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Research article

COVID-19 Global Humanitarian Response Plan: An optimal distribution model for high-priority countries

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A B S T R A C T

Background: The 2019 novel coronavirus disease (COVID-19) has spread rapidly worldwide, and the outbreak of the disease was designated a global pandemic by the World Health Organization. Such outbreaks would certainly be catastrophic for some of the best-ranked health systems and would be more catastrophic in countries with more fragile health systems. Accordingly, the World Health Organization and other organizations have been appealing to donor countries to support a rapid response plan. The primary objectives of this response plan are to appeal for funds from donors and to distribute these funds to the most affected countries based on the requirements.

Methods: In this study, we developed a mathematical model to provide initial insights into the efficient and equitable distribution of urgent funds to high-priority countries. Three phases were proposed for the construction of this mathematical model. In the first phase, the final epidemic sizes in all the target countries were predicted by using three epidemiological models. In the second phase, the urgent requirements for each country were estimated in parallel with the estimates issued by the humanitarian response plan, based on the size of the epidemic and several other factors. In the third and final phase, a multi-objective optimization model was proposed. The first objective was to maximize the funds from donors to cover all the requirements. The second objective was to minimize the unmet demands by ensuring a fair distribution of the urgent funds based on the requirements of the target countries.

Results: Predictions of the basic reproduction numbers and the final epidemic sizes were calculated for all target countries. The urgent requirements were estimated, and the requirements issued by the humanitarian response plan for all target countries were also considered. Moreover, a proposed response plan for the distribution network was demonstrated. Donors must provide urgent funds exceeding US$ 2,608,084,209 to cover at least 40% of each target country’s requirements. Overall, results demonstrate the importance of an urgent and fair distribution of funds to the target countries to overcome the outbreak of COVID-19.

Conclusions: Rapid responses by donor countries to humanitarian appeals will facilitate the immediate and fair distribution of relief supplies to the poorest countries. This distribution may help to support health systems, restrain the spread of COVID-19, and prevent an unlimited catastrophe.

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1. Introduction

The 2019 novel coronavirus disease (COVID-19) is an infectious disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first confirmed case of COVID-19 was reported in Wuhan, China, and the disease has since spread fiercely throughout the world. On March 11, 2020, COVID-19 was officially declared a pandemic disease by the World Health Organization (WHO). The rates of morbidity and mortality increase daily in COVID-19 epicenters. As of December 31, 2020, the cumulative number of the confirmed cases and deaths was reported 83,969,814 and 1,833,738, respectively. The average global death rate per number of diagnosed cases is 2.18%. This percentage fluctuates according to the sex, age, and health status of the patient as well as the health system in each country. The COVID-19 pandemic has now affected more than 219 countries and territories worldwide and continues to spread and affect additional areas. Accordingly, COVID-19 is among the most daunting

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health challenges faced by countries around the world, especially the most miserable ones.

Globally, many health systems report that they have become overwhelmed with the influx of COVID-19 cases, which leads to questions about the potential consequences of COVID-19 in the poorest countries where the health systems are already fragile. Most of the poorest countries are already facing enormous challenges, including humanitarian crises, food insecurity, malnutrition, socioeconomic and political unrest, conflict or civil unrest, famines, weakened immunity, disasters, poverty, inequality, discrimination, poor health, water scarcity, poor services and sanitation, weak infrastructure, low education levels, and limited social services.

Moreover, some poorer countries are under the effects of armed conflicts that have destructed the infrastructure in all sectors, including the health sector. In such areas, few central public health laboratories are able to perform COVID-19 diagnostic tests, and this limited capacity leads to delays in the treatment and isolation of patients. The situation is further complicated by a shortage of healthcare workers and a lack of available personal protective equipment to protect them from infection, as well as the unavailability of ventilators, medicines, beds, and basic necessities such as electricity and water. All of these challenges are expected to lead to very high infection rates relative to those in other countries, as well as very high basic reproductive numbers (R0). Additionally, it is difficult to adhere to health sector instructions and to avoid breaking local curfews. The health sector and the general public will be affected on a daily basis, and classical social systems cannot respond to such challenges. Furthermore, traditional cultural and social practices such as handshaking and hugging, community gatherings in worship spaces, low levels of health literacy and COVID-19 awareness, the paucity of masks and effective physical distancing, and multi-generational housing and high population densities increase these challenges. Substandard technological infrastructure also poses challenges to delivery systems and the ability to work at home or remotely.

These poorer countries will likely find it difficult to control the COVID-19 outbreak. This challenge will add to the many difficulties already faced by these countries. In this setting, COVID-19 is likely to spread more rapidly, and it will be more difficult to diagnose and restrain it. Consequently, an increasing number of people will be at risk of disease.

To address these challenges, the COVID-19 Global Humanitarian Response Plan (GHRP) aims to identify the most affected and highest-priority regions and countries [1–3]. The GHRP has classified the countries with an ongoing GHRP, refugee camps, and countries that appealed for assistance against the COVID-19 pandemic. In summary, fighting COVID-19 in the world’s poorest countries by meeting the needs of the most vulnerable population is the primary goal of the GHRP.

In this work, we selected the following countries with an ongoing humanitarian response plan: Afghanistan, Burkina Faso, Burundi, Cameroon, Central African Republic (CAR), Chad, Colombia, Democratic Republic of the Congo (DRC), Ethiopia, Haiti, Iraq, Libya, Mali, Myanmar, Niger, Nigeria, Palestine, Somalia, South Sudan, Sudan, Syria, Ukraine, Venezuela, and Yemen. Three of these countries, Colombia, Ukraine, and Venezuela, were excluded because they have a good gross domestic product (GDP), high rankings on Human Development Index (HDI), and LEGATUM Prosperity Index (LPI) indicators. Thus, we selected the poorest and most war-torn nations with the most affected and vulnerable population groups and those with ongoing humanitarian response plans as the high-priority countries.

Table 1 lists these high-priority countries with related information, including population count, population density, GDP, health system rank [4], poverty rate, HDI rank [5], LPI rank, and LPI in the health sector rank [6].

