Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Modeling a sustainable vaccine supply chain for a healthcare system

Naimur Rahman Chowdhury a, Mushaer Ahmed b, Priom Mahmud c, Sanjoy Kumar Paul d, *, Sharmine Akther Liza a

a Department of Mechanical and Production Engineering, Ahsanullah University of Science and Technology, Dhaka, Bangladesh
b Department of Industrial and Production Engineering, Dhaka University of Engineering and Technology, Gazipur, Bangladesh
c Department of Industrial and Production Engineering, Military Institute of Science and Technology, Mirpur Cantonment, Bangladesh
d UTS Business School, University of Technology Sydney, Sydney, Australia

* Corresponding author.
E-mail addresses: naimur20rahman.mpe@aust.edu (N.R. Chowdhury), mushaerahmed@duet.ac.bd (M. Ahmed), priom@ipe.mist.ac.bd (P. Mahmud), sanjoy.paul@uts.edu.au (S.K. Paul), liza.ipe@aust.edu (S.A. Liza).

https://doi.org/10.1016/j.jclepro.2022.133423
Received 2 February 2022; Received in revised form 27 July 2022; Accepted 1 August 2022
Available online 12 August 2022

ABSTRACT

This study develops a vaccine supply chain (VSC) to ensure sustainable distribution during a global crisis in a developing economy. In this study, a multi-objective mixed-integer programming (MIP) model is formulated to develop the VSC, ensuring the entire network’s economic performance. This is achieved by minimizing the overall cost of vaccine distribution and ensuring environmental and social sustainability by minimizing greenhouse gas (GHG) emissions and maximizing job opportunities in the entire network. The shelf-life of vaccines and the uncertainty associated with demand and supply chain (SC) parameters are also considered in this study to ensure the robustness of the model. To solve the model, two recently developed metaheuristics—namely, the multi-objective social engineering optimizer (MOSEO) and multi-objective feasibility enhanced particle swarm optimization (MOFEPSO) methods—are used, and their results are compared. Further, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model has been integrated into the optimization model to determine the best solution from a set of non-dominated solutions (NDSs) that prioritize environmental sustainability. The results are analyzed in the context of the Bangladeshi coronavirus disease (COVID-19) vaccine distribution systems. Numerical illustrations reveal that the MOSEO-TOPSIS model performs substantially better in designing the network than the MOFEPSO-TOPSIS model. Furthermore, the solution from MOSEO results in achieving better environmental sustainability than MOFEPSO with the same resources. Results also reflect that the proposed MOSEO-TOPSIS can help policymakers establish a VSC during a global crisis with enhanced economic, environmental, and social sustainability within the healthcare system.

1. Introduction

The COVID-19 pandemic has jeopardized billions of people’s lives, livelihoods, and psychological well-being. At present, other than mass vaccination, no other remedy exists to protect people from this outbreak (WHO, 2021). In the 21st Century, the world has witnessed a number of virus outbreaks, including SARS in 2003, Ebola in 2014 and 2018, MERS in 2015, and Zika in 2016 (Barry et al., 2018; Campos et al., 2015; Cho et al., 2016; Zhong et al., 2003). In all of the abovementioned cases, vaccination can test the ability of healthcare systems and reveal any flaws in existing healthcare systems and vaccine supply chains (VSCs). During the COVID-19 pandemic, the production, supply, storage, and delivery of vaccines have been particularly disrupted because of the massive quantity required by each affected country at a given time to reduce infection rates and avoid nationwide lockdowns. To ensure 100% vaccination coverage of any country’s population, the total vaccine required is almost 2–2.5 times greater than the population (Alam et al., 2021). Therefore, widespread vaccination can test the ability of healthcare systems and reveal any flaws in existing healthcare systems and vaccine supply chains (VSCs). To address the current outbreak, even if just 75% of the population is targeted for immunization, approximately 12–15 billion vaccines will be required worldwide (Rele, 2021).

