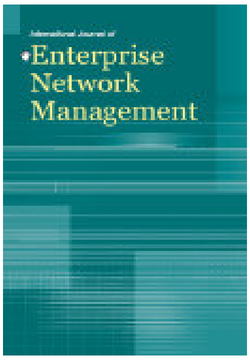

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Distribution and transportation model for COVID-19 vaccine

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Abstract: The pandemic that began in December 2019 in Wuhan, China has spread worldwide and infected millions of people across the globe. To combat COVID-19, scientists developed vaccines in record time. Without proper vaccine distribution, the country would suffer from low coverage rates and the virus would continue to spread. We are losing over 3,000 lives each day to COVID-19; this means a single day of delay in the distribution of vaccine is costing thousands of innocent lives. In this paper we have formulated a distribution model using mixed integer programming (MIP) that maximises the number of people vaccinated, minimises the cost of transportation over the entire network while ensuring widespread access.

Keywords: COVID-19; vaccine hub; vaccine supply chain; cost-effective; mixed integer programming; MIP; public health; COVID-19 vaccine; distribution model; transportation model.

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1 Introduction

The pandemic that started in late 2019 has already enveloped the entire world and the worst affected country is the USA. The USA has lost more than 650,000 people to this disease (Centers for Disease Control and Prevention, 2021). The rate at which this disease is affecting people is disturbing. As per Visser (2020), the USA is registering more than 3,000 deaths daily due to COVID-19. Given the fact that vaccination is the only effective ways to control the COVID-19 pandemic (Newton et al., 2020) boosting vaccine efforts is of paramount importance. The CDC has already rolled out its plan to distribute vaccine in three phases. In phase 1 and phase 2 COVID-19 vaccine is being given to high priority population such as healthcare professional, elderly, and high-risk individuals and in Phase 3 the vaccine will be available to the general population (Kim et al., 2021).

The first phase of COVID 19 vaccine distribution in the United States is behind schedule. The vaccination process currently lacks coordinated transportation and distribution that is delaying the vaccination process. As per Trends (2021) as on 28 January 2021 out of total 48,386,275 distributed doses only total 26,193,682 doses were administered.

This raises fears of slower vaccine distribution in the third phase of vaccination when the US needs to distribute the vaccine to a vast population. The delay in vaccine distribution means the loss of thousands of lives each day. Furthermore, the delay in vaccine distribution will delay the US from getting closer to a herd immunity threshold that is needed to curb the pandemic (Clemente-Suárez et al., 2020). Also, the delay in vaccine distribution will decelerate the recovery of social and economic normalcy.

Therefore, the mass vaccination of a sufficient percentage of the population with successful dispersion of that vaccinated group raises many questions about how to distribute the vaccine (Brewer et al., 2007; Bone et al., 2010; Clark et al., 1987).

In this paper, we amalgamated the preferences of the World Health Organization to create vaccine supply chain with an Operations Research and Operations Management standpoint (WHO, 2020). The World Health Organization (2021), guidelines provide three vaccine logistics priority areas (Sasikumar and Haq, 2010). These three areas are products and packaging, immunisation supply system efficiency, and environmental impact of immunisation supply systems (Sohrabi et al., 2020). The Immunisation supply system efficiency priority can further be divided into product, production, allocation and distribution (Saxena et al., 2009). This research focuses on the distribution of the vaccine. In this paper, we have developed vaccine transportation and distribution model that will help in the distribution of COVID-19 vaccine fast and effectively.

2 Literature review

There is a plethora of operation research articles that examine vaccine logistics, however, the most closely related research to the current work is that of Verter and Lapierre (2002). They examined maximising participation in prevention of healthcare programs. The authors observed that distance is a major factor of participation and as the distance to the adjacent facility increases participation probability decreases. They used an integer programming formulation and elucidated with an example of public health centres in Georgia, USA and in Quebec, Canada (Verter and Lapierre, 2002). Furthermore, Daskin and Dean (2005) described the implications of location decisions and develop three models for location planning in healthcare namely the location set covering model, maximal covering model and P-median model.

