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Relief Supply Chain Management Using Internet of Things to Address COVID-19 Outbreak

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Abstract

Nowadays, due to the COVID-19 outbreak, the most significant factor to be considered all over the world is to manage this pandemic and especially to address positive cases, efficiently and effectively. This can be achieved by simultaneously utilizing the present network with supply chain settings and also the Internet of Things (IoT). This consideration enables the accurate monitoring of suspected cases in real-time to optimize total service time. Hence, this paper firstly designs two sub-models to minimize distance and traffic while minimizing total response time. Our main contribution in this paper is to develop a dynamic scheme using IoT to deal with suspected cases. We also investigate the proposed methodology on a real case problem in Canada. A comprehensive analysis of the proposed methodology behavior has been conducted and the results showed the managerial decision-making process to address COVID-19 patients. The proposed approach establishes efficient strategies to identify suspicious COVID-19 cases and provide them with medical observance in a short time when utilized with IoT. The obtained results of the considered scenarios show 12% up to 15% improvement in the ambulance response time when using IoT.

Keywords: Supply Chain Design; Relief Supply Chain; Humanitarian Logistics; COVID-19; Industry 4.0.

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1. Introduction

Recent pandemic caused by a virus from coronavirus family, namely COVID-19, affected on every aspects of our life, especially, our health, and till now, attempts to find a vaccine or effective drugs have failed to cure the patients (Ran et al., 2020). In this regard and due to the high infection rate of this pandemic, specialists advise social distancing for unaffected people or supportive care cure for hospitalized ones (Lai et al., 2020; Rothan & Byrareddy, 2020; C. Wang et al., 2020). On the other hand, since the COVID-19 pandemic is highly contagious and the cases are increasing (as you can see in Fig. 1), designing a supply chain network while devising new strategies that efficiently exploit hospitals, medical clinics, and other potential places are inevitable and crucial in this situation (Ochalek et al., 2020).
While human life is the most important factor facing these pandemics (Karlsson et al., 2014), many major worldwide industries affected notoriously. Gigantic industries including business tourism and travel, aviation, oil, high tech, and much other business and automotive sectors have decreased in their growth rate due to total quarantine and decrease in demand rate. For instance, the effect of COVID-19 on the two major industries is illustrated in Fig. 2. This issue derived many business managers to implement new approaches to both cost reduction and fatality rates.

This major impact on the different economy would result in a reduction in total Gross Domestic Product (GDP) in many countries especially in Asia where the pandemic aroused and later to developed countries, such as the United States, since most countries’ resources would spend on health section to face and address myriad patients. Moreover, relying on supply chain concepts would be beneficial especially in-home health (Glied & Hong, 2018; Milburn, 2012). In this regard, utilizing the healthcare section with supply chain settings not only survive many lives, but also from the economic perspective reduces the total costs regarding this issue. This is a vital subject because in most governments the medical resources are somehow limited and in a long run, there would be a lot of fatigue among these participants.
Generally, relief supply refers to the supply of vital materials such as social welfare, food, water, medication, clothes, etc. for people who are in a harsh environment like disaster areas. Relief supply chain network includes designing an efficient scheme for these critical situations (Davoodi & Goli, 2019; Shu et al., 2021). Meaning that utilizing emergency management activities with relief supply chain design, could notoriously affect the medical section performance and also helps the manager by the means of strategic decisions (Ellis et al., 2015). Accordingly, delivering the right amount of medical items when everything including demand rate dynamically changes is highly regarded (Hajiaghaei-Keshteli & Sajadifar, 2010; Hong et al., 2015; Safaei et al., 2018). According to Altay & Green III, (2006), we can devide relief operations into four different categories which are (1) preparation for the incident, (2) mitigation, (3) immediate response after the incident, and (4) reconstruction after the incident. Among the mentioned criteria, emergency management involves planning for pre-and-post and also during a disaster with the aim of immediate response (Ghaffari et al., 2020).

In the time of vast and public pandemics or natural disasters, various organizations and governments come together to provide medical care cures, needed medical items, and to supply medicine, food, and etc. for affected people (Jensen & Hertz, 2016). If a society fails to meet the required care or items for the people, the result of these incidents could be profound and it would result in an increased mortality rate especially during pandemics such as COVID-19 (Sohrabi et al., 2020). Therefore, developing a supply chain design that considers public health particularly in vast pandemics could be highly effective to address people and their medical needs.
Generally, the primary privileges of designing an optimal relief supply chain network for managers are as follows:

- Addressing and covering all the affected cases,
- Planning to address affected people in a relatively short time,
- Allocating right and a specific number of medical items,
- Reducing total response time,
- Proactive to the future possible cases,
- Centralized decision-making.

As a result, in most affected countries, a relief supply chain network is needed to both provide better service for affected COVID-19 people and also consider better response time and reliability. For example, in the time of the COVID-19 outbreak in China, the government was able to build two new hospitals with updated medical facilities in less than two weeks (Ran et al., 2020) or in the same situation in Iran, the country utilized field hospitals by mobilizing potential sites such as garrisons, mosques, stadiums, and etc. in a pre-disaster decision-making process (www.independent.com, 2020). Therefore, high governmental decision-makers can proactively affect costs, program efficiency, and most prominently human lives.

According to the World Health Organization (WHO.int, 2020), while many countries suffer from insufficient healthcare systems, but some factors can harmfully worsen this condition during pandemics especially the COVID-19 outbreak. These factors are exemplified in Fig. 3:

![Fig. 3. Major contributive factors that intensify the pandemic condition.](image)

Also, to face pandemics, (WHO.int, 2020) suggested that the best way to protect themselves and others from this condition is quarantine and lockdown. In this situation, self-accessing to medical care centers for suspicious or healthy cases may be harmful as they have to go to the hospitals which are the main sources of pandemic inpatients. In this
situation, utilizing the healthcare system with the Internet of Things (IoT) could sufficiently address the problem (Akbarpour et al, 2021).

IoT applies to track people’s behavior in the healthcare section. For example, it can be used to monitor patients or to diagnose their symptoms at a low cost and in real-time. It provides patients with better observation and to address their needs in a quite short time (Pizam, 2017).

To utilize the proposed network with IoT application, there is a need for interconnected devices and control centers to monitor and schedule ambulances for the suspected cases (Zahedi et al, 2021). One possible solution to track each suspected case is to design a special mobile (android or ios) application in which people could simply register and fill in simple questions to verify their related symptoms. This practical and user-friendly application can detect the probability of infection by asking simple questions from its users. If the probability of infection reaches a certain predefined rate, it can call its center where a special ambulance approaches different homes which are situated in various sits for further examination. At the time of detection of any possible suspected case, the control center programs the visitation of each patient dynamically and based on their critical condition. Hence, the program whether allocates ambulances or prioritize the suspected case based on the current situation and in a dynamic fashion. After planning and finding an optimal route based on timing, the control center notifies each ambulance and even updates their current route. Therefore, special devices such as routers, Bluetooth devices, special WIFI connection, and antenna are mobilized in both control center and also ambulances with a fast internet connection to send and receive data about the current plan or any possible changes. Fig. 4 illustrates the schematic of the proposed IoT system.
Proposed IoT system for pandemics.

