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COVID-19 outbreak: A data-driven optimization model for allocation of patients

Sobhan Sarkar \(^a,\ast\), Anima Pramanik \(^b\), J. Maiti \(^b,\ast\), Genserik Reniers \(^d\)

\(^a\) Division of Management Science, Business School, University of Edinburgh, 29 Buccleuch Place, Edinburgh EH8 9JS, UK
\(^b\) Department of Industrial & Systems Engineering, IIT Kharagpur, Kharagpur-721302, India
\(^c\) Centre of Excellence on Safety Engineering & Analytics, IIT Kharagpur, Kharagpur-721302, India
\(^d\) Safety and Security Science, Faculty TPM, Delft University of Technology, The Netherlands

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ABSTRACT

COVID-19 is an unprecedented pandemic that puts the entire world at stake and the healthcare systems across the globe have faced pressing challenges. The number of COVID-19 patients increases rapidly every day. The hospitals across many countries are starving to provide adequate service to the patients due to the shortage of resources and as a consequence, patients do not get admitted to hospitals on time, which in turn creates panic and might contribute to the spread of the pandemic. Under this resource constraint situation, this study proposes a data-driven optimization model for patient allocation in hospitals. First, a compartmental model is developed for characterizing the spread of the COVID-19 virus. Then, Pareto analysis is carried out to identify the most COVID-affected cities. An optimization model is then developed for optimal patient allocation in hospitals in different cities. Finally, a sensitivity analysis is also conducted to investigate the robustness of our decision model. Using published data for Indian cities, obtained from different websites, the proposed methodology has been validated. Experimental results reveal that the proposed model offers some efficient strategies for optimal allocation of patients. A total of ten cities are identified as the most affected. Besides, four factors, namely cooperation, distances between cities, number of patients, and bed capacity per city emerge as important determinants.

1. Introduction

While COVID-19 was declared as a global pandemic by the World Health Organization (WHO) on March 11 in 2020, the virus had already been dominantly circulating in different populations of different countries across the world, which resulted in 7,037,810 confirmed cases and 403,360 deaths worldwide (Worldometers, 2020), the majority of them being from the United States of America (USA). In India, 256,736 people are infected, and 7,187 people died of this infection at the time of writing this paper (Worldometer, 2020). The number of active cases in India is reported to be as high as 125,984, and the number of serious cases as 8,944. As of now, 123,565 patients have recovered from this disease. Therefore, this present statistics reveals that there is a lack of awareness among common people of how this virus spreads and that is why people get easily infected. The virus that causes Covid-19 disease is thought to spread mainly from person to person, mainly through respiratory droplets (aerosol) produced when an infected person coughs or sneezes. These droplets can land in the mouths or noses of people who...
are nearby or possibly be inhaled into the lungs. Spread is more likely taken place when people are in close contact with one another (within about 6 feet) (CDCP, 2020). The disease seems to be spreading easily and sustainably in the community (so-called “community spread”) in different affected geographic areas. Community spread means people have been infected with the virus in an area, including some who are not sure how or where they got infected. Therefore, under such circumstances, the common people should be aware of the process of the spread of this virus.

To curve down the potential loss of human lives due to the COVID-19 outbreak, lockdown measures came into force in different countries during this time. For example, in India, the first lockdown was started on March 25 in 2020 for 21 days, rigorously limiting movement of people as a preventive measure. The measure eventually helped to slow down the growth rate of this pandemic by April 6 to a rate of doubling every six days (Sandhya, 2020), and by April 18, to a rate of doubling every eight days. This lockdown continued in five phases with the fourth phase ending on May 31 in 2020. During this period, free movement across states has been made restricted with 14-days mandatory quarantine in some cases. For other countries, such as ‘Italy’, ‘Greece’, ‘France’, and ‘Germany’, the lockdown was started from March 9, 23, 17, and 23, respectively (Wikipedia, 2020). With factories and workplaces shut down totally during this time, there was a shortage of food, medicine, and other resources observed. The transportation system has been severely limited. Under such an untoward situation imposed by this global pandemic, many countries have been suffering seriously from limited resources, including a proper health care system with an adequate public health infrastructure. A hospital plays a crucial role in the healthcare system in providing essential medical care to communities, particularly at crisis. During this time, many designated hospitals in different countries, including ‘Georgia’, ‘Armenia’, ‘Tajikistan’, and ‘Uzbekistan’ have been taking advantages of the tool and technical aids from the World Health Organization (WHO) (WHO, 2020) to combat with such unpropitious circumstances. Their guidelines help hospitals in reviewing systems, resources, and protocols, and eventually outline particular tasks to strengthen their immediate responsiveness to COVID-19. However, under normal working conditions, many hospitals in different countries, including India frequently operate at near-surge capacity. Consequently, even a modest rise in admission volume of patients can overwhelm a hospital beyond its functional reserve. Even for a well-prepared hospital, coping with the health consequences of such COVID-19 outbreak is a complex challenge. During the current ongoing situation of COVID-19, well-prepared health facilities are at the centre of an effective response. The rapidly evolving outbreak requires all hospitals to be able to adapt to a swift increase in demands while continuing to ensure safe environments for health workers and patients. However, these facilities are often jeopardized due to the interruptions of critical support services, and shortages of equipment and supplies. This situation leads to the disruption in healthcare systems. As a consequence, the newly infected people (COVID-19 patients) are not further allowed to be inhaled into the lungs. Spread is more likely taken place when people are in close contact with one another (within about 6 feet) (CDCP, 2020). The disease seems to be spreading easily and sustainably in the community (so-called “community spread”) in different affected geographic areas. Community spread means people have been infected with the virus in an area, including some who are not sure how or where they got infected. Therefore, under such circumstances, the common people should be aware of the process of the spread of this virus.

With these limitations of healthcare facilities across the world, there is an uncertainty reigning among people, whether any particular country can accommodate mass hospitalization at the culmination of this pandemic. The pressing challenge seems to be originated from both an increasing number of patients and a lower grade of the infrastructure of hospitals. From one of the recent studies by Kapoor, Sriram, Joshi, Nandi, & Laxminarayana (2020), it has been estimated that India owns 1.9 million hospital beds, 95 thousand intensive care unit (ICU) beds, and 48 thousand ventilators. The majority of the ventilators and beds belong to seven states, namely ‘Uttar Pradesh’ (14.8%), ‘Karnataka’ (13.8%), ‘Maharashtra’ (12.2%), ‘Tamil Nadu’ (8.1%), ‘West Bengal’ (5.9%), ‘Telangana’ (5.2%), and ‘Kerala’ (5.2%). All these reported figures (in percentage) primarily focus on inadequate healthcare facilities, which result in a lack of proper medical treatment. If any hospital faces a shortage of facilities, such as the number of beds, ICUs or ventilators, patients are bound to wait for the time of next allocation by the respective hospitals. During this time, their situation becomes poor and they may succumb to death (Suh, 2020). Therefore, the healthcare system of any country should be as efficient as possible. The management of any healthcare organization, for example, hospital, should ensure a rapid and effective response to this outbreak. Therefore, at this stage, healthcare professionals must have some strategies which help the patients in allocation in other hospitals. However, the strategy or decision is not straightforward. There are plenty of factors required to be assessed to obtain a final decision. Therefore, under such circumstances, an optimization model is required, which can efficiently consider all the factors before generating an optimal solution. Based on this solution, decision-makers can take effective decisions for this above-mentioned problem. Besides, the decision should be as prompt as possible since the number of COVID-19 cases have been escalating day-by-day and hitting the healthcare system badly. In such cases, the decision can be efficient and bias-free, if it is obtained from reliable data available on websites. An avalanche of scientific reports and statistics are generated daily on the effects of COVID-19. The use of this information effectively and quickly can lead to a data-driven efficient decision making on optimal patient allocation and thus minimizing the number of infected cases.

