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ORIGINAL RESEARCH

A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries

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Abstract
Developing countries scramble to contain and mitigate the spread of coronavirus disease 2019 (COVID-19), and world leaders demand equitable distribution of vaccines to trigger economic recovery. Although numerous strategies, including education, quarantine, and immunization, have been used to control COVID-19, the best method to curb this disease is vaccination. Due to the high demand for COVID 19 vaccine, developing countries must carefully identify and prioritize vulnerable populations and rationalize the vaccine allocation process. This study presents a mixed-integer linear programming model for equitable COVID-19 vaccine distribution in developing countries. Vaccines are grouped into cold, very cold, and ultra-cold categories where specific refrigeration is required for their storage and distribution. The possibility of storage for future periods, facing a shortage, budgetary considerations, manufacturer selection, order allocation, time-dependent capacities, and grouping of the heterogeneous population are among the practical assumptions in the proposed approach. Real-world data is used to demonstrate the efficiency and effectiveness of the mathematical programming approach proposed in this study.

Keywords Vaccine supply chain · Coronavirus vaccine · Equitable distribution · Location-inventory problem · Mixed-integer linear programming model · COVID-19

1 Introduction

The Developing Countries Vaccine Manufacturers Network (DCVMN) is a public-health agency representing vaccine manufacturers from emerging countries. The DCVMN is committed to protecting all people through research and development activities and manufacturing and distributing coronavirus disease 2019 (COVID-19) vaccines to developing countries (Pagliusi et al., 2020). COVID-19 has stressed the importance of preventing pulmonary infections and stopping the pandemic with vaccinations (Dinleyici et al., 2020). The World Health Organization (WHO) statistics show that nearly 84,000,000 cases of

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the virus have been identified worldwide by the end of 2020, and about 1,800,000 people have lost their lives (https://coronavirus.jhu.edu). The coronavirus outbreak has drastically changed global social norms and has brought about disruptions in health services provision (Chandir et al., 2020). Since the beginning of the disease outbreak, various strategies such as border closure, social distance, widespread testing, and homestay have been proposed by statesmen, the WHO, and other relevant centers to reduce the virus's spread and cut its transmission chain (Coudeville et al., 2020). Some researchers, such as Govindan et al. (2020), have tried to reduce this disease's prevalence by classifying people in the community and offering solutions to each class of people. Although these protective measures are crucial to managing this disease, vaccination is a critical defensive behavior to control and eradicate it (Reiter et al., 2020). More than 100 companies are developing the COVID-19 vaccine worldwide, some of which are placed in phase III trials (Degeling et al., 2020). With the mass production of the vaccine, demand is expected to outstrip supply in the early stages. Therefore, the vaccine distribution process will be of great importance. Government budget constraints, cold supply chain management, prioritization of people in the community, and waiting time for receiving vaccines are essential factors affecting vaccine distribution worldwide. Therefore, this study develops a mixed-integer linear programming (MILP) model for equitable COVID-19 vaccine distribution considering the factors mentioned above.

Duijzer et al. (2018) examined the literature on the vaccine supply chain. They categorized these studies into the product, production, allocation, and distribution modeling groups by combining the WHO's priorities for creating a robust and flexible vaccine supply chain with an operations research perspective. Similarly, De Boeck et al. (2019) studied the vaccine distribution studies in low- and middle-income countries. They identified several problems that had received little or no attention in the operations research literature. They found operations researchers heavily concentrate on the strategic decisions in vaccine distribution chains and, to a lesser extent, tactical and operational decisions. Hovav and Tsadikovich (2015) used mathematical programming and proposed an optimization model to design a healthcare supply chain to control influenza vaccines' distribution and inventory control. Saif and Elhedhli (2016) developed a cold supply chain for the distribution and inventory management of vaccines considering environmental issues. For this purpose, they proposed a mixed-integer programming (MIP) model to minimize total costs and used a Lagrangian decomposition algorithm to solve the proposed model. Lim et al. (2019) proposed a MIP model for redesigning a cold supply chain for vaccine distribution by considering the location problem and limitations. They developed a hybrid heuristic algorithm for large-scale problem-solving and validated their model using several African countries' data. A bi-objective model was developed by Zandkarimkhani et al. (2020) to design a perishable pharmaceutical supply chain network and minimize total costs and lost demands. They used an integrated inventory-location-routing problem and developed a chain to distribute Avonex (prefilled syringe for multiple sclerosis disease).

One of the issues that should be considered in developing a vaccine distribution supply chain is the ambient temperature in which the vaccines are stored and transported. The transportation of vaccines at unfavorable temperatures has led to adverse events, especially in developing countries. Hence, Lin et al. (2020) proposed a model to solve this problem by implementing inspection strategies. Their intended chain includes distributors and retailers, and they analyze inspection policies of vaccines' transportation in the cold supply chain. Gamchi et al. (2020) presented a novel bi-objective model using the susceptible-infected-recovered epidemic model and vehicle routing problem for vaccine distribution. Their model simultaneously minimizes social costs and the costs of operating vehicles and groups of people in the community. They validated their model using data from a cholera vaccine distribution chain. Yang et al. (2020) developed a MIP model for vaccine distribution in low- and middle-income countries in line with the WHO Expanded Program on Immunization (EPI). Their model aims to minimize total costs with validation using data from a vaccine distribution chain in African countries. Bulula et al. (2020) used a micro-costing approach to analyze costs in the vaccine supply chain. They showed the delegation of the vaccine supply chain's responsibilities from the medical stores to the EPI would lead to a 27% reduction in the vaccine distribution and storage costs.

The trade-offs between the equitable allocation of resources have been studied in energy (Sasse & Trutnevyte, 2019), bicycle-sharing (Conrow et al., 2018), and food donation (Fianu & Davis, 2018; Orgut et al., 2016, 2017). Equitable distribution of resources must consider a fair sharing of the resources among recipients; however, studies emphasizing equitable distribution of resources are limited (Fianu & Davis, 2018). Equity and fairness are among the most critical issues to be considered in the vaccine distribution chain (Abila et al., 2020). In this regard, Enayati and Özaltın (2020) proposed a mathematical programming model for equitable influenza vaccine distribution. They divided the population into several subgroups and prevented the epidemic outbreaks by allocating the necessary vaccines to each subgroup equitably. Rastegar et al. (2021) went one step further and developed a MILP model for equitable influenza vaccine distribution by considering the location-inventory problem under pandemic COVID-19 conditions. The possibility of storage for future periods, being faced with a shortage, and budget constraints are among the practical assumptions considered in this research. They proposed a novel objective function to consider the concept of equitable distribution. They then evaluated their proposed model's performance using data from an influenza vaccine distribution chain in Iran.

The remainder of this paper is organized as follows. In Sect. 2, we present our motivation and contributions. The proposed mathematical model is presented in Sect. 3. In Sect. 4, we present a case study to demonstrate the applicability of the method proposed in this study. A sensitivity analysis is conducted in Sect. 5 to exhibit the efficacy and robustness of our vaccine distribution method. We conclude the paper with our conclusions and future research directions in Sect. 6.

2 Motivation and contributions

A review of the vaccine distribution literature shows the research in this field is in its infancy. Some researchers, such as De Boeck et al. (2019) and Corey et al. (2020), have studied strategic and managerial approaches to vaccine distribution. Other researchers such as Gamchi et al. (2020), Yang et al. (2020), and Rastegar et al. (2021) have proposed mathematical models for vaccine distribution and supply chain network optimization. Supply chains for vaccine distribution require unique features. For example, some vaccine distribution requires a cold or very cold supply chain (i.e., Gamchi et al., 2020; Lim et al., 2019; Yang et al., 2020). Other vaccine distributions may require waiting time considerations in the supply chain (i.e., Gamchi et al., 2020). There is also the concern for fair and equitable access to vaccines. Sometimes it is impossible to provide vaccines for all members of society. Therefore, equitable distribution becomes a critical consideration and assumption in vaccine distribution networks (Enayati & Özaltın, 2020; Rastegar et al., 2021). Distribution of COVID-19 vaccines requires cold, very cold, and ultra-cold refrigeration. Waiting time to receive the vaccines from manufacturers also directly affects the delivery of vaccines to the public. This study presents the first mathematical model for equitable COVID-19 vaccine distribution considering time-dependent capacity and triple refrigeration requirement (i.e., cold, very cold, and ultra-cold).

Rastegar et al. (2021) proposed a mathematical model for equitable influenza vaccine distribution. The current study presents a MILP model for equitable distribution of the COVID-19 vaccines. The model proposed by Rastegar et al. (2021) is a single-product model. However, the current study addresses the need for a multi-product model for COVID-19 vaccine distribution requiring cold, very cold, and ultra-cold refrigeration. Moreover, this study considers multiple cold supply chains with varying refrigeration requirements. This capability does not exist in the model proposed by Rastegar et al. (2021). The ordering and delivery times of vaccines can vary in the current study because of the potential waiting time between ordering and receiving the vaccines. However, the model proposed by Rastegar et al. (2021) does not consider waiting time because vaccines are provided in the same period they are ordered.

In summary, the contributions of this study are to (i) introduce a location-inventory MILP model for a fair and equitable COVID-19 vaccine distribution in developing countries; (ii) propose a model to consider cold, very cold, and ultra-cold supply chain network design and; (iii) take into consideration an equitable vaccine distribution model capable of manufacturer selection, order allocation, capacity planning, and waiting time management; and (iv) validating the proposed model with real-world data.