- **Cloud-base system**: Working with online platform
- **Data transmission**: Sending and receiving real-time data
- **Data analysis**: Analyzing the obtained data dynamically
- **Planning**: Decision-making by allocating ambulances or prioritizing

- **Data monitoring**: Monitoring a real-time data and sending and receiving orders and special codes
- **Planning and routing the ambulances**: Analyzing and scheduling ambulances by the means of allocating them to the suspected cases or prioritizing them
- **Data analysis & transmission**: Analyzing the real-time data which is received by control centers
- **Decision-making**: Optimizing the plan by the means of total spent time

- **Mobile device**: An smart and android or IOS based application with user friendly interface
- **Registration**: Registration in primary evaluation
- **Questionnaire**: Completing simple forms to identify the severity of each cases
- **Completing form**: Completing simple forms for the purpose of primary evaluation
- **Online monitoring**: Online and up-to-date information about the visitation time by medical staff

- **Sensors**: A special sensor device to identify coded signals
- **Actuators**: An actuator requires a control signal and a source of energy
- **Wireless systems**: WIFI device which connects computers to the high-speed internet
- **Monitors**: A device for online screening the changes in the system
- **Detectors**: A special detector which notifies the users in time of any change
- **Bluetooth system**: To connect some devices such as printers, mobile phone, etc.
- **Camera systems**: Mobilized in each ambulance to monitor routes and condition of the roads

![Fig. 4. Proposed IoT system for pandemics.](image-url)
The contributions of the present study are:

- Developing a relief network to deal with patients in a pandemic, especially the COVID-19 outbreak,
- Considering IoT to identify and real-time trace of the changes for suspected cases,
- Allocating each ambulance to each district to visit and cover all the suspected cases in a given area,
- Reducing total response times for suspected cases with higher severity conditions by prioritizing,
- Utilizing the problem with innovative two sub-models,
- Analyzing the effect of increasing and decreasing on a number of ambulances, visiting time, and ambulance sanitizing time on the response time.

According to the aforementioned reasons, motivations, and importance of the problem, designing such networks is inevitable. So, in this work, we are to answer the big and important question for the government and focus on designing such a supply chain for nations considering its limitations, maps, roads, infrastructures, cultures and etc. Therefore, we briefly explain and detail how to model and design this network, how to respond to possible cases, how to solve the model to reach optimum decision variables for the government. This can raise questions about how to assigning the right amount of medical supplies to address patients in various districts and how to address patients considering the various emergency rate and road limitations.

Hence, the objectives of the study are as follows:

- Considering multiple ambulances to address suspected cases situated in various districts,
- Allocating each ambulance to the multiple suspected cases in each district,
- Application of IoT system to verify positive COVID-19 cases,
- Prioritizing suspected cases dynamically by means of severity, traffic density, and distance,
- Planning ambulances to reduce the total response time.

In this regard, the mode objective is to optimize the main part of this system. Therefore, we model and minimize the response time for each ambulance by using IoT. To address the aforementioned issues, a new time-effective relief supply chain network is taken into account. This network not only considers time as the most significant factor to address suspicious patients, but also dynamically tries to present a comprehensive scheme for healthcare managers and also supreme governmental decision-makers to reduce the contagious rate of pandemics and hence save human lives by implementing IoT. In this regard, the presented modeling decides to allocate each ambulance to one district in the first place and then considering the visit priority of each suspected case, the model tries to cover all patients while reducing the total response time.
What follows is categorized into six sections. We survey most relevant works in relief supply chain networks and newly published literature on COVID-19 in section 2. The proposed methodology and solution approaches are presented in section 3 and section 4. In section 5 we study a case and in section 6 we conduct a comprehensive analysis and investigate the application of the proposed methodology. Finally, the conclusion, in addition to managerial insights, and future scope are explained in section 7.

2. Study background

This section presents literature regarding the relief supply chain for disasters and natural crisis-like outbreaks. Therefore, we first categorized the application of designing various relief supply chain networks along with its application in the real world. Secondly, the recent trends to design the supply chain network for outbreaks are verified in the following sub-section.

2.1. Relief supply chain

Toregas et al. (1971) firstly introduced this term to cover the total demand. Later, Özdamar et al. (2004) proposed a model to send goods into affected areas by minimizing the unmet demand. Alçada-Almeida et al. (2009) used shelters as a base camp and developed a multi-objective model to find optimum travel time and distance. They aimed to find the best locations of shelters and find the best routes for backup. A transportation network was developed by considering maximization of facility access by Horner & Widener (2011).

Several previous works focused on real-life cases. Rottkemper et al. (2011) formulated a model to distribute relief commodities and to cover the uncertain. Lin et al. (2011) considered various vehicles to deliver multiple relief goods using deterministic and meta-heuristics. Bozorgi-Amiri et al. (2012) developed a model to locate distribution centers and solved the model by meta-heuristics. Zheng & Ling (2013) proposed a fuzzy multi-objective model with different transportation modes. They aimed to deliver relief commodities in crisis conditions and solved the model by the same approach.

Another multi-objective model to minimize the total cost and maximize the unfulfilled demand was developed by Bozorgi-Amiri et al. (2013). Rezaei-Malek & Tavakkoli-Moghaddam (2014) considered the time of earthquakes and aimed to minimize both costs and response time. Gutjahr & Dzubur (2016) utilized a bi-level programming for the same decision variables and aimed to select the best facilities. Zokaee et al. (2016) also proposed a network based on different scenarios about uncertainty. They also considered a real case problem. Several studies also employed meta-heuristic approaches to address their networks variables in this area such as Saeidian et al. (2016).

Fahimnia et al. (2017) developed a model for blood distribution considering uncertainty and humanitarian aid. Similarly, Salehi et al. (2019) developed a model for the same network to meet the uncertain demands of various blood types. Tavana et al. (2018) developed a model to design supply chain considering before and after disaster conditions, and aiming to make location decisions to manage perishable products. Dubey & Gunasekaran (2016)
considered different sustainability aspects in designing such chains. Zhang et al. (2020) proposed a model for a three-level distribution chain and considered the same decision variables like Tavana et al. (2018). A survey on related works is depicted in Table 1.