1.1. Research issues

Based on the above-mentioned discussion on ongoing adverse situations due to this global pandemic, some issues are identified and mentioned below.

(i) Under the current adverse circumstances imposed by the COVID-19 pandemic, movement across territories or regions or states of various countries, such as India becomes relatively difficult. Since the current lockdown is strictly maintained in every state during this time, free movement of any person or patient between states becomes very limited. Under such circumstances, optimal allocation of patients in hospitals in patient’s state is extremely essential. However, there may be a number of hospitals available in different cities in a state. Therefore, determining an optimal city for patient allocation is eventually a challenging issue.

(ii) Of late, handling adequately the increasing number of COVID-19 patients has become critical for the healthcare system. This is basically due to a limited number of beds, and other resources, and sometimes, sub-standard co-operation among different hospitals. This situation often puts any hospital in deep trouble as they are supposed to make a quick decision, which consequently results in inefficient decision making, thus endangering many patients’ lives.
(iii) Although there is a substantial amount of information present in the literature on COVID-19, modeling of COVID-19 spread mathematically for patient allocation is still unavailable.

(iv) The ongoing COVID-19 is an unprecedented event in modern times affecting the entire world, including India. Till now, no studies have been carried out for optimal patient allocation in an Indian scenario.

1.2. Contributions

Based on the issues identified, the current study contributes in the following ways:

(i) We have developed an optimization model for finding an optimal city for patient allocation. A cost function is developed in this model based on co-operating factor, distance, bed capacity, and the number of patients. The co-operating factor is the weight assigned between two cities to check the degree of their co-operation for patient allocation. Finally, a patient can be allocated to the optimized city based on minimizing the cost function.

(ii) We have mathematically defined and modeled the spread of COVID-19 using a schematic diagram.

(iii) A new parameter called relocation equity has been defined in this study as a significant contributing factor. It is a weight parameter, which is calculated from the sum of weighted distance (between patient’s city and the new city), and the weighted bed capacity of the city. The aim of the inclusion of this parameter in our analyses is to capture the influence of the distance and bed capacity on finding an optimal city.

(iv) An extensive study is conducted in an Indian scenario to demonstrate the effectiveness of our proposed methodology.

Therefore, the objective of this study is to develop a data-driven optimization model for patient allocation under the current uncertain pandemic situation. To do this, a case study of an Indian scenario is presented. First, a compartmental model is introduced for characterizing the spread of the COVID-19 virus among the people. The spread of COVID-19 results in the number of infected people in a city/state/country. Thereafter, an optimization model is developed for determining an optimal city for patient allocation. Co-operating factor, the number of patients in cities, distances between cities, and bed capacities in cities are used in this model. The co-operating factor is used to see the cooperation between two cities for patient allocation. In addition, the bed capacity is defined for each city. Finally, a sensitivity analysis is also conducted to investigate the robustness of our optimization model.

The rest of the paper is organized as follows: In Section 2, the proposed methodology for real-time patient allocation is discussed in details. A case study of the Indian scenario has been presented in Section 3. Data collection & its description, and its pre-processing are also mentioned in this section. In Section 4, the results are presented and discussed in details. Finally, conclusions are drawn with limitations, and scopes for future studies in Section 5.

2. Proposed methodology

In this methodology, we have first demonstrated how COVID-19 spreads and then, we have developed an optimization model for patient allocation. The characteristics of this spread, and the optimization modeling are described in Sections 2.1, and 2.2, respectively. All the notations used in this study have been mentioned in Table A.2 in Appendix A.

2.1. Spread of COVID-19

This section mathematically describes the spread of COVID-19 from one person to other persons. The number of COVID-infected patients in a city depends on the nature of its spread. The more the virus will spread, the more the number of infected patients will increase. Based on the strategy adopted by Brauer (2008, 2019), we develop a compartmental model to characterize the spread of COVID-19 through interacting persons. A schematic diagram of such spread is depicted in Fig. 1.

In Fig. 1, there are seven compartmental stages based on the nature of the spread of COVID-19, which include (i) infected, (ii) suspected, (iii) immediate quarantine, (iv) delayed quarantine, (v) newly infected, (vi) strict quarantine, and (vii) recovery. The Infected stage, as a first stage in the compartmental model, is related to the initial state of the COVID-19 spread, where a person gets infected by this virus. The second stage is the Suspected stage, where a person is suspected to be infected by the disease. Let \( i \) be the \( i \)-th COVID-infected patient. Let \( S_i \) be the number of suspected persons who are either a family member or come in contact with the infected \( i \)-th patient. Next, the suspected persons are required to be quarantined. Here, two types of quarantine are possible; first, immediate quarantine and second, delayed quarantine. If suspected persons are quarantined immediately just after being suspected, then, it is called ‘Immediate quarantined’; whereas, if they are quarantined after a few days, it is then called the ‘delayed quarantined’. Let \( m_i \) be the number of suspected persons who are quarantined after a few days, and let \( S_i - m_i \) be the number of suspected persons who are quarantined at hospitals immediately after being detected. Then, the number of newly infected persons from the \( i \)-th patient is equal to \( N_i \). \( N_i \) is defined as the following Eq. (1):

\[
N_i = S_i - 2m_i - n_i - r_i
\]  

(1)

where \( S_i \) indicates the number of suspected persons, \( m_i \) is the number of suspected persons who are quarantined lately, and \((S_i - m_i)\) denotes the number of suspected persons who are quarantined immediately. Out of \( m_i \), and \((S_i - m_i)\), the number of non-infected persons are \( r_i \), and \( n_i \), respectively. In the strict quarantine stage, patients are allocated to hospitals for getting proper treatment. The final stage is the recovery, where patients are cured completely from this disease and released from hospitals. Initially, if there are \( N_i \) number of COVID patients, then, a total of \( N_i^N \) newly infected cases can be found. In this way, COVID-19 spreads drastically. Hence, every new infected person should be kept in strict quarantine to reduce the spread. After a span of 14 days of regular observation, if the patient is found COVID-free, he/she can be released from hospitals. In any city/state, the number of patients is approximately equal to \( P_i \). This is defined as Eq. (2):

\[
P_i = N_i + N_i^N
\]  

(2)

As we can observe from the above-mentioned schematic diagram of the COVID-19 spread, a large number of people are likely to be infected from only one patient or infected person. Suppose, one COVID-19 patient is not admitted in the hospital due to the shortage of beds and he/she is kept home-quarantined. After getting the proper hospital facility, the patient is transferred to the hospital. In this scenario, it is highly possible that one careless act of this patient during his/her stay at home can spread this COVID-19 virus to his/her family members or other persons, knowingly or unknowingly. Therefore, a proper modeling is required for the optimal allocation of patients under such circumstances with minimum cost. This is explained in the next section.