Table 1 reports some factors and indexes that elicited interest in the global ranking sectors. Population density is an important factor for the spread of COVID-19. An inverse proportionality between population density and physical distance has been identified, which affects the increased or decreased spread of the virus.

Similarly, the HDI is a comprehensive indicator that highlights the average performance in the main dimensions of human development, namely, the health dimension, the educational dimension, and the living dimension.

Another important index is the LPI, which measures 12 dimensions which are safety and security, personal freedom, governance, social capital, investment environment, enterprise conditions, market access and infrastructure, economy quality, living conditions, health, education, and natural environment. Clearly, most of the 21 included countries have a low rank according to the LPI-health ranking. The factors reported in Table 1 will be considered when predicting the final size of the epidemic and estimating the demands of the target countries. Overall, the selected countries have the lowest indices in all sectors.

A slow and ineffective approach to the COVID-19 pandemic and a delay or failure to take steps such as curfew and lockdown, physical distancing, and personal hygiene can increase the initial number of cases. These issues can increase the challenge associated with outbreak control and makes it difficult to track and isolate the contact cases. Consequently, the outbreak may become out of control in a short period of time.

Many of the target countries have increased their readiness to fight COVID-19 in terms of building capacity, staff, and medical supplies and in the application of some detection, prevention, and control procedures. These efforts include the monitoring and tracking of suspected cases, the transfer and isolation of the patient, and the diagnosis, tracking, and follow-up of potential contacts. The implementation of such a wide range of technical and operational interventions depends on the general infrastructure and the health and laboratory resources of a country.

However, these preparations are modest and do not meet the scale of this horrific event. Accordingly, these countries desperately need financial and logistical support. For this reason, their responses have made them a high priority for the receipt of emergency support.

The main contributions of this work can be summarized as follows: (1) Three epidemiological models, namely, SIR, logistic, and generalized SEIR model are used to predict the final epidemic size in each target country. (2) The total costs are calculated to estimate the demands that should be funded in each country, based on the size of the epidemic and several other factors. (3) A multi-objective optimization model is proposed to distribute the funds to these target countries efficiently and equitably. The main objectives of the proposed model are to maximize the funds received from the donor countries and humanitarian organizations and to minimize the unmet demand in each target country. Moreover, the most important constraint of the proposed model is equitable and fair distribution of funds, which ensures that all countries will receive a percentage of the required assistance.

The remainder of this paper is organized as follows: Section 2 contains a short literature review. Section 3 includes three subsections, namely, the estimated final epidemic size, estimated costs, and mathematical model formulation. Section 4 describes data and results with discussion. Finally, Section 5 discusses the conclusions and future work.

2. Literature review

Since the advent of COVID-19 at the end of 2019, all sectors in the world have mobilized to fight this dangerous and evolving
First, it addresses the statistics and predictions associated with this pandemic. The collection and analysis of data and predictions of epidemic curves comprise the first step towards understanding the COVID-19 pandemic. Shinde et al. (2020) [7] reviewed the various types of data analysis and prediction methods, such as machine learning methods and mathematical models.

SIR and logistic models and their various extensions are the most efficient options for analyzing and predicting the infection. Barcelo (2020) [5–10] employed SIR and logistic growth regression models to estimate the final COVID-19 pandemic size. Massonnaud et al. (2020) [11] estimated the dynamics of the COVID-19 epidemic in France and evaluated the healthcare resources and propagation of a deterministic, age-structured, Susceptible–Exposed–Infected–Removed (SEIR) model. The authors also estimated the daily number of cases, hospitalizations, deaths, ICU needs, and ICU capacity limits for the next month (until April 14, 2020) under three different scenarios (R0 = 1.5, R0 = 2.25, R0 = 3). The results suggested that the French healthcare system would be overwhelmed very quickly even under the best scenario. Many studies [12–19] employed the SIR, SEIR, or logistic models to predict the spread of COVID-19 in different countries and regions. Alimohamadi et al. (2020) [29] reviewed many articles that estimated the R0. The authors found that the average of the recorded R0 values in those articles was 3.38 ± 1.40 (range: 1.9–6.49). That review also indicated that the apparent overall R0 was higher than the WHO estimates. Klabunde and Giegerich, (2020) [23] modeled the daily infection growth rates in both Italy and Germany using the exponential decline function. The authors concluded that social distancing and the growth rate are inversely related. Briefly, greater adherence to social distancing would lead to a lower growth rate. Likewise, the authors predicted the numbers of diagnosed and fatal cases from April 10 to May 31 using a linear model and estimated the daily number of required hospital beds and ICU capacity.

The authors in [24, 25] addressed the relationship between COVID-19 and environmental conditions such as humidity and temperature. Kumar et al. (2020) [26] used an Auto-Regressive Integrated Moving Average Model (ARIMA) with a machine learning approach to forecast some disease trajectories up to April 30, 2020. Perone (2020) [27] applied an ARIMA model to predict the epidemic trajectory in Italy after April 4, 2020. To control the COVID-19 outbreak, it is necessary to determine key parameters such as the R0, which is calculated as the average number of secondary infections resulting from an infected person during the entire period of infection at the beginning of the outbreak (D’Arienzo & Coniglio, 2020) [28]. In general, an R0 < 1 means that the disease will die out and no infection will be transmitted. Conversely, if the R0 is >1, the disease will be transmitted between humans via sustainable transmission chains. The prevalence increases as the R0 increases.

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Ranjan (2020) in [30] estimated the final epidemic size using three epidemiological models, while Conghui X. et al. (2020) [31] predicted the epidemic size using a fractional generalized SEIR model. A similar study [32] employed a generalized SEIR model to forecast the epidemic trend in Brazil. Singh P. and Gupta A. (2020) [33] generalized the SIR model to predict multiple waves of COVID-19 cases. Several other studies tried to address the interactions of the COVID-19 pandemic on other outbreaks such as cholera [34], dengue [35], HIV [36], Ebola [37], or the impact of COVID-19 pandemic on TP patients [38], or on unemployment problem [39].
Second, this paper addresses the critical issue of medical cost estimation. A few studies calculated the costs associated with a case of COVID-19. Wang et al. (2020) [40] demonstrated the effectiveness of personal protection, isolation, quarantine, gathering restrictions, and community containment, which were determined as the most cost-effective options. These authors used a SEIR model to construct a virtual community and measured the cost-effectiveness ratios (CERs) and incremental cost-effectiveness ratios (ICERs) in two scenarios. The results identified additional costs associated with averting isolation and quarantine. They estimated a median medical cost of US$ 6500 per COVID-19 case. The authors considered the average hospitalization cost for each SARS patient in China and Canada. In Guangzhou, China, the total direct and indirect medical cost per SARS patient was US$ 2900 (Du et al. 2007) [41], and the average hospital stay was 17 days. In Canada, the average medical cost was US$10,000 per SARS case (Gupta et al. 2005) [42].

