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Strategic planning for the optimal distribution of COVID-19 vaccines

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A B S T R A C T

This work presents a multi-objective optimization strategy for fair vaccine allocation through different fairness schemes. The proposed approach considers a diverse series of parameters related to different public health data and social behaviors that influence the correct distribution of vaccines, such as corruption and crime. Simultaneously, the formulation includes prioritizing those groups with the highest risk based on the epidemiological traffic light. Furthermore, the presented strategy involves different budget constraints that allow identifying trade-off solutions through Pareto fronts. Therefore, vaccine allocations are obtained by combining fairness concepts with multi-objective optimization. The applicability of the model is illustrated using the case study of Mexico. The solution to the proposed scenarios was carried out using different justice schemes and an economic objective function. The results show the compromises between a satisfaction index and costs, which are shown through Pareto optimal solutions that allow selecting the solutions that balance the objectives. The solutions provided by the social welfare scheme suggest a greater allocation of vaccines to those states with higher epidemiological risk, which may be helpful in the first stage of vaccination. On the other hand, the Rawlsian scheme provides more balanced solutions that can be useful in situations with lower rates of infection. Finally, the Nash scheme is the one that provides the most balanced solutions, favoring to a lesser extent the areas with the highest epidemiological risk, which may be useful in the later stages of vaccination.

1. Introduction

The global pandemic caused by COVID-19 has caused various problems as well as certain benefits. For example, novel models to accelerate the development of next-generation vaccines have been guided by the scale of the humanitarian and economic impact of the pandemic [1]. On the other hand, vaccines used to require many years of development as it is a slow, complex, and expensive process. Furthermore, many candidate vaccines may be discarded during this process to produce a certified vaccine [2]. Previously, the manufacturing process was done step by step due to cost and high failure rates, requiring multiple breaks for data analysis, which is why it is such a time-consuming process. The COVID-19 pandemic has caused a significant demand for vaccines around the world, leading to major changes in vaccine development. Regarding the distribution of vaccines, in order to establish a fair vaccine allocation system worldwide, it was necessary to carry out clinical and serological studies to confirm which populations remained at greater risk and prioritize their inoculation [3].

For instance, various studies determined that people with obesity suffer worse reactions, and a significant proportion of them may require intensive care [4]. Furthermore, diabetes, cardiovascular, cerebrovascular, and pulmonary diseases, as well as age and male gender, are multiple risk factors associated with mortality in patients with COVID-19 [5]. Unfortunately, older patients are more likely to progress to severe disease. In addition, these patients are at increased risk of death because they are more prone to multisystem organ dysfunction or failure [6].

Various issues have arisen in the allocation of medical resources globally due to the COVID-19 pandemic. The allocation of medical resources has already been profoundly affected by factors unrelated to COVID-19, including waste and inefficiency on the part of health workers, clumsy and costly bureaucratic systems, and excessive consumption [7]. Therefore, the difficulties generated by COVID-19 increased the importance of the improved distribution of available resources. During the worst part of the pandemic, in some regions, an intense debate about the right of all people to access health care has arisen since professionals considered prioritizing patients with the best chance of surviving over those with little chance. They argued that treating people as equals may no longer be accepted due to the sheer number of people who suffer and are directly affected by the

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implications of allocating scarce resources [8]. Approximately 200 experimental vaccines against COVID-19 were developed in the world. Still, only a few manufacturers, such as Moderna, Johnson & Johnson, Pfizer, and AstraZeneca, managed to produce vaccines that passed phase 3 and achieved certification from the health authorities of different countries where safety and efficacy have been demonstrated [9,10]. At the initial stage of the production of vaccines, the main concern was if there would be enough capacity to produce the number of vaccines needed [11]. AstraZeneca, Pfizer, and Moderna anticipated being able to produce 5.3 billion doses in 2021, while Russia's production capacity (Gamaleya vaccine) sought to produce an additional 500 million doses. Even China, the country with the highest production of COVID-19 vaccines with its Sinovac vaccine, declared that it did not have sufficient production capacity to fill advance orders [12]. Currently, it is estimated that the production of vaccines will reach 12 billion doses, which requires a production capacity never seen before. Since the manufacturers have different expansion capacities, it is expected that in the coming years, the Sinovac vaccine will begin to gain greater relevance in the market [13].

Resource management problems have been widely explored in different research fields [14,15], where various distribution methodologies capable of addressing inequality have been proposed in different areas [16,17]. The use of these methodologies could seem non-related to the distribution of vaccines; however, these methodologies help establish the theoretical background of this work that seeks to establish fair distributions for participants under different contexts.

The different vaccine manufacturers faced various challenges, including the equitable allocation of vaccines between countries. This problem arose mainly due to the conditions that occurred at the time of the distribution of the vaccines.

- Half of the vaccines produced by AstraZeneca, Pfizer, Moderna, and Gamaleya were reserved by 32 countries: 27 from the European Union and 5 other wealthy countries that, together, represent only 13% of the world's population [18].
- In some places, the pre-ordered vaccines only covered a certain part of their populations. Thus, some countries ordered vaccines from different manufacturers to vaccinate a greater part of their population. In contrast, other countries only ordered vaccines for a minimum percentage of their population [11].

The allocation of resources played a critical role because, due to the lack of vaccines during the initial stage of the pandemic, it was necessary to consider the different contexts of the population. For example, those presented by Torres-Ramírez et al. [12].

- Low capacity to purchase vaccines.
- Low vaccine efficacy among older adults or other subgroups of the population.
- Unforeseen adverse events due to the vaccine.
- Availability of more than one type of vaccine.
- The continuing spread of the virus despite the availability of vaccines.

Before the market release of the different vaccines, Munguía-López and Ponce-Ortega [19] developed an optimization strategy for the allocation of COVID-19 vaccines through different equity schemes. Here, various allocation schemes were analyzed and applied using the case study of Mexico. However, in this study, the simultaneous availability of the developed vaccines was not considered.

Justice schemes allow the allocation of resources to be based on specific considerations. In this paper, we consider three schemes of justice: social welfare, Rawlsian justice, and the Nash approach. The differences between these schemes are explained below. The main concern of social welfare analysis is how the total income should be distributed among different individuals [20]. For this classical utilitarian scheme, the distribution is given by maximizing the sum of the stakeholders' allocations [21]. However, inequitable solutions can be obtained in the presence of multiple allocations with different scales, making this scheme deficient in some scenarios. On the other hand, the Rawlsian distribution scheme arises from Rawls' theory called "justice as fairness". Chung [22] indicated that this theory is structured by the following three principles that are established in strict priority order as follows.

1. The Principle of Maximum Equal Basic Liberties: Each person should have the same right to basic liberties.
2. The Principle of Fair Equal Opportunity: Positions and offices opened to all under conditions of fair equal opportunity should be attached to social-economic inequalities.
3. The Difference Principle: Social and economic inequalities must be organized in a way that is of the greatest benefit to the least favored members of society.

However, this scheme might identify non-unique solutions because the distribution is given by maximizing the smallest allocated beneficiaries. Alternatively, the Nash scheme has been proposed. Originally, this scheme was a unique arbitration scheme for two-person bargaining games. Later, the Nash axioms were modified, giving a functional scheme of n-people [23]. According to Nash, the objective function should be to maximize "happiness". Here, the Pareto optimal allocation x_{op} compares favorably with any other Pareto optimal allocation x with the purpose that, when changing from x to x_{op}, the percentage of gains in happiness must be greater than the percentage of losses [24]. Two of the most notable attributes of this scheme are:

1. Scale-freeness: Allocations are independent of stakeholder scales.
2. Fairness and efficiency are their natural compromise. For this work, fair distribution is understood to be capable of reducing the rate of COVID-19 infections. The term efficiency here refers to obtaining Pareto optimal solutions.