2.2. Optimization model for patient allocation

As mentioned above, as soon as the infected/suspected patient will be allocated to the hospital, the chances of spreading of COVID-19 among the common people (either at home, road, or any common places) will be reduced. In addition, a proper patient allocation is essential at this stage to minimize the transportation cost. In order to handle all these issues, we have defined an optimization model to allocate the COVID-infected patients to hospitals in a city optimally so that the overall cost function will be minimized. The proposed methodological
flowchart for patient allocation under the COVID-19 pandemic is shown in Fig. 2. It has three steps: (i) data pre-processing, (ii) optimization modeling, and (iii) patient allocation. All these steps are explained below.

**Step 1: Data pre-processing**

In the first step, we choose cities where patient allocation is urgently required. To do this, first, Pareto analysis is conducted using the information on the number of patients in the cities. Then, the cities containing 80% of the total patients are only considered. Information related to these cities, such as distance, number of beds & people, and number of patients are used to formulate the optimization model for patient allocation, which is defined in the next step.

**Step 2: Optimization modeling**

In this second step, a cost function under a certain constraint is formulated using the optimization model for the allocation of patients to hospitals in an optimal city. Here, the cost function is formulated based on three types of data: (i) the distance between cities, (ii) bed capacity in each city, and (iii) the number of patients in each city. In addition to this, a relocation equity constraint to enforce the minimum cost among different cities is also introduced. This constraint is the weighted parameter based on the distance between cities, and bed capacities. The modeling step consists of five stages, (i) identify a co-operating factor, (ii) define the bed capacity, (iii) calculate the inter-city distance, (iv) calculate the number of patients in a city, and finally, (v) develop an optimization model. All these stages are explained below.

- **Stage-1: Identify a co-operating factor**- First, a co-operating factor (denoted as $z_{ij}$) between two cities is found. Here, $z_{ij}$ indicates the co-operating factor between the $i$-th and $j$-th city. $z_{ij}$ is defined as:

$$z_{ij} = \begin{cases} 1, & \text{if } (i - \text{th, } j - \text{th cities) \in same state } \\ 0, & \text{otherwise} \end{cases}$$

(3)

In other words, the value of this factor is either 1, if the two cities belong to the same state or 0 if the two cities belong to different states. This factor is considered based on a COVID-related Governmental policy in a country (here, India). As it is known that COVID-19 is an extremely infectious disease, it is hard to detect a person when he/she gets affected by it. India has been severely affected by COVID-19 since March 2020. In India, the Government of each state frames rules and mandates them to maintain the patient allocation process. It is a strict rule that no COVID-19 patient from one state cannot get admitted to the hospital which is present in the other state. The government undertook this decision because, in each state, while the number of patients gradually increases; nevertheless, the bed capacities do not increase. They are very limited. Under such a pressing challenge arising from the scarcity of beds, it can be concluded that there is very less or no cooperation between the two states in terms of COVID-19 patient allocation. Therefore, the co-operating factor between any two cities within the same state is considered as 1, and the co-operating factor between two cities from different states is considered as 0.

- **Stage-2: Define the bed capacity**- The bed capacity is an important factor as patients are allocated to an optimal city where the hospitals have sufficient number of beds available for patients. The bed capacity of a city (say, $C_i$) can be expressed as the following Eq. (4):

$$C_i = \frac{C_{i}^{M}}{C_{i}^{L}} \times C_{i}^{M}$$

(4)

where $C_{i}^{C}$, $C_{i}^{L}$, and $C_{i}^{M}$ denote the population of the city, population of the state, and the number of beds in hospitals in the corresponding state, respectively.

- **Stage-3: Calculate the inter-city distance**- The distance (denoted as $d_{ij}$) is calculated between the patient’s city (i.e., $i$-th city) and the optimized city (i.e., $j$-th city) where he/she needs to be shifted is computed. This distance is the most important factor in defining the cost function in our model.

- **Stage-4: Find the number of patients in a city**- As already mentioned in Section 2.1, the number of patients in a city is calculated based on the spreading of COVID-19. Therefore, the number of patients in an optimal city is approximately equal to $P_i$.

- **Stage-5: Develop an optimization model**- Using the cost function, an optimization model is developed to find the minimum cost obtained at each iteration in our experiment. Based on this minimum cost, the patients will be allocated optimally to a particular city. The model can be formulated as an optimization problem and expressed as the following Eq. (5):

$$\text{Min } \sum_{i, j \in S} P_i \times d_{ij} \times z_{ij}$$

subject to $w_i(i) > w_j(j)$

$0 \leq z_{ij} \leq 1$

(5)

where $z_{ij}$ denotes the co-operating factor, $P_i$ and $P_j$ represent the number of COVID patients in the city $i$, and $j$, respectively, and $w_i(i)$ indicates the relocation equity for city $i$. It is the weighted parameter based on the information of distance between patient’s cities and the optimized cities. This equity parameter can be defined by the following Eq. (6):

$$w_i(i) = \alpha_1 \times \log \left( \frac{d_{ij}}{\sum_{k \neq i, j} d_{ik}} \right) + \alpha_2 \times \log \left( \frac{C_j}{C_i} \right)$$

(6)

where $\alpha_1$ and $\alpha_2$ indicate the weight values. In our experiment, we have chosen $\alpha_1 = \alpha_2 = 0.5$ to give equal importance to both factors, namely distance between cities ($d_{ij}$) and bed capacities ($C_i$). Both the factors are equally important in the present context. Suppose the distance between a patient’s (say, $p$-th patient) location and hospital’s location is less, and the bed capacity is also less. Then, the hospital authority will give priority to those patients living near the hospital. Therefore, in such a situation, if the number of patients, whose distance from the hospital is less than $p$-th patient, is higher than the bed capacity, then, $p$-th patient cannot get admission to this hospital. Again, if the distance between the patient’s location and the hospital’s location is higher, and the bed capacity is also higher, then, the transportation cost will be higher for the admission of the patient to the hospital. It is, therefore, required to bring a good trade-off between the distance and bed capacity, i.e., distance should not be very long and simultaneously, the bed capacity should not be very less. These two factors are weighted to obtain the normalized value of $w_i(i)$. The weighted factors are obtained by multiplying $a_1$ with $\log \left( \frac{d_{ij}}{\sum_{k \neq i, j} d_{ik}} \right)$ and $a_2$ with $\log \left( \frac{C_j}{C_i} \right)$, where the sum of $a_1$ and $a_2$ is equal to one. Therefore, $a_1 = a_2 = 0.5$ is chosen to give equal importance to these factors in defining $w_i(i)$. We need to allocate patients in a suitable city where bed capacity and distance are set at optimal levels. Using this optimization model, we can determine one city optimally at each iteration. This information is used for patient allocation, as discussed in the next step.

**Step 3: Patient allocation**

At this final step of our experimental study, initially a set of seven iterations (set as minimum) is conducted for each city. At the first iteration, two neighbor cities of the patient’s city are considered to find the optimal city. In the second iteration, three neighbor cities are considered and an optimal/optimized city is determined. In the similar way, all the iterations are carried out. At the final iteration, i.e., iteration-7, a set of eight neighbor cities are considered for analysis. At each iteration, the minimum cost and its corresponding city are determined. After completing the iteration process, we count the maximum time that a city takes. The city with the
maximum number of counts is selected as optimal for patient allocation. If the optimal city (within the patient’s city) cannot be found during these seven iterations, the number of iterations can be increased, and when optimal city within the same state can be found, the iterations will be stopped. For example, if the patient’s city is present within the middle area of a state, then, all eight neighbor cities may belong to the same state. Then, further iterations are not required to find the optimal city. If one city is present near the border area of a corresponding state, then, there is a high possibility of not getting the optimal city within the same state. In such a case, the required number of iterations will be higher than seven. The iteration will be stopped after obtaining the optimal city within the same state of the patient’s city. After each iteration, one optimal city is obtained. After the completion of all iterations, an optimal city, which occurs in maximum number of times over the iterations, will be considered for patient allocation. The pseudo-code of the overall optimization algorithm for patient allocation is given in Algorithm 1. If any COVID-19 patient is further detected, a new record will be generated and accordingly, all the previous records/datasets are updated. Based on the updated datasets, all the aforesaid three steps are repeated (refer to the feedback path of Fig. 2) to allocate the patient dynamically to an optimal city.

