georgiadis & Georgiadis (2021) for COVID-19 vaccines and Ng et al. (2018) for influenza vaccines aimed to minimize distribution costs, while work by Bertsimas et al. (2022), Bravo et al. (2022), Leithäuser et al. (2021), and Tang et al. (2022) focused on minimizing travel distances between vaccination sites and targets. Furthermore, investigations by Jahani et al. (2022), Soria-Arguello et al. (2021), and Sripada et al. (2021) pertained to COVID-19 vaccine optimization, while Lim et al. (2019), Yang et al. (2021), and Yang & Rajgopal, (2020) addressed World Health Organization-expanded programme on immunization (WHO-EPI) vaccine strategies. Finally, Li et al. (2019) developed an updated distribution network for optimizing vaccine dissemination.

The mathematical models proposed by Abbasi et al. (2020), Enayati & Özaltın (2020), Golan et al. (2021), Kim & Jung (2019), Lim et al. (2019), Rastegar et al. (2021), Sripada et al. (2021), and Tang et al. (2022) is a single-product model for vaccine distribution optimization for both influenza and COVID-19 vaccines that only uses one type of product. Thus studies did not incorporate the number of vaccines into the proposed mathematical model. Handling the COVID-19 pandemic globally involves using several types of vaccines. According to the literature review conducted, there is no research that specifically includes the type of vaccine in its analysis.

In this study, we present a multi-product mixed-integer nonlinear programming (MINLP) model designed to optimize the distribution of COVID-19 vaccines. The model seeks to ensure an equitable allocation by classifying the population into five distinct age groups. The local government's vaccination initiative enables elderly and pre-elderly individuals to receive their vaccines at the nearest healthcare facilities, while individuals from other age groups can access vaccinations at various sites. Key decision variables in our model include the distribution of vaccine doses to each age group, the selection of vaccination facilities, and the scheduling of vaccination sessions to maximize coverage and minimize waiting times.

The contribution of our paper are the following. Firstly, we developed a MINLP model that incorporates various types of COVID-19 vaccines to ensure fair and equitable distribution. Secondly, we enhanced the model by categorizing the population into five age groups for vaccination during the pandemic. Furthermore, our model advances existing frameworks by shifting the application context from influenza vaccines to COVID-19 vaccines and introducing greater technical complexity through the consideration of multi-product usage, which has not been addressed in previous models.

Finally, the remainder of this paper is organized as follows. In Section 1, we introduce our research on vaccine distribution, optimization, and mathematical programming. In Section 2, we provide a comprehensive review of previous studies on vaccine supply chain and vaccine distribution optimization using mathematical programming approach. In Section 3, we present the proposed mathematical model to show the applicability of the proposed method in this study. In Section 4, we present the case study, the data used, and the results. Section 5 contains conclusions and suggestions for future research.

2. LITERATURE REVIEW

2.1 Vaccine Supply Chain

Vaccination is one of the most effective ways to control infectious disease outbreaks. Vaccination is a medical intervention that is not possible without good logistics. Duijzer et al. (2018) introduced the identified vaccine supply chain including: product, production, allocation, and distribution. With an operations research perspective, the four categories were categorized by incorporating World Health Organization (WHO) priorities to realize a robust and flexible vaccine supply chain.

de Boeck et al. (2019) scrutinized the vaccine distribution chain, spanning from national stock to final procurement in various low- and middle-income nations. They noted a dearth of attention to distribution chain issues in operations research literature. Abila et al. (2020) contended that, drawing from past vaccination endeavors, the vaccine distribution chain remains a formidable obstacle in vaccine reception and dissemination. Their study underscores the necessity of early community involvement for equitable distribution in ongoing vaccination efforts.