To serve all demand points to minimise total weighted distances Hakimi and Maheshwari (1972) recommended the P-centre location problem. However, there were some computational challenges with this model which was addressed by the authors in their maximum covering location problem (MCLP). The model proposed by Church and ReVelle was efficient and could be used to maximise the population covered or coverage within the desired service distance by identifying an optimal fixed number of facilities (Church and ReVelle, 1974). They argued that coverage is binary and if the demand location is within an acceptable service distance all of the demand is covered else not. Berman and Drezner (2007) further refined the MCLP and used the p-median problem under uncertainty approach to managing the multiple dimensions and uncertainty (Berman and Drezner, 2007). Research conducted by Brachner and Hvattum (2017), proposed a mathematical model that combined a routing and a covering problem to balance the minimisation of operational cost and capacity requirements. More recently, Kramer et al. (2020) has proposed new mathematical models and algorithms for the capacity P-Centre problem.

3 Problem development and model

To develop an optimal vaccine distribution network strategy and operational policies for the USA, in our model we have set our objective to minimise the overall cost of transportation over the whole network, while ensuring widespread access. In our model, vaccines flow from the vaccine hub in the region to the state capital and from there it is distributed to the public health department, large healthcare organisations, affiliated clinics, hospital, doctor's office, and pharmacies. In this model vaccine hub locations were chosen strategically to determine the best regional distribution hub. We make the following assumptions to model the COVID-19 vaccine network:

3.1 Model assumption-1

We consider the two-level supply chain, composed of 'V' vaccine hub and 'D' distribution points. For each vaccine hub $i \in V$ we consider a fixed capacity C_i, while each distribution point $j \in D$ has a demand d_j that should be satisfied. Each vaccine hub is connected to each vaccine distribution point node by an arc a_{ij} with a cost e_{ij} for every batch of vaccine sent.

Given this topology, we strive to minimise the total costs for satisfying the whole demand of each distribution point with an amount q_{ij} sent from any vaccine hub i to each specific distribution point j. The quantity sent from vaccine hub i must be lower or equal to the capacity C_i of that vaccine hub. The received quantity at distribution point j must be equal to the demand d_j of the distribution point j. The total capacity of vaccine hub must be greater or equal to the total demand at the sales point [Hiller and Liberman, (2001), p.325; Hillier et al., 2001].

3.2 Model assumption-2

We add another assumption that considers the option of not satisfying the demand d_j at a certain distribution point by a quantity ς_j but with a cost penalty L_j that depends on the distribution point j considered [Hiller and Liberman, (2001), p.328]. We are adding this assumption because our research expects that certain individuals will be ineligible for COVID-19 vaccination due to age either too young or too old, immunocompromised situation, and other preexisting medical conditions. Furthermore, some individuals may be hesitant to receive the vaccine because of fake news or misinformation (Marco-Franco et al., 2021).

3.3 Model assumption-3

The vaccine transportation activity is normally done with vaccine trucks, so the total transportation costs depend on the number of vehicles used to undertake transportation activity. We assume that N_{ij} is the number of vehicles used to ship a certain amount of vaccine q_{ij} from vaccine hub i to distribution point j, given a nominal vehicle capacity ϕ and vehicle transportation costs k_{ij}. Furthermore, for simplicity, these models assume that only one vehicle is used and its nominal capacity ϕ is fixed.

3.4 Model assumption-4

We also consider the temporal horizon in this model. In this way, given basic forecasted data concerning distribution point demand and vaccine hub capability, it is possible to formulate a proper master distribution schedule on a temporal horizon T (over three months) with a time bucket detail t (month). The objective is to minimise the total transportation costs under a temporal horizon T. The main introduction along the temporal horizon is represented by stock quantity at time t, named σ^t, for each vaccine hub i and for each distribution point j. Stock quantity at time t, named σ^t, represents each vaccine hub i and for each distribution point j. We are assuming that vaccine hub and distribution points can store some products, incurring a holding cost equal to h. At vaccine hub we are also introducing the possibility that authorities/managers might decide to activate or not during a time unit t, under a setup cost ρ_i. At the vaccine distribution point, we are introducing the possibility that the stock held between two time periods is used to satisfy the demand of the next period. We formulate the placement between the stocks at time t and $t - 1$, the whole incoming batch of vaccine, the lost cost, and the demand. Further, we include production activation and vaccine stock existing between time t and $t - 1$.