Algorithm 1. Pseudo-code of the optimization algorithm for patient allocation problem.

Input: \( \{z_{ik}\}_{k=1}^{4} \): A set of co-operating operators; \( \{C^M_l\}_{l=1}^{t} \): A set of beds in states; \( \{d_{ik}\}_{k=1}^{4} \): A set of distance matrix; \( \{P\}_{l=1}^{t} \): A set of number of COVID patients in cities; \( \{C^S_l\}_{l=1}^{t} \): A set of population in cities; \( \{C^P_l\}_{l=1}^{t} \): A set of population in states.
Output: \( Q_i \): Optimized city for \( i \)-th patient’s city.

Initialize the set of matches \( \{M\} \leftarrow \phi \);
Initialize the set of costs \( \{N\} \leftarrow \phi \);
Compute bed capacity for \( i \)-th city, \( C_i \) using Eq. (4);
for \( m=1 \) to 7 do
  set \( \{COST\} \leftarrow \phi \);
  for \( k=1 \) to \( j \) do
    Compute \( Cost_{ij} \) using Eq. (5);
    \( \{COST\} \leftarrow Cost_{ij} \);
  end
  \( \{M\}_m \leftarrow \{City|\min\{Cost \neq 0\}\} \);
  \( \{N\}_m \leftarrow \min\{Cost \neq 0\} \);
end
Set \( \{Count\} \leftarrow \phi \);
for \( m=1 \) to 7 do
  for \( k=1 \) to \( j \) do
    if \( City_k = \{M\}_m \) then
      \( \{Count\}_k \leftarrow \{Count\}_k + 1 \)
    end
end
for \( k=1 \) to \( j \) do
  if \( \{Count\}_k = \max \{Count\}_k \) then
    Optimized city \( Q_i \leftarrow City_k \)
  end
end
return \( Q_i \).

3. Case study

In this section, we present a case study to validate our proposed methodology. A set of four datasets are used, which are based on Indian scenario. All the data sources and their attributes are discussed below, in brief. Additionally, data pre-processing is also mentioned.

3.1. Data sources and description

The distances between origin cities (i.e., patient’s city), and destination cities (i.e., the optimized city) are obtained from the Distance Matrix application programming interface (API) of Microsoft Bing Map (Corporation, 2020). The API requires longitudes, and latitudes of each city to generate inter-city distances. We name the dataset containing all inter-city distance values as ‘Distances_between_cities’. The total number of beds in each state is obtained from a Kaggle dataset (Pai, 2020). We named the dataset as ‘Hospital_Beds_statewise’. In this dataset, the attribute ‘Accommodation capacity’ refers to the number of beds available for COVID-19 patients in a particular city. Due to the unavailability of city-wise accurate statistical data, we approximated it from the ratio of the population of a city to its corresponding state. Both the population statistics, and location coordinates (i.e., latitudes, and longitudes) of each city are obtained from the website ‘Simplemaps’ (SimpleMaps, ...
We named the dataset as ‘Population_citywise’. Finally, the data related to COVID-19 active cases in cities of each state in India is collected from Kaggle dataset (Devakumar, 2020), and is named as ‘Patients_citywise’. The states and cities are coded as ‘state1’, ‘state2’, ‘state3’, ..., up to ‘state28’, and ‘city1’, ‘city2’, ‘city3’, ..., up to ‘city212’, respectively for our analyses. The attributes of all the above-mentioned datasets and their brief descriptions are presented in Table 1.

### 3.2. Data pre-processing

In the data pre-processing phase, all the samples having missing values in their respective attributes are deleted (Sarkar & Maiti, 2020; Sarkar, Verma, & Maiti, 2018; Sarkar, Vinay, Djeddi, & Maiti, 2020; Sarkar, Vinay, Raj, Maiti, & Mitra, 2019; Verma, Chatterjee, Sarkar, & Maiti, 2018). The outliers are also checked for each dataset and accordingly, removed.

### 4. Results & Discussions

In this section, the effectiveness of the proposed methodology is discussed in details. The experimental set up, results from the analysis on patient allocation & sensitivity analysis, and finally, key findings from analyses are mentioned in the following sections.

#### 4.1. Experimental setup

To build the optimization model for the patient allocation problem, Python 3.6 (Anaconda)² has been used in Windows 7 operating system (OS) using an Intel i3 processor clocked at 2.50 GHz, and 8.00 GB of memory. The libraries used for modeling include ‘pandas’, ‘numPy’, and ‘matplotlib’.

#### 4.2. Experimental results

In this study, we have considered 212 cities in India. As there is a benchmark dataset, namely ‘Distances_between_cities’ provides the distances between 212 cities, so we have considered these cities only for our experiment. Of them, a total of 12 cities are identified as the most COVID-affected cities using Pareto analysis (refer to Fig. 3). This analysis is done based on the number of COVID-19 cases across the 212 cities. Pareto chart for all these 212 cities are not shown in the Fig. 3. To visualize the results, we have displayed only 20 cities in this figure, out of which a total of twelve cities are found to be the most critical, which are ‘city1’, ‘city2’, ‘city3’, ..., ‘city11’, and ‘city12’ (marked by the red color in Fig. 3). However, for simple understanding of the functionality of our proposed method and the interpretation of its results, we have presented and explained the results of the four critical cities only in this paper, which are ‘city2’, ‘city9’, ‘city1’, and ‘city3’. Another important reason for choosing these cities is that the analyses of these four cities represent the nature of the overall analysis of all twelve cities. It implies that the analytical results for city1 are almost similar to city4, city6, and city10. Whereas the results of city2 are almost similar to city5, and city8, city3 are similar to city7, and city9 are similar to city12. Therefore, in this study, we have shown a detailed analysis of these four cities only. It is, therefore, sufficient to consider them only in the present study, not
demonstrating the results of rest of them. The results reveal the effectiveness of the proposed method for patient allocation. In Section 4.2.1, the results of patient allocation for the above-mentioned cities are discussed. Finally, a sensitivity analysis is carried out, which is reported in Section 4.2.2.

4.2.1. Allocation of patients

In this study, a series of experiments are carried out to demonstrate the effectiveness of our proposed methodology in order to provide an optimal solution in patient allocation problem under COVID-19 situation. In this problem, patients are optimally allocated to hospitals in different cities. Based on the information of co-operating factor, bed capacity, inter-city distances, number of patients of cities, a cost function is formulated as an objective function of the optimization problem. This optimization aims to obtain the optimal city for patient allocation. Based on the minimum value of this function, an optimal/optimized city is determined. Initially, a total of seven iterations are considered to be run for this optimization. At each iteration, an optimized city is determined for a particular city. The detailed results of each iteration for the 'city2' is depicted in Fig. 4; whereas, the results of each iteration of 'city9', 'city1', and 'city3' are depicted in Fig. B.10, B.11, and B.12, respectively in Appendix B.