In this scheme, the distribution is given by maximizing the sum of the logarithms of the stakeholders' allocations. Therefore, a unique solution can be found.

The allocation of resources in agricultural and industrial systems has been previously addressed using justice schemes through the development of different mathematical models [25,26]. On the other hand, the concepts of some allocation schemes, including Rawlsian justice and the social welfare approach, have been incorporated into the allocation of medical resources from an ethical point of view [27]. Moreover, care settings for older adults have been compared using the Nash approach [28].

Associated with the medical supply, a mathematical approach to predict the number of ICU patients and the mortality rate during the COVID-19 emergency has been proposed by Manca et al. [29]. Here, regression models were used to predict the behavior of the analyzed variables. Furthermore, the use of optimization and modeling techniques was recommended by Sy et al. [30], especially in scarce scenarios.

In this work, a multi-objective optimization model is proposed for the allocation of vaccines, considering the minimization of cost functions along with the objective functions of the distribution schemes. The estimate of the associated costs includes the costs of transportation and storage of vaccines. The multi-objective strategy helps find the optimal distribution of vaccines considering the epidemiological risk of each region and social factors that may affect the allocation. All these aspects allow the decision maker to consider medical factors and social and economic functions such as the epidemiological traffic light, the crime rate, and the investment capacity of the region where the allocation will be made.

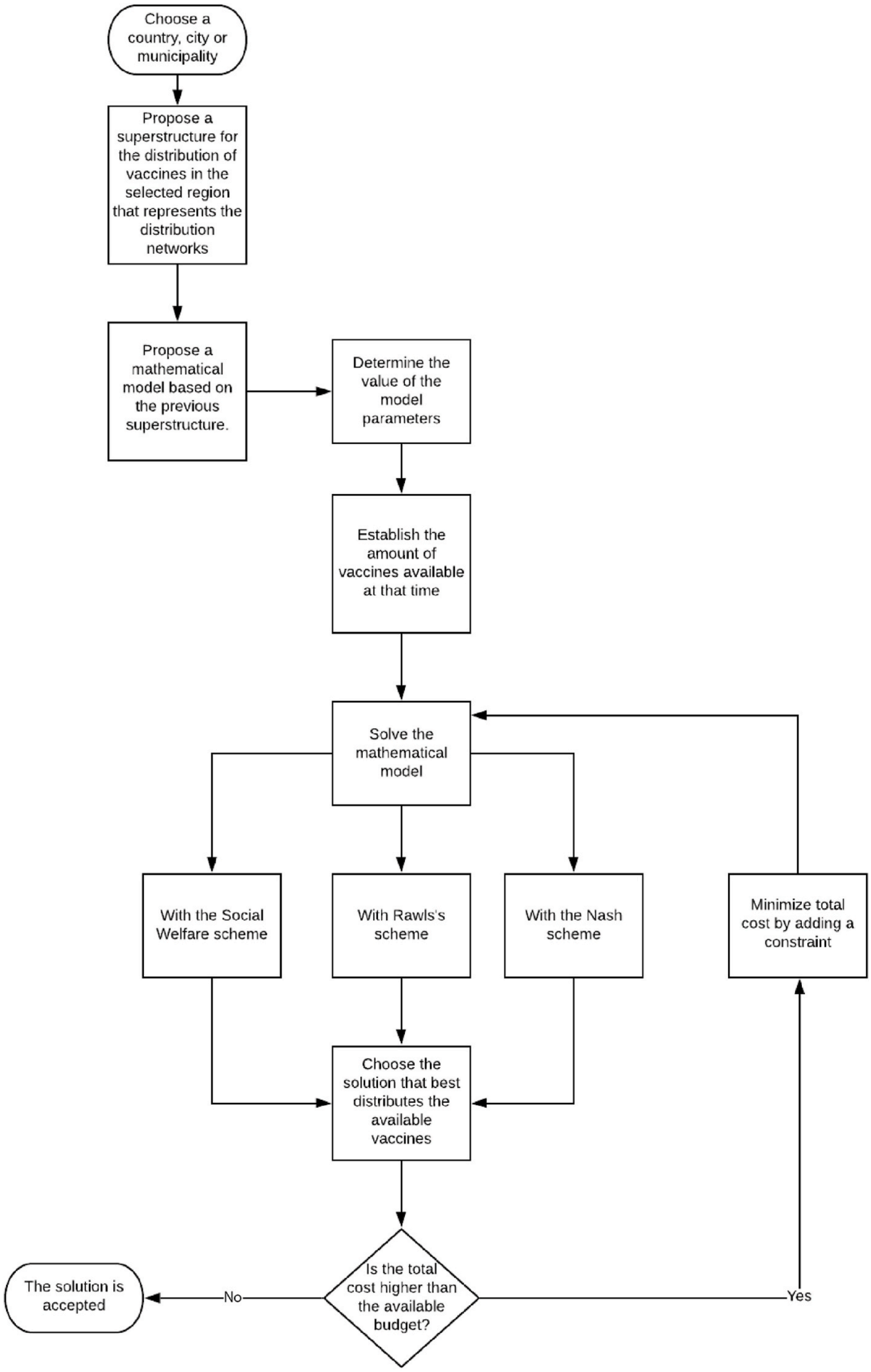

Fig. 1. Proposed algorithm to solve the vaccine distribution problem.

2. Problem statement

Due to the pandemic caused by COVID-19, efforts have been made to develop models to evaluate different vaccination strategies. Around 200 vaccines were developed, but only 122 came to carry out tests on humans [31]. Furthermore, only a few reached the quality levels required in different regions of the world [32]. In terms of distribution, there are different challenges. For example, the number of vaccines available in the short term and the time that these can be effective. Based on these challenges, the main unknown of this problem was generated: Who should be vaccinated to reduce the rate of infections, where, and why?

Matrajt et al. [33] examined multiple possible vaccine distribution scenarios classifying the population by age and classifying vaccines according to their efficacy and availability. Persad et al. [27] considered three approaches to the ethical distribution of scarce medical resources, such as organs and vaccines. The first one considered treating the entire population as equals (regardless of their social or health status), the second approach sought to prioritize the least favored members of society (elderly and sick), and finally, the third approach prioritized the youngest members of society. Munguía-López and Ponce-Ortega [19] developed an optimization model where the importance of involving

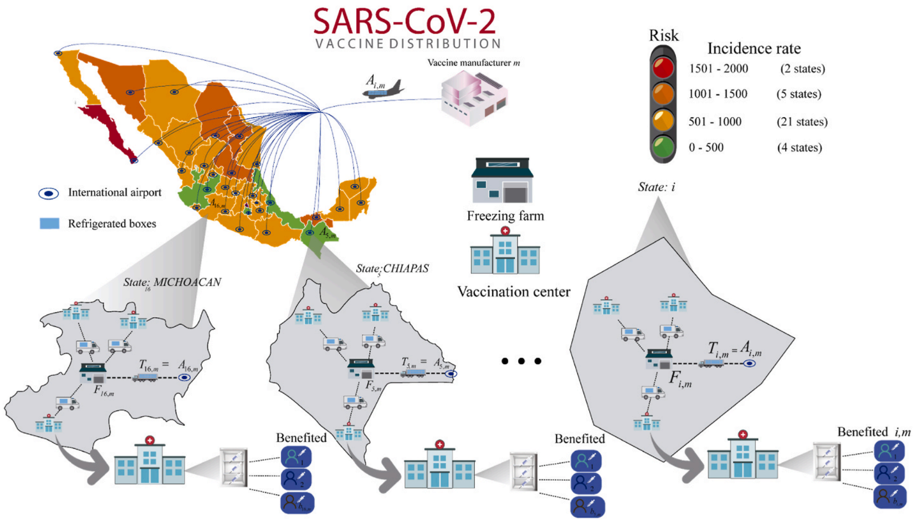

Fig. 2. Superstructure proposed for the allocation of potential vaccines among the different states in Mexico.

justice schemes was highlighted. The results showed that the social welfare scheme tends to favor large stakeholders, which are the states with large population sizes. However, this approach was developed without considering the availability of different vaccines, the epidemiological traffic lights, and the crime incidence rate.