4 Selection criteria

To solve the given problem greedy heuristics were used. The selection criteria was formulated for choosing pairs of distribution points and vaccine hub in a way to satisfy the demand of distribution point j from vaccine hub i. The greedy algorithm starts by identifying the sales point where there is a potential maximum lost sales cost, with the intent of improving the objective equation by reducing this cost. The candidate distribution point j is selected with the criteria for a given planning time t after the selection of the distribution point. The next procedure is to select a vaccine hub to satisfy the corresponding demand at the given distribution point. The vaccine hub selection is based on a combine minimum cost of Setup cost $\rho_{it}\ y_{it}$, holding cost $L_j\ \varsigma_j$, transportation cost $N^t_{ij}\ k_{ij}$, where each of these costs is homogenised. The y_i in this algorithm depends on two things, it will have the value of zero if the vaccine has not been procured in this time period or the residual capacity it has (after being activated in the same period) is lesser than the demand. It also would have the value of 1 if is chosen to be activated, and/or the residual capacity in the vaccine hub. With each step of the calculation, the residual demands at each vaccine hub are updated and if there is enough quantity of products in a given vaccine hub to satisfy demand at a vaccine distribution point those will be used first without another activation.

5 Mathematical model

Objective function

$$\min \sum_{t=1}^{T} \left(\sum_{i=1}^{V} h_i^t \sigma_i^t + \rho_i^t y_i^t + \sum_{j=1}^{D} \left(h_j^t \sigma_j^t + L_j \zeta_j \right) + \sum_{i=1}^{V} \sum_{j=1}^{D} N_{ij}^t k_{ij} \right)$$

Subject to

$$\sum_{j=1}^{D} q_{ij} \le C_i \qquad \forall_i\,,$$

$$\sum_{i=1}^{V} q_{ij} = d_j \qquad \forall_j ,$$

$$\sum_{i=1}^{V} C_i \geq \sum_{j=1}^{D} d_j$$

$$\sum_{i=1}^{V} q_{ij} + \zeta_j = d_j \qquad \forall_j ,$$

$$q_{ij} \leq N_{ij}\varphi \qquad \forall_{i,j} ,$$

$$\sigma_j^{t-1} + \sum_{i=1}^{V} q_{ij}^t + \zeta_j^t - d_j^t = \sigma_j^t \qquad \forall_{i,j} ,$$

$$\sum_{j}^{D} q_{ij}^t + \sigma_i^t = C_i y_i^t + \sigma_i^{t-1} \qquad \forall_i , \forall_t ,$$

Parameters

V vaccine hub

D distribution point

T temporal horizon

h_i holding cost

σ_t stock quantity at time t

ρ_i setup cost

L lost sales costs

ς lost sales product

N_{ij} number of vehicles used to ship from i to j

k_{ij} transportation cost from i to j

q_{ij} vaccine amount sent from i to j

d_j demand at distribution point j

L_j cost penalty at distribution point j

ς_j not satisfying demand d_j at j by quantity ς_j

ϕ vehicle capacity $y_{ij} = 0$ if $C_i < d_{ij}$; 1 otherwise

$e \in R+$

$d, C \in N$

$q \in N$

$L \in R+$

$\varsigma \in N$

$k \in R+$

$\phi \in N$

$N \in N$

$k, h, \rho \in R+$

$\phi, L \in N$

$\sigma, N, \varsigma, q \in N$

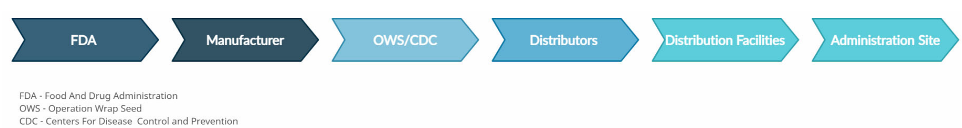
$y_{ij} \in [0, 1]\ \forall_i, \forall_j.$

where R^+ is set of real numbers and N is set of natural numbers.

6 Illustration in the context of the USA

The US government founded a public-private partnership known as Operation Warp Speed (OWS) to combat COVID-19. The OWS has developed a plan for centralised distribution that will be executed in phases by the federal government, the 64 jurisdictions CDC works with, tribes, industry partners, and other entities. The current vaccine distribution flow can be seen in Figure 1.