Jin et al. (2020) [43] estimated the total cost of the outbreak in China at US$ 3267 billion. This value was divided into US$ 0.62 billion for total healthcare expenditures and US$383 billion for the associated societal costs. The authors also classified the infected cases into three categories and estimated an average cost of US$ 3235, with estimated costs of US$ 939, US$ 8879, and US$ 25,578 for non-severe, severe, and critical cases, respectively. They also estimated the cost of diagnosing a case of close contact with an infected case (US$ 85) and the cost of diagnosing a suspected case of COVID-19 (US$ 141) that tested negative. Moreover, they found that 81.5% of the total cases were mild illness, 13.8% were severe cases while 4.7% were critical cases.

Bartsch et al. (2020) [44,45] estimated that the median direct medical cost of US$3045 per infection, US$ 96 per mild illness, and US$ 14,366 per hospitalized case would be incurred only during the disease course. These authors estimated the total costs in two scenarios. In the first scenario, the direct cost during the epidemic would be US$ 654 billion when 80% of the US population was infected. In the second scenario, the cost would be US$163.4 billion for total healthcare expenditures and US$383 billion in China at US$ 3267 billion. This value was divided into US$ 0.62 billion for total healthcare expenditures and US$383 billion for the associated societal costs. The authors also classified the infected cases into three categories and estimated an average cost of US$ 3235, with estimated costs of US$ 939, US$ 8879, and US$ 25,578 for non-severe, severe, and critical cases, respectively. They also estimated the cost of diagnosing a case of close contact with an infected case (US$ 85) and the cost of diagnosing a suspected case of COVID-19 (US$ 141) that tested negative. Moreover, they found that 81.5% of the total cases were mild illness, 13.8% were severe cases while 4.7% were critical cases.

Additionally, a few related reports estimated the average cost for a hospitalized case as US$2,395 in China [52], US$ 4,633.43 in India [53], US$10,000 in Canada [40], and US$ 12,916.31 in Sweden [54].

3. The model

This section is presented in three subsections. First, we briefly review the epidemiological models that will be used to predict the epidemic size and the basic reproduction number in each of the 21 countries. Based on the pandemic size that is obtained in Section 3.1 and other factors, the initial medical costs in the 21 countries will be estimated as mentioned in Section 3.2. In Section 3.3, we will employ the related data that were obtained in the previous subsections in the proposed model formulation.

3.1. Estimated epidemic size

In this subsection, we aim to estimate the epidemic size and peak time in each country using three models, namely original SIR model, logistical, and the generalized SEIR model. The average of the epidemic size will be used to estimate the requirement demand. The original SIR system of differential equations can be described as:

\[
\frac{dS}{dt} = -\frac{\beta IS}{N}
\]

\[
\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I
\]

\[
\frac{dR}{dt} = \gamma I
\]

where \( t \) is time, \( S = S(t) \) is the number of susceptible persons at time \( t \) (i.e., unprotected individuals with a weakened immune system), \( I = I(t) \) is the number of infected persons at time \( t \) (i.e., individuals who are patients and can transmit infection), \( R = R(t) \) is the number of removed individuals at time \( t \) (i.e., individuals who are no longer transmitting infection because of isolation, death, recovery, or discharge), \( \beta \) is the transmission rate, and \( \gamma \) is the average duration of infection.

The initial conditions for the above system were \( S(t_0) = N - 1, R(t_0) = 0, I(t_0) = 1 \) and \( N = S + I + R = \text{const} \), and the R0 was given as \( R_0 = \frac{\beta}{\gamma} \).

Similarly, the logistic model could be also applied to describe the dynamics of the epidemic:

\[
\frac{dC}{dt} = rC \left( 1 - \frac{C}{K} \right)
\]

where \( C = C(t) \) is the total number of cases at time \( t \), \( r > 0 \) is the infection rate, and \( K > 0 \) is the final epidemic size. \( C(0) = C_0 \) is the initial cases. The solution of (1) is:

\[
C = \frac{K}{1 + Ae^{-rt}}
\]

where \( A = \frac{K - C_0}{C_0} \). The maximum number of cases is \( C_p = \frac{K}{1 + e^{-rt_0}} \) when \( A \) is a peak in a pandemic curve is reached at the time \( t_0 = \ln A \).

In the logistic regression model, the form becomes:

\[
C = \frac{b_1}{1 + b_2e^{-b_3t}}
\]

where \( b_1, b_2, \) and \( b_3 \) are time-dependent parameters dependent on the numbers of cases \( C_1, C_2, \ldots, C_n \) at times \( t_1, t_2, \ldots, t_n \).

The third epidemiological model is the generalized SIR (SEIRQDP) system of differential equations that can be described as:

\[
\frac{dS}{dt} = -\frac{\beta IS}{N} - \mu S
\]
\[
\begin{align*}
\frac{dE}{dt} &= \frac{\beta}{N} IS - \alpha E \quad (8) \\
\frac{dI}{dt} &= \alpha E - \rho I \quad (9) \\
\frac{dQ}{dt} &= \rho I - (\gamma + \sigma) Q \quad (10) \\
\frac{dR}{dt} &= \gamma Q \quad (11) \\
\frac{dD}{dt} &= \sigma Q \quad (12) \\
\frac{dP}{dt} &= \mu S \quad (13)
\end{align*}
\]  

where \( E = E(t) \) is the number of the exposed persons at time \( t \) (i.e., individuals who are patients and cannot yet transmit infection), \( Q = Q(t) \) is the number of the quarantined persons at time \( t \) (i.e., confirmed, and isolated individuals), \( D = D(t) \) is the number of the dead persons at time \( t \) (i.e., individuals who are perished due to COVID-19), \( P = P(t) \) is number of the susceptible persons but not exposed to the external environment at the time \( t \). Moreover, \( \mu \) indicates the protection rate, \( \alpha \) refers to the incubation rate, \( \rho \) is the quarantined rate, and \( \sigma \) is the death rate.