Bangladesh, a developing country in South Asia, confirmed the first COVID-19 case on its territory on March 11, 2020 (Gautam et al., 2022). At the time of writing, the country had reported 1,595,931 cases of COVID-19, with 28,105 death cases resulting from the disease (Directorate General of Health Services [DGHS], 2022; Fig. 1). Whenever the
number of reported cases starts to rise, the Bangladesh Government, including the DGHS and the Institute of Epidemiology, Disease Control, and Research (IEDCR), imposes an alert at a national level following the WHO COVID-19 strategic preparedness and response plan (WHO, 2020a) However, a lack of knowledge and awareness, widespread panic and anxiety about the COVID-19 pandemic, as well as limited healthcare facilities have created obstacles and posed a significant threat to the population (Yeasmin et al., 2020).

Attempts to establish an efficient and effective COVID-19 VSC have been an important part of the healthcare network system in Bangladesh. However, the process has been hindered due to a set of complexities that are different from the SC of other healthcare commodities. One of the most difficult challenges is dealing with such a large volume of orders while navigating the complex networks comprising vendors, shipping companies, distribution centers, and healthcare centers, all of which are spread across multiple locations (Alam et al., 2021). Even though Bangladesh began mass vaccination on February 8, 2021, at the time of writing, only 54,189,253 people had been vaccinated with a second dose (DGHS, 2022). This indicates that implementing a well-structured VSC, examining demand rates and inventory requirements, and identifying appropriate vaccine distribution locations are required to accelerate the vaccination process (Rastegar et al., 2021). The success of the vaccination program in Bangladesh is unquestionably dependent on the efficiency and effectiveness of SC planning and operation; otherwise, a large number of doses will be scrapped, imposing significant financial losses. Additionally, due to the unique characteristics of vaccines, such as a short shelf-life and storage temperatures of below freezing, their management presents a significant logistical challenge in the disruptive environment that often characterizes developing countries (Georgiadis and Georgiadis, 2021).

While the vaccine industry has concentrated on developing and determining the effectiveness of necessary vaccines to combat COVID-19, the ongoing struggle to comprehend and adequately address the challenges of the VSC has significantly slowed the progress of any vaccination program, particularly in developing countries like Bangladesh. Nevertheless, when the issues of VSC are addressed through a rapid foundation of facilities, distribution, and procurement plans, the question of sustainability in the supply chain network (SCN) is raised (Sazvar et al., 2021). In other words, when facilities in numerous locations accelerate their operations and logistical activities, the VSC may pose a severe environmental challenge, such as incorporating increased GHG emissions (Varsei and Polyakovskiy, 2017). For example, Yadav and Kumar (2022) introduced a lean-agile-green (LAG) approach to develop the operational, economic, and environmental efficiency of VSC. Yadav and Kumar (2022) also used the same framework to overcome the challenges of sustainable VSC. Mukherjee et al. (2022) proposed a structural equation modeling (SEM) to investigate the relationship between environmental, economic, and social sustainability for COVID-19 VSC development. However, a resilient VSC also needs to accept the challenge of environmental sustainability and ensure sufficient social sustainability through job creation in the SCN (Biuki et al., 2020). Socially sustainable and resilient supply chains are essential during a crisis (Hervani et al., 2022). In light of such sustainability challenges and the abovementioned barriers, combating the COVID-19 pandemic by ensuring an effective and resilient VSC in Bangladesh becomes extremely difficult.

The current study strives to answer the following research questions (RQs):

- **RQ1:** What are the relationships among economic, environmental, and social sustainability in VSC, and how do they affect the SC model in an emerging economy?
- **RQ2:** How can a systematic VSC model be developed to address the uncertainties and challenges of a pandemic?
- **RQ3:** How practically can an integrated approach solve the complex VSC problems and provide practical solutions to policymakers?

In this regard, this paper aims to establish a VSC in the context of Bangladesh to ensure proper utilization of facilities and distribution of vaccines in a multi-echelon SCN. The study also addresses the uncertainty across different parameters of the SCN. Moreover, it will also ensure environmental and social sustainability while establishing facilities and allocating transpiration routing. The main objectives of the current study are as follows:

- to establish a VSC in the context of Bangladesh using a multi-objective, multi-echelon, and multi-category MIP model.
- to ensure the economic sustainability of the VSC by minimizing the overall SCN cost with optimal facility location, inventory policies, and the routing plan of transportation under uncertainty considering the shelf-life of COVID-19 vaccines.
- to ensure environmental sustainability of the VSC by minimizing GHG emissions and social sustainability of the VSC by maximizing job opportunities in the network.