According to the reviewed literature, none of the previous strategies have used multi-objective optimization to simultaneously consider the associated costs and the allocation of vaccines in pandemic conditions. These conditions include parameters such as the epidemiological risk and the availability of multiple vaccines. Furthermore, previous studies have not considered how social factors (corruption and insecurity) may affect the fair distribution of vaccines. Therefore, we account for different weight factors to consider each state's epidemiological risk. The proposed model also considers the distribution of several types of vaccines while calculating and minimizing the estimated costs related to doses, transport, and storage of vaccines. Incorporating the cost-reduction function helps select the best possible solution through cost-benefit interaction, which can be especially attractive for countries with low budgets.

Mexico was taken as a case study for this work, particularly the distribution among its states. Note that the formulation can also be used for the allocation among cities or municipalities. The 32 states of the country were considered as interested stakeholders, where different scenarios of the availability of different types of vaccines were proposed. Different parameters that are characteristic of each state were included considering their respective loss factors related to corruption and crime, as well as their respective color in the COVID-19 epidemiological traffic light scheme. The case rate, the number of available beds, and the death rate from COVID-19 are some of the parameters involved. It is essential to account for these values to guide the allocation of vaccines.

The formulation is general and can be applied to any case study following the algorithm in Fig. 1. It should be noted that the mathematical model may or may not be slightly modified depending on the specific case study. For this work, it is assumed that fair distribution can reduce the rate of COVID-19 infections.

3. Mathematical model formulation

We proposed Fig. 2 to represent the mathematical model formulation graphically. Here, we can see some elements included in the formulation, such as the epidemiological risk traffic light and the proposed vaccine distribution. We include the transportation of the vaccines from the manufacturer to freezing farms and then to the vaccination centers.

The model considers the fair allocation of vaccines among the states while minimizing the costs associated with the unitary cost of vaccines, storage, and transportation. Distribution schemes are used to obtain optimal solutions according to the proposed scenarios. The constraints

Table 1
Nomenclature used in the model formulation.

Parameters	
AB	Available budget
B_i^{av}	Available beds in each state i for all diseases
c_i	Threshold of each state i (refers to the minimum amount of population that should receive a vaccine)
CI_i	Crime incidence rate per state i
$\overline{CI}_i$	Average crime incidence rate per state i
d_i^p	Discharged patients in each state i per year for all diseases
d^y	Days in the year
f_i^{dm}	Prevalence of diagnosed diabetes mellitus in adults in each state s
f_i^e	Fraction of the elderly population in each state i
f^h	Fraction of COVID-19 patients who require hospitalization
f_i^{hy}	Prevalence of hypertension in adults in each state i
f_i^{ob}	Prevalence of obesity in adults in each state i
i^o	Occupancy index
l_i	Demand for hospital beds for COVID-19 patients that cannot be satisfied
M_i	COVID-19 mortality rate per state i
M^{dm}	Mortality of COVID-19 patients with diabetes mellitus
M^e	Mortality of elderly patients with COVID-19
M^{hy}	Mortality of COVID-19 patients with hypertension
M^{ob}	Mortality of COVID-19 patients with obesity
p_i	Population of each state i
r_i	Rate of COVID-19 cases of each state i
s_i^a	Average stay in days of patients in each state i for all diseases
VT_m	Total available vaccines per vaccine type m
w_i	Weight factor for each state i
γ_i	Fraction of losses per state i
Variables	
$A_{i,m}$	Airborne vaccines for state i of vaccine type m
$b_{i,m}$	Beneficiaries for each state i per vaccine type m
CPV_m	Costs per vaccine type m
$CTAR_{i,m}$	Transport cost for airplanes for each state i per vaccine type m
$CT_{i,m}$	Unit refrigeration cost m for trucks for each state i per vaccine type m
$CTT_{i,m}$	Unit transport cost for trucks for each state i per vaccine type m
$F_{i,m}$	Vaccines transported by land for the state i and of vaccine type m
nh	Variable to denote the objective function in the Nash scheme
$RCA_{i,m}$	Unit refrigeration cost for airplanes for each state i per vaccine type m
rw	Variable to denote the objective function in the Rawlsian justice scheme
$SCF_{i,m}$	Unit storage costs for freezing farms for each state i per vaccine type m
sw	Variable to denote the objective function in the social welfare scheme
TC	Total costs
$v_{i,m}$	Allocated vaccines for each state i per vaccine type m
Φ_i	Satisfaction variable for each state i

Table 2
Parameters for each state including population (p_i) [34,35], rate of COVID-19 cases (r_i), and COVID-19 mortality rate (M_i), as well as available beds (B_i^{av}), discharged patients (d_i^p), and the average stay of patients in days (s_i^a) for all diseases. The information related to COVID-19 is based on the reported cases by DGE [36] and SINAISCAP [37].

States by population		p_i	r_i	M_i	B_i^{av}	d_i^p	s_i^a
1	Estado de México	17,42,790	0.0001640	0.073	8356	303,939	4.3
2	Ciudad de México	9,018,645	0.0005300	0.067	15,632	249,752	5.7
3	Veracruz	8,539,862	0.0000602	0.086	4999	163,327	3.5
4	Jalisco	8,409,693	0.0000388	0.077	6460	176,843	4.1
5	Puebla	6,604,451	0.0000940	0.135	4012	118,039	4.4
6	Guanajuato	6,228,175	0.0000384	0.092	3657	158,514	3.7
7	Chiapas	5,730,367	0.0000288	0.042	2260	108,258	3.3
8	Nuevo León	5,610,153	0.0000558	0.038	4077	54,699	3.7
9	Michoacán	4,825,401	0.0000576	0.130	2648	100,186	2.6
10	Oaxaca	4,143,593	0.0000314	0.138	2352	76,420	3.5
11	Chihuahua	3,801,487	0.0000855	0.212	2915	81,911	4.1
12	Guerrero	3,657,048	0.0000733	0.183	2075	78,186	3.2
13	Tamaulipas	3,650,602	0.0000844	0.058	2977	77,266	3.8
14	Baja California	3,634,868	0.0004110	0.142	2153	40,627	4.5
15	Coahuila	3,218,720	0.0001150	0.111	2915	39,205	3.7
16	Sinaloa	3,156,674	0.0002600	0.162	2382	54,142	3.9
17	Hidalgo	3,086,414	0.0000784	0.112	1367	56,521	4.2
18	Sonora	3,074,745	0.0000657	0.109	2894	90,264	2.9
19	San Luis Potosí	2,866,142	0.0000342	0.071	2021	60,832	4
20	Tabasco	2,572,287	0.0003660	0.124	1583	81,367	2.9
21	Querétaro	2,279,637	0.0000561	0.078	881	51,749	3.2
22	Yucatán	2,259,098	0.0001790	0.064	1800	53,173	4.3
23	Morelos	2,044,058	0.0001360	0.112	1047	44,348	2.7
24	Durango	1,868,996	0.0000310	0.104	1542	48,582	2.6
25	Quintana Roo	1,723,259	0.0004130	0.153	1030	40,320	3.6
26	Zacatecas	1,666,426	0.0000420	0.100	999	38,496	3.4
27	Aguascalientes	1,434,635	0.0001290	0.011	966	39,160	3.3
28	Tlaxcala	1,380,011	0.0001300	0.101	714	54,655	2.2
29	Nayarit	1,288,571	0.0000559	0.167	714	19,665	2.8
30	Campeche	1,000,617	0.0000869	0.196	790	24,245	3.9
31	Baja California Sur	804,708	0.0003740	0.053	695	19,639	3.2
32	Colima	785,153	0.0000331	0.115	649	19,049	3.5

proposed for the model are explained in the following, and the nomenclature used is presented in Table 1.