3.2. Estimated requirements of the target countries

For many reasons, it is difficult to estimate the requirements needed to fight COVID-19 in the target countries. Most of these countries are suffering from wars, famine, and fragile health systems. Most people in these countries depend on daily wages to meet their dietary needs. Therefore, it is difficult to impose curfews. Most people cannot provide sanitation and protection for themselves and their dependents. In most of these countries, it is difficult to find water to drink or use for personal hygiene. Therefore, the estimation of the requirements that must be satisfied is intertwined with other sectors. Although the GHRP issued estimates of the requirements of priority countries, we aimed to estimate the urgent costs that would cover only the direct expenditures related to fighting COVID-19, regardless of the infrastructure costs, the basic operational costs, or the interactions of the health sector with other sectors. The populations were divided into three categories, namely, infected people (i.e., confirmed cases demonstrated by laboratory testing to be infected with the virus, irrespective of clinical signs and symptoms according to WHO), susceptible people (i.e., those who are potentially infected and must be quarantined in the epicenters), and the poorest members of the population, who require support with sterilizers, masks, hygiene, and cleaning tools.

Therefore, we estimated the minimum medical requirements, including hospitalization, medication, testing kits, ventilators, basic equipment, laboratory equipment, personal protective equipment for health workers, and oxygen concentrators, as overhead costs.

In this work, we consider four kind of costs, namely, the first kind of cost related to the confirmed infected cases that were predicted using the three epidemiological models. To estimate the cost of the infected cases, we classified the infected cases into three categories: critical, severe, and non-severe cases.

We will assume that the potential cost for the critical case is US$ 21,173.22 as in the study [51], the potential cost for the severe case is US$ 3045, and the potential cost for mild illness is US$96 such as in the study [45]. We calculate the percentages for these categories based on the real data from GitHub repository [55]. Therefore, the first kind of cost is given as:

\[
\begin{align*}
\text{COST}_1 &= (RC_k \times N_k \times 21,173.22) + (RS_k \times N_k \times 3045) \\
&\quad + (RM_k \times N_k \times 96) \quad (14)
\end{align*}
\]

where \( RC_k \) indicates the percentage of the critical cases for country \( k \), \( RS_k \) indicates the percentage of the severe cases for country \( k \), \( RM_k \) indicates the percentage of mild cases for country \( k \), and \( N_k \) is the average confirmed cases that are predicted using the three epidemiological models.

The second cost refers to the diagnosis and quarantine of close contacts and suspected cases. Close contacts are all people who have physically met a COVID-19 patient within 2 weeks, whether they are unprotected healthcare workers who have come in contact with COVID-19 patients or family members, co-workers, friends, neighbors, classmates, teachers, passengers, or other people who were accompanied by a COVID-19 patient on a plane or public transport, as well as people who are under isolation. In this study, we assumed a cost of US$ 90.31 (CN¥ 532) for each diagnosed close contact case and a cost of US$154.95 (CN¥ 1002) for each diagnosed or suspected case as mentioned by Zhao et al. (2020) [46]. We also considered the cost associated with the quarantine of close contacts as the direct and indirect costs of quarantine of close contacts reported by Wang et al. (2020) [40]. The direct daily cost was US$ 50 for each close contact. The indirect quarantine cost was calculated as the (PCDI/365.25*) days of quarantine. A quarantine time of 14 days per COVID-19 patient was assumed.

The cost of the close contact, susceptible, quarantined individuals and testing kits is given as:

\[
\begin{align*}
\text{COST}_2 &= \left( CN_k \times 90.31 \right) + (SN_k \times 154.95) \\
&\quad + \left( QN_k \times 50 \times \frac{GDP}{365.25} \times 14 \right) + (TK \times RO_k \times N_k) \quad (15)
\end{align*}
\]

where \( CN_k \) is number of close contact individuals for country \( k \), \( SN_k \) is the number of the suspected individuals for country \( k \), \( QN_k \) is the number of the quarantine individual for country \( k \). \( TK \) indicates the cost of one unit of the testing kits, \( RO_k \) is basic reproduction number for country \( k \). The last term of Eq. (15) estimates the cost of the testing kits for the people who should be tested [43,55].

The third type of cost is related to personal protection such as masks and sanitizers that will be distributed to the poorest segment of the population. The cost of masks and handwashing sanitization is given as:

\[
\begin{align*}
\text{COST}_3 &= 0.77 \times E_k \times \text{Population} \times \text{Poverty rate} \quad (16)
\end{align*}
\]

This cost depends on the population, the poverty rate, and \( E_k \) that indicates to the rate of the eligible population in country \( k \). The cost of the masks and handwashing sanitization (US$ 0.77) was estimated by Wang et al. (2020) [40] in their detailed calculations of the cost of personal protection.

The final kind of cost considered in this work refers to the essential medical services and equipment such as ventilator, PCR, diagnostic devices, and other related devices. This cost considers the cost of one unit of essential medical equipment and services.

Hence, the urgent requirements of the target countries are estimated using Eq. (18):

\[
\text{Total demand} (D) = \text{COST}_1 + \text{COST}_2 + \text{COST}_3 + \text{COST}_4 \quad (18)
\]

3.3. Model formulation

In this subsection, we formulated a multi-objective optimization model. The first objective was to maximize the funds from donors and humanitarian organizations. The second objective was
to minimize the unmet demands of the target countries. The main constraint of the proposed model is equitable and fair distribution of funds among the target recipients.