Ocampo & Yamagishi (2020) asserted that mitigating potential pandemic losses hinges on vaccine availability. Thus, comprehensive planning and response are imperative to ensure equitable coverage for the entire population. Alizadeh (2021) elucidated that amidst the COVID-19 crisis, other health issues have taken a backseat in the healthcare sector, with relentless efforts directed towards pandemic combat. Given the urgency, COVID-19 vaccine distribution demands heightened sensitivity compared to other vaccinations.
Alam (2021) contended that the COVID-19 pandemic has posed substantial challenges to the vaccine supply chain, prompting significant disruptions. Their study identified 15 challenges crucial for shaping a resilient COVID-19 vaccine distribution network. Golan (2021) argued that the increasingly globalized vaccine supply chain faces potential bottlenecks that could precipitate systemic failure. Effective COVID-19 vaccination necessitates not only a robust supply chain for quality product manufacturing but also comprehensive coverage across the target population, transcending mere efficiency.

Rastegar et al. (2021) argued that an effective vaccine distribution chain requires an efficient overall structure, level of demand, vaccine inventory requirements. In addition, the identification of vaccine distribution locations is also very important. It can be used to distribute vaccines from the manufacturer to each consumer.

2.2 Vaccine Distribution Optimization Using Mathematical Programming Approach

A number of studies employed mathematical programming approach to optimize vaccine distribution. Ng et al. (2018) proposed a model to determine the ideal influenza vaccine allocation across vulnerable groups in various immunization programs. Their model advocated a strategy of initially evenly distributed mass vaccination, transitioning to targeted vaccination later, proving both cost-effective and efficient. Lim et al. (2019) utilized the mixed-integer programming (MIP) model to revamp the optimal expanded programme on immunization (EPI) vaccine distribution network in Africa, resulting in a new network that saves both time and costs.

Kim & Jung (2019) developed a mathematical model for the 2009 A/H1N1 influenza outbreak in South Korea, considering five age groups. Their research provided a sound strategy for prioritizing vaccinations based on age to mitigate the epidemic. Li et al. (2019) proposed a MINLP model to pinpoint vaccination station locations, factoring in travel distance, operational costs, and work schedules. The study's solution can identify vaccination sites, thus conserving public health resources.

Enayati & Özaltın (2020) delved into optimal influenza vaccine distribution within a heterogeneous population with several subgroups. Their mathematical model forecasted the required vaccine stock for future outbreaks. Abbasi et al. (2020) developed an MIP model to allocate vaccines in Australia, considering various factors. The result of their research yields policy recommendations for vaccine distribution based on different allocation scenarios.

Matrajt et al. (2020) utilized an age-graded mathematical model with an optimization algorithm to optimize vaccine allocation, enabling prioritization based on need. Georgiadis & Georgiadis (2021) devised an mixed-integer linear program (MILP) model to enhance the efficiency of the COVID-19 vaccine supply chain, increasing the number of vaccines transferred at each vaccination site.

Leithäuser et al. (2021) employed mathematical programming approach to determine optimal vaccination site locations, workforce requirements, and community access in Germany, minimizing distance to maximize vaccination efficiency. Ma et al. (2021) proposed an MIP model for vaccine allocation in New York City, prioritizing locations with higher vulnerability and prolonged outdoor exposure.

Marie et al. (2021) formulated a multi-objective linear programming model for COVID-19 vaccine distribution in Quezon City, prioritizing the elderly. Shim (2021) structured a mathematical model by age to allocate vaccines, significantly reducing pandemic deaths in South Korea.

Rastegar et al. (2021) introduced an MILP model for equitable influenza vaccine distribution, considering different human groups during the COVID-19 pandemic. Soria-Arguello et al. (2021) proposed a mathematical model for COVID-19 vaccine distribution in Mexico, optimizing the distribution network.

Sripada et al. (2021) developed a programming model for various aspects of vaccine distribution, yielding an optimal model useful for decision-making frameworks. Yang et al. (2021), Yang & Rajgopal (2020) designed mathematical models for vaccine EPI distribution network optimization in Sub-Saharan Africa.

Bravo et al. (2022) formulated a large-scale MIP model to meet vaccination demand while minimizing travel distance, improving access to vaccination sites. Jahani et al. (2022) devised a bi-objective nonlinear programming model for efficient COVID-19 vaccine distribution, considering different susceptibility levels.

Bertsimas et al. (2022) devised a bilinear, non-convex model to optimize COVID-19 vaccine distribution. Their model determines optimal vaccination site locations, crucial for mass vaccination programs. Bluth et al. (2022) developed an MIP model to schedule vaccine distribution and supply efficiently, aiming to minimize infection risks. Their model aids in decision-making regarding initial vaccine distribution.