Table 1
Overview of related literature (Y: Yes, N: No).

| Author(s) | Description | Period | Problem Formulation | Applying Heuristics (Y/N) | Application of IoT |
|-----------|-------------|--------|---------------------|--------------------------|-------------------|
| (X. Wang et al., 2016) | Implementing disaster response model in a relief supply chain (Walmart case study) | Single | Deterministic | Y | N |
| (Nagurney & Nagurney, 2016) | Delivery of relief products in post- and pre-disaster | Multi | Stochastic | N | N |
| (Mohammadi et al., 2016) | Designing a pre-response emergency supply chain model (A case study in the United States) | | | Y | N |
| (Sung & Lee, 2016) | Utilizing location model to address patients in relief supply chain network | | | N | N |
| (Zhou et al., 2016) | Emergency resource scheduling model to distribute resources in post-disaster | | | Y | N |
| (Jha et al., 2017) | Utilizing relief supply chain network to distribute goods | | | Y | N |
| (Al Theeb & Murray, 2017) | Using VRP model to address relief supply chain network | | | Y | N |
| (Manopiniwes & Irohara, 2017) | Implementing a relief model for pre and post disaster response | | | N | N |
| (Li et al., 2017) | Distribution of supplies in aftermath natural disasters (A case study in the United States) | | | N | N |
| (Samani et al., 2018) | Designing a blood supply chain network for disaster relief (A case study in Iran) | | | N | N |
| (Cao et al., 2018) | Introducing relief distribution network in natural disasters (A case study in China) | | | Y | N |
| (Safaei et al., 2018) | Designing an optimized framework for relief logistics operations (A case study in Iran) | | | N | N |
| (Hong & Jeong, 2019) | Designing a relief supply chain network for disaster planning | | | N | N |
| (John et al., 2019) | Modeling humanitarian supply chain considering food relief network | | | N | N |
| (Ghaffari et al., 2020) | Emergency scheduling problem in disaster relief operations (A case study in India) | | | Y | N |
| (Akbarpour et al., 2020) | Designing a pharmaceutical relief supply chain network (A case study in Iran) | | | N | N |
| (Aghajani et al., 2020) | Supplier selection for humanitarian relief supply chain network (A case study in Iran) | | | N | N |
| This study | Implementing a dynamic relief supply chain network based on IoT with two sub-models to | | | Y | Y |
2.2. Recent trends on designing supply chain network for pandemics (Case of COVID-19)

Due to the recent COVID-19 outbreak, there were some attempts to design supply chain networks to satisfy the demands of the infected people. The effect of the COVID-19 outbreak on the global supply chain was firstly investigated by Ivanov (2020). Later, other works in this topic which mainly focused on economic aspects were done by Fernandes (2020), K. D. S. Yu & Aviso (2020), and Currie et al. (2020). An intertwined supply chain network was designed by Ivanov & Dolgui (2020). In their work, they aimed to reduce the mortality rate in the pandemic and addressed their model by dynamic game-theoretic.

Employing IoT and mobile service operations to monitor positive cases was firstly studied by Singh et al. (2020) and Choi (2020). Similarly, using smart communication channels was investigated by Rowan & Laffey (2020). They found that it can improve the efficiency of healthcare system in the network. H. Yu et al. (2020) considered the locations of temporary locations in their model.

According to the aforementioned literature review presented in Table 1, there is only one study that addresses the emergency response and reportedly, there is no research conducted in designing such chains during the pandemic. While multiple studies tried to implement a scheme to supply, distribute, and deliver goods and medical supplies to the affected people in disasters, the present study considers allocating the resources (ambulances) to various districts to cover all suspected cases of COVID-19 to minimize the response time. In addition, recent trends toward designing a supply chain network are quite limited as most of them are abstract and also there is an urgent need to address this issue. Besides, we firstly introduced the application of IoT in this field. Previous studies have focused on integrated modeling. While using IoT, we firstly allocate each ambulance to each district and in the next step based on data derived from the application-based system, we prioritize each patient visit.

3. Mathematical model

Reportedly, the COVID-19 spreads rapidly among most countries and also there is no specific structure to stand against this virus because of its unknown symptoms and behaviors. In addition, the more increase in patients (confirmed cases, suspected cases), the more pressure on the medical system for responsiveness. Therefore, most countries have considered the timely identification of patients and maintaining a physical distance between people (especially confirmed cases, suspected cases) as an effective solution (Organization, 2020). In the current research, the real-time responsiveness is discussed to not only improve system efficiency available resources, but also to deal with instant changes. Here, the responsiveness is defined evaluation, identification, and visit suspected cases and transportation confirmed cases to COVID-19 Medical Center (CMC). To identify the suspected case, an internet evaluation should be designed based on common symptoms of the COVID-19 virus that is named primary evaluation. The people participate in the primary
evaluation and will be analyzed based on transferred data over the network to Data Center (DC) in the primary evaluation.

The received data to distribution centers are compiled and the suspected cases to COVID-19 are specified. The suspected cases need to be visited in their own locations, not only to keep away healthy people (the people who don’t have COVID-19) from the dangerous zone (COVID-19 medical centers or testing COVID-19 spots), but also to prevent the spread of this disease. Afterward, the suspected people will be visited and examined by the smart and equipped ambulances. After the evaluation, people need more specialized treatments and are transferred to CMC by the same ambulance. The structure of the proposed methodology for encountering the COVID-19 virus is shown in Fig. 5.
The assumptions of the proposed methodology are as follow:

- There are conditions which enable utilizing the internet or software for people in this study area (through smart cellphone, laptop, and personal computers).
- The sub-areas of the CMC zone are pre-determined
- There is an ambulance in each sub-area. Actually, each sub-area expresses an ambulance.
- The distance, traffic, and capacity of each sub-area is known.
• The time parameters are determined.
• The suspected cases are available at all scheduled times and their locations are pre-specified.

Although it is important to identify patients, it is equally important to respond to more suspected people in the shortest possible time. Each CMC covers the treatment area (town, a part of the city, city, and etc.), which is divided into several sub-areas due to the size of the area. Each sub-area has a different size, distance from the CMC, traffic jam, and population density. As a result, suspected cases may have different accessibility and responsivity times in each sub-area. The number of suspected cases in each sub-area does not follow a specific pattern. Probably, the number of suspected cases in some sub-areas might be more than in others. Therefore, the allocation of suspected cases to each sub-area (ambulance) only based on geographical location would significantly increase the number of suspected cases (needing a visit) in some sub-areas from the others. In addition, the capacity of the ambulance and response time will not be determined. Hence, before prioritizing the ambulance route, the suspected cases should be assigned to the ambulance (sub-area) based on the capacity, distance, and traffic of each sub-area. Therefore, two sub-models are needed in order to firstly allocate suspected cases to each sub-areas (ambulances) and secondly to prioritize the visit of each suspected case for each ambulance. Considering two sub-models has been utilized in previous papers such as (Jun-yan et al., 2020; Shah et al., 2018).