![Fig. 1. Number of daily COVID-19 deaths in Bangladesh (as of January 10, 2022; DGHS, 2022).](chart.png)
In order to achieve the objectives, the VSC model is solved using two state-of-the-art metaheuristics, namely MOSEO and MOFEPSO. Their results are then compared. Furthermore, the Pareto-optimal solutions from the model are analyzed to obtain the best solution that emphasizes environmental sustainability using an integrated MCDM method, namely TOPSIS.

The remainder of the paper is organized as follows. Section 2 presents a literature review of the relevant research addressing the above-mentioned problems. Next, the formulation of the sustainable VSC model is discussed in detail in section 3. Section 4 contains the solution framework using the two metaheuristics proposed. Section 5 presents the computation results of the problem and a discussion of the results. Following this, the research implications of the current study are presented in section 6. Finally, the conclusion, limitations, and future scope of the current research are given in section 7.

2. Literature review

While non-pharmaceutical interventions (NPIs) like social distancing, home quarantine, and so on have effectively mitigated COVID-19 transmission (Liza et al., 2022; Courtemanche et al., 2020), considerable effort and resources have been invested in developing and implementing COVID-19 vaccines (Li et al., 2022; Wouters et al., 2021). This led to a breakthrough in vaccine development at an unprecedented rate. The first mass vaccination program for COVID-19 began in early 2020, and as of November 26, 2021, seven vaccines have been validated by the WHO for emergency use with an Emergency Use Listing (EUL) (WHO, 2022). The WHO also launched the “Access to COVID-19 Tools (ACT) Accelerator”, a globally coordinated effort driven by those in academia, scientists, and private and government initiatives. It ultimately accelerated the research and development around, and equitable access to, COVID-19 tests, treatments, and vaccines (WHO, 2020b). However, as only a few countries can produce COVID vaccines on their own, it is very critical to ensure their availability to every corner of the world (Asundi et al., 2021; The Lancet Infectious Diseases, 2021). Consequently, governments and academic institutions must act quickly and devise a plan to make the vaccine available to the public (Ocampo and Yamagishi, 2020). However, given the projected global magnitude of the pandemic, scaling up VSC to meet the resulting demand surge represents a significant hurdle. Ramping up vaccine production to meet the increasing demand and building a sustainable distribution network constitutes a major engineering challenge (Yu et al., 2020). The global scientific community has, therefore, prominently shifted its focus from the production phase to concentrate more on the distribution phase, and a good number of literary contributions demonstrating various frameworks and solutions have been published (Bamakan et al., 2021; Georgiadis and Georgiadis, 2021; Rastegar et al., 2021). In this section, we present a literature review focusing on the present state-of-the-art research on VSC and their associated mathematical approaches, followed by a discussion on the identified research gaps.

2.1. Vaccine supply chain

According to Rastegar et al. (2021), VSC comprises four essential components: product (type of vaccine), production (quantity to be produced), allocation, and distribution. Larson (2001) divided these components into the development and fulfillment phases. Each vaccine must undergo these phases after receiving approval for mass production. Lessening the obstacles in both the VSC development and fulfillment phases can significantly impact the vaccine’s availability in the future (Refael, 2021). Apart from ensuring the quality of vaccines, it is also important to understand and deal with VSC issues to make vaccines more effective (Lee and Haidari, 2017).

Among the recent literature on SC optimization, only a few address the issue of VSC. Most of these works focus on the pharmaceutical SC and problems such as vehicle routing (Goodarzian et al., 2021a,b; Kramer et al., 2019; Liu et al., 2014), product perishability (Savadkoohi et al., 2018), and inventory location and scheduling (Jankauskas et al., 2019). In the last decade, there has been a growing interest in VSC, especially in the complexity of designing a network of vaccine supply in developing nations. Zaffran et al. (2013) stated that developing countries’ transportation systems must be optimized as they implement the latest and more expensive vaccines and attempt to reach different aged cohorts in various environments. To make the SC of vaccines robust, Yadav et al. (2014) proposed a decision-making framework for integrating VSC with the SCs of other health commodities to operate at an optimal level. Moreover, Assi et al. (2013) examined the efficacy of shortening the levels of SC in terms of vaccine distribution. Their model demonstrated that by eliminating the regional level operations from Niger’s VSC and instituting a collection-based shipping policy from district stores, vaccine availability could be increased by an average of 70–100%. Similarly, the work of Lee et al. (2016) and Brown et al. (2014) on the VSC emphasized the importance of incorporating a redesign option when introducing a new vaccine to achieve maximum reach.