For the 'city2', the results of seven iterations are exhibited in Fig. 4 a–g. At the first iteration, we have considered two nearest neighbor cities of 'city2'. Four types of data, namely (i) the distance between 'city2', and its two neighbor cities, (ii) bed capacities of 'city2', and its two neighbor cities, (iii) total number of COVID-19 patients in 'city2', and its two neighbor cities, and (iv) co-operating factors between 'city2', and its two neighbor cities are used to obtain the minimum cost for optimal patient allocation. First, two neighboring cities of 'city2', namely 'city90', and 'city1' are considered in the first iteration (refer to Fig. 4 a). Of them, 'city1' is evaluated as the optimal/optimized city for 'city2'. Similarly, in the second iteration, three neighboring cities of 'city2', i.e., 'city90', 'city1', and 'city56' are considered to get optimized cost and city. In this way, in each iteration, the number of neighboring cities of 'city2' is increased by one. Therefore, at seventh (i.e., final) iteration, the nearest cities of 'city2', namely 'city90', 'city1', 'city56', 'city3', 'city143', 'city165', 'city9', and 'city181' are considered. It is to be noted that the cities, 'city2', 'city90',

![Flowchart](image-url)

Fig. 2. The proposed methodology for patient allocation under COVID-19 pandemic.

Note: \( z_i \) = Co-operating factor, \( P_i \) = Number of COVID-19 cases at j-th city, \( d_{ij} \) = Distance between i-th and j-th cities; \( w_{ij} \) = Equty parameter for i-th city due to j-th city and its neighbor cities.
From these two figures, it is evident that 'city1' is the best choice for patient allocation from 'city2'. Therefore, the co-operating factor for these three states is considered zero, and a patient cannot be allocated to these cities despite they have minimum distance and sufficient bed capacity. Therefore, these cities are set equal to zero. An optimal city is selected based on the minimum value of non-zero costs. As these cities are from different states, they are not considered in finding the optimal city, and hence, these cities and their corresponding costs are not displayed in Fig. 4 g. If the optimized city is not obtained after the seven iterations, then, the number of iteration is doubled. Following this way, the optimized city for patient allocation is determined. The determination of the optimal city for 'city2' is shown in Fig. 4 h. 'city1' is determined as optimized one for the 'city2' from this experiment as observed by the plot being flat from the iteration first to seven. In addition, the cost per iteration is also computed and displayed in Fig. 4 i. From iteration one to seven, number of participating cities are increased by one and so on. As more number of cities are involved, the value of relocation equity gradually decreases. Therefore, optimized cost also decreases per iteration. From these two figures, it is evident that 'city1' is the best choice for patient allocation from 'city2'.

Similarly, an analysis is conducted for 'city9'. The results are shown in Fig. B.10 a-g in Appendix B. According to the strategy mentioned for 'city2', first, two neighboring cities of 'city9' are considered for analysis (refer to Fig. B.10a). Then, the number of neighboring cities is increased in each iteration, for example, three cities are considered in iteration-2 (Fig. B.10b), four cities are taken in iteration-3 (Fig. B.10c), and so on. Finally, in iteration-7, a total of eight neighbor cities are considered (Fig. B.10g). From Fig. B.10g, it is seen that costs for four neighbor cities, 'city7', 'city90', 'city1', and 'city56' are involved in finding optimum city. Other four neighbor cities, 'city143', 'city165', 'city198', and 'city68' are from different states; thereby resulting in co-operating factors for these cities being zeros. Hence, their corresponding cost are zero and not shown in this figure. The evaluation of optimized cities for 'city9' are displayed in Fig. B.10h. From Fig. B.10h, it is observed that the city called 'city56' is evaluated as an optimized city for once, whereas the cities, 'city7' and 'city1' occur four times, and two times, respectively as an optimized city. 'city7' occurs in most of the cases, and thus, we have considered 'city7' as the optimized city for patient allocation from 'city9'. Fig. B.10i shows the patient allocation costs for optimized cities per iteration for 'city9'. In a similar note, for the cities 'city1', and 'city3', all seven iterations are depicted in Fig. B.11 a-g, and Fig. B.12 a-g, respectively. The optimized cities and optimized costs for 'city1' are shown in Fig. B.11 h and i, respectively, and for 'city3' are shown in Fig. B.12 h and i, respectively. From these figures, it is evident that optimized cities for 'city1' and 'city3' are 'city2' and 'city1', respectively.

Additionally, the determination of optimized city is shown in Fig. 5 for a particular city for different iterations. For example, in Fig. 5(b), the optimal city for 'city8' is determined. A set of seven iterations are
checked, and the 'city10' is found as the optimized city. The decision is the same from iteration one to seven. The cost value corresponding to 'city10' is also obtained and exhibited in Fig. 6(b). Similarly, in Fig. 5(a), two cities, 'city9', and 'city3' are found optimal for the 'city7'. From iteration one to two, the optimal city is found as 'city9'; whereas, the decision is changed to 'city3' from the iteration three to seven. The corresponding cost values of 'city9' and 'city3' are determined from iteration one to two, and iteration three to seven, respectively in Fig. 6(a). In the similar note, for the cities, 'city11', 'city4', 'city6', 'city10', 'city5', and 'city12', the optimized cities and the corresponding costs are shown in Fig. 5 (c-h), and Fig. 6 (c-h), respectively.

In summary, it is observed from Fig. 5 that optimized city for (i) 'city7' is 'city3' (refer to Fig. 5(a)), (ii) 'city8' is 'city10' (refer to Fig. 5(b)), (iii) 'city11' is 'city104' (refer to Fig. 5(c)), (iv) 'city4' is 'city85' (refer to Fig. 5(d)), (v) 'city6' is 'city17' (refer to Fig. 5(e)), (vi) 'city10' is 'city8' (refer to Fig. 5(vii)) 'city5' is 'city17' (refer to Fig. 5(g)). For the 'city12' (refer to Fig. 5(h)), cities 'city75', 'city17', and 'city6' occur for three times, one time, and three times, respectively. Under such circumstances, the city with lower distance from the patient’s city is considered as an optimized city for patient allocation. Here, the distance between 'city6' and 'city12' is lower than the distance between 'city75' and 'city12'. Therefore, 'city6' is considered as the optimized city for 'city12'. The cost of optimized cities per iteration for the corresponding cities 'city7', 'city8', 'city11', 'city4', 'city6', 'city10', 'city5', and 'city12' are displayed in Fig. 6(a) to (h), respectively. These figures demonstrate the costs for patients allocation per iteration for obtaining optimized cities for patients’ cities, namely 'city7', 'city8', 'city11', 'city4', 'city6', 'city10', 'city5', and 'city12'.

4.2.2. Sensitivity analysis

After the allocation of patients, sensitivity analysis is carried out. The aim of this analysis is to investigate the impact of the input factors, namely inter-city distances, and bed capacity of cities on the output results of patient allocation. The sensitivity analysis is done for all the cities under study; however, a detailed illustration of results has been done for only four cities, namely ‘city2’, ‘city1’, ‘city3’, and ‘city9’. The results of the analysis for ‘city2’ is depicted in Fig. 7; whereas, sensitivity analyses for ‘city1’, ‘city3’, and ‘city9’ are exhibited in Appendix C in Figs. C.13, C.14, and C.15, respectively. As already discussed, the relocation equity, which is the most important weighted parameter to get the optimal cost for patient allocation, is based on two factors, namely $d_{ij}$ and $C_i$. We have checked the effect of relocation equity in finding optimal patient allocation cost in two ways: (i) by keeping $C_i$ constant and changing $d_{ij}$, and (ii) by keeping $d_{ij}$ constant and changing $C_i$. The former is termed as “Sensitivity analysis 1”, and the latter is termed as “Sensitivity analysis 2”.