Figure 1 Distribution and administration of COVID-19 vaccine (see online version for colours)



In Figure 1, we can see that after Food and Drug Administration (FDA) approval, the vaccine flows from manufacturer to OWS/CDC then to distributors and distribution facility and lastly reaches the administration site. While distributing COVID-19 vaccine the key challenge is to maintain cost-effectiveness across supply chains that arise because the vaccines are more temperature-sensitive products that are priced higher and packaged in larger unit volumes. Given the requirement of significant investment to distribute new vaccines across USA through vaccine hub at all the state capitals, an alternative option for the timely, cost-effective, safe delivery of vaccines could be through regional distribution vaccine hub strategically located at major cities across tactically selected zones (Chiu et al., 2007).

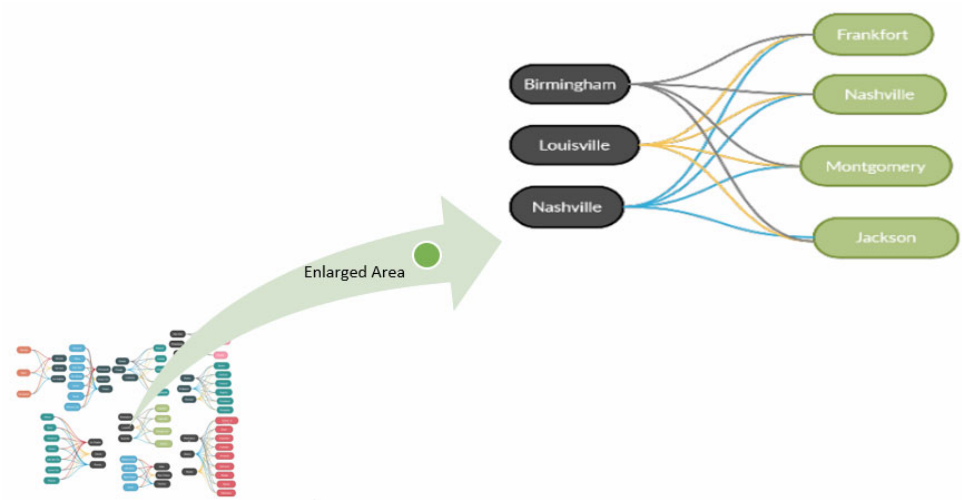
In this paper, we have divided the USA into nine zones based on Census Bureau-designated regions and divisions and for each zone, we have created three vaccine hub centres based on their strategic location. Following are the detailed description of each zone and description of three cities selected as vaccine hub in each zone.

- Zone 1 is the New England Division (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont). In this zone, we have strategically selected three cities – Boston, Bridgeport and Portland where vaccine hubs can be located.
- Zone 2 is the Mid-Atlantic Division (New Jersey, New York, and Pennsylvania). In Zone 2 we have suggested 3 cities - New York, Philadelphia, and Pittsburgh to open vaccine hub.
- Zone 3 is East North Central Division (Illinois, Indiana, Michigan, Ohio, and Wisconsin). In this zone, we have suggested vaccine hubs at cities Miami, Atlanta, and Washington.
- Zone 4 is West North Central Division (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota). In this zone, three strategic cities suggested for vaccine hubs are Kansas City, Minneapolis, and Omaha.
- Zone 5 is South Atlantic Division (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, and West Virginia). In Zone 5 we have suggested 3 cities Miami, Atlanta, Washington to open vaccine hub.
- Zone 6 is East South-Central Division (Alabama, Kentucky, Mississippi, and Tennessee. In this zone, three suggested cities for vaccine hubs are Birmingham, Nashville and Louisville.
- Zone 7 is West South-Central Division (Arkansas, Louisiana, Oklahoma, and Texas). In this zone, three prominent and strategically located cities are Houston, Dallas and New Orleans.
- Zone 8 is Mountain Division (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming). In this zone three strategically located vaccine hubs can be opened at Phoenix, Denver and Las Vegas.
- Zone 9 is the Pacific Division (Alaska, California, Hawaii, Oregon, and Washington). In this zone, three cities suggested for vaccine hubs are Los Angeles, San Jose, and Olympia.

It may be noted here that, we have not included Alaska and Hawaii in our model because the distance to their geographical locations necessitates a separate model.