3 Proposed model

Satisfying the global demand for COVID-19 vaccines is not a short-term problem due to limited production and supply. Consequently, vaccine delivery is subject to the waiting time. This study presents a MILP model for equitable COVID-19 vaccine distribution in developing countries by considering the location-inventory problem. In addition to limited production and supply constraints, the refrigeration requirement for the COVID-19 vaccine and the need for cold, very cold, and ultra-cold supply chains is a huge hurdle in developing countries. Furthermore, the need for grouping and prioritizing the population is another added complexity for the COVIS-19 vaccine distribution. The proposed model is considered a budget constraint and allows the applicant country to make the following customizations to the model: Which manufacturer should be selected? What period should the vaccine be ordered to the manufacturer, and how much? What is the waiting time for each manufacturer? Which distribution centers are needed? Which distribution centers need ultra-cold refrigeration equipment? How many vaccines should be transferred from distribution centers to warehouses in different states in each period? How many vaccines should be stored in the state warehouses in each period? How many vaccines should be allocated to each group in each state and period?

To better understand the problem under study, the assumptions of the proposed model are given as follows:

- The proposed model is considered as multi-product and multi-period.
- The model determines the location of distribution centers.
- The established distribution centers can handle cold and very cold refrigeration.
- Ultra-cold refrigeration can only be installed in previously established distribution centers equipped with very cold refrigeration.
- An order can be placed after an existing order is received.

- One order can be placed with each manufacturer in each period.
- Time-dependent capacity is considered for the manufacturers.
- Distribution centers are capacitated.
- Each manufacturer produces only one type of vaccine.
- The possibility of storage in the state warehouses for future periods is considered.
- The possibility of facing a shortage is considered.

3.1 Mathematical model

Indices	
i	Vaccine type
d	Distribution center
s	State
g	Group type
$w, \hat{w}$	Period (ordering time)
$t, \hat{t}$	Period (delivery time)

Parameters	
DM_{gs}	The total demand of group g for COVID-19 vaccines in state s
$VR_i \begin{cases} 1 \\ 0 \end{cases}$	If vaccine i requires very cold or ultra-cold refrigeration Otherwise (vaccine i requires cold refrigeration)
$VT_i \begin{cases} 1 \\ 0 \end{cases}$	If vaccine i requires ultra-cold refrigeration Otherwise (vaccine i requires very cold refrigeration)
FX_{it}^{MN}	The ordering cost to the manufacturer of vaccine i in period t
FY_d^{DS}	The set-up cost of the distribution center d equipped with cold refrigeration
FX_d^{DS}	The set-up cost of the distribution center d equipped with very cold refrigeration
EXC	The additional cost required to convert very cold refrigeration to ultra-cold refrigeration in a distribution center
VP_i	The purchasing cost of two-doses of vaccine i
TR_{id}^{MN}	The transportation cost of two-doses of vaccine i from manufacturer location to distribution center d
TR_{ids}^{DS}	The transportation cost of two-doses of vaccine i from distribution center d to the warehouse is state s
HC_{is}	The holding cost for two-doses of vaccine i in the state warehouse s
CP_{iwt}^{MN}	The maximum vaccine i production capacity, if ordering and delivery time are in periods w and t, respectively
CP_d^{NR}	The maximum distribution center d capacity for cold refrigeration vaccines
CP_d^{DFR}	The maximum distribution center d capacity for vaccines requiring ultra-cold refrigeration
CP_d^{SR}	The maximum distribution center d capacity for vaccines requiring very cold refrigeration
ξ_g	The minimum percentage coverage rate for group g
Φ	Available budget
$bigM$	A big number

Variables		
$X_{iwt}^{MN}\begin{cases}1\\0\end{cases}$	*Binary*	$\begin{cases}\text{If the manufacturer of vaccine } i \text{ is ordered in period } w \text{ to receive the vaccine in period } t\\\text{Otherwise}\end{cases}$
$Y_{d}^{DS}\begin{cases}1\\0\end{cases}$	*Binary*	$\begin{cases}\text{If distribution center } d \text{ is capable of handling vaccines requiring cold refrigeration}\\\text{Otherwise}\end{cases}$
$X_{d}^{DS}\begin{cases}1\\0\end{cases}$	*Binary*	$\begin{cases}\text{If distribution center } d \text{ is set up for vaccines requiring very cold refrigeration}\\\text{Otherwise}\end{cases}$
$X_{d}^{EX}\begin{cases}1\\0\end{cases}$	*Binary*	$\begin{cases}\text{If equipment of ultra - cold refrigeration is added to distribution center } d\\\text{Otherwise}\end{cases}$
Y_{idwt}	*Integer*	The doses of vaccines i ordered in period w by distribution center d received in period t
u_{idt}	*Integer*	The doses of vaccines i allocated to distribution center d in period t
μ_{igst}	*Integer*	The doses of vaccines i allocated to group g in state s in period t
ψ_{ist}	*Integer*	The doses of vaccines i stored in the warehouse of state s in period t
θ_{idst}	*Integer*	The doses of vaccines i shipped from distribution center d to warehouse of state s in period t

3.2 Objective function

$$Max\ Z = Min\left\{\frac{\sum_{i,t} \mu_{igst}}{DM_{gs}}\right\} \tag{1}$$

The proposed model's objective function is derived from the model presented by Rastegar et al. (2021) that focuses on the equitable distribution of the vaccine. In this objective function, vaccines are distributed based on maximizing the minimum delivery-to-demand ratio.

$$s.t.$$

$$\sum_{i,t} \mu_{igst} \geq \xi_g \times DM_{gs} \qquad \forall g, s \tag{2}$$

Constraint (2) ensures that each group receives the vaccine at least up to the coverage rate.

$$\psi_{ist} = \sum_{d} \theta_{idst} - \sum_{g} \mu_{igst} \qquad \forall i, s, t = 1 \tag{3}$$

$$\psi_{ist} = \psi_{is(t-1)} + \sum_{d} \theta_{idst} - \sum_{g} \mu_{igst} \qquad \forall i, s, t > 1 \tag{4}$$

Constraints (3) and (4) are related to the inventory balance in the state warehouses in period 1 and the periods greater than one, respectively.

$$\sum_{d} Y_{idwt} \leq CP^{MN}_{iwt} \qquad \forall i, w, t \tag{5}$$

Not exceeding the capacity of vaccine manufacturers has been shown by constraint (5).

$$\sum_{i} u_{idt} \times (1 - VR_i) \leq CP^{NR}_{d} \times Y^{DS}_{d} \qquad \forall d, t \tag{6}$$

$$\sum_{i} u_{idt} \times VR_i \times (1 - VT_i) \leq CP^{SR}_{d} - CP^{DFR}_{d} \times X^{EX}_{d} \qquad \forall d, t \tag{7}$$

$$\sum_{i} u_{idt} \times VR_i \times VT_i \leq CP^{DFR}_{d} \times X^{EX}_{d} \qquad \forall d, t \tag{8}$$

Not exceeding the distribution centers' capacity of cold, very cold, and ultra-cold refrigeration is guaranteed in constraints (6) to (88), respectively.

$$Y_{idwt} \leq bigM \times X^{MN}_{iwt} \qquad \forall i, d, w, t \tag{9}$$

The condition for the purchase of vaccines from manufacturers is that the order should be placed with the manufacturer. This condition is considered in constraint (9).

$$Y_{idwt} \leq bigM \times Y^{DS}_{d} \qquad \forall i, d, w, t \tag{10}$$

$$Y_{idwt} \leq bigM \times X^{DS}_{d} \qquad \forall i, d, w, t \tag{11}$$

According to constraint (10), if a distribution center with proper equipment for cold refrigeration vaccines has not been set up, it will not receive orders from manufacturers. Similarly, based on the constraint (11), if a distribution center has not been equipped with very cold and ultra-cold refrigeration, it will not receive orders from manufacturers.

$$\sum_{w} X^{MN}_{iwt} \leq 1 \qquad \forall i, t \tag{12}$$

One order can be placed with each manufacturer in each period. This condition is satisfied by constraint (12).

$$\theta_{idst} \times (1 - VR_i) \leq bigM \times Y^{DS}_{d} \qquad \forall i, d, s, t \tag{13}$$

$$\theta_{idst} \times VR_i \times (1 - VT_i) \leq bigM \times X^{DS}_{d} \qquad \forall i, d, s, t \tag{14}$$

$$\theta_{idst} \times VR_i \times VT_i \leq bigM \times X^{EX}_{d} \qquad \forall i, d, s, t \tag{15}$$

$$X^{EX}_{d} \leq bigM \times X^{DS}_{d} \qquad \forall d \tag{16}$$

According to the location conditions, if a distribution center with proper equipment for cold refrigeration vaccines has not been set up, it will not be allowed to send cold refrigeration vaccines to the states' warehouses. This condition is considered in constraint (13). Also, if a distribution center equipped with very cold refrigeration has not been set up, it will not be allowed to send very cold refrigeration vaccines to the states' warehouses. Similarly, suppose a distribution center equipped with ultra-cold refrigeration has not been set up. In that case, that distribution center will not send ultra-cold vaccines to the states' warehouses. These conditions are considered in constraints (14) and (15), respectively. Moreover, there is no possibility of setting up the distribution centers equipped with ultra-cold refrigeration until the distribution centers equipped with very cold refrigeration are set up. This condition is also expressed by constraint (16).

$$u_{idt} \leq \sum_{s} \theta_{idst} \qquad \forall i, d, t \tag{17}$$

$$u_{idt} = \sum_{w} Y_{idwt} \qquad \forall i, d, t \tag{18}$$

The amount of vaccines delivered to each distribution center in each period is calculated by constraint (14). Constraint (15) is responsible for establishing the inventory balance in distribution centers.