Tang et al. (2022) addressed vaccination planning, optimizing travel distance and operating costs using the MILP model. Their model minimizes total vaccination recipient distance, ensuring optimal vaccination processes in Tongzhou's case study.

Through these studies, we can see that mathematical programming has become a very reliable approach to optimizing vaccine distribution.

3. METHOD

3.1 PROPOSED MODEL

3.1.1 Set and Indices

The set and indices included in the proposed model are shown in Table 1.

Table 1. Set and indices

Notation	Definition
$h \in H$	Demand
$v \in V$	Vaccine type
$g \in G$	Age group
$d \in D$	Distribution center
$t \in T$	Time period

3.1.2 Parameters

The parameters used in the proposed model are shown in Table 2.

Table 2. Parameters

Notation	Definition
DG_{gh}	Amount of vaccine needed for age group g at location h
SC_d	Set-up cost for distribution center d
PC_v	Purchase cost per dose of COVID-19 vaccine v
TC_{vdh}	Transportation cost per dose of COVID-19 vaccine v at distribution center d to location h
HC_{vh}	Storage cost per dose of COVID-19 vaccine v in location h
θ_g	Minimum percentage of age group g to be vaccinated
MC_{dt}	Maximum capacity of distribution center d to supply vaccine in period t
AB	Available budget
M	A big number

3.1.3 Decision Variables

The decision variables in the proposed model are shown in Table 3.

Table 3. Decision variables

Notation	Definition
p_{vght}	Integer variable, donates the number of vaccine v allocated to age group g at health facility h in period t
r_{vdht}	Integer variable, donates the number of vaccine v delivered from distribution center d to location h in period t
q_{vht}	Integer variable, donates the number of vaccine v stored at health facility h in period t

3.1.4 Objective Function and Constraints

The objective function in the mathematical model is as follows:

$$\text{maximize } Z = min \left\{ \frac{p_{vght}}{DG_{gh}} \right\} \tag{1}$$

The objective function (1) is adapted from the model developed by Rastegar et al. (2021), which is a mathematical model for influenza vaccine distribution during the COVID-19 pandemic. This adaptation aims to maximize the minimum delivery-to-demand ratio per age group at each demand point. The foundation of the objective function is that vaccine demand at each demand point is based on the delivery-to-demand ratio. This ratio serves as an objective function to illustrate the mathematical relationship between the amount of vaccine delivered and the amount of vaccine received.

$$\sum_{v \in V, t \in T} p_{vght} \geq \theta_g \, DG_{gh} \quad \forall g \in G, h \in H \tag{2}$$

Constraint (2) ensures that the COVID-19 vaccine is distributed to each age group at or above the coverage rate. This constraint guarantees that the number of vaccines allocated exceeds the total demand.

$$q_{vht} = \sum_{d \in D} r_{vdht} - \sum_{g \in G} p_{vght} \quad \forall v \in V, h \in H, t \in \{1\} \tag{3}$$

$$q_{vht} = q_{v,h,t-1} + \sum_{d \in D} r_{vdht} - \sum_{g \in G} p_{vght} \quad \forall v \in V, h \in H, t \backslash \{1\} \tag{4}$$

Constraint (3) aims to determine the supply of the COVID-19 vaccine at the point of demand in the first period, while constraint (4) addresses the supply in the following period. This is achieved by reducing the inventory of COVID-19 vaccine shipments by the number of vaccines allocated.

$$\sum_{h \in H} r_{vdht} \leq MC_{dt} \quad \forall v \in V, d \in D, t \in T \tag{5}$$

Constraint (5) ensures that the capacity of the distribution center is not exceeded by considering that the number of vaccines delivered remains within the specified limit.

$$r_{vdht} \leq M \;\omega_d \quad \forall v \in V, d \in D, h \in H, t \in T \tag{6}$$

Constraint (6) ensures that all potential distribution centers in this model can receive the vaccine. If a distribution center is not ready, it cannot receive any vaccine supply.

$$\sum_{d \in D} SC_d \;\omega_d + \sum_{v \in V, d \in D, h \in H, t \in T} PC_v \; r_{vdht} + \sum_{v \in V, d \in D, h \in H, t \in T} TC_{idh} \; r_{vdht} + \sum_{v \in V, h \in H, t \in T} HC_{ih} \, q_{vht} \leq AB \tag{7}$$

Constraint (7) aims to ensure that the provided budget is sufficient to cover the total cost of distributing the COVID-19 vaccine. The distribution cost includes purchasing, transportation, and storage expenses.