We have also provided a diagrammatic representation of zones and vaccine hub. Figure 2 shows how three cities that have been chosen as vaccine hub in the zone are connected to the state capital (see Figure 2). For instance, in zone 6 which is located in East South-Central Division and consists of four states Alabama, Kentucky, Mississippi, and Tennessee. In this zone respective state capitals Nashville, Montgomery, Frankfort, and Jackson are connected to three suggested vaccine hubs located at cities namely Birmingham, Nashville and Louisville. The detailed diagrammatic representation of all the zones can be seen in Appendix.

Figure 2 Diagrammatic representation of selection of vaccine hub in the zone and connected state capitals (see online version for colours)



For each vaccine hub we consider a fixed capacity equal to one-third of the total population in that region, while each distribution point i.e., the state capital has a demand equal to the total population of that state that should be satisfied. Each vaccine hub is connected to each vaccine distribution point node by a road route with a transportation cost of $1.82/mile i.e., the average trucking cost per mile in the U.S as per the American Transportation Research Institute (ATRI) for every batch of vaccine sent via road. Furthermore, the option of not satisfying the demand at a certain distribution point due to age, immunocompromised situation, and other preexisting medical conditions or hesitation to take a vaccine is taken as maximum 10% of the population because a vaccine refusal rate more than ten percent could significantly impede the attainment of the required goal (DeRoo et al., 2020). Hence, we modelled the refusal as a cost penalty at each distribution point. We have considered a temporal horizon in this model. Since the supply of vaccine is probably limited in the beginning and it is expected that the first batch of vaccine will cater one-third of the population, therefore, we have formulated a proper master distribution schedule on a temporal horizon over three months with a time bucket of one month. Finally, the costs for each facility such as setup cost, cold storage, human resources, and holding cost has been modelled based on Benin's vaccine supply chain (Brown et al., 2014).

In this study, we used a MATLAB, an interactive system for numerical computation directly to code these mixed integer programming (MIP) models (Cavadas et al., 2015). In our model, the selection of vaccine hub in the region is binary (Table 1). We consider that multiple vaccine hub can be selected for each time period and the activation status of vaccine hub is denoted by '1' and non-activation of vaccine hub is denoted by '0'. The output of MATLAB is shown in Table 1. The green colour represents activation of the hub, the blue colour represents the time period, the grey colour represents the location and the number in cells represents the number of doses of vaccine in hundred thousand.

Table 1 New England Region – activation of vaccine hub and shipping matrix (see online version for colours)

		Shipping matrix					
		New England Region					
		Massachusetts	*Connecticut*	*New Hampshire*	*Maine*	*Rhode Island*	*Vermont*
1st month	Vaccine hub	Boston	Hartford	Concord	Augusta	Providence	Montpelier
	Boston	23	12	5	4	4	0
	Bridgeport	0	0	0	0	0	0
	Portland	0	0	0	0	0	2
2nd month	Vaccine hub	Boston	Hartford	Concord	Augusta	Providence	Montpelier
	Boston	0	0	0	0	0	0
	Bridgeport	0	0	0	0	0	0
	Portland	23	12	5	4	4	2
3rd month	Vaccine hub	Boston	Hartford	Concord	Augusta	Providence	Montpelier
	Boston	0	0	0	0	0	0
	Bridgeport	0	0	0	0	0	0
	Portland	23	12	5	4	4	2

Notes: – represents activation of the hub; – represents the time; – represents location.

Table 1 shows that, in the 'New England Region' during the first month of vaccination we need to activate two hubs in Boston and in Portland that is represented by green highlighted cells and in the second and third month we need to activate only one vaccination hub in Portland which is again represented by green highlighted cell. Furthermore, the number in the cell represents the number of vaccine doses in hundred thousand and at a particular state that will be shipped by the activated vaccine hub in the 'New England Region' In the first month while Boston will cater to Massachusetts, Hartford, New Hampshire, Rhodes Island, Portland and Vermont. In the second and the third month will cater all the six states.