3.1. Constraints for a feasible design

The allocation of medical resources is subject to specific constraints. These restrictions help establish limits for the allocation of resources to each state. Therefore, an over-allocation for any state is avoided, and a minimum number of vaccines that must be allocated for each state is established. The proposed superstructure to represent the addressed system is shown in Fig. 2. Here, the indices used are shown: i represents each state, and m represents the type of vaccine. The following constraints are included for the vaccines allocation:

$$\sum_{i \in I} v_{i,m} \leq VT_m, \forall m \in M \tag{1}$$

$$\sum_{m \in M} v_{i,m} \leq p_i, \forall i \in I \tag{2}$$

$$\sum_{m \in M} v_{i,m} \geq c_i, \forall i \in I \tag{3}$$

$$\sum_{m \in M} b_{i,m} \geq p_i, \forall i \in I \tag{4}$$

The first of these constraints specifies that the sum of the sent vaccines to each state i ($v_{i,m}$) for each type of vaccine m must be less than or equal to the total available vaccines (VT_m). Furthermore, Constraint (2) specifies that the vaccines sent to each state i must be less than or equal to the population (p_i) to avoid waste. Similarly, Constraint (3) establishes that the vaccines sent to each state i must be at least equal to a minimum threshold (c_i). This minimum threshold is a parameter that considers patients who would require hospitalization but will not receive this service due to a lack of medical resources. The estimation of this parameter is presented in the next subsection. Note that when Constraint (2) is active, the maximum number of vaccines is allocated to each state. On the other hand, when Constraint (3) is active, the minimum number of vaccines is allocated to each state. Finally, Constraint (4) establishes that the beneficiaries (people receiving the vaccine) ($b_{i,m}$) must be less than or equal to the population (p_i).

3.2. Parameter setting

Due to the large variance in the number of vulnerable individuals within each state, it is necessary to establish parameters to estimate, quantify and prioritize these differences. The calculation of these parameters is carried out as follows.

$$c_i = l_i + p_i r_i \left(M_i + M^e f_i^e, M^{ob} f_i^{ob} + M^{hy} f_i^{hy} + M^{dm} f_i^{dm} \right), \forall i \in I \tag{5}$$

$$l_i = p_i r_i f^h + \frac{d_i^p s_i^a}{d^y i^o} - B_i^{av}, \forall i \in I \tag{6}$$

First, we estimate the minimum threshold c_i (mentioned above in Constraint (3)) considering parameters related to the mortality rate (M_i) and the most vulnerable groups for COVID-19 in Constraint (5). These groups include the elderly and the population with an underlying condition such as obesity, hypertension, and diabetes mellitus. Specifically, the mortality rate due to COVID-19 in these groups ($M^e, M^{ob}, M^{hy}, M^{dm}$) and the fraction of the population that is part of these vulnerable groups are involved (f_i^e, f_i^{ob}, f_i^{hy}, f_i^{dm}). Also, c_i considers the rate of COVID-19 cases per state (r_i) and the demand for hospital beds for COVID-19 patients that cannot be satisfied (l_i). The values for r_i can be found in Table 2 l_i is estimated as presented in Constraint (6). The first term of this equation refers to the fraction of COVID-19 patients who required hospitalization, the second term represents the beds needed per year in each

Table 3
Fraction of losses per state based on crime incidence rate.

NUMBER	STATE	γ_i
1	Estado de México	0.302
2	Ciudad de México	0.270
3	Veracruz	0.111
4	Jalisco	0.209
5	Puebla	0.158
6	Guanajuato	0.163
7	Chiapas	0.087
8	Nuevo León	0.158
9	Michoacán	0.118
10	Oaxaca	0.120
11	Chihuahua	0.160
12	Guerrero	0.201
13	Tamaulipas	0.122
14	Baja California	0.214
15	Coahuila	0.121
16	Sinaloa	0.145
17	Hidalgo	0.116
18	Sonora	0.195
19	San Luis Potosí	0.165
20	Tabasco	0.158
21	Querétaro	0.142
22	Yucatán	0.129
23	Morelos	0.195
24	Durango	0.122
25	Quintana Roo	0.184
26	Zacatecas	0.130
27	Aguascalientes	0.184
28	Tlaxcala	0.144
29	Nayarit	0.139
30	Campeche	0.132
31	Baja California Sur	0.141
32	Colima	0.130

state for other diseases, and the third term is the available beds per state. The required beds for other diseases can be estimated as a function of the use rate, discharges, average stay, and percentage of bed occupancy. In this work, the beds required per year in each state for other diseases were estimated using Brigdman's formula [31]. It should be noted that the minimum threshold c_i varies depending on the parameters of each state. The population, available beds, discharged patients, and the average stay of patients can be found in Table 2. The complete parameters can be consulted in the work by Munguía-López and Ponce-Ortega [19].

Simultaneously, there are factors outside the medical sector that can affect the correct distribution of vaccines, such as the high levels of insecurity and corruption existing in different states. Calculating a value for this parameter can be especially complicated since it implies carrying out a complex social analysis. To simplify this, it is possible to estimate a factor of losses statistically as presented in Constraint (7). Here, the fraction of losses (γ_i) is a known parameter between 0 and 1. This parameter can be estimated using the crime incidence rate per state (CI_i), which includes the theft of goods or money, extortion, theft of merchandise in transit, damage to facilities, machinery, or equipment, and total or partial theft of a vehicle. The value of this parameter for each state over 8 years can be found in Table 1 of the Appendix. To obtain a representative value for the fraction of losses, we consider the average fraction of crime per state ($\overline{CI}_i$) divided by two as shown in Constraint (7). The resulting values for this parameter can be found in Table 3.

$$\gamma_i = \frac{\overline{CI}_i}{2}, \forall i \in I \tag{7}$$

3.3. Balances in the distribution network

The series of steps that vaccines follow from the manufacture until their delivery to the intended population is of vital importance as some vaccines require special care in terms of how they are transported and stored (i.e., at very low temperatures). The balances in the distribution network are detailed below:

$$v_{i,m} = A_{i,m}, \forall i \in I, m \in M \tag{8}$$

$$F_{i,m} = A_{i,m} - v_{i,m}^{lost}, \forall i \in I, m \in M \tag{9}$$

$$v_{i,m}^{lost} = \gamma_i A_{i,m}, \forall i \in I, m \in M \tag{10}$$

$$F_{i,m} = b_{i,m}, \forall i \in I, m \in M \tag{11}$$

$$\varphi_i = \frac{\sum_{m \in M} b_{i,m}}{p_i}, \forall i \in I \tag{12}$$

Constraint (8) specifies that the total number of vaccines sent is equal to every type of vaccine (m) carried by airplanes ($A_{i,m}$). Similarly, Constraint (9) specifies that the transported vaccines are stored in freezer farms ($F_{i,m}$) (these farms store all types of vaccines). However, vaccines transported in refrigerated trucks can suffer losses (related to the high-risk indices existing in some regions). Therefore, this possible loss of vaccines is considered ($v_{i,m}^{lost}$). Constraint (10) establishes how to estimate this variable. Finally, Constraint (11) establishes that vaccines stored in freezer farms are delivered to the members of the target population (Beneficiaries ($b_{i,m}$)). The main objective of this work is to provide a fair distribution allocation for the available vaccines. Therefore, when it is not possible to satisfy all the demands of vaccines, it is useful to establish a satisfaction index (φ_i) which is defined in Constraint (12). This index must be between the 0–1 interval, where 1 represents the maximum satisfaction level, and 0 represents the minimum satisfaction level (results are presented using this satisfaction index).