3.2 CASE STUDY AND DATA

The case study for this research focuses on Balikpapan City, one of the largest city in Indonesia. Balikpapan has a population of 672,328, making it relatively dense compared to other cities in the country (East Kalimantan Provincial Department of Population, Women's Empowerment, and Child Protection, 2022). In 2021, the local government initiated a vaccination program targeting the elderly and pre-elderly at nearby health facilities. A total of 59 healthcare facilities across the city served as vaccination points. The number of COVID-19 vaccine requirements for each age group is detailed in Table 4, while the coverage rates for each age group are shown in Table 5. The number of COVID-19 vaccine doses required per age group at the point of demand varies with the coverage rates for each group. The specific needs for each age group are detailed in Table 4.

Table 4. The demand for vaccine doses for each age group and each healthcare facility (not shown in full due to page limitations)

No.	Healthcare facility	Age group				
		1	2	3	4	5
		12-18 yo	19-30 yo	31-45 yo	46-59 yo	>60 yo
1	Baru Ilir	1385	2435	2816	1849	877
2	Baru Tengah	1974	3472	4015	2636	1250
3	Baru Ulu	2008	3532	4084	2681	1272
4	Marga Sari	906	1593	1842	1210	574
…	…	…	…	…	…	…
59	Klinik Prodia	183	316	302	235	92

Source: East Kalimantan Prov. Dept. of Population, Women's Empowerment, and Child Protection (2022)

Table 5. The coverage rate for each age group

	Age group				
	1	2	3	4	5
	12-18 yo	19-30 yo	31-45 yo	46-59 yo	>60 yo
Vaccinated	66,623	115,402	144,833	98,139	31,987
Target	81,103	141,376	173,357	109,661	51,091
Coverage rate	0.85	0.85	0.87	0.93	0.64

Source: Balikpapan City Health Office (2021)

The coverage rate represents the minimum level of vaccination required within a population. It is calculated by determining the ratio of vaccinated individuals to the target population within a specific age group. Table 5 presents the coverage rates for the five age groups.

4. RESULT

4.1 Model Outputs

Data processing was conducted using AMPL software (https://ampl.com/) in conjunction with the Gurobi solver (https://www.gurobi.com/) to implement the proposed mathematical model. The optimal value of the objective function is 0.049, which reflects the ratio of delivery to demand. With a budget of IDR 150 billion, a total of 574,748 doses of the COVID-19 vaccine can be distributed. This allocation consists of 112,954 doses of type 1 vaccine, 115,733 doses of type 2 vaccine, 115,649 doses of type 3 vaccine, 112,171 doses of type 4 vaccine, and 118,241 doses of type 5 vaccine. All potential distribution centers are eligible for use in the COVID-19 vaccine distribution effort. The optimal allocation of type 1 vaccine doses among various age groups is detailed in Table 6.

Table 6. The optimal number of type 1 vaccine doses allocated to all age groups and each healthcare facility in period 1 (not shown in full due to page limitations)

No.	Healthcare facility	Age group				
		1	2	3	4	5
		12-18 yo	19-30 yo	31-45 yo	46-59 yo	>60 yo
1	Baru Ilir	68	120	139	91	43
2	Baru Tengah	97	171	197	130	62
3	Baru Ulu	99	174	201	132	63
4	Marga Sari	45	79	91	60	29
…	…	…	…	…	…	…
59	Klinik Prodia	9	16	15	12	5

Table 7. The optimal number of type 1 vaccine doses shipped to all age groups and each healthcare facility in period 1 (not shown in full due to page limitations)