$$\sum_{\hat{t}>w}^{\hat{t}<t} \sum_{\hat{w}\leq\hat{t}} X^{MN}_{i\hat{w}\hat{t}} \leq bigM \times (1 - X^{MN}_{iwt}) \qquad \forall i, w, t \tag{19}$$

As long as the order is being processed (i.e., it has not yet been delivered to the distribution center), it will not be possible to place a new order with that manufacturer. This condition is satisfied by constraint (16).

$$\sum_{i} X^{MN}_{iwt} = 0 \qquad \forall w > t \tag{20}$$

In all the constraints of the proposed model, the ordering time should always be less than or equal to the delivery time. Constraint (17) has been used to meet this condition.

$$\sum_{i,w,t} FX^{MN}_{it} \times X^{MN}_{i,w,t} + \sum_{d} FY^{DS}_{d} \times Y^{DS}_{d} + \sum_{d} FX^{DS}_{d} \times X^{DS}_{d} + \sum_{d} EXC \times X^{EX}_{d} + \sum_{i,d,w,t} VP_{i} \times Y_{idwt} + \sum_{i,d,t} TR^{MN}_{id} \times u_{idt} + \sum_{i,d,s,t} TR^{DS}_{ids} \times \theta_{idst} + \sum_{i,s,t} HC_{is} \times \psi_{ist} \leq \Phi \tag{21}$$

In the end, constraint (18) states that the supply chain's total costs should not exceed the available budget. These costs include ordering cost to manufacturers, set-up cost of distribution centers for cold refrigeration, very cold refrigeration, and ultra-cold refrigeration vaccines, purchasing cost of vaccines, transportation cost from manufacturers' location to distribution centers, transportation cost from distribution centers to state warehouses, and holding cost at the state warehouses.

As can be seen, the objective function of the proposed model is nonlinear. To linearize it, we define a new free variable (ϖ) and replace it with $Min\left\{\frac{\sum_{i,t} \mu_{igst}}{DM_{gs}}\right\}$. Therefore, the following holds true:

$$\varpi = Min\left\{\frac{\sum_{i,t} \mu_{igst}}{DM_{gs}}\right\} \tag{19}$$

Based on Eq. (19), the following formula always holds true:

$$\varpi \le \left\{\frac{\sum_{i,t} \mu_{igst}}{DM_{gs}}\right\} \qquad \forall g, s \tag{20}$$

Therefore, based on Eq. (19) and Eq. (20), the proposed nonlinear model is converted to a linear one as follows:

$$Max\ Z = \varpi \tag{21}$$

$$s.t.$$

$$\varpi \le \left\{\frac{\sum_{i,t} \mu_{igst}}{DM_{gs}}\right\} \qquad \forall g, s \tag{22}$$

Constraints (2) to (18).

4 Case study

This section demonstrates the applicability of the model proposed in this study with the data obtained from the Ministry of Health and Family Welfare (MOHFW) in India. COVID-19 vaccines have been discovered not so long ago, and, thereby, adequate information and data on their distribution are not yet fully available and accessible. As a result, some data, including transportation costs, vaccine prices, and manufacturers' capacities, are simulated based on the MOHFW's preliminary estimations. As in the study carried out by Rastegar et al. (2021), the heterogeneous population in this study is also divided into eight groups. The group numbers are not representative of priorities. These group numbers simply identify a segment of the population:

- Group (1): infants and toddlers ages 6–35 months,
- Group (2): pregnant women with pre-existing medical conditions,
- Group (3): adults aged 65 years and older with pre-existing medical conditions,
- Group (4): critical healthcare providers and first responders,
- Group (5): pregnant women without pre-existing conditions,
- Group (6): adults aged 65 years and older without pre-existing medical conditions,
- Group (7): people with pre-existing medical conditions, and
- Group (8): other people.

This study considers five vaccine types. Vaccine types 1 and 2 require ultra-cold refrigeration (−70 °C ± 10 °C), vaccine types 3 and 4 require very cold refrigeration (−25 °C

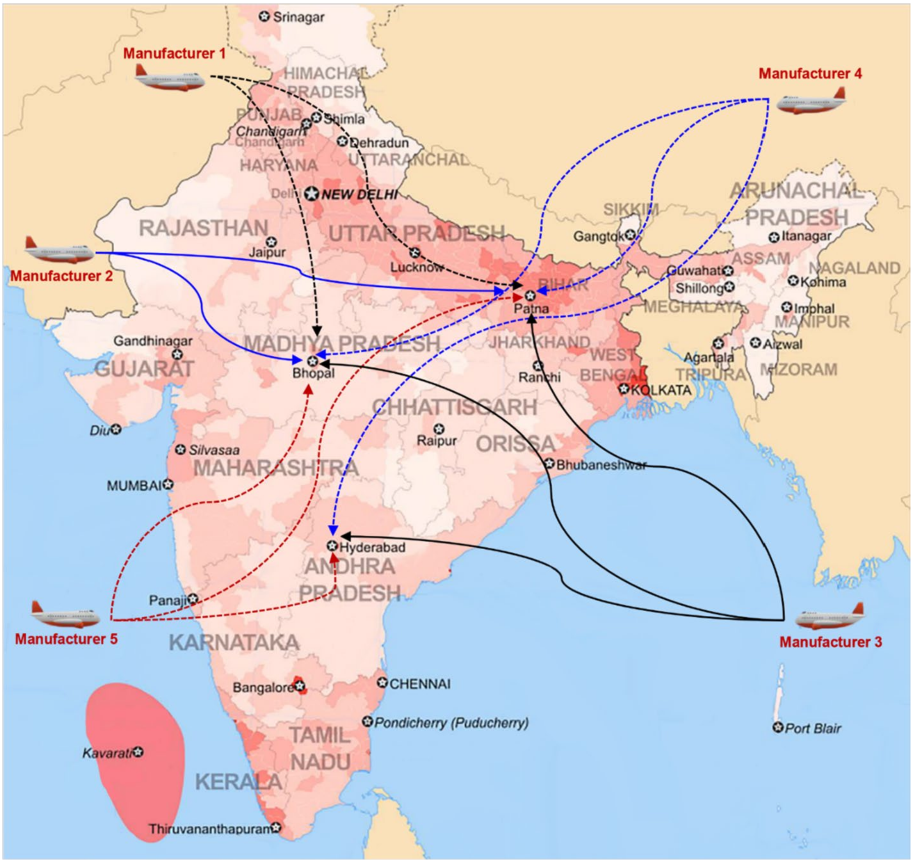

Fig. 1 The vaccine distribution network

to – 15 °C), and vaccine type 5 requires cold refrigeration (– 8 °C to – 2 °C). The vaccines are purchased from manufacturers outside India and are then transported to distribution centers. Afterward, vaccines are shipped to different distribution centers and distributed equitably among multiple warehouses in multiple states according to demand (See Fig. 1).

We should note data such as the demand for each group in each state, holding cost for the vaccines, coverage rate, and transportation cost between distribution centers and states have been extracted from historical data proposed by the MOHFW. Furthermore, the MOHFW's estimated budget for vaccine purchase and distribution is 4.5 billion dollars. Table 1 presents the vaccine manufacturers' capacities. Additional data is provided in Appendix A (Tables 8, 9, 10, 11, 12, 13, 14, 15 and 16).

The 7,500,000 in the first row of Table 1 indicates that if the order is placed to manufacturer 1 in period 1, the manufacturer will deliver a maximum of 7,500,000 doses of vaccines in period 3. The proposed model was run with the described data in GAMS software using CPLEX solver. The obtained results are as follows:

- Distribution centers in Patna, Bhopal, and Hyderabad were set up to distribute the vaccines. Patna and Bhopal distribution centers can distribute vaccines requiring cold, very

Table 1 The maximum delivery capacity of vaccine i for period t ordered in period w

CP_{iwt}^{MN}		t							
i	w	1	2	3	4	5	6	7	8
1	1	0	0	7,500,000	10,000,000	15,000,000	19,000,000	25,000,000	30,000,000
1	2	0	0	3,000,000	7,000,000	11,000,000	15,000,000	20,000,000	25,000,000
1	3	0	0	0	5,000,000	9,000,000	13,000,000	18,000,000	22,000,000
1	4	0	0	0	0	5,000,000	9,000,000	15,000,000	20,000,000
1	5	0	0	0	0	0	7,500,000	12,500,000	17,500,000
1	6	0	0	0	0	0	0	6,000,000	10,000,000
1	7	0	0	0	0	0	0	0	15,000,000
1	8	0	0	0	0	0	0	0	2,500,000
2	1	0	6,000,000	15,000,000	20,000,000	28,000,000	32,000,000	40,000,000	60,000,000
2	2	0	0	10,000,000	14,000,000	20,500,000	27,000,000	35,000,000	42,000,000
2	3	0	0	0	8,000,000	13,500,000	20,000,000	27,500,000	34,000,000
2	4	0	0	0	0	12,000,000	18,000,000	25,500,000	32,000,000
2	5	0	0	0	0	0	9,500,000	16,000,000	30,000,000
2	6	0	0	0	0	0	0	10,000,000	25,000,000
2	7	0	0	0	0	0	0	0	20,000,000
2	8	0	0	0	0	0	0	0	0
3	1	0	4,000,000	7,000,000	13,000,000	20,000,000	25,000,000	30,000,000	35,000,000
3	2	0	0	4,000,000	8,000,000	15,000,000	20,000,000	25,000,000	30,000,000
3	3	0	0	0	5,000,000	9,000,000	15,000,000	21,000,000	25,000,000
3	4	0	0	0	0	4,000,000	8,000,000	14,000,000	19,000,000
3	5	0	0	0	0	0	4,000,000	8,000,000	15,000,000
3	6	0	0	0	0	0	0	6,000,000	9,000,000
3	7	0	0	0	0	0	0	0	5,000,000
3	8	0	0	0	0	0	0	0	0
4	1	0	4,000,000	7,000,000	11,000,000	17,500,000	21,000,000	27,500,000	34,000,000
4	2	0	0	1,500,000	3,000,000	6,000,000	8,750,000	11,250,000	15,500,000
4	3	0	0	0	2,000,000	3,750,000	6,000,000	8,750,000	11,500,000
4	4	0	0	0	0	1,500,000	3,000,000	4,500,000	6,000,000
4	5	0	0	0	0	0	5,000,000	8,000,000	11,000,000
4	6	0	0	0	0	0	0	2,000,000	5,250,000
4	7	0	0	0	0	0	0	0	6,000,000
4	8	0	0	0	0	0	0	0	0
5	1	0	5,000,000	9,000,000	14,000,000	18,000,000	25,000,000	30,000,000	36,000,000
5	2	0	0	4,000,000	7,500,000	12,000,000	16,000,000	22,000,000	27,000,000
5	3	0	0	0	4,000,000	7,500,000	13,000,000	18,000,000	24,000,000
5	4	0	0	0	0	4,000,000	8,000,000	13,000,000	20,000,000
5	5	0	0	0	0	0	5,000,000	10,000,000	16,000,000
5	6	0	0	0	0	0	0	6,000,000	12,000,000
5	7	0	0	0	0	0	0	0	7,000,000
5	8	0	0	0	0	0	0	0	0