The following nomenclature were used to describe the parameters and the variables:

**Nomenclature.**

| Sets | Meaning |
|------|---------|
| $S$  | Set of all the donor countries, indexed by $i$; |
| $\mathcal{J}$ | Set of all the humanitarian organizations, indexed by $j$; |
| $\mathcal{K}$ | Set of all the target countries, indexed by $k$. |

**Decision variables**

- $x_{ij}$: The amount of funds from donor country $i$ to humanitarian organization $j$;
- $y_{jk}$: The amount of funds from humanitarian organization $j$ to target country $k$;

**Parameters**

- $w_{ij}$: The prioritization weight for sending funds from donor country $i$ to humanitarian organization $j$;
- $u_{jk}$: The prioritization weight for sending funds from humanitarian organization $j$ to target country $k$;
- $D_k$: The demand of target country $k$;
- $P_i$: The maximum funds from donor country $i$;
- $H_i$: The funding available from donor country $i$;
- $Q_j$: The requirement from humanitarian organization $j$;
- $\omega_{min}$: The minimum level of satisfaction in affected area $k$;

The multi-objective optimization model was formulated as follows:

$$z_1 = \max \left[ \sum_{i \in S} \sum_{j \in \mathcal{J}} w_{ij} x_{ij} + \sum_{j \in \mathcal{J}} u_{jk} y_{jk} \right]$$  \hspace{1cm} (19)

$$z_2 = \min \left[ \sum_{k \in \mathcal{K}} \left( D_k - \sum_{j \in \mathcal{J}} y_{jk} \right) \right]$$  \hspace{1cm} (20)

$$\sum_{j \in \mathcal{J}} x_{ij} \leq P_i, \quad \forall i \in S$$  \hspace{1cm} (21)

$$\sum_{j \in \mathcal{J}} x_{ij} \geq H_i, \quad \forall i \in S$$  \hspace{1cm} (22)

$$\sum_{j \in \mathcal{J}} x_{ij} \geq Q_j, \quad \forall j \in \mathcal{J}$$  \hspace{1cm} (23)

$$\sum_{i \in S} \sum_{j \in \mathcal{J}} y_{jk} \leq Q_j, \quad \forall j \in \mathcal{J}$$  \hspace{1cm} (24)

$$\sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{J}} y_{jk} \leq D_k, \quad \forall k \in \mathcal{K}$$  \hspace{1cm} (25)

$$\sum_{j \in \mathcal{J}} y_{jk} \geq \frac{1}{D_k} \omega_{min}, \quad \forall k \in \mathcal{K}$$  \hspace{1cm} (26)

$$x_{ij} \geq 0, \quad \forall i \in S, j \in \mathcal{J}, \quad \text{and} \quad y_{jk} \geq 0, \quad \forall j \in \mathcal{J}, k \in \mathcal{K}.$$  \hspace{1cm} (28)

The first objective function of the proposed model appears in Eq. (19) and is related to the aim of the decision-makers to maximize the funds from the donors and humanitarian organizations to cover the requirements of the high-priority countries. Eq. (20) represents the second objective function of the present model, which aims to minimize the unmet demands. Constraint (21) ensures that the donor countries cannot send more than the maximum funds from donor country $i$. Constraint (22) guarantees that the funds sent from donor $i$ are greater than or equal to the funding available from the same donor $i$. Constraint (23) reflects that humanitarian organization $j$ received funds from the donor countries that were equal to or exceeded the requirements. Constraint (24) dictates that the humanitarian organization $j$ sends the same funds received from the donor countries. Constraint (25) ensures that humanitarian organization $j$ cannot send funds exceeding the available funds. Constraint (26) dictates that the funds received must satisfy the demand of each target country $k$. We considered that if the funds are available, the remaining material, medical, and other requirements would be provided. Constraint (27) represents the equity constraint, which refers to fairness in the distribution of funds among the target countries. In other words, constraint (27) enforces the requirement to satisfy a percentage of the total demand for funds in the recipient countries. Constraint (28) indicates the non-negative distribution of funds from the donor country $i$ to the humanitarian organization $j$, and the subsequent donation of funds from the humanitarian organization $j$ to the recipient countries.

### 4. Data description, results, and discussion

The financial data and the number of the cases affected by COVID-19 are constantly being updated. Accordingly, we considered the data reported by the accompanying sources as of December 31, 2020.

All COVID-19-related data were downloaded from GitHub repository https://github.com/owid/covid-19-data/tree/master/public/data. The financial data were collected from the Financial Tracking Service (FTS) [57], and the detailed funding requirement of each country was taken from [1].

The 10 largest donors were selected, and the remaining donors were referred to as "other donors". Table 2 lists the amounts of response plan/appeal funding provided by the largest donors.

The amounts required to fight COVID-19 and the amounts of available funds according to the GHRP are reported in Table 3. The 10 largest humanitarian organizations that appealed for fundraising and distributed the funds to the target countries were the WHO, United Nations Children’s Fund, World Food

|
| Donor name (i) | Funding for response plan/appeal $H_i$ (US$) | As a share of overall funding to the response plan/appeal (%) |
|----------------|------------------------------------------|--------------------------------------------------|
| USA            | 910,710,526                              | 24%                                              |
| Germany        | 424,600,218                              | 11%                                              |
| EC             | 277,249,583                              | 7%                                               |
| UK             | 245,438,789                              | 7%                                               |
| CERF           | 212,374,423                              | 6%                                               |
| Japan          | 193,666,486                              | 5%                                               |
| WB             | 160,445,073                              | 4%                                               |
| Denmark        | 89,006,575                               | 2%                                               |
| Private (individuals & organizations) | 66,760,974 | 2% |
| Canada         | 64,526,915                               | 2%                                               |
| Other donors   | 1,081,054,668                            | 29%                                              |

| Table 2 | The largest donors to the response plan. |
|---------|------------------------------------------|
| Table 3 | The total financial requirements. |
| Cluster/Sector Required (US$) Funded (US$) Coverage (%) | |
| Pandemic response for GHRP | 9,501,285,986 3,740,456,436 39.40% |
| Pandemic response for Target countries | 4,188,202,778 1,864,089,728 45% |

The 10 largest humanitarian organizations that appealed for fundraising and distributed the funds to the target countries were the WHO, United Nations Children’s Fund, World Food...
The estimated pandemic sizes using the three models.