No.	Healthcare facility	Distribution center					
		1	2	3	4	5	6
		RS Bersalin Sayang Ibu	RS Medika Utama Manggar	RSUD Kanujoso Djatiwibowo	RS Restu Ibu	RS Siloam Balikpapan	RS Pertamina Balikpapan
1	Baru Ilir	461	0	0	0	0	0
2	Baru Tengah	657	0	0	0	0	0
3	Baru Ulu	669	0	0	0	0	0
4	Marga Sari	0	304	0	0	0	0
…	…	…	…	…	…	…	…
59	Klinik Prodia	0	57	0	0	0	0

Table 6 outlines the strategic distribution of COVID-19 vaccine doses across diverse age groups and health facilities over multiple time periods. It describes the allocation process to ensure each age group, including the initial cohort (12-18 years), receives an optimally calculated dosage. For example, the first health facility in this age group was allocated 68 doses of COVID-19 vaccine type 1 during the initial period.

Furthermore, Table 7 provides a detailed insight into the logistics of vaccine distribution from centralized centers to various health facilities. The table elucidates the distribution process, facilitating efficient vaccine supply throughout each period. Notably, distribution center 1 precisely delivered 461 doses of COVID-19 vaccine type 1 to health facility 1 during the first period.

Table 8 illustrates the critical inventory of COVID-19 vaccine doses stored at key distribution centers, essential for facilitating widespread distribution and mitigating the pandemic's impact on public health. Specifically, during the first period, healthcare facility 4 houses 304 doses of COVID-19 vaccine type 1, as recorded based on shipments and allocations.

Table 8. The optimal number of vaccine doses stored for each vaccine type in period 1

No.	Healthcare facility	Age group				
		1	2	3	4	5
		AstraZeneca	Sinopharm	Moderna	Pfizer	Sinovac
4	Marga Sari	0	0	0	0	304
7	Klinik Mulawarman	326	0	326	0	0
11	Teritip	0	808	0	0	0
12	Batu Ampar	0	0	0	1124	562
16	Karang Joang	0	0	626	0	0
17	Klinik Kimia Farma KM 5	0	0	33	0	0
26	Klinik Kimia Farma Karang Jati	0	165	0	0	0
29	RS Restu Ibu	0	0	746	0	0
30	Sumber Rejo	0	0	542	542	0
35	Klinik Mirabell	0	0	63	63	63
42	RSIA Asih	0	0	369	0	0
47	RS Medika Utama Permata	0	0	0	0	96
48	RS Pertamina Balikpapan	0	0	0	208	0
49	RS Dr. R. Hardjanto	0	0	0	0	199
50	RSUD Kota Balikpapan	0	0	0	0	336
52	Prapatan	0	347	0	0	0
53	RS Bhayangkara Balikpapan	0	216	0	216	216
54	Klinik Hesti Wira Sakti	0	0	0	678	0
57	BK Lanal Balikpapan	0	0	0	383	0