3.1. Sub-model one

After evaluating and identifying, the suspected cases should be allocated to each sub-area (ambulance) in order to minimize both the distance and traffic of direction and also don’t exceed the capacity of each ambulance. For this purpose, a mathematical model is designed to allocate suspected cases to different areas. Due to the above description, the elements of the sub-model one are as follow:

Indices:
- \( r = \{1, 2, \ldots, R\} \) : Set of sub-areas
- \( s = \{1, 2, 3, \ldots, N\} \) : Set of suspected cases

Parameters:
- \( DS_{s,r} \) : Distance between the suspected case \( s \) and the center of sub-area \( r \)
- \( TS_r \) : The traffic density in sub-area \( r \)
- \( IDS_r \) : The ideal distance in sub-area \( r \)
- \( ITS_r \) : The ideal traffic density in sub-area \( r \)
- \( TDM_s \) : Travers time from suspected case \( s \) to CMC
- \( TMD_s \) : Travers time from CMC to suspected case \( s \)
- \( TP \) : Preparing and sanitizing time ambulance after returning to CMC
- \( CT_r \) : The most available time for responsivity in sub-area \( r \)
- \( w_d \) : The importance weight of distance factor \( (w_d + w_t = 1) \)
- \( w_t \) : The importance weight of traffic factor \( (w_d + w_t = 1) \)
Variables:
\( X_{s,r} \): 1, if the suspected case \( s \) is allocated to sub-area \( r \); otherwise, 0
\( S_j \): The time to start visiting suspected cases with priority of \( j \)

The sub-model one is formulated as an ILP in equations (1)-(3):

\[
\begin{align*}
\text{Min distance\&traffic} &= \text{Min} \left( w_d \times \left( \sum_s \sum_r \left( \frac{DS_{s,r} - IDS_r}{IDS_r} \right) \times X_{s,r} \right) + w_t \times \left( \sum_s \sum_r \left( \frac{TS_{r} - ITS_r}{ITS_r} \right) \times X_{s,r} \right) \right) \\
\sum_r X_{s,r} &= 1 \quad \forall s \quad (2) \\
\sum_s \left( TDM_s + TMD_s + TP \right) \times X_{s,r} &\leq CT_r \quad \forall r \quad (3)
\end{align*}
\]

The objective function of the sub-model one is illustrated as equation (1) that minimizes both distance and traffic differences from their ideals of each allocated suspected case to ambulance due to the importance of distance and traffic. The modules of the suspected cases of distance and traffic in each sub-area are different. Therefore, it’s not possible to minimize both values of assigned suspected cases simultaneously. In order to add two values in one objective function, the distance difference of each suspected case from the ideal distance and the difference between each sub-area traffic and ideal traffic are divided into their ideal, respectively. As a result, the amount of obtained distance and traffic for each assigned suspected case doesn’t have a module. So, they can be minimized with a single objective function. The same approach is considered in Hwang et al. (1980). Constraint (2) ensures that each suspected case is assigned to only one sub-area. Equation (3) expresses that the worst condition of response time must not exceed the available time of each ambulance (sub-area).

3.2. Sub-model two

After identifying and solving the sub-model one, suspected cases are allocated to the sub-areas (ambulances), but the route of the ambulance to respond to these cases has not been determined in the shortest possible time. As a result, the priority and direction of the smart ambulance should be determined to better respond to such patients. Due to the independence of suspected cases in each sub-area, the priority of them and the direction of each ambulance are also independent. Therefore, for each ambulance, the visit priority is also independent. As a consequence, after allocating people to sub-area, the number of suspected cases of each sub-area is obtained using equation (4).

\[
\sum_s X_{s,r} = N_r \quad \forall r \quad (4)
\]

A supposed schematic of the ambulance route is shown in Fig. 6. Prioritization visits of suspected cases by ambulance and determining ambulance route are resulted to prevent
sub-tours, increase in travers distance, and increase in the number of returns to CMC and also rising response time. The main purpose is followed by a mathematical model to minimize response time. In addition, a pseudo-code is presented in Fig. 7 to illustrate how a data center can reschedule the priority of cases when an instant change happens in the real-time situation (including receiving a new suspected case, change in the number of suspected cases, the importance of severity, etc.).

![Fig. 6](image_url). The schematic of responsiveness flow with one IoT Ambulance.

CMC has a list of assigned suspected cases from primary evaluation to visit. Meanwhile, the severity of each case can be different that could cause a change in the direction of an ambulance. Then, the proposed methodology verifies the priority of the cases based on response time and severity. The ambulance follows the proposed direction until a change occurs. According to the described sub-model two, the notations, parameters, and variables are as follows:

**Indices:**
- \( i, i' = \{1, 2, 3, \ldots, N_r\} \): Suspected cases
- \( j = \{1, 2, 3, \ldots, N_r\} \): Priorities

**Parameters:**
- \( TV_i \): Time of visiting suspected case \( i \)
- \( TP \): Time of preparing ambulances after returning to CMC
- \( TD_{i,i'} \): Travers time from suspected case \( i \) to location \( i' \) \( i \neq i' = \{1, 2, 3, \ldots, N_r\} \)
- \( TDM_i \): Travers time from suspected case \( i \) to CMC
- \( TMD_s \): Travers time from CMC to suspected case \( i \)
- \( Y_i \): Severity of suspected case \( i \)

**Variables:**
- \( X_{ij} \): 1, if we visit the suspected case \( i \) with priority of \( j \); otherwise, 0
$S_j$: The time to start visiting suspected cases with priority of $j$

$T_{\text{max}}$: Total response time

Based on defined notation, parameter, variables and the proposed sub-model two descriptions, the objective function (total response time) and constraints are formulated as equations (5)-(9):

$$
Objective\ function = \min T_{\text{max}} = \min \left( S_{N_i} + \sum_i (T_{Vi} + T_{DMi}) \times X_{i,N_i} \right)
$$

(5)

S.T:

$$
\sum_j X_{ij} = 1 \quad \forall i
$$

(6)

$$
\sum_i X_{ij} = 1 \quad \forall j
$$

(7)

$$
S_1 = \sum_i T_{MDi} \times X_{i,1} \quad \forall i
$$

(8)

$$
S_j = S_{j-1} + \sum_i T_{Vi} \times X_{ij-1} + \sum_i \sum_i' T_{Di,i} \times X_{ij-1} \times X_{ij} \times (1 - Y_i)
+ \sum_i T_{DMi} \times Y_i \times X_{ij-1}
+ \sum_i \sum_i' (T_{MDi} + T_P) \times Y_i \times X_{ij-1} \times X_{ij} \quad \forall j = 2, \ldots, N_i; i \neq i'
$$

(9)

As mentioned above, the proposed sub-model two has one objective function. The objective function minimizes the total response time by a decrease in the response time of the last priority suspected case (5). Constraint (6) ensures each priority of schedule is assigned to a single suspected case whereas constraint (7) indicates that every suspected case has a specific priority. Constraint (8) computes the starting time of visit and constraint (9) illustrates that the starting time of other priorities. The starting time of each priority includes the starting time of visit with previous priority, the visit time of previous priority, the travers time between previous and considered priority (if the severity of previous priority is low), the travers return time from previous priority to CMC (if the severity of previous priority is high),Preparing and sanitizing time of ambulance after returning to CMC (if the severity of previous priority is high), and travers time between CMC and suspected case with considered priority (if the severity of previous priority is high).