3.4. Distribution schemes

The first objective function changes according to the distribution scheme used to solve the model, which also changes the type of model to solve. For the social welfare and Rawlsian justice schemes, the resulting models are linear programs (LP). On the other hand, for the Nash scheme, the model is a nonlinear program (NLP). The distribution schemes and their respective objective function are established as shown below:

$$\max\ sw \tag{13}$$

$$sw = \sum_{i \in I} \left(\sum_{m \in M} b_{i,m} \right) w_i \tag{14}$$

$$\min\ rw \tag{15}$$

$$\left(\sum_{m \in M} b_{i,m} \right) w_i \le rw, \forall i \in I \tag{16}$$

$$\max\ nh \tag{17}$$

$$nh = \sum_{i \in I} w_i \log \left(\sum_{m \in M} b_{i,m} \right) \tag{18}$$

Constraints (13), (15), and (17) establish the objective functions for the social welfare, Rawlsian, and Nash schemes, respectively. Constraint (14) establishes the variable for the social welfare scheme (sw). Here, the distribution is given by maximizing the sum of the beneficiaries' allocations. In Constraint (16), the Rawlsian variable (rw) is established to relate the number of beneficiaries according to Rawls's theory. Here, the distribution is given by maximizing the smallest allocated beneficiaries. Finally, in Constraint (18), the variable belonging to the Nash justice scheme (nh) is established, where the use of logarithms is implemented

Table 4
Weight factors based on the COVID-19 traffic light [38].

Traffic light color	w_i
Green	1
Yellow	2
Orange	3
Red	4

Table 5
The storage costs for freezing farms per month, per vaccine [39,40].

	Pfizer	AstraZeneca	Moderna
SCF*(Dollars per month/Vaccine) x10*^{3}	9.681	0.421	0.420

to eliminate the priorities generated by the different scale sizes of the stakeholders. Here, the distribution is given by maximizing the sum of the logarithms of the beneficiaries' allocations.

In the previous equations, an additional parameter is observed (w_i). This parameter is a weight factor, which depends only on the epidemiological risk shown in Fig. 2 (the risk changes according to the color of each state). It should be noted that these weights add a priority that does not depend on the different sectors of the population affected by different diseases. It only depends on the epidemiological risk present in each state. The values that this variable can take are shown in Table 4. It should be noted that separating states by their incidence rate color allows for prioritizing states with higher levels of infected people.

3.5. Costs

The implementation of the cost function helps compare the different possibilities between the availability of the vaccine and the availability of investment (multi-objective model). Thus, it is possible to obtain optimal Pareto solutions, maximizing beneficiaries' allocations (objective function of distribution schemes) and minimizing costs (total cost objective function). The proposed cost function considers the transportation cost, storage cost, as well as cost associated with each vaccine type. The equations that allow implementing the costs to the model are shown in the following:

$$TC = transportation\ cost + storage\ cost + vaccine\ costs \tag{19}$$

$$TC \le AB \tag{20}$$

$$transportationcost = \sum_{m\in M}\sum_{i\in I}\left(RCA_{i,m} + CTAR_{i,m} + CT_{i,m} + CTT_{i,m}\right)A_{i,m} \tag{21}$$

$$storage\ cost = \left(\sum_{m\in M}\sum_{i\in I} SCF_{i,m}F_{i,m}\right) \tag{22}$$

$$vaccine\ costs = \left(\sum_{m\in M} CPV_m VT_m\right) \tag{23}$$

The first of these equations (Constraint (19)) calculates the total costs (TC). Constraint (20) limits these costs as a function of the available investment capacity (AB) which is a parameter. It should be noted that Constraint (20) works as the second objective function of the model (to ensure that the purchase and associated expenses do not exceed the available budget of a region). Constraints (21), (22), and (23) are used to compute the total transportation, storage, and vaccine costs, respectively. The transportation costs are linked to the type of vaccine m and the state i (since the costs of the refrigerant used for each vaccine are different). Constraint (21) specifies how to calculate these costs, where $RCA_{i,m}$ is the unit refrigeration cost m for airplanes, $CTAR_{i,m}$ is the unit transport cost for airplanes, $CT_{i,m}$ is the unit refrigeration cost m for trucks, and $CTT_{i,m}$ is the unit transport cost for trucks. It is necessary to consider different types of costs due to the refrigerant for each vaccine. Furthermore, in Constraint (22), the calculation of the storage costs is specified, where $SCF_{i,m}$ is the unit storage cost for freezing farms. As mentioned before, different types of vaccines may require different refrigerators, therefore, it needs to be specified. For this work, a month of storage will be considered to obtain the unit cost (see Table 5). Finally, in Constraint (23) the costs associated with each type of vaccine are established, where CPV_m are the costs per vaccine that can be found in Table 6.

Table 6
Vaccine costs [41].

	Pfizer	AstraZeneca	Moderna
CPV(Dollars per Vaccine)	19.5	3.5	34.5

4. Case study

The addressed problem consists of the strategic planning for the optimal distribution of vaccines under several scenarios with different conditions. We consider the allocation among the states of Mexico as a case study. This work presents a multi-objective optimization formulation that uses justice schemes to find such allocations. The following schemes are included as objective functions: the social welfare, Nash, and Rawlsian approaches. Also, for the minimization of costs, an objective function is presented that restricts the maximum amount of investment. The solution to the problem involves finding the optimally allocated vaccines for each state through different distribution schemes, minimizing the associated costs, and obtaining Pareto solutions showing cost-satisfaction relationships. Note that the model is general and can be applied to different case studies by modifying the parameters. In addition to considering the states of Mexico for the case study, the municipalities can also be involved. On the other hand, countries could be included in the analysis to identify the worldwide allocation of potential vaccines. Regarding the case study data, information from the Mexican government and other references were used for the different parameters. The data relating to COVID-19, such as the rate of cases or the mortality rate, were taken from previous work by Munguía-López and Ponce-Ortega [19].

For the addressed case study, the following scenarios were evaluated. The quantities of available vaccines and relative percentages were established based on the data proposed in the government statement no. 080 [42].

Scenario 1:

- The total number of vaccines available on the market is equivalent to 33% of the population (42,000,000 vaccines).
- 40% are Pfizer vaccines, 30% are Moderna vaccines, and 30% are AstraZeneca vaccines.
- All types of vaccines require two doses per beneficiary.
- The fraction of losses is depreciated ($\gamma_i = 0$), which means that there are no lost vaccines.
- The weight factors are 1 for all cases ($w_i = 1$)

Scenario 2:

- The total number of vaccines available on the market is equivalent to 33% of the population (42,000,000 vaccines).
- 40% are Pfizer vaccines, 30% are Moderna vaccines, and 30% are AstraZeneca vaccines.
- All types of vaccines require two doses per beneficiary.
- The fraction of losses is considered (see Table 3).
- The weight factors are 1 for all cases ($w_i = 1$).

Scenario 3:

- The total number of vaccines available on the market is equivalent to 33% of the population (42,000,000 vaccines).

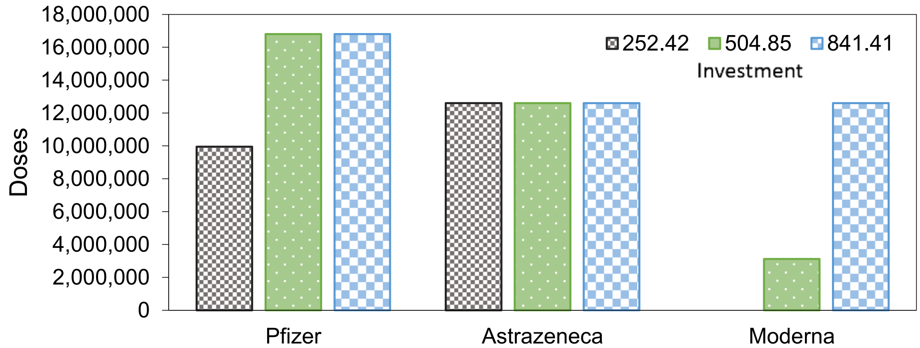

Fig. 3. Purchased vaccines for all scenarios with different investment capacities in MM$ (252.42, 504.85, and 841.4).