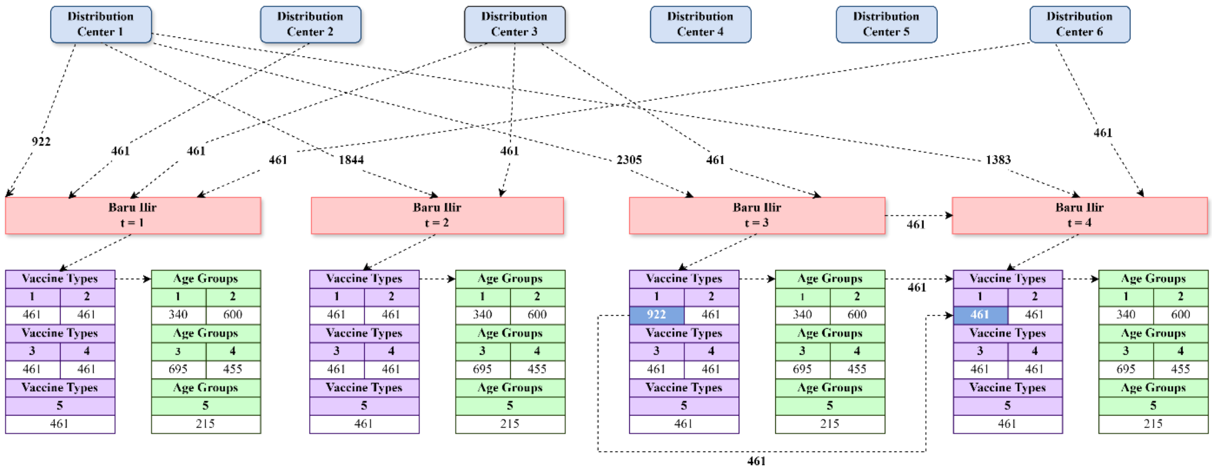

Figure 1. The visualization of vaccine doses allocated to each age group and each vaccine type at healthcare facility 1 in periods 1-4

Figure 1 illustrates the delivery of COVID-19 vaccine doses from various distribution centers to healthcare facility 1, specifically Baru Ulu, over four periods. The doses delivered were 2,305 in the first and second periods, 2,766 in the third period, and 1,844 in the fourth period. The 461 surplus doses from the third period were carried forward to the fourth period, resulting in healthcare facility 1 receiving a total of 2,305 doses in that period. The vaccine allocation for healthcare facilities is divided into five types, each tailored to different age groups. During the third period, Health Facility 1 received an excess of type 1 vaccine, leading to the transfer of 461 doses of type 1 vaccine to the fourth period.

4.2 Sensitivity Analysis

The sensitivity analysis conducted in this study investigates the allocation of budget resources concerning the distribution of COVID-19 vaccine doses. This detailed analysis involves varying budget inputs within the programming model, documented in Table 9. Through systematic adjustments to financial parameters, the study explores the effects of different budgetary allocations on the effective distribution of COVID-19 vaccine doses, offering critical insights into optimizing resource allocation strategies for vaccination programs.

Table 9. Several scenarios for sensitivity analysis

Scenario	Budget (in billion IDR)	Total number of vaccine doses purchased
S1	120	531,297
S2	130	542,433
S3	140	566,879
S4 (existing)	150	574,748
S5	160	698,222
S6	170	731,807
S7	180	793,020

In Table 9, scenarios S1, S2, and S3 illustrate cases where the total budget is lower than in scenario S4, which represents the actual situation. Conversely, scenarios S5, S6, and S7 depict instances where the total budget exceeds that of scenario S4. Therefore, it is clear that reducing the total budget results in a decrease in the allocated number of vaccine doses, while increasing the total budget leads to an increase in the number of vaccine doses allocated.