cold, and ultra-cold refrigeration, whereas Hyderabad distribution center can distribute vaccines requiring cold and very cold refrigeration.
- Orders are placed with all five manufacturers. Patna and Bhopal distribution centers receive vaccines from all five manufacturers, but vaccines are purchased only from manufacturers 3, 4, and 5 for the Hyderabad distribution center.
- With the available budget of 4.5 billion dollars, 186,096,615 doses of COVID-19 vaccines were purchased. The optimal doses of vaccines ordered to each manufacturer and the optimal doses of vaccines delivered by each distribution center are shown in Tables 2 and 3, respectively.

For example, 7,500,000 in the first row of Table 2 indicates that distribution center 1 (Patna) has ordered type 1 vaccine in period 1 and received 7.5 million doses of vaccines in period 3.

The numbers included in Table 3 indicate the optimal doses of vaccines delivered to each distribution center in different periods. For example, 11,123,260 in the first row and last column of this table suggests that 11,123,260 doses of vaccine type 1 have been delivered to the Patna distribution center in period 8. Table 2 shows that this order has been placed in period 7.

- The optimal doses of vaccines assigned to group 1 are given in Table 4. Similarly, in Appendix B (Tables 17, 18, 19, 20, 21, 22 and 23), the optimal doses of vaccines allocated to groups 2 to 8 are presented, respectively.
- The optimal doses of vaccines shipped from distribution centers to the state warehouses in each period are shown in Table 5.
- Finally, Table 6 presents the number of vaccine doses stored in the state warehouses in each period.

For example, 3,967,289 in the first row of Table 5 represents the number of type 1 vaccine doses shipped from Patna distribution center to state 1 (Uttar Pradesh) in period 3. Figure 2 presents the total doses of vaccines delivered to each state.

The following items have been depicted in Fig. 3 to provide a more accurate interpretation of the obtained result: the optimal doses of vaccines purchased from each manufacturer by the distribution centers, the optimal doses of vaccines assigned to the Kerala State to each group in each period, and the optimal doses of vaccines shipped from the Hyderabad distribution center to the Kerala State in each period.

The results presented in Fig. 3 show that a total of 186,096,615 double-dose vaccines have been purchased from each of the five manufacturers, where 85,096,615 vaccines required ultra-cold refrigeration, 66,000,000 vaccines required very cold refrigeration, and the remainder required cold refrigeration. From the total purchased vaccine, 111,668,835 and 44,965,339 double-dose vaccines have been allocated to the Patna and Bhopal distribution centers, respectively. The remaining 29,462,441 double-dose vaccines have been allocated to the Hyderabad distribution center. In addition, the equitable vaccine distribution in Kerala State is depicted in this figure. 1,397,340 double-dose vaccines are transferred to this state from the Hyderabad distribution center in period 4, out of which 1,387,340 vaccines were assigned to group 1, and the remaining 9793 vaccines were allocated to group 2. Similarly, vaccines assigned to each group in periods 5 to 8 are shown in this figure. It is worth noting again some parameters, including transportation costs, vaccine prices, and manufacturing capacities, have

Table 2 The optimal doses of vaccines delivered to distribution centers in each period

Y_{idwt}			t						
i	d	w	2	3	4	5	6	7	8
1	1	1	0	7,500,000	0	0	0	0	0
1	1	6	0	0	0	0	0	6,000,000	0
1	1	7	0	0	0	0	0	0	11,123,260
1	2	3	0	0	0	0	10,488,400	0	0
1	2	7	0	0	0	0	0	0	3,876,740
2	1	1	0	13,011,028	0	0	0	0	0
2	1	3	0	0	0	0	0	16,736,140	0
2	1	7	0	0	0	0	0	0	9,756,236
2	2	1	0	1,988,972	0	0	0	0	0
2	2	3	0	0	0	0	0	4,615,839	0
3	1	1	4,000,000	0	0	0	0	0	0
3	1	2	0	3,812,266	0	0	0	0	0
3	1	3	0	0	3,518,782	0	0	0	0
3	1	4	0	0	0	4,000,000	0	0	0
3	1	5	0	0	0	0	1,289,245	0	0
3	1	6	0	0	0	0	0	338,181	0
3	1	7	0	0	0	0	0	0	3,389,863
3	2	3	0	0	286,488	0	0	0	0
3	2	5	0	0	0	0	2,710,755	0	0
3	2	6	0	0	0	0	0	5,491,595	0
3	2	7	0	0	0	0	0	0	1,610,137
3	4	2	0	187,734	0	0	0	0	0
3	4	3	0	0	1,194,730	0	0	0	0
3	4	6	0	0	0	0	0	170,224	0
4	1	1	0	0	0	0	0	0	11,522,299
4	2	1	0	0	0	0	0	0	4,080,327
4	4	1	0	0	0	0	0	0	18,397,374
5	1	2	0	3,690,682	0	0	0	0	0
5	1	3	0	0	1,405,615	0	0	0	0
5	1	4	0	0	0	529,233	0	0	0
5	1	5	0	0	0	0	4,492,539	0	0
5	1	7	0	0	0	0	0	0	5,553,466
5	2	1	4,999,780	0	0	0	0	0	0
5	2	2	0	309,318	0	0	0	0	0
5	2	3	0	0	170,980	0	0	0	0
5	2	4	0	0	0	3,154,955	0	0	0
5	2	7	0	0	0	0	0	0	1,181,053
5	4	1	220	0	0	0	0	0	0
5	4	3	0	0	2,423,405	0	0	0	0
5	4	4	0	0	0	315,812	0	0	0
5	4	5	0	0	0	0	507,461	0	0
5	4	6	0	0	0	0	0	6,000,000	0
5	4	7	0	0	0	0	0	0	265,481

Table 3 The optimal doses of vaccines delivered to distribution centers in each period

u_{idt}		t						
i	d	2	3	4	5	6	7	8
1	1	0	7,500,000	0	0	0	6,000,000	11,123,260
1	2	0	0	0	0	10,488,400	0	3,876,740
2	1	0	13,011,028	0	0	0	16,736,140	9,756,236
2	2	0	1,988,972	0	0	0	4,615,839	0
3	1	4,000,000	3,812,266	3,518,782	4,000,000	1,289,245	338,181	3,389,863
3	2	0	0	286,488	0	2,710,755	5,491,595	1,610,137
3	4	0	187,734	1,194,730	0	0	170,224	0
4	1	0	0	0	0	0	0	11,522,299
4	2	0	0	0	0	0	0	4,080,327
4	4	0	0	0	0	0	0	18,397,374
5	1	0	3,690,682	1,405,615	529,233	4,492,539	0	5,553,466
5	2	4,999,780	309,318	170,980	3,154,955	0	0	1,181,053
5	4	220	0	2,423,405	315,812	507,461	6,000,000	265,481

been simulated based on preliminary estimates at MOHFW. In summary, this study demonstrated a practical, structured, and yet flexible scientific approach for equitable COVID-19 vaccine distribution in developing countries. The obtained results confirm the efficiency and effectiveness of the proposed model.

5 Sensitivity analysis

In this section, we study the performance of the model proposed in this study according to various budgetary constraints. We begin the sensitivity analysis by increasing (decreasing) the total budget and expect that the total doses of the purchased vaccine will increase (decrease) accordingly. For this purpose, we consider nine budgeting scenarios and calculate the total doses of the purchased vaccine for each scenario. The total doses of purchased vaccines for these scenarios are presented in Table 7 and Fig. 4.

As shown in Table 7 and Fig. 4, as the budget amount increases (i.e., scenarios 6 to 9), the total doses of the purchased vaccine increase, and as the budget amount decreases (i.e., scenarios 4 to 1), the total doses of the purchased vaccine decreased. The results are logical and meet our expectations of the proposed model behavior. This sensitivity analysis confirms the applicability and logical performance of the model.