Table 4

| Country name       | R0 on 31-12-2020 | The final epidemic size using SIR model | The final epidemic size using logistic model | The final epidemic size using the generalized SEIR model | Average |
|-------------------|------------------|----------------------------------------|--------------------------------------------|-------------------------------------------------------|---------|
| Afghanistan       | 1.49             | 51,526                                 | 63,074                                     | 72,052                                                | 68,782  |
| Burkina Faso      | 1.28             | 6707                                   | 142,501                                    | 79,980                                                | 93,565  |
| Burundi           | 1.05             | 818                                    | 7539                                       | 1104                                                  | 8980    |
| Cameroon          | 2.47             | 26,277                                 | 25,031                                     | 28,935                                                | 28,134  |
| CAR               | 1.9              | 4961                                   | 6309                                       | 5189                                                  | 12,288  |
| Chad              | 3.05             | 2113                                   | 2046                                       | 5806                                                  | 4897    |
| DRC               | 1.08             | 17,658                                 | 85,015                                     | 200,987                                               | 139,545 |
| Ethiopia          | 1.64             | 124,264                                | 143,288                                    | 127,638                                               | 183,505 |
| Haiti             | 4.35             | 9999                                   | 8763                                       | 27,503                                                | 25,529  |
| Iraq              | 3.36             | 595,291                                | 698,282                                    | 617,638                                               | 655,338 |
| Libya             | 3.61             | 100,277                                | 159,707                                    | 108,063                                               | 161,005 |
| Mali              | 1.01             | 7090                                   | 51,854                                     | 100,219                                               | 59,688  |
| Myanmar           | 1.11             | 124,630                                | 728,723                                    | 135,412                                               | 371,049 |
| Niger             | 1.37             | 3323                                   | 7488                                       | 4872                                                  | 6020    |
| Nigeria           | 1.01             | 87,607                                 | 280,960                                    | 1,035,571                                             | 557,707 |
| Pakistan          | 1.13             | 138,004                                | 811,502                                    | 819,036                                               | 700,625 |
| Somalia           | 2.03             | 4714                                   | 4408                                       | 4707                                                  | 12,188  |
| South Sudan       | 1.38             | 3788                                   | 3175                                       | 4027                                                  | 13,514  |
| Sudan             | 1.04             | 23,316                                 | 259,374                                    | 24,034                                                | 115,533 |
| Syria             | 1.04             | 11,434                                 | 222,922                                    | 40,192                                                | 114,835 |
| Yemen             | 3.25             | 2099                                   | 2162                                       | 2266                                                  | 6219    |

Programme, United Nations High Commission for Refugees, Not reported, International Organization for Migration, save the children, NGOs, Food and Agriculture Organization of the United Nations, United Nations Population Fund, and the remaining organizations are described here as “other organizations”.

Table 5 lists the following columns, the high-priority target countries, basic reproduction numbers, confirmed cases reported by health systems in these countries up to December 31, 2020, predicted pandemic sizes using the original SIR model, predicted pandemic sizes using the logistic model, and predicted pandemic sizes using the SEIQRP model. The MATLAB codes in [58–60] are employed. Haiti had the highest R0, 4.35, whereas Nigeria had the lowest R0, 1.01. The R0 values in other countries ranged from 1.05 to 3.61. The highest predicted population size using the original SIR model reached 811,502 in Palestine, while the highest predicted population size using the logistic model came to 1,035,571 in Nigeria, and the highest predicted population size using the SEIQRP model reached 650,095 in Iraq. The lowest predicted population size using the original SIR model was 2,046 in Chad, while the lowest size using logistic model reached 1104 in Burundi, and the lowest size using the SEIQRP model was 5701 in Niger. The lowest average size was 4597 in Chad, while the highest average size was 700,625 in Palestine.

Figs. 2 to 22 (in Appendix) present graphical representations of the results from the logistic model and the generalized SEIR model along for the 21 countries.

To avoid repetition and redundancy in the manuscript, we only take Afghanistan as an example. The left panel of Fig. 2 displays the fitting data (to 31/12/2020) using the logistic model. It is clear that there were two waves, the first size was 36,595 with \( r = 0.0759 \), while the second wave was estimated at 35,4571 with \( r = 0.0248 \), and the total size of the two waves reached 72,052. Also, it shows that the RMSE is equal to 294,893. The right panel of Fig. 2 depicts the fitting data using the generalized SEIR model. It illustrates the reported and fitted curves of the pandemic for active, recovered, and deceased cases. It also shows two waves of the epidemic.

Notably, the reported confirmed cases do not represent the actual number of COVID-19 cases in most of the target countries, due to the lack of adequate testing. Additionally, most governments have hidden the scale of the disaster for political and other reasons. Therefore, the actual number of the affected people is much larger than the reported number.

Table 5 presents our estimated requirements for the target countries and the classified requirements according to the GHRP estimates [1]. According to our estimates, the largest demand for funds reached US$ 399,368,737, and US$ 389,752,113 for Iraq and Nigeria respectively, while the smallest demand came to US$ 63,596,747, and US$ 71,386,815 for Niger, and Burundi respectively. According to the GHRP, Afghanistan, and Yemen would have the highest requirement, at US$ 395,689,175, and US$ 385,681,703 respectively, while Libya and Burundi would have the lowest demand at US$ 46,657,297, and US$ 71,445,000 respectively.