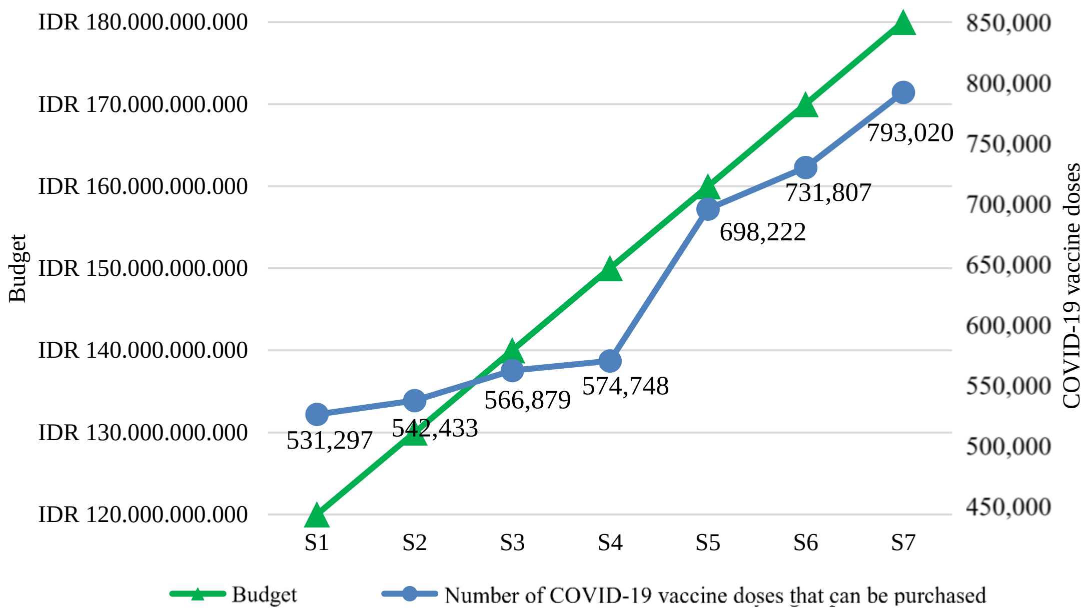

Figure 2. The total number of vaccine doses purchased for each scenario

Figure 2 illustrates how the government's budget allocation impacts the distribution of COVID-19 vaccines within the community. It influences both the quantity of vaccine doses allocated to various age groups and the distribution of different types of COVID-19 vaccines. Optimally, activating all five distribution centers would utilize a total budget of IDR 150 billion to procure 574,748 doses of COVID-19 vaccines across five distinct types. Increasing the budget by IDR 10 billion would enable an additional distribution of 123,474 doses throughout the chain, thereby raising the objective function from 0.049 to 0.056.

5. DISCUSSION

The results from our MINLP model provide a framework for optimizing COVID-19 vaccine distribution, corroborating previous research. Our optimal delivery ratio demonstrates an effective allocation process that fulfills demand, consistent with findings from Wen et al. (2023), which highlight the importance of strategic distribution in pandemic response. In contrast, our results differ from those of Ariyarajah et al. (2022), who identified logistical constraints and regional disparities as barriers to equity. This discrepancy underscores the need for continuous evaluation and adjustment of distribution strategies to ensure equitable access across different demographics.

The managerial implications for public health authorities are significant, as our model categorizes the population by age groups, allowing for the development of vaccination strategies tailored to different risk profiles. The data suggest that prioritizing certain demographics can improve resource utilization and increase vaccination rates. We recommend that the government develop guidelines based on these findings to ensure data-driven vaccination distribution that is adaptive to changing circumstances.

Our sensitivity analysis shows that variations in budget allocation and resource availability significantly affect the effectiveness of vaccine distribution strategies. These findings emphasize the importance of proactive planning to manage resource fluctuations, especially during public health emergencies. The vaccine delivery-to-demand ratio serves as an important indicator, reflecting the proportion of demand met at each point and highlighting the need for governments to prioritize resource allocation in developing an efficient logistics infrastructure for crisis response and ensuring equitable vaccine distribution Abila et al. (2020) and Georgiadis & Georgiadis (2021).

We recommend that reducing the budget for vaccine purchases decreases the percentage of public health needs met, underscoring the importance of strategic resource allocation. A limited budget reduces the supply-to-demand ratio, while an increased budget facilitates the procurement of additional doses, thereby enhancing the minimum supplied-to-demand ratio. These findings emphasize that the government should create contingency plans that allow for flexible resource allocation during health emergencies. Adjusting budgets based on demand fluctuations will enable public health authorities to optimize overall distribution.

6. CONCLUSION

We have developed a MINLP model to address the challenge of COVID-19 vaccine distribution. The model includes five different vaccine types and categorizes the population into five age groups: adolescents, young adults, middle-aged adults, older adults, and seniors. Validation was conducted through a case study in one of Indonesia's major cities, demonstrating that the model can be practically applied in real-world scenarios. The results indicate that, with sufficient budget allocation, the government can effectively procure a large number of vaccine doses and distribute them evenly across different vaccine types. The optimized objective function reflects a favorable delivery-to-demand ratio, highlighting the model's efficiency in resource allocation. Additionally, the sensitivity analysis shows the impact of budget adjustments on vaccine distribution across age groups, underscoring the importance of strategic financial planning in vaccination efforts.

Our research demonstrates that the development of this model can accommodate different types of vaccines and age groups, producing efficient and practical vaccine distribution strategies in real-world scenarios. However, to increase complexity and improve the accuracy of case study results, future research should consider adding more urgent constraints, such as variations in storage temperatures between vaccine types that require different cooling facilities, limited vaccine storage capacity in healthcare facilities, and the risk of vaccine degradation due to temperature fluctuations during transportation. Additionally, future research could take into account the varying expiration times of vaccines and optimize delivery schedules to ensure doses arrive on time and remain viable, contributing significantly to the model's improvement.