To address uncertainty, Jacobson et al. (2006) presented a stochastic inventory model to capture the pediatric vaccine supply during production shortages and assessed the impact of vaccine stockpile levels on future shortages. Moreover, Shrestha et al. (2010) investigated pediatric vaccine stockpiling and developed a model to account for supply shortages, costs, and health consequences. Using a scenario analysis, they examined the cost of 14 pediatric vaccine shortages and the associated health consequences. Privett and Gonsalvez (2014) identified the VSC issues in developing countries via a two-step interview and survey methodology. They prioritized lack of coordination, inventory management, and insufficient demand information as the top three issues to be addressed by practitioners and researchers. Again, several recent literature reviews on VSC shed light on key issues for VSC design, mathematical modeling, and scope for further development (Duijzer et al., 2018; Lemmens et al., 2016; Nishanth et al., 2020).

The COVID-19 vaccine and its SCN have been extensively researched in the academic literature since the pandemic’s beginning. Guttières et al. (2021) established a system-level framework to develop an analytical tool for time-sensitive decisions regarding global access to vaccines. They implied that the framework could be helpful in scenario planning and comparing vaccination strategies. Abbasi et al. (2020) created a mathematical model to aid in vaccine allocation decisions by considering exposure risk, spread rate, and operational constraints such as medical facility capacity, vaccine stocks, and the transportation medium. Additionally, Jarrett et al. (2020a,b) examined manufacturers’ responsibility to detect counterfeit vaccines and implement a global standard procedure to trace and track them along with the VSC.

Besides qualitative and case-study or survey-based analysis, researchers have started to take an interest in the mathematical modeling of vaccine distribution chains. For instance, Chen et al. (2014) developed a mathematical model of the World Health Organization’s Expanded Program on Immunization (WHO-EPI) VSC and successfully adapted it for three developing countries (i.e., Niger, Vietnam, and Thailand). Another study by de Carvalho et al. (2019) proposed a multi-objective and multi-period mixed-integer linear programming (MO-MILP) model to design a VSC that guarantees a high level of service at minimum cost but also incorporates social and environmental aspects. Yang (2020) optimized the model of distributing the WHO-EPI vaccine in four different countries in sub-Saharan Africa. He developed the model as a MIP model and also expanded the scope to use machine learning algorithms when the optimization model needs to be updated to tackle unprecedented situations.

Recently, Kis et al. (2021) presented a techno-economic feasibility analysis of the production phase of vaccine development in terms of resources, production scales, and time required to meet global COVID-19 vaccine demand. Among the most recent works on the
distribution phase of the COVID-19 vaccine, the inventory location model for vaccine distribution during pandemics developed by Rastegar et al. (2021) is notable. They set it as a MILP model with an equitable objective function to optimize the supply of influenza vaccines. Georgiadis and Georgiadis (2021) also proposed a MILP model to optimize the allocation of vaccines in different locations, the inventory levels of central hubs and vaccination centers, and the schedule vaccination plan on a daily basis.

Bamakan et al. (2021) concentrated on the bullwhip effect of COVID-19 VSC due to the massive wave of unforeseen demand. Furthermore, Sinha et al. (2021) implemented an inventory hedging strategy to maintain a high level of customer service in the event of major disruptions (e.g., lead-time disruptions). This study also identified critical disruption scenarios in which the inventory hedging strategy failed. Aside from these mathematical frameworks, Rahman et al. (2021a) explored the application of emerging technologies like the Internet of things (IoT), software-defined networking (SDN), and blockchain (BC) to develop IoT-based SDN architecture for COVID-19-infected zones to strategize around vaccine distribution.