6 Conclusion

This study proposed a mathematical programming model for equitable COVID-19 vaccine distribution in developing countries in the context of a location-inventory problem, considering the concepts of equity and taking into account the needs for cold, very cold, and ultra-cold supply chains. This model is the general form of Rastegar et al.'s (2021) model that provides the possibility of distributing vaccines requiring cold, very cold, and

Table 4 The optimal doses of vaccines assigned to group 1 in each period

μ_{igst}			t						
i	g	s	2	3	4	5	6	7	8
1	1	1	0	0	0	0	0	0	6,378,820
1	1	5	0	0	0	0	10,488,400	0	0
1	1	15	0	2,264,514	0	0	0	0	0
1	1	16	0	0	0	0	0	0	2,842,904
1	1	21	0	0	0	0	0	0	945,494
1	1	32	0	0	0	0	101,776	0	0
2	1	1	0	6,649,020	0	0	0	0	0
2	1	2	0	0	0	0	0	5,997,907	0
2	1	4	0	0	0	0	0	0	7,930,872
2	1	13	0	2,835,839	0	0	0	0	0
2	1	18	0	0	1,620,474	0	0	0	0
2	1	33	0	0	48,706	0	0	0	0
3	1	10	0	0	778,223	0	0	0	0
3	1	11	1,951,197	0	0	0	0	0	1,048,502
3	1	17	0	0	0	2,126,958	0	0	0
3	1	19	0	0	0	0	0	0	964,793
3	1	24	0	0	0	0	0	270,044	0
3	1	35	27,549	0	0	0	0	0	0
4	1	6	0	0	0	0	0	0	5,341,673
4	1	7	0	0	0	0	0	0	4,650,605
4	1	8	0	0	0	0	0	0	4,248,935
4	1	9	0	0	0	0	0	0	4,080,327
4	1	12	0	0	0	0	0	0	2,400,540
4	1	27	0	0	0	0	0	0	116,027
5	1	3	4,999,780	0	0	0	0	0	1,982,588
5	1	10	0	0	0	0	0	4,034,871	0
5	1	14	0	0	1,387,547	0	305,733	0	0
5	1	20	0	0	0	0	0	0	892,038
5	1	22	0	0	0	0	0	0	401,632
5	1	23	0	0	0	0	0	0	300,895
5	1	25	0	0	0	0	0	0	294,686
5	1	26	0	0	0	0	0	0	141,741
5	1	28	0	94,005	0	0	0	0	0
5	1	29	0	0	0	0	0	0	107,595
5	1	30	0	0	0	0	0	0	100,614
5	1	31	0	0	0	0	66,816	0	0
5	1	34	0	0	0	0	29,898	0	0
5	1	36	0	0	0	0	0	0	5757

Table 5 The optimal vaccine doses shipped from distribution centers to warehouses in each period

θ_{idst}			t						
i	d	s	2	3	4	5	6	7	8
1	1	1	0	3,967,289	0	0	0	6,000,000	7,334,862
1	1	13	0	603,075	0	0	0	0	0
1	1	15	0	2,264,514	0	0	0	0	0
1	1	16	0	0	0	0	0	0	2,842,904
1	1	21	0	0	0	0	0	0	945,494
1	1	32	0	117,292	0	0	0	0	0
1	1	33	0	547,830	0	0	0	0	0
1	2	5	0	0	0	0	10,488,400	0	0
1	2	6	0	0	0	0	0	0	3,853,421
1	2	9	0	0	0	0	0	0	22,785
1	2	27	0	0	0	0	0	0	534
2	1	1	0	6,783,182	0	0	0	0	0
2	1	2	0	0	0	0	0	14,198,023	0
2	1	4	0	0	0	0	0	0	8,478,729
2	1	13	0	3,592,781	0	0	0	0	0
2	1	15	0	0	0	0	0	1,863,893	0
2	1	16	0	0	0	0	0	0	1,269,092
2	1	17	0	0	0	0	0	115,090	0
2	1	18	0	1,921,328	0	0	0	0	0
2	1	21	0	663,083	0	0	0	0	0
2	1	25	0	0	0	0	0	0	8415
2	1	32	0	0	0	0	0	559,134	0
2	1	33	0	50,654	0	0	0	0	0
2	2	5	0	843,147	0	0	0	4,533,260	0
2	2	6	0	1,145,825	0	0	0	0	0
2	2	18	0	0	0	0	0	82,579	0
3	1	1	1,165,607	0	3,518,782	0	0	0	0
3	1	4	0	0	0	1,873,042	0	0	0
3	1	11	1,951,197	3,812,266	0	0	0	338,181	0
3	1	15	0	0	0	0	0	0	448,851
3	1	17	147,179	0	0	2,126,958	1,289,245	0	0
3	1	18	0	0	0	0	0	0	688,132
3	1	19	0	0	0	0	0	0	2,252,880
3	1	24	480,220	0	0	0	0	0	0
3	1	30	228,248	0	0	0	0	0	0
3	1	35	27,549	0	0	0	0	0	0
3	2	3	0	0	0	0	0	5,491,595	1,424,874
3	2	9	0	0	286,488	0	2,710,755	0	185,263
3	4	8	0	0	409,197	0	0	170,224	0
3	4	10	0	0	778,223	0	0	0	0
3	4	23	0	186,578	0	0	0	0	0
3	4	28	0	0	7310	0	0	0	0
3	4	35	0	1156	0	0	0	0	0

Table 5 (continued)

θ_{idst}			t						
i	d	s	2	3	4	5	6	7	8
4	1	4	0	0	0	0	0	0	4,458,437
4	1	6	0	0	0	0	0	0	5,355,224
4	1	13	0	0	0	0	0	0	1,085,490
4	1	15	0	0	0	0	0	0	121,062
4	1	17	0	0	0	0	0	0	436,095
4	1	21	0	0	0	0	0	0	50,777
4	1	24	0	0	0	0	0	0	15,214
4	2	9	0	0	0	0	0	0	4,080,327
4	4	7	0	0	0	0	0	0	4,686,209
4	4	8	0	0	0	0	0	0	8,403,048
4	4	10	0	0	0	0	0	0	28,580
4	4	12	0	0	0	0	0	0	4,976,826
4	4	27	0	0	0	0	0	0	216,703
4	4	28	0	0	0	0	0	0	86,008
5	1	6	0	0	0	0	0	0	243,032
5	1	10	0	2,300,165	0	529,233	4,492,539	0	238,053
5	1	13	0	0	138,940	0	0	0	0
5	1	16	0	0	0	0	0	0	826,400
5	1	18	0	0	0	0	0	0	963,539
5	1	20	0	0	0	0	0	0	1,765,361
5	1	22	0	0	0	0	0	0	870,248
5	1	23	0	0	0	0	0	0	390,773
5	1	25	0	496,780	0	0	0	0	0
5	1	26	0	297,214	0	0	0	0	0
5	1	28	0	112,285	0	0	0	0	0
5	1	30	0	0	110,398	0	0	0	0
5	1	31	0	0	1,146,816	0	0	0	0
5	1	33	0	0	9461	0	0	0	0
5	1	34	0	412,194	0	0	0	0	0
5	1	35	0	0	0	0	0	0	256,060
5	1	36	0	72,044	0	0	0	0	0
5	2	3	4,999,780	309,318	170,980	3,154,955	0	0	0
5	2	9	0	0	0	0	0	0	1,181,053
5	4	7	0	0	1,019,244	0	0	4,000,764	0
5	4	12	0	0	0	0	0	0	177,136
5	4	14	0	0	1,397,340	315,812	305,733	1,999,236	88,345
5	4	27	0	0	6821	0	0	0	0
5	4	29	0	0	0	0	201,728	0	0
5	4	36	220	0	0	0	0	0	0

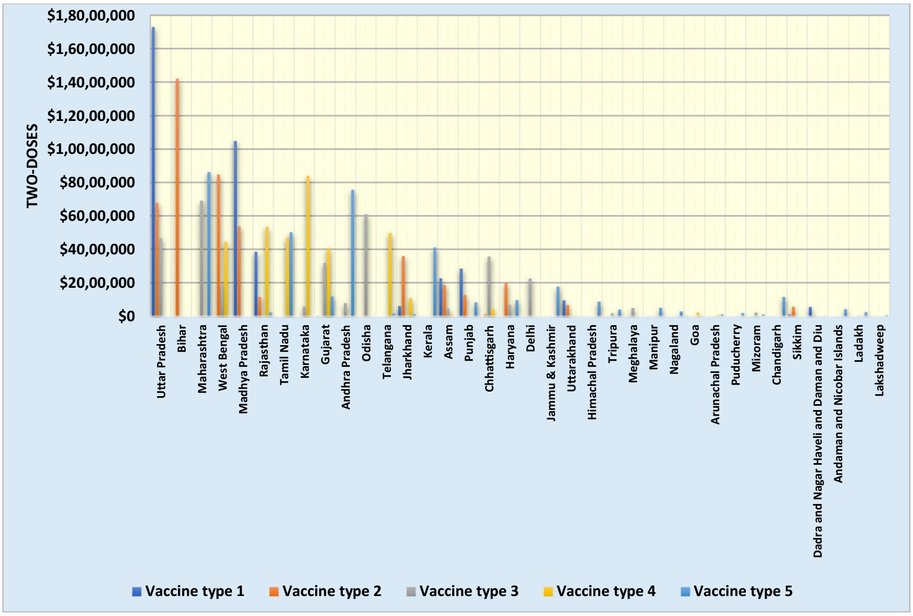

Fig. 2 The total doses of vaccines allocated to each state

ultra-cold refrigeration among heterogeneous populations. Budgetary considerations, manufacturer selection, and time-dependent capacities are considered some of the proposed model's more general and practical assumptions. Data from a case study in India is used to validate the practical application of the proposed model. The results showed that with 4.5 billion dollars, the Indian government could purchase over 186 million double-dose COVID-19 vaccines, including over 85 million for ultra-cold, 66 million for very cold, and 35 million double-doses for cold supply chains. Finally, sensitivity analysis was used to confirm the applicability and logical performance of the model.