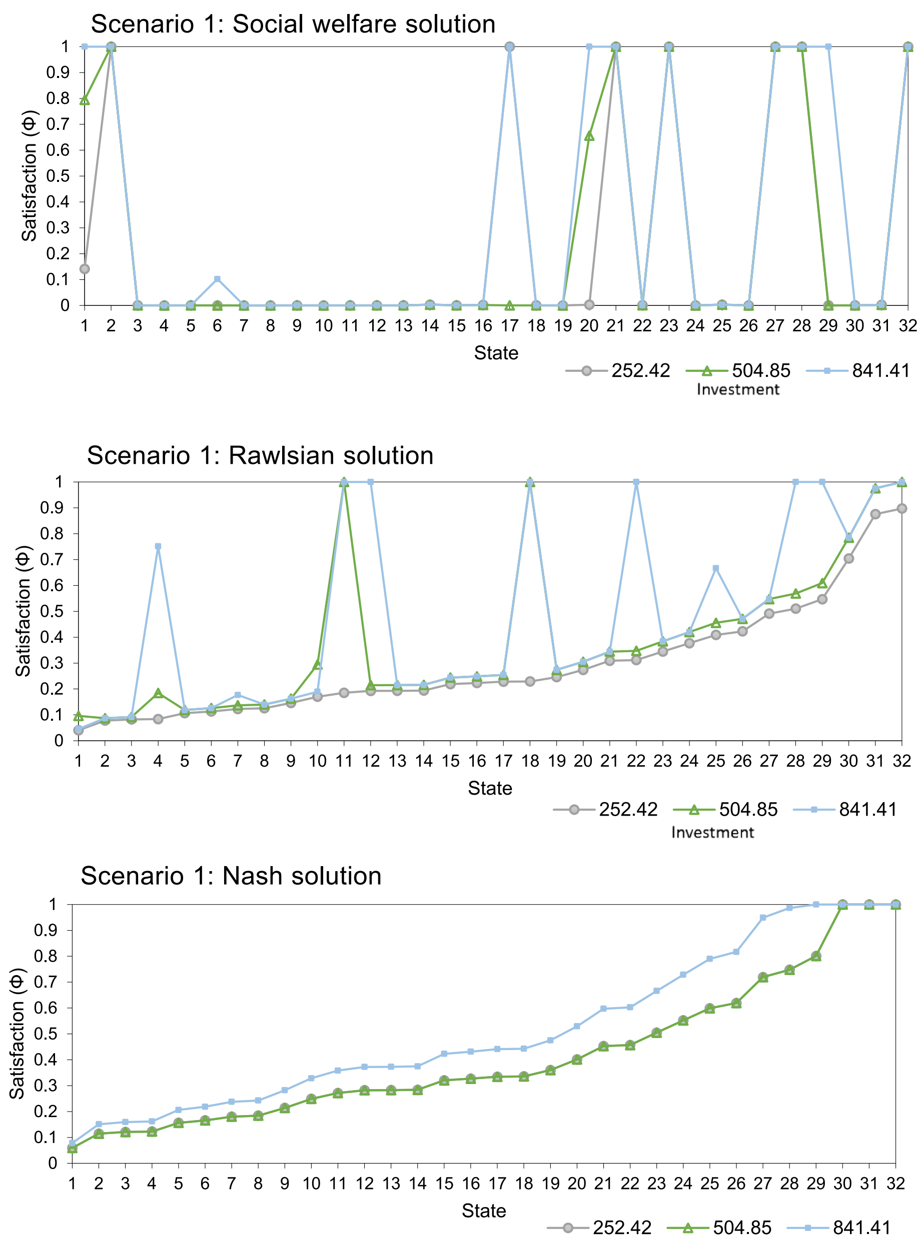

Fig. 4. Pareto solutions for the vaccines allocation with different distribution schemes (social welfare, Rawlsian, and Nash) and investment capacities in MM$ (scenario 1: without vaccines losses and weight factors equal to 1).

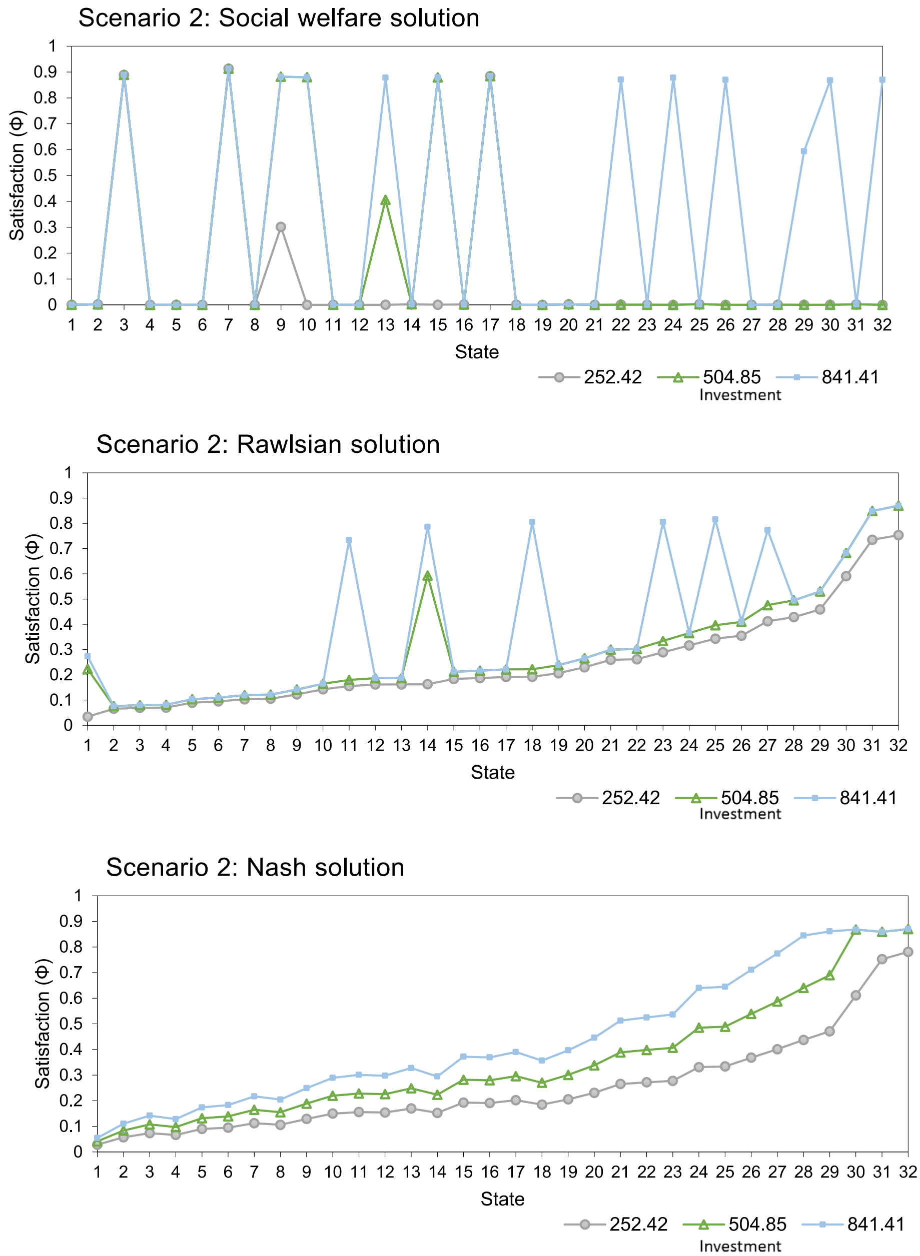

Fig. 5. Pareto solutions for vaccine allocation with different distribution schemes (social welfare, Rawlsian, and Nash) and investment capacities in MM$ (scenario 2: considering vaccines losses and weight factors equal to 1).