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APPENDIX A. CALCULATION OF MINIMUM DELIVERY-TO-DEMAND RATIO

Minimum delivery-to-demand ratio indicates the lowest proportion of vaccine demand that is met at each demand point, based on the delivery-to-demand ratio by age group. This study identifies that the minimum delivery-to-demand ratio is 0.049. The process to calculate this value is illustrated as follows.

The objective function is to maximize Z, which defined as the minimum ratio of vaccine deliveries (p_{vght}) to demand (DG_{gh}) across all age groups (g), health facilities (h), and time periods (t). The ratio is calculated as

$$\text{maximize Z} = \min\left\{\frac{p_{vght}}{DG_{gh}}\right\}. \tag{8}$$

Here, p_{vght} represents the integer decision variable denoting the number of doses of vaccine v alloocated to age group g at health facility h during period t. DG_{gh} represents the demand for vaccines by age group g at healt facility h. For multiple scenarios, example calculation is demonstrated as follows

$$= \min\left\{\frac{p_{v=1,\ g=1\, h=1\, t=1}}{DG_{g=1,\ h=1}}\right\}, \dots, \dots, \left\{\frac{p_{v=5,\ g=5,\ h=5,}}{DG_{g=5,\ h=5}} \tag{9}$$

where, in this calculation, each fraction represents the delivery-to-demand ratio for different combinations of vaccines, age groups, health facilities, and time periods. For instance, the calculation for the ratio includes

$$= \min\left\{\frac{68}{1385}\right\}, \left\{\frac{97}{1979}\right\}, \left\{\frac{99}{2008}\right\} \dots, \left\{\frac{5}{92}\right\} = 0.049. \tag{10}$$

The value of 0.049 in the above calculation is obtained by determining the minimum ratio of demand that can be met across different vaccine types, age groups, health facilities, and time periods. This ratio indicates the percentage of vaccine demand that can be fulfilled with the available budget in each scenario. In particular, this ratio represents the real-world scenario (S4) as shown in Table A1.

Table A1 presents the results for scenarios S1, S2, and S3, where the total allocated budgets are smaller compared to S4 (the real-world scenario with a budget of IDR 150 billion). As the budget decreases in these scenarios, the number of vaccine doses that can be purchased also decreases, resulting in a lower percentage of demand being met. Consequently, the minimum ratio in these scenarios is lower than in scenario S4. In contrast, scenarios S5, S6, and S7 show an increase in the total budget compared to S4. With a higher budget, the number of vaccine doses that can be purchased and distributed also increases.

Table A1. Calculation of minimum delivery-to-demand ratio

No.	Scenario	Budget (in billion IDR)	Total number of vaccines doses purchased	The difference in purchasable doses	Delivery-to-demand ratio
1	S1	120	531,297	43,451	0.042
2	S2	130	542,433	32,315	0.041
3	S3	140	566,879	7,869	0.035
4	S4	150	574,748	0	0.049
5	S5	160	698,222	-123,474	0.056
6	S6	170	731,807	-157,059	0.037
7	S7	180	793,020	-218,272	0.048

This results in a higher minimum ratio between the number of doses distributed and demand, meaning that a larger proportion of vaccine needs can be met. For example, in S4, with a budget of IDR 150 billion, the number of vaccine doses that can be purchased is 574,748, and the minimum ratio value is 0.049. If the budget is increased by IDR 10 billion in S5, the number of doses that can be purchased rises to 698,222, and the minimum ratio increases to 0.056. This illustrates that an increase in budget directly correlates with a higher proportion of vaccine needs being met. These scenarios demonstrate how changes in the budget impact the number of vaccine doses that can be allocated and the value of the minimum ratio, which reflects the efficiency of vaccine distribution in meeting demand. The number of doses allocated decreases if the total budget is reduced (as in scenarios S1 to S3) and, conversely, increases if the total budget is raised (as in scenarios S5 to S7). The ratio is calculated using a predefined formula, and the results vary based on the allocated budget. Table A1 provides the ratio calculations for each scenario with different budgets and delivery-to-demand ratio.