This study has proposed an operational model with strategic consideration under certainty for equitable COVID-19 vaccine distribution. Life is full of uncertainty, and failing to fully consider operational uncertainties can have detrimental consequences in any operations, including vaccination efforts in developing countries. Future research is needed to study some of our operational assumptions under uncertain conditions. In addition, more complex models with additional objective functions (i.e., emission reduction) can improve the real-world applicability of the vaccine distribution model proposed in this study. Future advanced analytics research is needed to coordinate manufacturing and distribution with healthcare providers and pharmacies to deploy vaccines more effectively and efficiently through specialized supply chain networks.

Table 6 The doses of vaccines stored in the state warehouses in each period

ψ_{ist}		t					
i	s	2	3	4	5	6	7
1	1	0	1,011,454	1,011,454	1,011,454	0	4,130,234
1	32	0	117,292	117,292	117,292	281	0
2	2	0	0	0	0	0	1,993,059
2	5	0	582,218	547,399	547,399	547,399	4,840,779
2	13	0	216,566	0	0	0	0
2	15	0	0	0	0	0	35,094
2	18	0	1,620,474	0	0	0	82,579
2	21	0	138,736	50,628	0	0	0
2	33	0	50,654	1948	0	0	0
3	1	1,165,607	0	0	0	0	0
3	8	0	0	409,197	158,375	158,375	0
3	11	0	3,812,266	3,812,266	3,812,266	3,812,266	3,918,662
3	17	147,179	147,179	0	0	1,289,245	0
3	23	0	186,578	186,578	186,578	186,578	0
3	24	467,762	453,607	453,607	453,607	453,607	177,519
3	28	0	0	7310	7310	7310	7067
3	30	228,248	228,248	228,248	228,248	228,248	219,140
5	3	0	309,318	0	2,687,340	2,687,340	2,649,723
5	7	0	0	1,019,244	1,019,244	1,019,244	3,723,069
5	10	0	0	0	529,233	4,289,143	254,272
5	13	0	0	138,940	0	0	0
5	25	0	496,780	484,414	484,414	327,079	325,079
5	26	0	297,214	297,214	297,214	297,214	297,214
5	27	0	0	6821	6821	6821	6821
5	29	0	0	0	0	128,440	128,440
5	30	0	0	110,398	102,179	102,179	100,794
5	31	0	0	1,146,324	1,146,324	1,072,392	1,058,658
5	33	0	0	7555	0	0	0
5	34	0	412,194	412,194	412,194	381,045	5168
5	36	0	6979	6979	6979	6979	6979

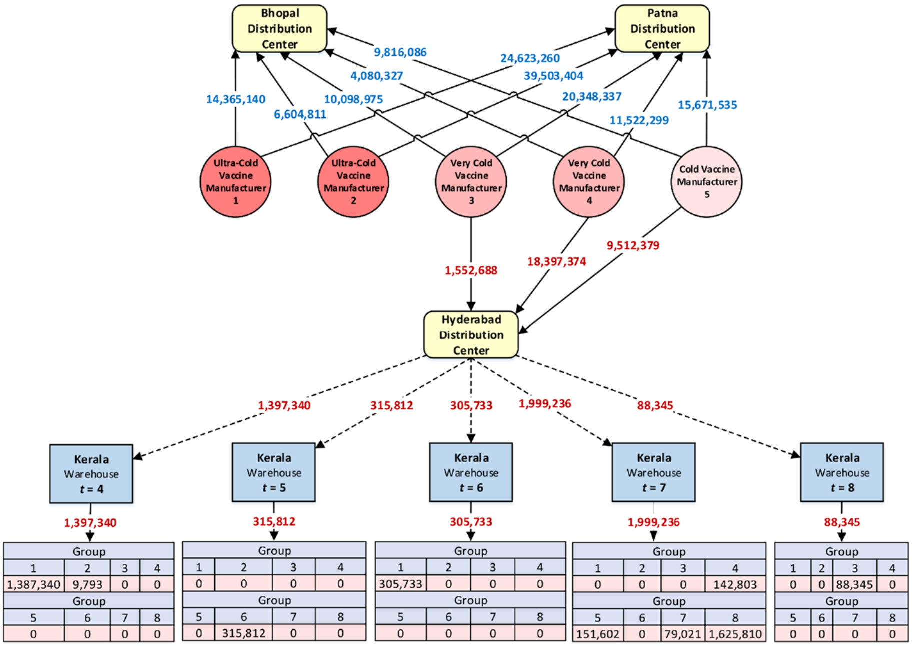

Fig. 3 Assigned vaccines to each group in each period in Kerala state

Table 7 Sensitivity analysis procedure using budget changes

Scenario	Budget	Total doses of the purchased vaccine
1	4,100,000,000	178,183,484
2	4,200,000,000	180,073,849
3	4,300,000,000	181,308,864
4	4,400,000,000	184,706,426
5 (main problem)	4,500,000,000	186,096,615
6	4,600,000,000	186,943,712
7	4,700,000,000	188,607,348
8	4,800,000,000	189,013,640
9	4,900,000,000	189,956,071

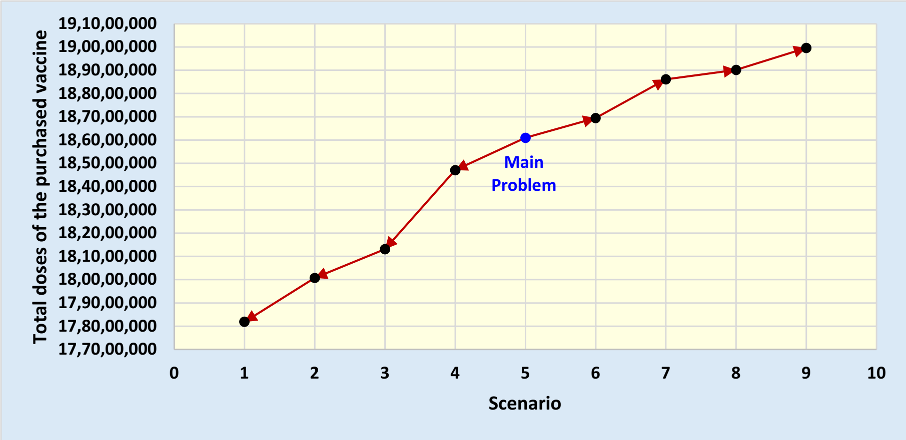

Fig. 4 Total doses of the purchased vaccine for each scenario

Appendix A

See Tables 8, 9, 10, 11, 12, 13, 14, 15 and 16.

Table 8 The demand for each group

State	s	Group (g)							
		1	2	3	4	5	6	7	8
Uttar Pradesh	1	17,370,453	136,901	1,189,945	1,165,607	1,232,233	2,210,133	610,884	213,966,569
Bihar	2	7,997,209	32,182	331,682	499,204	607,293	1,628,062	177,995	113,526,299
Maharashtra	3	9,309,824	38,385	684,242	480,298	531,381	2,047,686	220,520	109,831,887
West Bengal	4	10,574,496	47,384	366,198	547,857	510,432	1,682,009	209,009	85,671,917
Madhya Pradesh	5	13,984,533	35,530	267,620	495,085	272,592	1,021,796	137,209	69,144,601
Rajasthan	6	7,122,230	13,828	243,591	243,032	291,359	1,001,599	176,547	71,940,504
Tamil Nadu	7	6,200,806	36,331	158,305	233,510	332,000	849,269	239,867	69,791,179
Karnataka	8	5,665,246	23,414	92,349	405,377	373,408	978,112	180,654	59,844,125
Gujarat	9	5,440,436	23,251	293,834	185,263	206,762	957,655	182,568	56,582,632
Andhra Pradesh	10	6,417,458	29,164	122,473	204,846	306,568	703,711	115,883	46,003,290
Odisha	11	3,999,598	10,641	65,970	231,785	249,602	558,257	113,151	41,127,330
Telangana	12	3,200,720	19,292	83,460	177,136	226,847	616,784	73,655	34,964,837
Jharkhand	13	3,781,118	10,536	159,971	138,940	246,098	417,573	68,429	33,771,283
Kerala	14	2,257,706	9993	90,611	142,803	172,275	421,083	88,788	32,516,184
Assam	15	3,019,352	19,518	35,994	121,062	213,633	572,966	70,924	31,553,590
Punjab	16	3,790,538	15,739	179,620	84,395	203,320	428,190	57,741	25,381,830
Chhattisgarh	17	2,835,943	6468	103,989	147,179	123,582	369,434	64,755	25,784,881
Haryana	18	2,160,631	8392	154,933	112,818	148,955	401,139	83,545	25,134,279
Delhi	19	1,071,993	6964	42,554	84,195	115,861	205,254	48,186	17,135,916
Jammu & Kashmir	20	1,189,383	8989	18,020	40,819	48,076	161,670	42,380	12,096,984
Uttarakhand	21	1,050,549	2830	15,251	50,628	40,805	117,478	27,271	9,946,045
Himachal Pradesh	22	446,258	3248	8481	20,122	29,587	80,285	9042	6,854,931
Tripura	23	334,328	2205	22,485	12,093	17,280	41,963	7894	3,731,546
Meghalaya	24	300,049	2237	15,605	12,458	16,086	35,218	6792	2,978,266
Manipur	25	327,429	2041	15,333	12,366	9563	40,525	9727	2,674,562