3.3. The real-time responsiveness

The methodology has two sub-models. The first sub-model minimizes distance and traffic to allocate suspected cases to sub-area (ambulance) and the second one minimizes the response time to determine the appropriate priority of each suspected case in each sub-area. In addition, it is considered that smart ambulance can receive online information of
evaluated people including receiving new suspected case information, change in the number of suspected cases, the importance of severity, and so on. The recommended method to encounter this type of variation is illustrated in Fig. 7.

**Fig. 7.** Pseudo-code for the recommended method.

4. **Solution Approach**

The employed solution encoding and decoding also the metaheuristic approaches are proposed and detailed in this section. It is still an open question to use exact methods to solve large-scale problems in terms of consuming cost and time (Paydar & Olfati, 2018). The theory proposed by Wolpert & Macready (1997) signifies that to optimize all mathematical problems, no unique algorithm reported. Hence, this issue motivated this study to utilize the problem with number of efficient metaheuristic and hybrid algorithms. To utilize the abilities and strength of the metaheuristics, we hybridize the algorithms expecting to find better results. (Akbarpour et al., 2020a,b). Besides, we utilized various approaches to both validate output results and verify the best approach to solve the considered formulation.
In this respect, Keshtel algorithm (KA), social engineering optimization (SEO), genetic algorithm (GA), and hybrid GA and SEO (GASEO).

4.1. Encoding and decoding

So far, several methods to encode optimization problems have been proposed. Devising an encoding plan is highly needed because it has a crucial effect on the output solutions (Farrokhi-Asl et al., 2018). In this manner, a method that can effectively be used in this problem is the “random key” approach (Abdi et al., 2020). Therefore, Fig. 8 shows applying the current method to visit each patient and obtain their priority (Abdi et al., 2021).

![Random Key Method](image)

SEO was developed by Fathollahi-Fard et al. (2018) according to social engineering logic. The representation of each solution shows each person with their features. The proposed pseudo-code of the SEO is shown in Fig. 9.

```
Initialize an attacker and defender
It=0;
while It < Maxit
    Do training and retraining;
    Num_attack=0;
    while Num_attack < Max_attack
        Spot an attack;
        Check the boundary;
        Respond to attack,
        if the Objective Function (OF) of the defender is lower than the attacker
            Exchange the defender and attacker position;
        end if
        Num_attack=Num_attack+1;
    end while
    Create a new solution as a defender,
    It=It+1;
end while
Return the attacker
```

![Pseudo-code of SEO](image)

For solving real-world problems, GA comes handy due to its robust optimization technique. This concept was firstly presented by Holland (1992). In each search iteration, this search technique employs some operators in order to refine the solution. First, GA generates the candidate solutions for the problem, known as population. In the reproduction phase, the best set of chromosomes from the current population is copied by typical genetic operators to the next generation Hajiaghaei-Keshteli et al. (2011). In the selection phase, the chromosomes are selected randomly by the operator from the current population as parents.
This phase is also called Roulette wheel selection, in which the most valuable fit is more probable to be selected (Amiri et al., 2020).

The Keshtel algorithm (KA) firstly developed and introduced by Hajiaghaei-Keshteli & Aminnayeri (2014). They studied the feeding behavior of a special kind of a duck living in North. The local name in north of Iran is Keshtel. They have an amazing feeding behavior and by swirling, they inform each other, as a kind of swarm intelligence, once they find a good food place (Hajiaghaei-Keshteli & Aminnayeri, 2013). This algorithm can be categorized as a smart algorithm which search carefully the feasible area and also flexible one which opens the users’ hand to use its features according to the nature of the problem (Salehi-Amiri et al, 2021). The main phases of this algorithm are shown in Fig. 10.

Fig. 10. Pseudo-code for KA.

Generally, based on GA, the characteristic of other algorithms can be defined (Mollanoori et al., 2019; Cheraghalipour et al., 2019). This time, the mutation step is replaced
with the SEO algorithm to find the best solutions in a quite short time. Fig. 11, shows the pseudocode of the proposed approach.

```
Initialize the population X
calculate the fitness of each individual
X* = Best solution
while (It < MaxIt)
    Select the fittest individuals for Reproduction
    Select a pair of chromosomes as parent by roulette wheel
    Perform crossover operation
    Select a chromosome and input to the SEO, in order to do
    mutation
    It = It +1
end while
return X*
update T=alpha*T
```

Fig. 11. Pseudo-code for H-GASEO.

5. Industrial case and a numerical example

In this section, three various problem sizes are suggested to probe the efficiency of the proposed algorithms, along with the real data from the healthcare section in Montreal, Quebec, Canada. According to WHO, Quebec is the second province to have the most confirmed cases of COVID-19 virus and also the first one in COVID-19 death. Among the different cities of Quebec, Montreal is the largest city in Quebec province with 4,247,446 estimated populations\(^1\). We consider a real case study in Montreal, Quebec, Canada. The contributive data were obtained from daily observations and Canada governmental organizations\(^2\). The problem setting and instances are shown in Table 2-3. The MP7, MP10, and MP11 are based on the real-case.