For instance, if we first consider the ‘city2’, Fig. 7 show the optimized cities and the corresponding cost per iteration when bed capacity is made constant in determining the relocation equity. The relocation equity is based on the distances between the patient’s city and its neighbor cities. From Fig. 7(a), it is observed over the seven iterations that always the nearest city (i.e., city1) is selected as an optimized city for patient allocation. However, this cannot be true always. Suppose, if the nearest city has less bed capacity in its hospitals, a patient cannot be allocated to the hospitals of that city. On the other hand, Fig. 7 exhibit the optimized cities and corresponding costs per iteration, respectively when distances between cities are made constant in finding the value of relocation equity. Here, relocation equity is based on the bed capacity of any city. It is evident from Fig. 7(c) that the optimized city is based on bed capacity. This is also not true always. Suppose, one optimized city has a higher bed capacity; however, it is located far away from the patient’s city. Under this circumstances, the transportation cost for patient allocation will increase. To bring a trade-
Fig. 4. Patient allocation result for ‘city2’.
Fig. 5. Optimized cities per iteration for different cities.
Fig. 6. Optimized costs per iteration for different cities.
off between distance and bed capacity, we have considered both factors in finding the relocation equity; thereby resulting the cost function to obtain an accurate optimized city for patient allocation.

Another two important factors are the co-operating factor and the number of patients in cities. If co-operating factor between two cities is zero, the cost function will then always be equal to zero. It is not used further to find an optimized city. Therefore, the non-zero value of the co-operating factor is required to determine the cost. The cost function is directly proportional to the \( \left( \frac{P_i}{P_j} \right) w_{ij} \), where \( P_i \) and \( P_j \) represent the number of patients in \( i \)-th and \( j \)-th city, respectively. As discussed earlier, as the relocation equity for \( i \)-th city relies on both the bed capacity and distance, the cost function depends not only on one factor but also on rest of the three factors. In the similar vein, the results from the sensitivity analyses for the cities ‘city1’, ‘city3’, and ‘city9’ are shown in Fig. C.13, C.14, and C.15, respectively. From the above sensitivity analysis, it can be interpreted that all four factors, bed capacity, distances between cities, co-operating factor, and number of patients in a city are very important in finding the optimal city for patient allocation.

Further, following the strategy adopted by Suard et al (2013) for sensitivity analysis, we have conducted the full factorial design. The reason to keep the conventional sensitivity analysis in our study is to explore the effects of two factors, namely distance and bed capacity in defining the relocation equity. Whereas, the FFD analysis is carried out to demonstrate the main effects and interaction effects of four factors, namely distance, bed capacity, number of patients, and co-operating factor in defining the cost function for patient allocation. The FFD may be feasible in our study as we are considering a small number of factors for patient allocation. It is typically used to maximize the amount of information collected with a number of simulations. During this process, the range of each input is discretized into two levels, high and low and thus, the experiment requires \( 2^k \) runs, where \( k \) implies the number of factors/inputs. In our study, we have four input factors (i.e., \( k = 4 \)), namely the distance between patient’s location and hospital’s location, number of patients (NP), bed capacity (BC), and co-operating factor (CF); whereas, the response attribute is “patient allocation status” with two classes, “allocation” and “no allocation”. Therefore, we have a total of 16 runs (i.e., \( 2^4 = 16 \)) in this FFD analysis, where we have captured the main effect and interaction effects of input factors on response attribute for each critical city.

The results of the sensitivity analyses for the ‘allocation’ and ‘no allocation’ of patients in hospitals in city2, city1, city3, and city9 are illustrated in Fig. 8 (a-d). For example, the sensitivity analysis for city 2 is demonstrated in Fig. 8a. The horizontal bar of this figure indicates the standard regression coefficient. It represents an effect of an input factor or a group of input factors on the response or output attribute. From Fig. 8a, the sensitivity analysis for the “allocation” of patients from city 2 indicates that CF has the maximum negative effect on patient allocation. It is followed by the factors, distance, NP, and BC. For the patients belonging to city2, we have conducted 524 experiments. Out of these, in 316 cases, CF = 1 (patient’s city and hospital’s city are located at the same state), and for the rest of the 208 cases, CF = 0 (i.e., there is no co-operation between patient’s city and hospital’s city, which implies patient’s city and hospital’s city are located in two different states). As CF = 0 for 208 cases, CF nullifies the effect of distance, NP, and BC in patient allocation. In such cases, a patient cannot be allocated to the hospital that is located in the optimized city (as the optimized city belongs to a different state). On the other hand, for 316 cases, CF = 1. It means, for this experiment, the patient can be allocated to the hospital based on other three factors, namely distance, NP, and BC.
Fig. 8. Sensitivity analysis for four cities based on full factorial design.
these experiments, we can observe that out of 316 cases, patients are allocated to the hospital (present in the optimized city) in 189 cases based on the information of distance, NP, and BC. Whereas, in 127 cases, based on the optimized cost function, a suitable (based on cost) hospital cannot be found in the desired city for patient allocation. Although here CF = 1, the patient cannot be allocated to the desired hospital due to other factors, such as high distance, minimum bed capacity, and more number of patients. From the aforesaid study, it can be noticed that if CF = 0, in any circumstance, a patient cannot be allocated; on the other hand, if CF = 1, then, the patient may be allocated based on the information of distance, NP, and BC. Therefore, it can be concluded that the factor CF has both positive and negative effects on no-allocation and allocation of patients, respectively. In two-way interactions, it is observed that the BC & CF have a maximum positive effect on patient allocation. It means, for maximum cases, we have found that bed capacity in the hospital is maximum and the number of patients is also less; therefore, the patient can be allocated to the hospital in the optimized city. In addition, NP & CF, distance & CF, and distance & NP have also positive effect on allocation; which are, however, comparatively less than that of BC & NP. Among the three-way interactions, BC & NP & CF, distance & NP & CF, and distance & BC & NP have negative effect on allocation. In four-way interaction, all four factors combinedly impact positively on allocation.

For the “no allocation” of patients in city 2, Fig. 8a indicates that CF has the maximum positive effect. It is followed by another major factor, distance. As the distance increases, the probability of patient allocation decreases. BC has a negative effect on “no allocation”. This is because the lack of BC eventually decreases the chance of patient allocation. In two-way interactions, it is observed that the BC & CF has the maximum negative impact on “no allocation”, which is followed by distance & BC and BC & NP. On the other hand, NP & CF, distance & NP have a positive impact. In addition, distance & NP & CF have jointly positively impacted no allocation of patients. In four-way interaction, all four factors combinedly impact positively on no allocation. Similarly, FFD-based sensitivity analyses are conducted for the rest of the three cities, i.e., city1, city3, and city9, separately and illustrated in Fig. 8b, c and d, respectively.