Table 8 (continued)

State	s	Group (g)							
		1	2	3	4	5	6	7	8
Nagaland	26	157,490	492	11,525	6749	14,501	21,820	7172	2,029,945
Goa	27	128,919	545	4518	6821	10,570	15,934	4849	1,414,093
Arunachal Pradesh	28	104,451	248	4145	7067	8911	24,374	3647	1,417,614
Puducherry	29	119,550	672	5682	4240	5909	18,446	2037	1,257,004
Mizoram	30	111,794	184	1421	4957	5529	12,144	3769	1,099,447
Chandigarh	31	74,240	503	3320	5213	8087	11,362	2974	1,052,775
Sikkim	32	113,085	287	2164	4003	2204	8263	1110	559,134
Dadra and Nagar Haveli and Daman and Diu	33	54,118	105	1851	1847	2214	7611	1341	546,637
Andaman and Nicobar Islands	34	33,221	195	848	1251	1779	4550	1285	373,908
Ladakh	35	30,611	191	1433	1156	894	3789	909	250,040
Lakshadweep	36	6397	48	97	220	259	870	228	65,065

Table 9 The ordering cost to the manufacturer of vaccine i in period t

FX_{it}^{MN}	t							
i	1	2	3	4	5	6	7	8
1	9100	9300	8200	9200	9300	8800	8800	8000
2	8200	8600	9100	9900	8900	10,000	9300	9000
3	9500	8400	8200	9400	9300	9200	8800	9900
4	9300	9300	9700	8700	9900	9600	8600	9000
5	9700	9600	9000	9200	8900	8400	9500	8400

Table 10 The cost of setting up distribution centers equipped with cold refrigeration

	Distribution center			
	Patna	Bhopal	New Delhi	Hyderabad
FY_{d}^{DS}	18,400,000	18,800,000	19,400,000	19,200,000

Table 11 The cost of setting up distribution centers equipped with very cold refrigeration

	Distribution center			
	Patna	Bhopal	New Delhi	Hyderabad
FX_{d}^{DS}	46,000,000	47,000,000	48,500,000	48,000,000

Amn $EXC = 2500000$

Table 12 The coverage rate of each group

	Group							
	1	2	3	4	5	6	7	8
Coverage rate (ξ_g)	0.75	0.9	0.85	1	0.7	0.6	0.75	0.05

Table 13 The purchasing cost for two doses of vaccine i

	Vaccine type				
	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$
VP_i	15.5	16.2	13.1	13.7	8.2

Table 14 Transportation cost for two doses of vaccine i from manufacturer's location to distribution center d

TR_{id}^{MN}	Distribution center			
i	Patna	Bhopal	New Delhi	Hyderabad
1	8.25	9.08	8.91	9.8
2	7.6	8.36	8.21	9.03
3	8.32	9.15	8.99	9.89
4	7.69	8.46	8.31	9.14
5	6.89	7.58	7.44	8.18

Table 15 The holding cost for two doses of vaccine i in the state s warehouse

State (s)	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$
1	1.7	1.7	0.68	0.68	0.58
2	1.63	1.63	0.65	0.65	0.56
3	1.5	1.5	0.6	0.6	0.52
4	1.75	1.75	0.7	0.7	0.6
5	1.78	1.78	0.71	0.71	0.61
6	1.13	1.13	0.45	0.45	0.39
7	0.98	0.98	0.39	0.39	0.34
8	2.05	2.05	0.82	0.82	0.71
9	1.05	1.05	0.42	0.42	0.36
10	0.83	0.83	0.33	0.33	0.28
11	1.53	1.53	0.61	0.61	0.52
12	1.4	1.4	0.56	0.56	0.48
13	1.15	1.15	0.46	0.46	0.4
14	1.38	1.38	0.55	0.55	0.47
15	1.3	1.3	0.52	0.52	0.45
16	0.8	0.8	0.32	0.32	0.28
17	1.55	1.55	0.62	0.62	0.53
18	1.53	1.53	0.61	0.61	0.52
19	1.45	1.45	0.58	0.58	0.5
20	1.23	1.23	0.49	0.49	0.42
21	1.3	1.3	0.52	0.52	0.45
22	1.1	1.1	0.44	0.44	0.38
23	0.95	0.95	0.38	0.38	0.33
24	1.2	1.2	0.48	0.48	0.41
25	1.28	1.28	0.51	0.51	0.44
26	1.08	1.08	0.43	0.43	0.37
27	1.28	1.28	0.51	0.51	0.44
28	1.33	1.33	0.53	0.53	0.46
29	1.13	1.13	0.45	0.45	0.39
30	1.23	1.23	0.49	0.49	0.42
31	1.3	1.3	0.52	0.52	0.45
32	1.09	1.09	0.93	0.93	0.81
33	1.01	1.01	0.86	0.86	0.75
34	0.98	0.98	0.83	0.83	0.72
35	0.94	0.94	0.8	0.8	0.7
36	0.84	0.84	0.71	0.71	0.62

Table 16 The distribution capacity of vaccines requiring cold, very cold, and ultra-cold refrigeration

	Distribution center			
	Patna	Bhopal	New Delhi	Hyderabad
CP_d^{NR}	36,000,000	38,000,000	40,000,000	37,000,000
CP_d^{SR}	90,000,000	90,000,000	97,500,000	87,000,000
CP_d^{DFR}	45,000,000	52,000,000	45,000,000	42,000,000

Appendix B

See Tables 17, 18, 19, 20, 21, 22 and 23.

Table 17 The optimal doses of vaccines allocated to group 2 in each period

μ_{igst}			t					
i	g	s	3	4	5	6	7	8
1	2	9	0	0	0	0	0	22,785
1	2	27	0	0	0	0	0	534
1	2	32	0	0	0	0	281	0
2	2	1	134,162	0	0	0	0	0
2	2	2	0	0	0	0	31,538	0
2	2	5	0	34,819	0	0	0	0
2	2	13	10,325	0	0	0	0	0
2	2	17	0	0	0	0	6338	0
2	2	18	0	0	0	0	0	8224
2	2	21	2773	0	0	0	0	0
3	2	11	0	0	0	0	0	10,428
3	2	15	0	0	0	0	0	19,127
3	2	19	0	0	0	0	0	6824
3	2	24	0	0	0	0	0	2192
3	2	28	0	0	0	0	243	0
4	2	4	0	0	0	0	0	46,436
4	2	6	0	0	0	0	0	13,551
4	2	7	0	0	0	0	0	35,604
4	2	8	0	0	0	0	0	22,945
4	2	10	0	0	0	0	0	28,580
4	2	12	0	0	0	0	0	18,906
5	2	3	0	0	0	0	37,617	0
5	2	14	0	9793	0	0	0	0
5	2	16	0	0	0	0	0	15,424
5	2	20	0	0	0	0	0	8809
5	2	22	0	0	0	0	0	3183
5	2	23	0	0	0	0	0	2160
5	2	25	0	0	0	0	2000	0
5	2	26	0	0	0	0	0	482
5	2	29	0	0	0	658	0	0
5	2	30	0	0	0	0	0	180
5	2	31	0	492	0	0	0	0
5	2	33	0	102	0	0	0	0
5	2	34	0	0	0	0	0	191
5	2	35	0	0	0	0	0	187
5	2	36	0	0	0	0	0	47

Table 18 The optimal doses of vaccines allocated to group 3 in each period

μ_{igst}			t					
i	g	s	3	4	5	6	7	8
1	3	1	0	0	0	1,011,454	0	0
1	3	32	0	0	0	2109	0	0
2	3	2	0	0	0	0	0	323,389
2	3	5	260,929	0	0	0	0	0
2	3	6	237,501	0	0	0	0	0
2	3	13	155,971	0	0	0	0	0
2	3	15	0	0	0	0	0	35,094
3	3	8	0	0	90,040	0	0	0
3	3	9	0	286,488	0	0	0	0
3	3	11	0	0	0	0	0	64,320
3	3	18	0	0	0	0	0	151,059
3	3	19	0	0	0	0	0	41,490
4	3	4	0	0	0	0	0	357,043
4	3	12	0	0	0	0	0	81,373
4	3	17	0	0	0	0	0	101,389
4	3	21	0	0	0	0	0	14,869
4	3	24	0	0	0	0	0	15,214
4	3	27	0	0	0	0	0	4405
4	3	28	0	0	0	0	0	4041
5	3	3	0	0	0	0	0	667,135
5	3	7	0	0	0	0	154,347	
5	3	10	0	0	0	0	0	119,411
5	3	14	0	0	0	0	0	88,345
5	3	16	0	0	0	0	0	175,129
5	3	20	0	0	0	0	0	17,569
5	3	22	0	0	0	0	0	8268
5	3	23	0	0	0	0	0	21,922
5	3	25	0	0	0	14,949	0	0
5	3	26	0	0	0	0	0	11,236
5	3	29	0	0	0	5539	0	0
5	3	30	0	0	0	0	1385	0
5	3	31	0	0	0	0	0	3237
5	3	33	0	1804	0	0	0	0
5	3	34	0	0	0	0	826	0
5	3	35	0	0	0	0	0	1397
5	3	36	0	0	0	0	0	94