Table 2
The classification of the model.

| Classification | Instance | Problem size (s, r) |
|----------------|----------|--------------------|
| Small          | SP1      | (3, 1)             |
|                | SP2      | (8, 2)             |
|                | SP3      | (10, 2)            |
| Medium         | SP4      | (6, 1)             |
|                | SP5      | (12, 3)            |
|                | SP6      | (18, 3)            |
|                | MP7      | (24, 4)            |
|                | MP8      | (30, 3)            |
|                | MP9      | (55, 5)            |
|                | MP10     | (36, 3)            |
|                | MP11     | (55, 5)            |
|                | MP12     | (65, 5)            |
|                | MP13     | (75, 5)            |

\(^1\) https://population.un.org/wup/
\(^2\) https://www.canada.ca/en.html
Table 3
Values of considered parameters.

| Parameters of the sub-model one | Value                   |
|---------------------------------|-------------------------|
| \(DS_{s,r}\)                    | Uniform~[500,25000]     |
| \(TS_r\)                        | Uniform~[3500,8700]     |
| \(IDS_r\)                       | Uniform~[4000,6000]     |
| \(ITS_r\)                       | Uniform~[2500,3000]     |
| \(TDM_s\)                       | Uniform~[15,60]         |
| \(TMD_s\)                       | Uniform~[15,60]         |
| \(TP\)                          | Uniform~[20,30]         |
| \(CT_r\)                        | Uniform~[480,720]       |
| \(w_d = w_t\)                   | 0.5                     |

Parameters of the sub-model two

| Parameters | Value       |
|------------|-------------|
| \(TV_i\)   | Uniform~[15,45] |
| \(TP\)     | Uniform~[20,30] |
| \(TD_{i,i'}\) | Uniform~[10,60] |
| \(TDM_i\)  | Uniform~[15,60] |
| \(TMD_s\)  | Uniform~[15,60] |
| \(Y_i\)    | Uniform~[0,1]  |

Obviously, the parameters must be tuned for every employed algorithm (Gholian Jouybari et al., 2016; Zahedi et al., 2021) (See Table 4).

Table 4
The parameters and their best levels for the proposed.

| Algorithm | Factor                        | Levels | Best level |
|-----------|-------------------------------|--------|------------|
| SEO       | A: Rate of collecting data (\(\alpha\)) | 0.15   | 0.2        | 0.25       | 0.2 |
|           | B: Rate of connecting attacker (\(\beta\)) | 0.035 | 0.05       | 0.065      | 0.05 |
|           | C: Number of connections (N)    | 45     | 55         | 65         | 55 |
| GA        | A: Population size (n-pop)      | 20     | 30         | 40         | 30  |
|           | B: Crossover percentage (Pc)    | 0.65   | 0.7        | 0.75       | 0.7 |
|           | C: Mutation percentage (Pm)     | 0.15   | 0.2        | 0.25       | 0.2 |
|           | D: Maximum iteration (MaxIt)    | 100    | 150        | 200        | 150 |
|           | E: Type of crossover (T_c)      | Roulette Wheel | Tournament | Random | Roulette Wheel |
| KA        | A: Population size (n-pop)      | 25     | 30         | 35         | 30  |
|           | B: Percentage of population of Lucky Keshtel (\(P_{N1}\)) | 0.5    | 0.6        | 0.7        | 0.6 |
|           | C: percentage of N2 Keshtel (\(P_{N2}\)) | 0.25   | 0.3        | 0.35       | 0.3 |
|           | D: the maximum number of swirling (\(N_{swirl}\)) | 4      | 5          | 6          | 5   |
The model is coded in GAMS software to obtain exact solutions. Table 5 shows the result of this coding and solutions for all algorithms. The results are reported in Table 5. Due to the severe increase in the problem-solving time in larger test problems, there is no exact answer from LP15 onward as it didn’t reach a feasible solution after approximately one and a half hours. Hence, due to (Fard & Hajiaghaei-Keshteli, 2016; Golmohamadi et al., 2017), the problem could benefit from applying an efficient metaheuristic.

| Obj. | MP1 | MP2 | MP3 | MP4 | MP5 | MP6 | MP7 | MP8 | MP9 | MP10 |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| GAMS | 1397.1 | 1670 | 1836.2 | 2085.6 | - | - | - | - | - | - |
| CPU-time | 2986.17 | 6067.08 | 1305.81 | 34982.44 | - | - | - | - | - | - |
| SEO | 1413.7 | 1689.3 | 1878.1 | 2116 | 2524.1 | 2514.1 | 2802.3 | 2877.2 | 3204.9 | 3332.4 |
| CPU-time | 55.85 | 88.82 | 97.26 | 143.06 | 185.3 | 147.65 | 103.52 | 162.26 | 181.35 | 264.74 |
| GA | 1420.1 | 1691.9 | 1884.9 | 2123.4 | 2503.7 | 2535.5 | 2849.4 | 2866.7 | 3294.1 | 3389.4 |
| CPU-time | 88.19 | 120.14 | 128.65 | 164.64 | 215.08 | 242.1 | 205.74 | 251.83 | 254.43 | 449.1 |
| KA | 1404.7 | 1675.1 | 1845.4 | 2099.2 | 2483.4 | 2522.3 | 2843.1 | 2854.7 | 3270.6 | 3325.5 |
| CPU-time | 100.52 | 137.6 | 182.24 | 227.05 | 248.54 | 300.43 | 313.39 | 357.61 | 438.44 | 576.57 |
| GASEO | 1412.8 | 1675.1 | 1849.2 | 2114.5 | 2521.8 | 2525.7 | 2847.6 | 2862.1 | 3270.5 | 3328.7 |
| CPU-time | 53.33 | 53.65 | 58.96 | 68.01 | 69.74 | 76.5 | 76.41 | 86.1 | 84.41 | 135.42 |

6. Discussion and managerial insights

According to the lack of knowledge of the symptoms of COVID-19 and the high rate of its infection, no comprehensive solution has been proposed. Therefore, one of the best strategies is to identify the suspected case and confirmed people to COVID-19 and separate
them quickly from healthy people in the community so that the COVID-19 spread chain is slower or even controlled. In this paper, the strategy of rapid identification, separation and transferring of suspected and confirmed cases by utilizing the IoT as well as adaptation to instant changes is proposed and studied.

6.1. More on allocation

According to the aforementioned sections, the importance of service suspected people, treatment of infected cases, and methodology to control and stop the outbreak is taken into account due to the defined method in a proper time. Initially people contact the IoT system using a convenient application. Then these data would analyze by the control center and accessed to verify suspected cases. The next step is to allocate each ambulance to each individual based on distance and current traffic. Now if based on the first defined model each individual (due to its geographical location and living place) is not assigned to an ambulance, the results might be a decrease in calculation time, but there is still a possibility that identified cases in various districts may be varied. Hence, the capacity and working time of each ambulance are disregarded.

6.2. More on prioritizing

Prioritizing patients determine the routing pass for each ambulance. In this regard, based on distance prioritizing, the ambulance chooses the shortest possible route disregarding other factors such as traffic density, present population in each area, rush hours, route characteristics, and etc. This shortest pass may not guarantee the shortest possible time due to different priority rates. Therefore, prioritizing based on service time which defines the shortest response time also involves distance.