4.3. Key findings

From the present analysis, some key findings are obtained, which are:

(i) Under the increasing pressure of incoming patients to hospitals during COVID-19 outbreak, the proposed data-driven optimization model can help the hospital management allocate a patient optimally to a hospital in a city of the patient’s state.
(ii) From the Pareto analysis, it is found that most critical cities are ‘city1’, ‘city2’, ‘city3’, ‘city4’, ‘city5’, ‘city6’, ‘city7’, ‘city8’, ‘city9’, ‘city10’, ‘city11’, and ‘city12’.
(iii) Patients are allocated to different cities but within the same state. After determining any optimized city, a patient will be allocated to that city if it has the higher bed capacity, and less number of COVID-infected patients as compared to the patient’s city, and both patient’s city and optimized city belong to same state. It is considered in the study that co-operating factor between two cities from two different states is zero. Suppose the distance between the patient’s city (denoted as A) and the hospital’s city (denoted as city B) is minimum and the bed capacity in the hospital in the city B (located in a different state) is higher than any hospital present in the patient’s city, A (within the same state). Under such circumstances, the patient cannot be allocated to the hospital in city B due to the zero value of the co-operating factor.

Therefore, patients are always allocated to different cities within the same state.

(iv) If two optimized cities are determined simultaneously for patient allocation, then, the patient will be allocated to the optimized city with less distance (between optimized city and patient’s city); thereby reducing the transportation cost.

(v) From sensitivity analysis, it is found that all four factors, namely co-operating factor, distances between cities, number of patients, and bed capacity per city are important in determining the optimal city. Of them, distance between cities and bed capacity are the two most important factors evaluated in this analysis (refer to Stage 5 in Step 2 in Section 2.2). Additionally, from FFD analyses, CF is found to be the most sensitive factor in both allocation and no allocation of patients in hospitals for city 2. For city 1, 2, and 9, CF is also found to be the most sensitive factor. The findings suggest that CF between states should be maintained properly to handle the patient allocation problem more efficiently.

(vi) In some cases, the optimized city, and patient’s city may belong to either the same state or different states. If the two cities are from the same state, co-operating factor between them is one; otherwise, its value becomes zero. If the co-operating factor is zero, patients are not shifted to the optimized city.

(vii) A city is determined as an optimized one in each iteration of our experiment. In any case, if such two different cities are found to be optimized in consecutive iterations, patients will then be allocated to the optimized city following the strategy used in Fig. 9. According to this figure, first, we check whether the patient’s city and optimized city belong to the same state or not. If yes, then, we check whether the bed capacity in the optimized city is greater than the patient’s city or not. If yes, then, we further check if the number of COVID cases in the optimized city is greater than the patient’s city. If no, then, patient will be allocated to the optimized city. If it is yes, then, patient will not be allocated to the optimized city, and iterations continue to find the next optimized city.
5. Conclusions

COVID-19 is a pandemic that has led to an unprecedented event in modern times, which has put the entire world at stake. When a person is detected COVID-19 positive, he/she needs to be transferred immediately to any nearby hospital having adequate facility for handling COVID-19 patients. However, not all times the nearby hospitals can accommodate those patients, which may be due to several reasons, including unavailability of beds or other resources. Then, they are recommended to different hospitals either in the same state or in the different state. This decision is very crucial and needs careful judgment on different factors. Besides, the decision is to be taken very quickly as the capacity of different hospitals goes changing in every time due to the increasing number of infected people. Therefore, there is a need to develop such a model which not only can help in the allocation of patient optimally in hospitals but also can speed up the decision process. In this paper, we have developed a data-driven optimization model to allocate patients to an optimized city. The important factors, namely distance, bed capacity, number of patient, and co-operating factors have been considered to build this model. From the analysis, some key findings are obtained. From the Pareto analysis, cities, namely ‘city1’, ‘city2’, ‘city3’, ‘city4’, ‘city5’, ‘city6’, ‘city7’, ‘city8’, ‘city9’, ‘city10’, ‘city11’, and ‘city12’ are found as the most affected by COVID-19 cases. Based on the results of optimization model, patients are allocated to different cities but within same state. The provision of patient allocation depends on whether the optimized city has the higher bed capacity, and less number of COVID-infected patients as compared to the patient’s city, and both patient’s city and optimized city belong to the same state or not. In addition, it is found from sensitivity analysis that the four factors, namely co-operating factor, distances between cities, number of patients, and bed capacity per city are very important in determining the optimal city. Of them, distance between cities and bed capacity are the most important factors evaluated in this study.

The present study has some limitations. The study is restricted to the distance between two cities, and their bed capacities only. Many other factors, including the condition of the hospital, and type of transportation are not considered in this study for finding the optimized city. Besides, transportation of patients can be varied based on the patient’s condition, and age. This is due to the fact of the unavailability of data. The useful information at hospital-level or state-level is unavailable. In addition, the data presented in this paper are being updated daily. Therefore, the findings of the present study is completely based on the data collected during our analysis. However, it is essential to emphasis on the above-mentioned factors during future analysis in this domain. Although many studies are being conducted in response to this global pandemic, an emphasis is essentially expected on hospital conditions or patient allocation of developing nations like India to handle such an unprecedented crisis. The Government should also put attention on revising and enforcing policies in the management of patients, if needed, to counteract the current global emergency. As future scope, if the proposed model is embedded into a decision support system (Sarkar, Chain, Nayak, & Maiti, 2019), a real-time decision can be undertaken which can help decision makers take decision promptly under such critical conditions. Moreover, with the availability of huge amount of data, which are unclassified or not properly classified, cluster analysis (Pramanik, Sarkar, Maiti, & Mitra, 2021; Xu, Wen, & Zhang, 2018) can be done and then our proposed model can be used for better results. Another important as well as interesting study is to determine the factors responsible for the patient non-allocation in hospitals. Rule generations from data and their interpretations could be a potential research in this domain (Sarkar, Baidya, & Maiti, 2017; Sarkar, Pramanik, Maiti, & Reniers, 2020). Another important facet of this study is that this type optimization modeling can be done for different countries, including USA, UK, Spain, and Italy under such pandemic-like situation.

CRediT authorship contribution statement

Sobhan Sarkar: Conceptualization, Data curation, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. Anima Pramanik: Conceptualization, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. Genserik Reniers: Writing – review & editing.

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.

Appendix A. Notations used

Table A.2

| Notations | Meaning |
|-----------|---------|
| $N_i$     | The number of newly infected persons from the i-th patient |
| $S_i$     | The number of suspected persons |
| $m_i$     | The number of suspected persons who are quarantined lately |
| $n_i$     | The number of non-infected persons out of ($S_i - m_i$) |
| $r_i$     | The number of non-infected persons out of $m_i$ |
| $P_i$     | The number of COVID patients in the i-th city |
| $N_i^{co}$| The number of newly infected cases from the i-th city |

Covid patients

- $\pi_0$: The co-operating factor between the i-th and j-th city
- $C_i$: The bed capacity of the i-th city
- $C_i^g$: Population of the i-th city
- $C_i^d$: Population of the i-th state
- $d_{ij}$: The distance between the i-th city (patient’s home city) and the optimized j-th city (where the patient is to be shifted)
- $w_{ij}$: The relocation equity for the i-th city
- $r_1, r_2$: Controlling parameters. $r_1$ controls the effect of distance and $r_2$ controls the effect of bed capacity in defining the relocation equity
- $k$: Variable that defines the number of neighbor cities for a patient

Appendix B. Experimental results on patient allocation

Fig. B.10, B.11, and B.12
Fig. B.10. Patient allocation result for 'city9'.