The big difference between our estimates and the GHRP estimates was in some countries. Our estimates were significantly higher than the GHRP’s estimates in Iraq, Myanmar, and Nigeria, while the GHRP’s estimates were significantly higher than our estimates in countries such as Afghanistan, Sudan, and South Sudan. This difference may be due to several considerations, the most important of which are the size of the epidemic, populations, and other factors. As for the rest of the countries, there are slight differences, and in general, our total estimates were slightly less than the total of the GHRP’s estimates.
Table 6
The solutions of $x_{ij}$ regarding transfers from donors to humanitarian organizations (US$).

| Country name | WFP       | UNICEF  | WHO      | UNHCR    | IOM       | NGOs     | UNPF     | Not reported | SCI      | FAO       | Other organizations | Sum      |
|--------------|-----------|---------|----------|----------|-----------|----------|----------|--------------|----------|-----------|----------------------|----------|
| USA          | –         | 364,349,400 | –       | 240,576,400 | –       | –       | –       | 32,571,560 | –       | –         | –                   | 637,497,360 |
| Germany      | 118,474,400 | –      | 110,668,700 | –       | –       | –       | –       | –           | 68,077,010 | –         | –                  | 297,220,110 |
| EC           | –         | –       | 194,075,000 | –       | –       | –       | –       | –           | –        | –         | –                  | 194,075,000 |
| UK           | 171,807,200 | –      | –       | –       | –       | –       | –       | –           | –        | –         | –                  | 171,807,200 |
| CERF         | –         | –       | –       | –       | –       | –       | –       | –           | –        | –         | –                  | 148,662,100 |
| Japan        | 40,637,690 | –      | –       | –       | –       | –       | –       | –           | –        | –         | –                  | 94,928,850  |
| WB           | –         | –       | –       | –       | –       | –       | –       | –           | –        | –         | –                  | 37,743,110  |
| Denmark      | –         | –      | 30,387,090 | –       | –       | –       | –       | –           | –        | –         | –                  | 288,060,100 |
| Private (individuals & organizations) | – | –     | –       | –       | –       | –       | –       | –           | –        | –         | –                  | 45,168,840  |
| Canada       | –         | –       | –       | –       | –       | –       | –       | –           | –        | –         | 45,168,840          | 45,168,840 |
| Other donors | –         | –       | –       | –       | –       | –       | –       | –           | –        | –         | 288,060,100         | 756,738,270 |
| Sum          | 330,919,290 | 364,349,400 | 453,405,800 | 270,963,490 | 78,080,870 | 390,597,300 | 390,597,300 | 44,181,360 | 32,571,560 | 68,077,010 | 417,704,730 | 2,833,839,760 |
Table 7
The solutions of $y_{jk}$ regarding transfers from humanitarian organizations to target countries (US$).

| Country name  | WFP | UNICEF | WHO | UNHCR | IOM | NGOs | UNPF | Not reported | SCI | FAO | Other organizations | Sum | Coverage to the estimated demand by “GHRP” (%) | Coverage to the estimated demand by our study (%) |
|---------------|-----|--------|-----|-------|-----|------|------|--------------|-----|-----|---------------------|------|------------------------------------------------|-------------------------------------------------|
| Afghanistan   | –   | –      | –   | –     | 181,225,600 | –   | –   | –            | –   | –   | –                   | 181,225,600 | 46%                                           | 147%                                            |
| Burkina Faso  | 14,052,250 | 55,819,480 | –   | –     | –   | –   | –   | –            | –   | –   | –                   | 69,871,730 | 66%                                           | 46%                                            |
| Burundi       | –   | –      | –   | –     | 35,575,810 | –   | –   | –            | –   | –   | –                   | 35,575,810 | 50%                                           | 50%                                            |
| Cameroon      | –   | –      | –   | –     | –   | 13,099,010 | –   | 64,835,250   | –   | –   | –                   | 77,934,260 | 51%                                           | 82%                                            |
| Chad          | –   | –      | –   | –     | –   | 72,999,010 | –   | –            | –   | –   | –                   | 72,999,010 | 59%                                           | 84%                                            |
| DRC           | –   | –      | –   | –     | –   | 129,636,900 | –   | –            | –   | –   | –                   | 129,636,900 | 47%                                           | 67%                                            |
| Ethiopia      | 98,871,770 | –      | –   | –     | –   | –   | –   | 26,712,970   | 24,843,080 | –   | –                   | 150,427,820 | 45%                                           | 48%                                            |
| Haiti         | –   | –      | –   | –     | –   | 76,638,850 | –   | –            | –   | –   | –                   | 76,638,850 | 53%                                           | 72%                                            |
| Iraq          | –   | –      | –   | –     | –   | 244,924,200 | –   | –            | –   | –   | –                   | 244,924,200 | 92%                                           | 61%                                            |
| Libya         | –   | –      | –   | –     | –   | –   | –   | 47,417,720   | –   | –   | –                   | 47,417,720 | 102%                                          | 44%                                            |
| Mali          | –   | –      | –   | –     | –   | –   | –   | 3,950,189    | 44,181,360 | –   | –                   | 48,131,549 | 64%                                           | 60%                                            |
| Myanmar       | 131,386,000 | 61,442,270 | –   | –     | –   | –   | –   | –            | –   | –   | –                   | 192,828,270 | 328%                                          | 73%                                            |
| Niger         | –   | –      | –   | –     | –   | –   | –   | 68,077,010   | –   | –   | –                   | 68,077,010 | 83%                                           | 107%                                           |
| Nigeria       | –   | –      | –   | –     | –   | 226,750,800 | –   | –            | –   | –   | –                   | 226,750,800 | 94%                                           | 58%                                            |
| Palestine     | –   | 63,605,700 | –   | –     | –   | –   | –   | –            | –   | –   | –                   | 63,605,700 | 88%                                           | 44%                                            |
| Somalia       | 86,609,320 | –      | –   | –     | –   | –   | –   | –            | –   | –   | –                   | 86,609,320 | 38%                                           | 61%                                            |
| South Sudan   | –   | –      | –   | –     | –   | –   | –   | 153,211,200  | –   | –   | –                   | 153,211,200 | 40%                                           | 61%                                            |
| Sudan         | –   | –      | –   | –     | –   | 106,046,300 | –   | –            | –   | –   | –                   | 106,046,300 | 37%                                           | 67%                                            |
| Syria         | –   | –      | –   | –     | –   | –   | –   | –            | 191,949,200 | –   | 191,949,200         | 191,949,200 | 50%                                           | 54%                                            |
| Yemen         | –   | –      | –   | –     | –   | –   | –   | 32,571,560   | –   | –   | –                   | 229,777,800 | 68%                                           | 73%                                            |
| Sum           | 330,919,340 | 364,349,380 | 453,405,780 | 270,963,460 | 78,080,879 | 390,597,240 | 44,181,360 | 32,571,560 | 68,077,010 | 191,949,200 | 382,989,000 | 2,608,084,209 | 62.3% | 66.5%                                      |
After we estimated the urgent requirement for each country, the weighted method was employed to solve the multi-objective optimization model. The mathematical model is implemented using LINGO 14. Furthermore, the prioritization weights were determined based on some criteria, where the current funding of the humanitarian organizations in [1–3] were standardized to determining the prioritization weights $w_{ij}, \forall j$. The HDI ranks [5] in Table 1 were standardized for determining prioritization weights $u_{jk}, \forall k$. Table 6 presents the numerical results corresponding to the solutions $x_{ij}$, which represent the decisions to send funds from the donors willing to fight COVID-19 via the GHRP to the humanitarian originsations. Regardless of the requirements of other countries for funding to fight COVID-19, US$ 2,833,839,760 must
be sent from the donors to the target countries through humanitarian organizations to cover 67.6% of the total requirements. USA sent the largest amount of funding, US$ 637,497,360. WHO received the largest amount of funding at US$ 453,405,800.