6.3. Sensitivity analysis on determinative factors

In this section, we consider determinative parameters and their effects and behavior on the response time and also prioritizing. Here, we considered six suspected cases with two ambulances which firstly the allocation and secondly prioritizing has taken into account. After solving the sub-model one, three suspected cases were assigned to each ambulance and then in sub-model two, the response time is achieved 303.025 minutes with one severity case. The sensitivity analyses on different parameters are shown in Fig. 12 (a)–(d).
(a) Sensitivity analysis on number of ambulances
(b) Sensitivity analysis on severity case
(c) Sensitivity analysis on preparing and sanitizing time
(d) Sensitivity analysis on visit time
Fig. 12. (a) Sensitivity analysis on number of ambulances, (b) Sensitivity analysis on severity case, (c) Sensitivity analysis on preparing and sanitizing time, (d) Sensitivity analysis on visit time.

Fig. 12. (a) illustrates that the more number of ambulances, the more the response time. In this regard, if the system utilizes more ambulances (sub-areas), then the response time would decrease (or more suspected cases are visited in a shorter time). This strategy would release the pressure on CMC and make it more convenient to confront the increasing rate of the outbreak. On the other hand, an increase in the number of ambulances always doesn’t lead to a decrease in the response time. Hence, managers would assign available resources to CMCs optimally to both decreasing the response time and preventing the allocation of extra resources. It is also notable to mention that an increase in the number of ambulances up to four does not change the response time as shown in Fig. 12. (a).

Fig. 12. (b) suggests that if the number of severe cases increases, then the response time would increase. It is due to the fact that the number of returned ambulances to the CMC has to be enhanced for further medical care cures. Here, the proposed IoT system contributes to an effective decision-making process for managers to optimize the visit priorities by instant alteration in the number of returned cases dynamically. In addition, improving a system of primary evaluation (IoT-based) would allow for better identification of the suspected cases and severity condition. As a result, the level of utilizing a system with better input settings (COVID-19 virus symptoms), the overall programming time, and also response time would decrease.

As shown in Fig. 12. (c), although response time generally increases with preparing and sanitizing time, the priorities do not change. This occurs because of this factor which is related to CMC not to ambulances, suspected cases, or COVID-19. As a consequence, pre-preparing and packaging required medical items before the return of each ambulance would result in shorter preparation time as it is totally independent of the overall program duration. Fig. 12. (d) illustrates that the more visit time, the more response time. In addition, this defines that it has a direct effect on priorities and response time. The managers could rely on the established methodology to improve the decision-making associated to visit time.

In this proposed methodology, we established an IoT system to confront real-time changes. It is presumed that the number of suspected cases within a whole area (CMC covered area) surprisingly increased in a way that the total number of ambulance fleets was unable to cover all suspected cases. Considering this assumption, managers have two potential approaches to address this issue. They may either decide to increase the number of ambulances (based on available resources) or to allocate ambulances to suspected cases with higher severity conditions and wait until the next free ambulance.

Another interesting factor that affects the visitation of suspected cases in each sub-area and also the total response time is that some of the ambulances finishing their task before the end of the scheduled time, while others are dealing with the number of suspected cases in other sub-areas. In this regard, the best available decision for managers to take to decrease the total response time is to allocate the free ambulances to the remained suspected cases into other sub-areas. In this regard, the proposed IoT-based methodology dynamically addresses this issue by reprogramming, reassigning, and rescheduling the total fleet of the ambulance to visit suspected cases and with any instant changes.
6.4. Weight analysis

Since it is possible that the importance weight of distance and traffic in the sub model one affects the response time. Therefore, in this section, three scenarios are considered. In the first scenario, the weight of distance and traffic are equal to 0.7 and 0.3, respectively. In this scenario, although the traveled distance is decreased, but the total response time is enhanced. In the second scenario, the weight of distance and traffic are equal that caused the total response time are significantly less than two other scenarios (scenario one and three). In the last scenario, the weight of distance and traffic are equal to 0.3 and 0.7, respectively. In the third scenario, the total response time is increased in comparison with second scenario. As shown in Table 6, although the total response time of both scenarios one and three are increased in comparison second scenario, but the amount of increase in scenario three are significantly less than scenario one. Since the main purpose of the proposed methodology is to decrease the total response time, therefore, Table 6 states that the traffic factor has more impact on the total response time than the distance factor. As a consequence, the managers should carefully decide on the weight of traffic and distance due to their value.

| (Suspected case, Ambulance) | Weight importance | Total traveled distance | Total traffic | Total response time |
|-----------------------------|-------------------|-------------------------|--------------|---------------------|
| (10,2)                      | 0.7 0.3           | 38716.06 meters         | 5973 (V/D)   | 494.02 minutes      |
| (10,2)                      | 0.5 0.5           | 45867.5     meters      | 4674 (V/D)   | 393.15 minutes      |
| (10,2)                      | 0.3 0.7           | 50208.75    meters      | 3815 (V/D)   | 441.67 minutes      |

6.5. More on IoT

In this section, we compare the proposed methodology with a medical system without IoT. In fact, this comparison aims to analyze the impact of real-time changes on responsiveness between two COVID-19 medical systems with IoT and without IoT. Therefore, six scenarios have been considered that shown in Table 7. Although two different systems with IoT and without IoT are compared, but prioritization and direction of each suspected case are determined by the proposed mathematical model (sub-model two).

| Scenario | Suspected cases | Ambulance | Definition                                                                 |
|----------|----------------|-----------|-----------------------------------------------------------------------------|
| 1        | 5              | 1         | All the suspected cases should be identified at the beginning.               |
| 2        | 5              | 1         | All of the suspected cases are identified after each trip.                   |
| 3        | 5              | 1         | The second and third suspected cases are identified after the first trip and also fourth and fifth suspected cases are identified after the second trip. |
| 4        | 5              | 1         | Four out of five suspected cases are identified after the first trip.        |
Changing the severity of a suspected case with first priority after visiting him/her. 
Changing the severity of first and third identified suspected cases after visiting them.

In the first scenario, at first, we define all the needed data, including the number of suspected cases and ambulances, severity, location, and other appropriate parameters don’t change in this planned horizon. According to Fig. 13, apart from the primary evaluation and assignment of suspected cases to each ambulance, the IoT has no other uses.

Scenario two expresses, at first, we only identify one suspected case. Then, the second suspected case, third, fourth, and fifth suspected ones are identified after first, second, third, and fourth trips, respectively. Like the previous scenario, apart from the primary evaluation and assignment of suspected cases to each ambulance, the IoT has no other uses. (See Fig. 14)
Fig. 14. The proposed travel network of an ambulance is based on scenario two.

The third scenario also states that we firstly only identify one suspected case. Afterward, the second and third suspected cases are identified after the first trip and then, fourth and fifth suspected cases are identified after the second trip. Fig. 15 illustrates the difference between two systems with IoT and without IoT. The more new suspected cases after scheduling causes, the more the number of ambulance trips and the total response time.