Table 2 Mid-Atlantic region activation of vaccine hub and shipping matrix (see online version for colours)

		Mid-Atlantic Region		
		New York	*Pennsylvania*	*New Jersey*
1st month	Vaccine hub	Albany	Harrisburg	Trenton
	New York	65	43	0
	Philadelphia	0	0	30
	Pittsburgh	0	0	0
2nd month	Vaccine hub	Albany	Harrisburg	Trenton
	New York	0	0	0
	Philadelphia	65	43	30
	Pittsburgh	0	0	0
3rd month	Vaccine hub	Albany	Harrisburg	Trenton
	New York	65	43	0
	Philadelphia	0	0	30
	Pittsburgh	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Similarly, in Table 2, in 'Mid-Atlantic Region' during the first month of vaccination, we need to activate two hubs at New York and in Philadelphia that are represented by green highlighted cells and in the second month we need to activate only one vaccination hubs in Philadelphia and in the third month again we will have to activate two hubs in New York and in Philadelphia which are again represented by green highlighted cell. Furthermore, the number in the cell represents the number of vaccine doses in a hundred thousand and at a particular state those who will be vaccinated by the activated vaccine hub in the 'Mid-Atlantic Region'. While, in the first month New York will cater to New York and Pennsylvania, the hub at Philadelphia will cater to New Jersey. In the second month, the hub at Philadelphia will cater all the three states and during the third month, we will need two hubs at New York and Philadelphia to cater all three states.

Table 3 South Atlantic Region – activation of vaccine hub and shipping matrix (see online version for colours)

		South Atlantic Region								
		Florida	*Georgia*	*North Carolina*	*Virginia*	*Maryland*	*South Carolina*	*West Virginia*	*Delaware*	*District of Columbia*
1st month	Vaccine hub	Tallahassee	Atlanta	Raleigh	Richmond	Annapolis	Columbia	Charleston	Dover	
	Miami	0	0	0	0	0	0	0	0	0
	Atlanta	72	35	35	28	20	17	6	3	2
	Washington	0	0	0	0	0	0	0	0	0
2nd month	Vaccine hub	Albany	Harrisburg	Trenton	Richmond	Annapolis	Columbia	Charleston	Dover	
	Miami	0	0	0	0	0	0	0	0	0
	Atlanta	72	35	35	28	20	17	6	3	2
	Washington	0	0	0	0	0	0	0	0	0
3rd month	Vaccine hub	Albany	Harrisburg	Trenton	Richmond	Annapolis	Columbia	Charleston	Dover	
	Miami	0	0	0	0	0	0	0	0	0
	Atlanta	72	35	35	28	20	17	6	3	2
	Washington	0	0	0	0	0	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Whereas in 'South Atlantic Region' we need to open only one vaccine hub at Atlanta for all three months. During all three months, Atlanta will cater Florida, Georgia, North Carolina, Maryland, South Carolina, West Virginia and DC as shown in Table 3.

Table 4 East South Central – activation of vaccine hub and shipping matrix (see online version for colours)

		East South Central			
		Tennessee	*Alabama*	*Kentucky*	*Mississippi*
1st month	Vaccine hub	Nashville	Montgomery	Frankfort	Jackson
	Birmingham	0	0	0	0
	Nashville	23	16	15	10
	Louisville	0	0	0	0
2nd month	Vaccine hub	Nashville	Montgomery	Frankfort	Jackson
	Birmingham	0	0	0	0
	Nashville	23	16	15	10
	Louisville	0	0	0	0
3rd month	Vaccine hub	Nashville	Montgomery	Frankfort	Jackson
	Birmingham	0	0	0	0
	Nashville	23	16	15	10
	Louisville	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Table 5 East North Central – activation of vaccine hub and shipping matrix (see online version for colours)

		East North Central				
		Illinois	*Ohio*	*Michigan*	*Indiana*	*Wisconsin*
1st month	Vaccine hub	Springfield	Columbus	Lansing	Indianapolis	Madison
	Chicago	42	39	33	22	19
	Columbus	0	0	0	0	0
	Detroit	0	0	0	0	0
2nd month	Vaccine hub	Springfield	Columbus	Lansing	Indianapolis	Madison
	Chicago	42	39	33	22	19
	Columbus	0	0	0	0	0
	Detroit	0	0	0	0	0
3rd month	Vaccine hub	Springfield	Columbus	Lansing	Indianapolis	Madison
	Chicago	42	39	33	22	19
	Columbus	0	0	0	0	0
	Detroit	0	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Table 6 West North Central – activation of vaccine hub and shipping matrix (see online version for colours)