- 40% are Pfizer vaccines, 30% are Moderna vaccines, and 30% are AstraZeneca vaccines.
- All types of vaccines require two doses per beneficiary.
- The fraction of losses is considered (see Table 3).
- The weight factors are considered for all cases (see Table 4).

It should be noted that scenario 3 is the most complex since it involves both the fraction of losses and the weight factors.

5. Results

The proposed model was coded in the software GAMS; it includes 644 continuous variables and 616 equations for each distribution scheme. The models for the social welfare and Rawlsian schemes are linear programming problems and were solved with the solver CPLEX. Here, the global optimal solution is guaranteed. For the Nash scheme, the model is a non-linear programming model and was solved using the LINDOGLOBAL solver.

First, Fig. 3 shows the purchased vaccines with different investment capacities. We consider that the total number of bought vaccines is equal for all scenarios. Note that the gray bars represent the lowest investment capacity, the green bars correspond to an intermediate capacity, and the blue bars refer to the highest investment. We can see that with the lowest investment, only AstraZeneca and Pfizer vaccines are bought because they are cheaper than Moderna vaccines. However, with larger investment capacities, the three types of vaccines are purchased.

As mentioned above, for the addressed case study, we consider the vaccine allocation among the states of Mexico. The states are ordered according to their population (see Table 2), and the results are shown in terms of satisfaction (φ_i). Fig. 4 presents the distribution of vaccines for the states of the case study under the different distribution schemes (social welfare, Rawlsian, and Nash) for the first scenario (the most ideal of all). Here, it is observed how the social welfare scheme greatly favors states 1 and 2 (“Estado de México” and “Ciudad de México”), which are

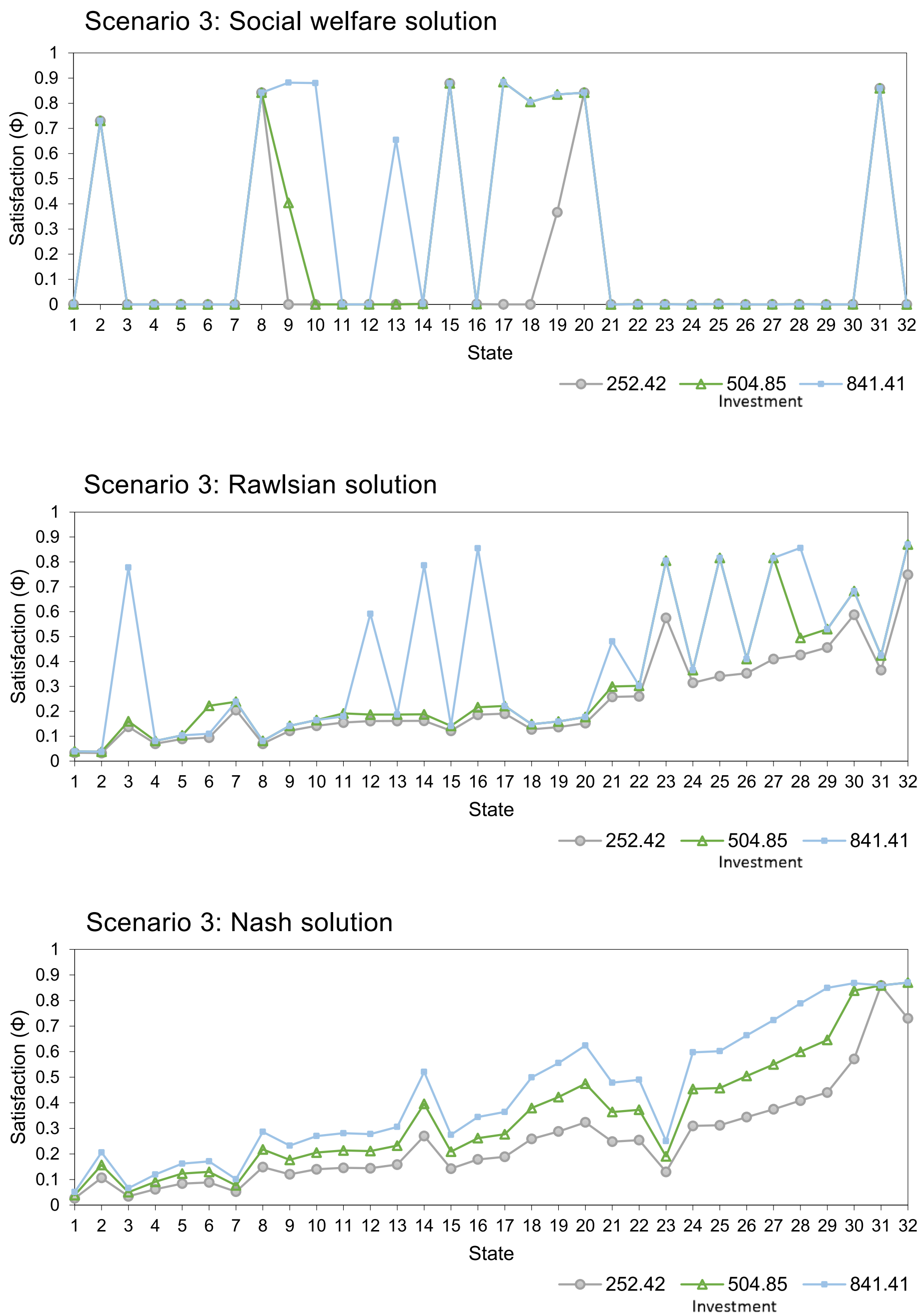

Fig. 6. Pareto solutions for vaccine allocation with different distribution schemes (social welfare, Rawlsian, and Nash) and investment capacities in MM$ (scenario 3: considering vaccines losses and weight factors based on the COVID-19 traffic light).

the states with the largest population in our case study. This prevents the distribution of vaccines to those states with smaller populations, but not as small as states 27, 28, or even state 32, where obtaining high levels of satisfaction implies fewer vaccines distributed (that means a very low level of satisfaction for the rest). In the case of the Rawlsian scheme, the satisfaction levels are higher in some states with smaller populations. For instance, for states 11 and 12 ("Chihuahua" and "Guerrero"). However, there are still extremely low levels of satisfaction (close to 0) for many states. It should be noted that an important characteristic of the Rawlsian scheme is that the smallest allocated beneficiaries are maximized. This results in a minimum proportional distribution for all stakeholders (for the lowest investment capacity). However, when the budget varies, the preferences of certain stakeholders can be observed due to the degeneracy of the Rawlsian solution [43]. On the other hand, the solution to the Nash model results in a more equitable allocation, where the allocation of vaccines among the states is similar. Therefore, the states with the smallest population (30, 31, and 32) attain the highest level of satisfaction with all the investment capacities. It should be noted that for the other states, there are changes in the allocations with the highest investment.

In scenario 2, the loss factors are added, and it is noticeably clear how the satisfaction indices decrease in general for all the states of the case study. Fig. 5 presents the distribution of vaccines for this scenario under the different distribution schemes (social welfare, Rawlsian, and Nash). As mentioned above, the loss factors refer to the fraction of losses due to corruption and crime. The estimated loss factors are reported in Table 3. Here, it is worth noting a trend where the higher the population, the higher the crime rate. Therefore, the states with the highest population are the most affected in their satisfaction index. For this scenario, we can observe that regardless of the scheme used or budget, no state can reach a satisfaction level of 1. For the addressed case study, it is essential to consider the fraction of losses since it represents a potential problem that can change the allocation significantly. However, these loss factors may not be needed for different case studies.