The fourth scenario is similar to the third scenario (identifying new suspected cases after scheduling) except that four patients are identified at once after the first trip of the ambulance. Scenarios three and four show that the lack of an IoT (re-planning after each change) greatly increases the number of trips and the total response time in comparison with the IoT system (instant scheduling by any change). In general, the more changes, the more
difference between the total response time and ambulance’s trips of the two systems (See Fig. 16 and 17).

![Diagram](image1)

**Fig. 16.** The proposed travel network of an ambulance is based on scenario four.

We also considered the severity of each suspected case (See Fig. 12, (b)). Scenarios five and six show the effect of instant changes in the severity of suspected cases to COVID-19 after each visit. In scenario five, the severity of the first priority suspected case increases so that this person should be transferred to the medical center for specialized treatments. In scenario six, the severity of the first and third identified suspected cases (suspected case one and three) increase.

![Diagram](image2)

**Fig. 17.** The proposed travel network of an ambulance is based on scenario five.

What stands out in Fig. 17 and 18 is the difference between two systems with IoT and without IoT. Although the amount of these factors is enhanced in two systems (with IoT and without IoT), but the increase in a system without IoT is much more than a system with IoT.
All in all, the more variation in system settings (the volume and the number of changes), the more difference in model outcome between the proposed IoT-based system and the traditional one.

![Diagram](image)

**Fig. 18.** The proposed travel network of an ambulance is based on scenario six.

### 6.6. Managerial insight

This study concerns the changeable nature of pandemics especially for COVID-19 by considering a flexible and dynamic plan to address multiple patients due to the alteration in their priority. Hence, a dynamic scheme has been introduced to re-plan the whole system instantly when these priorities vary. Consequently, a systemic approach is needed to address this issue whereby the implemented IoT based system effectively fulfilled all the requirements. Exerting such a system showed that potential affected COVID-19 cases could easily be identified with a simple mobile application and the system automatically sends ambulances to these cases for treatment agendas and if needed take the patients back to the main medical center for further care. This method leads to assign each cleaned ambulance to visit each patient in the shortest possible time while reducing the risk of infection by each individual.

National policy-makers and other supreme decision-makers in government and also the healthcare sector could aid myriad people by integrating the aspects of relief supply chain management with IoT by using the proposed model as the mentioned approach offers direct support toward such cutting-edge initiatives. The proposed methodology support governments not only in a short time, but also in the long run especially when the number of patients increasing daily and choosing the best strategy is quite complex.

The various factors and scenarios of sensitivity analyses provided the largest set of significant clusters of the behavior of the proposed model. The most obvious managerial finding to emerge from the analysis is shown as follows:
The proposed IoT-based system has a significant impact on the number of ambulance trips, total response time, identifying a suspected case, optimum allocation of the available resources, and social distancing.

Less human resources are needed due to the online and dynamic monitoring of the proposed medical COVID-19 system.

Managerial decisions are performed more smoothly due to smart and instant decision-making.

Controlling the instant changes by utilizing a flexible, agile, active, and precise system.

7. Conclusion and future research

The immediate response to the major outbreaks is a very challenging problem for governments and modern societies. In this regard, replacing old systems with dynamic ones that can observe and plan due to instant changes are highly regarded as they can reduce managerial concerns for the government in the time of severe pandemics. This paper contributes to an innovative approach to address COVID-19 outbreaks for managers and all the decision-makers in the healthcare section by utilizing them with IoT to verify patients in real-time conditions and service them at an optimum time within a real case study in Montreal. Therefore, a relief supply chain network is designed which efficiently identifies suspicious cases and sends ambulances for further medical care and examination in the shortest possible time and due to the patients’ priorities determined by IoT based system. The model is referred to as being totally novel for the current stage of the pandemics and also other daily use in relief supply chain management.

Generally, such works like this study which suffer time, cost, social, and medical conditions have several tough limitations. Hence, the limitations of the current study can be mentioned as follows to clear the conditions of current work and help future researchers to conduct similar works:

- Limitations to access data for the considered problem in which in some case should be gathered by some indirect sources,
- Challenges to define test problems and also considered scenarios,
- Lack of previous similar works with the considered methodology.

To start, the model determines the required sources due to the suspicious cases and then visits each individual on the safety of their home by sending a totally clean ambulance and all the medical requirements to avoid infection. Then, applying such a plan could urge managers to expand and make use of such intelligent-based technologies as it provides the safest possible way to avoid infection while covering all the potential cases in the considered planning horizon. Consequently, in this paper, not only the primary analyses for the proposed methodology have been conducted, also further complex analyses on various conditions were taken into account. These analyses help managers to deal with the intricate and critical issues of pandemics especially the COVID-19 virus outbreak. Therefore, decision-makers should follow this strategy to utilize the best decisions with any instant change.
The analyses of the proposed relief supply chain undertaken here have extended our knowledge toward the relief supply chain and also the application of IoT. Despite the exploratory nature of some related works, this study offers some insight into the application of IoT in the real case problem. Mobilizing such a setting both provides safety for declared cases and a more effective plan to cover all the system’s load. On the other hand, the accuracy and reliability of the current system could bring governments to the consensus to utilize its benefits in their nations worldwide as the outputs of the system are transparent and the planning is delicate. In this regard, the proposed IoT system is enabled to update the routes in the case of any change. It is found that instant changes significantly increase the response time in which the proposed IoT system has decreased the effects of such conditions. Considering such scheme enabled the model to visit each suspected case with an ambulance in which the shortest possible distance/traffic is selected. As a result, all suspected cases have been visited in the shortest time and based on their severities. Verifying the changes in the number of ambulances, visiting time, and ambulance sanitizing time revealed that the total response time was initially affected by these changes. However, utilizing IoT could effectively reduce the impacts of the changes.

Last but not least, the issue of relief supply chain management in the case of pandemics especially COVID-19 is an intriguing one that could be usefully explored in further research. Further works can be done to utilize the system with temporary centers in remote areas for the diagnostic test and then convey them to the central sits for subsequent treatments. Besides, further research needs to examine more closely the links between supply chain management and IoT by urging people to cooperate more with the current system and to use medical applications especially in the time of major outbreaks. Finally, other decision variables like the total number of ambulances in the medical center’s fleet, and opening new permanent or temporary sits for medical care can be considered for future works.

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Highlights

• Developing a relief supply chain management to address the issue of pandemics.
• Utilizing a new methodology based on Internet of Things (IoT) to manage outbreak.
• Proposing a new approach to allocate and prioritize COVID-19 cases.
• Developing a dynamic system to address instant changes in the proposed methodology.
• Conducting several sensitivity analyses and proposing managerial insights.
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