Table 19 The optimal doses of vaccines allocated to group 4 in each period

μ_{igst}			t						
i	g	s	2	3	4	5	6	7	8
1	4	32	0	0	0	0	4003	0	0
2	4	2	0	0	0	0	0	499,204	0
2	4	4	0	0	0	0	0	0	547,857
2	4	5	0	0	0	0	0	0	495,085
2	4	21	0	0	0	50,628	0	0	0
3	4	1	0	1,165,607	0	0	0	0	0
3	4	9	0	0	0	0	0	0	185,263
3	4	11	0	0	0	0	0	231,785	0
3	4	17	0	0	147,179	0	0	0	0
3	4	19	0	0	0	0	0	0	84,195
3	4	24	12,458	0	0	0	0	0	0
3	4	28	0	0	0	0	0	0	7067
3	4	30	0	0	0	0	0	0	4957
3	4	35	0	1156	0	0	0	0	0
4	4	8	0	0	0	0	0	0	405,377
4	4	15	0	0	0	0	0	0	121,062
5	4	3	0	0	480,298	0	0	0	0
5	4	6	0	0	0	0	0	0	243,032
5	4	7	0	0	0	0	0	0	233,510
5	4	10	0	0	0	0	204,846	0	0
5	4	12	0	0	0	0	0	0	177,136
5	4	13	0	0	0	138,940	0	0	0
5	4	14	0	0	0	0	0	142,803	0
5	4	16	0	0	0	0	0	0	84,395
5	4	18	0	0	0	0	0	0	112,818
5	4	20	0	0	0	0	0	0	40,819
5	4	22	0	0	0	0	0	0	20,122
5	4	23	0	0	0	0	0	0	12,093
5	4	25	0	0	12,366	0	0	0	0
5	4	26	0	0	0	0	0	0	6749
5	4	27	0	0	0	0	0	0	6821
5	4	29	0	0	0	0	4240	0	0
5	4	31	0	0	0	0	0	5213	0
5	4	33	0	0	0	1847	0	0	0
5	4	34	0	0	0	0	1251	0	0
5	4	36	220	0	0	0	0	0	0

Table 20 The optimal doses of vaccines allocated to group 5 in each period

μ_{igst}			t					
i	g	s	3	4	5	6	7	8
1	5	1	0	0	0	0	0	862,564
1	5	6	0	0	0	0	0	256,395
1	5	32	0	0	0	1939	0	0
2	5	2	0	0	0	0	0	534,417
2	5	5	0	0	0	0	239,880	0
2	5	13	0	216,566	0	0	0	0
2	5	15	0	0	0	0	187,997	0
2	5	17	0	0	0	0	108,752	0
2	5	25	0	0	0	0	0	8415
2	5	33	0	0	1948	0	0	0
3	5	8	0	0	0	0	328,599	0
3	5	9	0	0	0	181,950	0	0
3	5	11	0	0	0	0	0	219,649
3	5	19	0	0	0	0	0	101,957
3	5	24	14,155	0	0	0	0	0
4	5	4	0	0	0	0	0	449,180
4	5	12	0	0	0	0	0	199,625
4	5	21	0	0	0	0	0	35,908
4	5	27	0	0	0	0	0	9301
4	5	28	0	0	0	0	0	7841
5	5	3	0	0	467,615	0	0	0
5	5	7	0	0	0	0	292,160	0
5	5	10	0	0	0	0	0	269,779
5	5	14	0	0	0	0	151,602	0
5	5	16	0	0	0	0	0	178,921
5	5	18	0	0	0	0	0	131,080
5	5	20	0	0	0	0	0	42,306
5	5	22	0	0	0	0	0	26,036
5	5	23	0	0	0	0	0	15,206
5	5	26	0	0	0	0	0	12,760
5	5	29	0	0	0	0	0	5199
5	5	30	0	0	4865	0	0	0
5	5	31	0	0	0	7116	0	0
5	5	34	0	0	0	0	0	1565
5	5	35	0	0	0	0	0	786
5	5	36	0	0	0	0	0	227

Table 21 The optimal doses of vaccines allocated to group 6 in each period

μ_{igst}			t					
i	g	s	3	4	5	6	7	8
1	6	1	0	0	0	0	1,326,080	0
1	6	32	0	0	0	6197	0	0
2	6	2	0	0	0	0	0	976,838
2	6	5	0	0	0	0	0	766,347
2	6	6	751,198	0	0	0	0	0
2	6	13	313,179	0	0	0	0	0
2	6	18	300,854	0	0	0	0	0
2	6	21	0	88,108	0	0	0	0
3	6	3	0	0	0	0	0	1,228,612
3	6	11	0	0	0	0	0	418,692
3	6	15	0	0	0	0	0	429,724
3	6	19	0	0	0	0	0	153,940
3	6	24	0	0	0	0	0	26,413
3	6	30	0	0	0	0	9108	0
4	6	4	0	0	0	0	0	1,009,206
4	6	8	0	0	0	0	0	733,584
4	6	12	0	0	0	0	0	462,588
4	6	17	0	0	0	0	0	277,075
4	6	27	0	0	0	0	0	11,950
5	6	7	0	0	0	0	636,951	0
5	6	9	0	0	0	0	0	718,241
5	6	10	0	0	0	527,783	0	0
5	6	14	0	0	315,812	0	0	0
5	6	16	0	0	0	0	0	321,142
5	6	20	0	0	0	0	0	121,252
5	6	22	0	0	0	0	0	60,213
5	6	23	0	0	0	0	0	31,472
5	6	25	0	0	0	0	0	30,393
5	6	26	0	0	0	0	0	16,365
5	6	28	18,280	0	0	0	0	0
5	6	29	0	0	0	0	0	13,834
5	6	31	0	0	0	0	8521	0
5	6	33	0	0	5708	0	0	0
5	6	34	0	0	0	0	0	3412
5	6	35	0	0	0	0	0	2841
5	6	36	0	0	0	0	0	652

Table 22 The optimal doses of vaccines allocated to group 7 in each period

μ_{igst}			t				
i	g	s	3	5	6	7	8
1	7	1	0	0	0	543,686	0
1	7	32	0	0	987	0	0
1	7	33	1193	0	0	0	0
2	7	2	0	0	0	0	158,415
2	7	5	0	0	0	0	122,116
2	7	6	157,126	0	0	0	0
2	7	13	60,901	0	0	0	0
2	7	15	0	0	0	63,122	0
2	7	18	0	0	0	0	74,355
2	7	21	24,271	0	0	0	0
3	7	3	0	0	0	0	196,262
3	7	8	0	160,782	0	0	0
3	7	9	0	0	162,485	0	0
3	7	11	0	0	0	0	100,704
3	7	19	0	0	0	0	42,885
3	7	24	0	0	0	6044	0
4	7	4	0	0	0	0	186,018
4	7	12	0	0	0	0	65,552
4	7	17	0	0	0	0	57,631
4	7	27	0	0	0	0	4315
4	7	28	0	0	0	0	3245
5	7	7	0	0	0	213,481	0
5	7	10	0	0	0	0	103,135
5	7	14	0	0	0	79,021	0
5	7	16	0	0	0	0	51,389
5	7	20	0	0	0	0	37,718
5	7	22	0	0	0	0	8047
5	7	23	0	0	0	0	7025
5	7	25	0	0	8657	0	0
5	7	26	0	0	0	0	6383
5	7	29	0	0	0	0	1812
5	7	30	0	3354	0	0	0
5	7	31	0	0	0	0	2646
5	7	34	0	0	0	1143	0
5	7	35	0	0	0	0	809
5	7	36	0	0	0	0	202

Table 23 The optimal doses of vaccines allocated to group 8 in each period

μ_{igst}			t					
i	g	s	3	4	5	6	7	8
1	8	1	2,955,835	0	0	0	0	4,223,712
1	8	6	0	0	0	0	0	3,597,026
1	8	13	603,075	0	0	0	0	0
1	8	33	546,637	0	0	0	0	0
2	8	2	0	0	0	0	5,676,315	0
2	8	5	0	0	0	0	0	3,457,231
2	8	15	0	0	0	0	1,577,680	0
2	8	16	0	0	0	0	0	1,269,092
2	8	21	497,303	0	0	0	0	0
2	8	32	0	0	0	0	559,134	0
3	8	1	0	3,518,782	0	0	0	0
3	8	3	0	0	0	0	5,491,595	0
3	8	4	0	0	1,873,042	0	0	0
3	8	9	0	0	0	2,366,320	0	0
3	8	11	0	0	0	0	0	2,056,367
3	8	17	0	0	0	0	1,289,245	0
3	8	18	0	0	0	0	0	537,073
3	8	19	0	0	0	0	0	856,796
3	8	23	0	0	0	0	186,578	0
3	8	24	0	0	0	0	0	148,914
3	8	30	0	0	0	0	0	214,183
4	8	4	0	0	0	0	0	2,410,554
4	8	8	0	0	0	0	0	2,992,207
4	8	12	0	0	0	0	0	1,748,242
4	8	13	0	0	0	0	0	1,085,490
4	8	27	0	0	0	0	0	70,705
4	8	28	0	0	0	0	0	70,881
5	8	7	0	0	0	0	0	3,489,559
5	8	9	0	0	0	0	0	462,812
5	8	10	2,300,165	0	0	0	0	0
5	8	14	0	0	0	0	1,625,810	0
5	8	18	0	0	0	0	0	719,641
5	8	20	0	0	0	0	0	604,850
5	8	22	0	0	0	0	0	342,747
5	8	25	0	0	0	133,729	0	0
5	8	26	0	0	0	0	0	101,498
5	8	29	0	0	0	62,851	0	0
5	8	31	0	0	0	0	0	1,052,775
5	8	34	0	0	0	0	373,908	0
5	8	35	0	0	0	0	0	250,040
5	8	36	65,065	0	0	0	0	0

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Declarations

Conflict of interest The above authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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