(a) Iteration 1

(b) Iteration 2

(c) Iteration 3

(d) Iteration 4

(e) Iteration 5

(f) Iteration 6

(g) Iteration 7

(h) Optimized cities

(i) Optimized costs
Fig. B.11. Patient allocation result for ‘city1’.
Fig. B.12. Patient allocation result for 'city3'.
Appendix C. Experimental results on sensitivity analysis

Figs. C.13, C.14, and C.15

(a) When bed capacity is constant
(b) When bed capacity is constant
(c) When distance is constant
(d) When distance is constant

Fig. C.13. Sensitivity analysis for ‘city1’.
Fig. C.14. Sensitivity analysis for ‘city3’.
References

CDCP. Transmission: How covid-19 spreads, http://www.pulsetoday.co.uk/clinical/-clinical-specialities/respiratory/-transmission-how-covid-19-spreads/20040548/article (2020).

F. Brauer, Compartmental models in epidemiology, in: Mathematical epidemiology, Springer, 2008, pp. 19–79.

F. Brauer, C. Castillo-Chavez, Z. Feng, Simple compartmental models for disease transmission, in: Mathematical Models in Epidemiology, Springer, 2019, pp. 21–61.

M. Corporation, Distance matrix api, https://www.microsoft.com/en-us/maps/distance-matrix (2020).

Devakumar, Covid-19 corona virus india dataset, https://www.kaggle.com/imdevskp/covid19-corona-virus-india-dataset (2020).

Harlan, C., & Pitrelli, S., https://www.washingtonpost.com/world/europe/italy-corona-virus-patients-lombardy-hospitals/2020/03/12/36041dc6-63ce-11ea-8a8e-5c5336b32760_story.html.

Independent, Coronavirus: Footage captures chaotic scenes in moscow as ambulances ‘queue to enter hospitals’, https://www.independent.co.uk/news/world/europe/coronavirus-russia-moscow-ambulances-queueing-deaths-hospitals-a9460611.html (2020).

Independent, People queue in rain for coronavirus testing at new york hospital, https://www.independent.co.uk/news/world/americas/coronavirus-new-york-testing-hospital-treatment-lines-drive-thru-a9419846.html (2020).

Kapoor, G., Sriram, A., Joshi, J., Nandi, A., & Laxminarayan, R., https://cddep.org/publications/covid-19-in-india-state-wise-estimates-of-current-hospital-beds-icu-beds-and-ventilators/.

Kar, S. (2020). Coronavirus: Long queues outside hospitals, patients cramped on single beds; covid-19 exposes mumbai’s health sect, https://www.india.com/news/india/maharashtra-news-coronavirus-mumbai-long-queues-outside-hospitals-patients-cramped-on-single-beds-covid-19-exposes-health-sector-4033471/ (2020).

A. Kuhn, How a south korean city is changing tactics to tamp down its covid-19 surge, https://www.npr.org/sections/goatsanddodos/2020/03/10/812865169/how-a-south-korean-city-is-changing-tactics-to-tamp-down-its-covid-19-surge. opens in new tab (2020).

D.M. Pai, Hospitals and beds in india (statewise), https://www.kaggle.com/dheerajmpai/hospitals-and-beds-in-india (2020).

Pramanik, A., Sarkar, S., Maiti, J., & Mitra, P. (2021). RT-GSOM: Rough Tolerance Growing Self-Organizing Map. Information Sciences, 566, 19–37. https://doi.org/10.1016/j.ins.2021.01.039

Readfearn, G., https://www.theguardian.com/world/2020/apr/15/how-did-the-corona-virus-start-where-did-it-come-from-how-did-it-spread-humans-was-it-really-bats-pan-golins-wuhan-animal-market.

Sandhya, R., https://theprint.in/science/r0-data-shows-indias-coronavirus-infection-rate-has-slowed-gives-lockdown-a-thumbs-up-a99713/.

Sarkar, S., Baidya, S., & Maiti, J. (2017). Application of rough set theory in accident analysis at work: a case study. In In 2017 Third International Conference on Research in Computational Intelligence and Communication Networks (IRCICIN) (pp. 245–250). IEEE.

Sarkar, S., Chain, M., Nayak, S., & Maiti, J. (2019). Decision support system for prediction of occupational accident: a case study from a steel plant. In Emerging Technologies in Data Mining and Information Security (pp. 787–796). Springer.

Sarkar, S., & Maiti, J. (2020). Machine learning in occupational accident analysis: A review using science mapping approach with citation network analysis. Safety Science, 131, 104900. https://doi.org/10.1016/j.ssci.2020.104900

Sarkar, S., Pramanik, A., Maiti, J., & Reniers, G. (2020). Predicting and analyzing injury severity: A machine learning-based approach using class-imbalanced proactive and reactive data. Safety Science, 125, 104616. https://doi.org/10.1016/j.ssci.2020.104616

Sarkar, S., Verma, A., & Maiti, J. (2018). Prediction of occupational incidents using proactive and reactive data: A data mining approach. In Industrial Safety Management (pp. 65–79). Singapore: Springer.

Sarkar, S., Vinay, S., Djeddi, C., & Maiti, J. (2020). Text Mining-Based Association Rule Mining for Incident Analysis: A Case Study of a Steel Plant in India. In Mediterranean Conference on Pattern Recognition and Artificial Intelligence (pp. 257–273). Springer.

Sarkar, S., Vinay, S., Raj, R., Maiti, J., & Mitra, P. (2019). Application of optimized machine learning techniques for prediction of occupational accidents. Computers & Operations Research, 106, 210–224. https://doi.org/10.1016/j.cor.2018.02.021

SimpleMaps, India cities database, https://simplemaps.com/data/in-cities (2020).

Fig. C.15. Sensitivity analysis for ‘city9’.
Suard, S., Hostikka, S., & Baccou, J. (2013). Sensitivity analysis of fire models using a fractional factorial design. *Fire Safety Journal, 62*, 115–124.

The Guardian. https://www.theguardian.com/science/2020/jan/24/life-under-lockdown-in-china-hospital-queues-and-empty-streets.

Verma, A., Chatterjee, S., Sarkar, S., & Maiti, J. (2018). Data-driven mapping between proactive and reactive measures of occupational safety performance. In *Industrial Safety Management* (pp. 53–63). Singapore: Springer.

WHO. Who checklist to ensure hospitals in european region are ready for covid-19 patients, http://www.euro.who.int/en/health-topics/Health-systems/patient-safety/news/news/2020/4/who-checklist-to-ensure-hospitals-in-european-region-are-ready-for-covid-19-patients (2020).

Xu, Y., Wen, X., & Zhang, W. (2018). A two-stage consensus method for large-scale multi-attribute group decision making with an application to earthquake shelter selection. *Computers & Industrial Engineering, 116*, 113–129.

Wikipedia, National responses to the covid-19 pandemic, https://en.wikipedia.org/wiki/National_responses_to_the_COVID-19_pandemic (2020).

Worldometer. Indian statistics, https://www.worldometers.info/coronavirus/?_hsenc=--p2ANqtz-tZKvpgxMHiZoak-1Gms18BPWc7J_QFzZPrVwAQgHxVxXqJfzVbz-CCv04OGmUCp9WBKpw6m8Xj09kx0S-m2fepi3zvzqXc-OjvalFomDp6_hmsi--84525637#countries (2020).