		West North Central						
		Missouri	*Minnesota*	*Iowa*	*Kansas*	*Nebraska*	*South Dakota*	*North Dakota*
1st month	Vaccine hub	Jefferson City	Saint Paul	Des Moines	Topeka	Lincoln	Pierre	Bismarck
	Kansas City	20	19	11	10	6	3	0
	Minneapolis	0	0	0	0	0	0	3
	Omaha	0	0	0	0	0	0	0
2nd month	*Vaccine hub*	Jefferson City	Saint Paul	Des Moines	Topeka	Lincoln	Pierre	Bismarck
	Kansas City	0	0	0	0	0	0	0
	Minneapolis	20	19	11	10	6	3	3
	Omaha	0	0	0	0	0	0	0
3rd month	Vaccine hub	Jefferson City	Saint Paul	Des Moines	Topeka	Lincoln	Pierre	Bismarck
	Kansas City	0	0	0	0	0	0	0
	Minneapolis	20	19	11	10	6	3	3
	Omaha	0	0	0	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Similarly, 'East South-Central Region' we need to open only one vaccine hub in Nashville.

The hub at Nashville will cater to Tennessee, Alabama, Kentucky and Mississippi as shown in Table 4.

In the 'East North Central Region', we need to open only one hub at Chicago for all three months. During all three months, Chicago will cater to Illinois, Ohio, Michigan, Indiana, Wisconsin.

In the 'West North Central Region,' we need to open two hubs at Kansas City and Minneapolis during the first month of vaccine distribution but for the second and third month, we need to activate only one hub at Minneapolis.

Table 7 West South Central – activation of vaccine hub and shipping matrix (see online version for colours)

		West South Central			
		Texas	*Louisiana*	*Oklahoma*	*Arkansas*
1st month	Vaccine hub	Austin	Baton Rouge	Oklahoma City	Little Rock
	Houston	97	15	13	10
	Dallas	0	0	0	0
	New Orleans	0	0	0	0
2nd month	Vaccine hub	Austin	Baton Rouge	Oklahoma City	Little Rock
	Houston	97	15	13	10
	Dallas	0	0	0	0
	New Orleans	0	0	0	0
3rd month	Vaccine hub	Austin	Baton Rouge	Oklahoma City	Little Rock
	Houston	97	15	13	10
	Dallas	0	0	0	0
	New Orleans	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

In 'West South-Central Region' we need to open only one vaccine hub at Huston for all three months. That hub will cater to Texas, Louisiana, Oklahoma, and Arkansas.

In the 'Mountain Region,' we need to activate only one hub for all three phases located at Phoenix. The hub at Phoenix will cater to Arizona, Colorado, Utah, Nevada, Idaho, Montana, and Wyoming as shown in Table 8.

And, for the 'Pacific Region' as shown in Table 9, we need to activate two vaccine hubs at San Jose and Olympia during the first month of vaccine distribution San Jose will ship to California whereas Olympia will ship vaccine to Washington and Oregon but for the second and third month we need to activate only one hub located at San Jose.

Table 8 Mountain – activation of vaccine hub and shipping matrix (see online version for colours)

		Mountain						
		Arizona	*Colorado*	*Utah*	*Nevada*	*Idaho*	*Montana*	*Wyoming*
1st month	Vaccine hub	Phoenix	Denver	Salt Lake City	Carson City	Boise	Helena	Cheyenne
	Phoenix	24	19	11	10	6	4	2
	Denver	0	0	0	0	0	0	0
	Las Vegas	0	0	0	0	0	0	0
2nd month	Vaccine hub	Phoenix	Denver	Salt Lake City	Carson City	Boise	Helena	Cheyenne
	Phoenix	24	19	11	10	6	4	2
	Denver	0	0	0	0	0	0	0
	Las Vegas	0	0	0	0	0	0	0
3rd month	Vaccine hub	Phoenix	Denver	Salt Lake City	Carson City	Boise	Helena	Cheyenne
	Phoenix	24	19	11	10	6	4	2
	Denver	0	0	0	0	0	0	0
	Las Vegas	0	0	0	0	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

Table 9 Pacific – activation of vaccine hub and shipping matrix (see online version for colours)

		Pacific		
		California	*Washington*	*Oregon*
1st month	Vaccine hub	Sacramento	Olympia	Salem
	Los Angeles	0	0	0
	San Jose	132	0	0
	Olympia	0	25	14
2nd month	Vaccine hub	Sacramento	Olympia	Salem
	Los Angeles	0	0	0
	San Jose	132	25	14
	Olympia	0	0	0
3rd month	Vaccine hub	Sacramento	Olympia	Salem
	Los Angeles	0	0	0
	San Jose	132	25	14
	Olympia	0	0	0

Notes: – represents activation of the hub; – represents the time; – represents location.