Finally, in scenario 3, the loss and weight factors are considered. As mentioned above, the weight factors correspond to the epidemiological risk of each state. Fig. 6 presents the distribution of vaccines for this scenario under the different distribution schemes (social welfare, Rawlsian, and Nash). Here, we can observe significant changes in the allocations compared to scenario 2. As expected, we can see that using the weight factors changes the priority of the states in all the schemes. It is worth analyzing the drastic change that the social welfare scheme suffered, where now those states that are in red or orange in the epidemiological traffic light are highly prioritized. For example, "Ciudad de México" (state 2), "Nuevo León" (state 8), and "Coahuila" (state 15) have very different population sizes. However, these states are at high levels of epidemiological risk, and therefore the social welfare scheme prioritizes them. This approach can be beneficial when there are states with a high level of risk and limited availability of vaccines. For the Rawlsian scheme, something similar happens, but this scheme does not favor the states in red. Nevertheless, it tends to favor the states with a medium level of risk, which can be useful once the states with a high level of risk are controlled. On the other hand, the Nash scheme solution does not change significantly compared to the previous scenarios. This solution keeps resulting in a "ladder" shape, but with certain "peaks" that indicate the states in red or with higher risk. For example, "Ciudad de México" (represented as state 2) and "Baja California Sur" (state 14). Even so, the penalties to the other states are not significant compared to the other schemes, which can be quite useful once the states of higher priority (states in red) are controlled since the distribution is more systematic.

6. Conclusions

This work presented a multi-objective strategy for the fair distribution of vaccines. Parameters related to the population, the rate of infections by COVID-19, the mortality rate by COVID-19, and risk groups such as the elderly and people with special medical conditions (diabetes, hypertension, and obesity) were considered. Additionally, the proposed strategy involved social behaviors that affect the correct distribution of vaccines (such as crime and corruption) and prioritized groups at higher risk based on the epidemiological traffic light. The solutions were obtained through different fairness schemes (social welfare, Rawlsian justice, and Nash). The applicability of the presented model was illustrated using Mexico as a case study. Each state of the country was considered a stakeholder. The solution to the proposed scenarios was carried out using different justice schemes and an economic objective function that reduces the costs associated with the distribution of vaccines. In the results, it was possible to observe how the loss factors related to corruption and crime significantly affected the respective satisfaction levels of each state. The addition of the weight factors showed how the different justice schemes could be applied depending on the present vaccination stage. For instance, we observed that the social welfare scheme could give better results than the other schemes when there are population groups with a high incidence of COVID-19 cases (since states with high epidemiological risk were prioritized). On the other hand, when the incidence of cases is not high, the Rawlsian justice scheme may be a better option since it prioritizes states with higher epidemiological risk without leaving the other states without vaccines. Finally, the Nash justice scheme can be used once the pandemic is controlled since similar levels of satisfaction are achieved among the states. Furthermore, the allocation given by this scheme provided only a slight advantage to those states with greater epidemiological risk (where this difference was not significant).

The addition of cost functions allowed observing the interaction between cost-satisfaction, demonstrating the usefulness of the model to allocate different types of vaccines available in the market. The vaccines that best reduce costs were identified, and we observed that it is possible to reduce the required investment without compromising the satisfaction levels of each state (as long as there are a diverse number of available vaccines).

As with all strategies, some limitations can serve as a starting point for future research, some of which are suggested below.

- The introduction of a stochastic model would be very useful given how variable the spread of the virus can be in the different regions of the country.
- The incorporation of new parameters to the model, such as the lifetime of the vaccines and the population who cannot be vaccinated.

Author statement

Rogelio Ochoa-Barragán: Conceptualization, Methodology, Software, Visualization, Writing - Original draft preparation, Writing - Review & Editing. **Aurora del Carmen Munguía-López**: Conceptualization, Methodology, Supervision, Writing - Original draft preparation, Writing - Review & Editing. **José María Ponce-Ortega:** Conceptualization, Supervision, Writing- Reviewing & Editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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Appendix

Table 1
Crime incidence rate by the federal entity of occurrence for every one hundred thousand inhabitants [44].

State	Cases per-100,000 inhabitants (CI_i)								
	2010/1	2011/2	2012/3	2013/4	2014	2015	2016	2017	2018
México	32,958	40,416	56,752	93,003	83,566	56,835	62,751	65,381	51,520
Ciudad de México	44,055	40,790	49,198	51,786	59,545	52,718	49,913	68,954	69,716
Veracruz	19,867	22,579	23,411	28,101	20,832	22,157	19,892	18,300	25,350
Jalisco	32,980	29,351	49,083	47,278	43,076	49,317	41,874	43,023	40,543
Puebla	23,946	29,350	27,318	31,662	32,690	27,530	31,331	42,343	37,647
Guanajuato	23,365	26,705	34,391	34,110	40,737	33,154	33,384	29,231	38,067

(continued on next page)

Table 1 (*continued*)

State	Cases per-100,000 inhabitants (CI_i)								
	2010/1	2011/2	2012/3	2013/4	2014	2015	2016	2017	2018
Chiapas	15,028	13,663	12,827	19,215	19,160	16,687	20,055	20,464	19,409
Nuevo León	38,136	28,516	37,076	32,552	28,720	26,221	32,819	32,407	27,805
Michoacán	15,469	24,346	24,362	25,126	26,340	23,876	26,366	22,624	22,999
Oaxaca	25,193	20,991	18,009	20,749	29,073	24,961	27,897	22,152	26,221
Chihuahua	41,903	30,562	35,952	31,669	24,295	31,274	34,920	28,857	28,622
Guerrero	33,467	27,040	33,762	35,366	42,690	53,875	47,392	45,006	43,051
Tamaulipas	27,083	20,645	25,255	19,417	33,414	21,363	23,318	23,706	25,368
Baja California	31,791	29,446	39,297	57,066	56,632	32,758	51,286	43,921	42,725
Coahuila	29,279	26,558	17,870	25,451	18,318	24,800	25,215	25,299	24,813
Sinaloa	34,254	29,838	33,231	30,287	29,139	22,750	23,257	28,748	29,507
Hidalgo	22,662	25,106	21,874	23,468	23,211	21,159	23,564	22,135	25,987
Sonora	46,774	39,029	34,126	31,155	26,384	40,466	42,624	39,759	50,861
San Luis Potosí	30,827	33,878	35,124	39,558	41,384	25,838	25,867	31,673	32,342
Tabasco	32,185	21,357	24,368	32,037	29,508	30,409	31,664	45,604	36,546
Querétaro	19,516	22,860	27,197	27,975	31,572	30,991	26,860	35,395	32,756
Yucatán	37,647	16,599	22,945	23,728	31,857	25,862	23,736	24,098	26,462
Morelos	28,491	25,775	35,750	36,524	43,584	43,419	43,749	48,528	45,312
Durango	23,803	21,540	27,631	22,512	30,080	25,640	23,283	22,566	22,586
Quintana Roo	41,093	37,725	40,279	35,245	41,381	35,639	32,862	33,269	33,243
Zacatecas	29,688	18,772	20,506	27,290	30,058	21,501	24,160	34,642	26,670
Aguascalientes	56,089	25,511	32,368	24,711	39,453	35,457	41,254	39,912	36,500
Tlaxcala	26,065	22,387	18,530	26,660	33,700	30,699	27,707	33,847	40,336
Nayarit	31,741	28,751	26,006	26,609	32,936	21,288	26,260	33,105	23,670
Campeche	20,922	21,704	29,097	30,597	29,306	22,114	28,892	28,283	26,466
Baja California Sur	25,779	28,884	31,049	23,747	34,700	25,577	29,939	25,690	28,377
Colima	17,343	22,287	25,169	26,309	30,535	27,045	29,449	27,074	28,376

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