Table 7 lists the amounts of funding that should be distributed from the humanitarian originations to the high-priority target countries. The minimum funds sent to the target countries covered at least 62.3% of their total requirements, according to the GHRP estimates. Palestine and Libya have the lowest equity rate 44%, while Cameroon has the highest equity rate at 196% according to our estimates. Sudan and Somalia have the lowest equity rate 37% and 38%, while Cameroon also has the highest equity rate at 149% based on the GHRP’s estimates.

The main goal of this effort was to appeal to donor countries to increase their funding to levels that would meet the needs of poorer countries. Therefore, the first objective function was to maximize funding. The value of this function was US$ 2,608,084,209 which would cover (66.5%) of the total requirements of the target countries. The value of the second target function, which represents the unmet demand, was US$ 1,133,700,805.

Fig. 1 illustrates the optimal network of distribution from the donors to the humanitarian organizations, which in turn distribute the funds to the target countries.

In this work, we assumed an equity factor $\omega_{\min} = 40\%$. In other words, each target country received at least 40% of its requirements. We can assume another ratio of the equity factor $\omega_{\min}$ according to the availability of the funds. The results ensure fair distribution among the target countries; thus, equity can be achieved.

Overall, the numerical results confirm the importance of the proposed model on the pandemic. More importantly, the proposed model is flexible, and parameters such as the fairness ratio can be changed according to the available resources. The proposed model suggests an optimal distribution policy that would ensure efficient and equitable distribution of resources to contain a COVID-19 outbreak. Therefore, it gives the governments and the humanitarian organizations a glance overview of the optimal and fair distribution of aid funds, as well as the unmet demands of countries. (Note: Abbreviations and acronyms used in this article were listed in Table 8).

5. Conclusion

The COVID-19 outbreak is a major global disaster, and all countries are fighting this daunting challenge according to their abilities and capacities. However, poorer countries cannot face this pandemic alone and are in a dire need of support and assistance. The GHRP identifies the priority countries as targets for support. This work was designed to predict the scale of the pandemic in high-priority countries using SIR, logistic, and generalized SEIR models. Next, the urgent requirements of the target countries were estimated based on several factors. Subsequently, a multi-objective optimization model was proposed to maximize the funds received from the donors and humanitarian organizations and to minimize the unmet demands of the target countries. This model achieved a minimum ratio of equitable distribution among the high-priority target countries. Moreover, this paper suggested a response plan that would guarantee the fair and efficient distribution of funds among the high-priority target countries. In future studies, the proposed model can be extended to include new objectives or can be applied to other situations. Furthermore, to increase the similarity of the model to real-world scenarios, some parameters, such as the final epidemic size and demand, can be considered uncertain. A stochastic or robust model might be valuable in this case. Moreover, the authors in [61] applied the Multiple-criteria decision-making (MCDM) approach to determine the priority groups for the COVID-19 vaccine. Hence, we can consider the MCDM approach to determine the priority of the countries for urgent support.

CRediT authorship contribution statement

Ibrahim M. Hezam: Conceptualization, Design, Data curation, Formal analysis, Interpretation of results, Validation, Methodology, Writing - original draft, Revision of draft preparation, Read and approved the final manuscript.

Declaration of competing interest

The 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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Appendix

See Figs. 2–22.
Fig. 2. Prediction for Afghanistan with the logistic and generalized SEIR models.

Fig. 3. Prediction for Burkina Faso with the logistic and generalized SEIR models.

Fig. 4. Prediction for Burundi with the logistic and generalized SEIR models.
Fig. 5. Prediction for Cameroon with the logistic and generalized SEIR models.

Fig. 6. Prediction for CAR with the logistic and generalized SEIR models.

Fig. 7. Prediction for Chad with the logistic and generalized SEIR models.
Fig. 8. Prediction for DRC with the logistic and generalized SEIR models.

Fig. 9. Prediction for Ethiopia with the logistic and generalized SEIR models.

Fig. 10. Prediction for Haiti with the logistic and generalized SEIR models.
Fig. 11. Prediction for Iraq with the logistic and generalized SEIR models.

Fig. 12. Prediction for Libya with the logistic and generalized SEIR models.

Fig. 13. Prediction for Mali with the logistic and generalized SEIR models.
Fig. 14. Prediction for Myanmar with the logistic and generalized SEIR models.

Fig. 15. Prediction for Niger with the logistic and generalized SEIR models.

Fig. 16. Prediction for Nigeria with the logistic and generalized SEIR models.
Fig. 17. Prediction for Palestine with the logistic and generalized SEIR models.

Fig. 18. Prediction for Somalia with the logistic and generalized SEIR models.

Fig. 19. Prediction for South Sudan with the logistic and generalized SEIR models.
Fig. 20. Prediction for Sudan with the logistic and generalized SEIR models.

Fig. 21. Prediction for Syria with the logistic and generalized SEIR models.

Fig. 22. Prediction for Yemen with the logistic and generalized SEIR models.
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