7 Discussion and summary

The work reported here provides a formal modelling framework for decision making concerning the distribution and transportation of the COVID-19 vaccine. The model will help in the effective distribution of the COVID-19 vaccine by creating a strategic vaccination hub in a region and transporting batches of vaccine from the vaccine hub to the state capital. At present vaccine doses purchased by OWS/CDC is being sent from manufacturer to state capital and then it is distributed in the states. This process is delaying the distribution of the vaccine. If we add vaccine hubs as per our model to the distribution channel, then that would speed up the vaccine distribution process.

7.1 Theoretical contributions and academic implications

This research study makes four key theoretical and academic contributions to the literature. First, the results of this study confirmed the integrative and predictive power of theoretical frameworks of Set covering algorithm being applied to the study of the COVID-19 vaccine distribution. This study has determined that the proposed a distribution model can explain an efficient way of distributing vaccine across the USA. Second, this study reveals that in order to vaccinate the population in the USA we do not need to create multiple vaccine hub, only 21 vaccine hubs can cater to the entire United States. Third, this study provides a model that not only provides a strategy to cover geographical location but also provides a shorter duration under which the vaccination process can be attained. Finally, an important academic implication of this study is that the vaccine distribution model provides the location of a strategic vaccine hub that can be used for the efficient distribution of vaccine in a particular geographical region. This suggests a shift in the current distribution model which is flowing from manufacturer to centralised procurer and then to different states in the US. Moreover, the suggested model provides a more efficient model that can expedite the vaccination process. Furthermore, the mathematical model can be used for other countries and regions.

7.2 Practical contributions

The suggested model in this paper can be used to address a more general planning setting than the one discussed above. When resources are very limited, the model proposes distributing the majority of the vaccine among the vast majority of the population, thus yielding economic and health benefits. The vaccine hub may also consider service level efficiently compete with other Vaccine hubs. In case, if the normal forces of market fail, the regulator may impose a required minimal service levels on the vaccine hub to ensure some minimal service level. In order to take regulatory intervention into account, it can be assumed that service level is the maximum between the level imposed by the regulator and the service level originally set by the distribution centre.

7.3 Limitation and future research

As with any model-based approach, our work also has some limitations. First, our data were approximate and aggregated, and we did not have access to detailed and accurate data to validate our model. Second, we have assumed that the planner is not biased and the plans from our model can be executed in an unbiased manner. Third, the assumptions of many parameters such as vaccine doses, vaccine distribution and the technology required are constantly changing this also can affect our model. Fourth, we have not modelled two States Alaska and Hawaii in our model. Their geographical locations were a limitation of our model.

Future research could be conducted using different locations. The proposed approach can be extended to include a more rigorous treatment of lost sales, for instance, people who are denied vaccines due to their conditions. Furthermore, since the model is NP-hard and developed analytical as well as heuristic methods that can be used to solve the problem for larger-scale input data is also an important area for future research. Moreover, in this model, we have assumed a deterministic paradigm, but the model could be extended to consider a stochastic paradigm. Future researchers may replicate this study for COVID 19 booster doses transportation and distribution.

8 Conclusions

The results of the present study are meaningful in that the authors were able to create a plan for the effective distribution of the COVID-19 vaccine. In particular, the problem modelled in this paper is motivated by probable vaccination activities in the USA, and our approach is based on adapting transportation models to the set coverage problem. We feel that this model can aid policymakers and decision makers in establishing a proper distribution plan and frame outreach policies. Since healthcare systems in different countries and cultures might have different operating structures and organisational control levels, we suggest developing a distributed model based on the model proposed herein. The mathematical model developed in this paper is generalisable in context of other countries.

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Appendix

Figure A1 The USA into nine zones: diagrammatic representation of selection of vaccine hub in the zone and connected state capitals (see online version for colours)