Kumar et al. (2020) suggested that the global supply and production systems should consider more sustainable solutions to restructure the disrupted situation caused by COVID-19 in the post-pandemic era. Strategies such as the proper sourcing of raw materials, a safe workforce, inventory management, and digitalization are graciously imposed to improve the resilience and sustainability of the production and logistics process in the pandemic era. There is a multitude of papers that have investigated notions of sustainability during the COVID-19 pandemic, including Dastgerdi et al. (2021), Rume and Islam (2020), Sandeep Kumar et al. (2020), Severo et al. (2021), Taqi et al. (2020), and Vanapalli et al. (2021).

In order to incorporate the triple bottom line (TBL) objectives (economic, social, and environmental) for sustainable development (Azizmohammadi, 2013; Settanni et al., 2017; Weraikat et al., 2016), de Carvalho et al. (2019) modeled a sustainable multi-objective VSC. This model presented a realistic picture of the tradeoffs between the sustainability features and how they might impact a feasible solution. Goodarzian et al. (2020) also considered TBL in developing a sustainable multi-objective medical supply chain network. Their results revealed that a decrease in the economic and environmental impact and an increase in the social impact could lead to best sustainable practices.

2.2. Existing methods applied to VSC

The global COVID-19 crisis has tested the preparedness of the VSC, and a scaling up is required to meet the surging demand for vaccines. Global SCs have been disrupted due to a lack of labor, inadequate infrastructure, and under-resourced medical and vaccine storage facilities causing ripple effects that extend across national borders. Researchers have developed different mathematical models to address these constraints and employed various solution methodologies to address VSC problems. Despite this growing interest, the vaccine logistics literature is fragmented. Such literature also pays little attention to the broader perspective on vaccine logistics, making it difficult to contextualize. This is because improving one aspect of SCs without aligning it with other essential objectives will only lead to minor overall improvements. To represent the cross-connected and complex supply network, researchers increasingly tend to design and address the VSC as a multi-objective optimization problem.

Chen et al. (2014) developed the first multi-objective linear programming model for WHO-EPI vaccine distribution to maximize full immunization and stock extra dosages in each location to address shortages. This model was successfully adapted for three developing nations and solved using the CPLEX solver. Using the same solver-generated solution methodology (Abbasi et al., 2020), they modeled a vaccine allocation decision plan based on the risks associated with exposure, susceptibility, and capacity constraints at medical centers. de Carvalho et al. (2019) designed a sustainable VSC as a multi-objective MILP to maximize economic and social benefits while minimizing the environmental impact. The different prioritization models among the three objectives are highlighted in this research. Yang (2020) presents a novel MIP-based disaggregation-and-merging algorithm using a divide-and-conquer approach to generate optimal solutions for WHO-EPI vaccine distribution networks. Again, minimal contributions have been to the COVID-19 vaccine’s downstream SC optimization. Georgiadis and Georgiadis (2021) also approached a MILP-based decomposition algorithm to generate an optimal decision regarding a daily vaccination plan. Rastegar et al. (2021) proposed a novel equitable vaccine distribution model by customizing the objective function to maximize the minimum delivery-to-demand ratio for each heterogeneous population group. Their study was a single-product, multi-period model to decide the optimal location for vaccine distribution. As most large-scale SC optimization problems are of the NP-hard kind, meta-heuristics algorithms are widely adopted to solve these problems and achieve optimal solutions. The application of meta-heuristics or nature-inspired algorithms is considerably new to VSC, whereas, for pharmaceutical or healthcare SCs, it has been implemented numerous times. For example, Nasrollahi and Razmi (2021) proposed a multi-objective non-dominated ranked genetic algorithm to solve the integrated pharmaceutical SC model that maximizes demand coverage and minimizes total cost. They compared the Pareto front provided by the proposed approach with that of multiple objective particle swarm optimization (MOPSO) and non-dominated sorting genetic algorithm II to evaluate its capability toward increasing SC reliability. Goodarzian et al. (2020) tested the capability and performance of multi-objective social engineering optimization (MOSEO), multi-objective simulated annealing (MOSA), the multi-objective Keshet algorithm (MOKA), MOPSO, and the multi-objective firefly algorithm (MOFFA) to solve a three-objective pharmaceutical SC network model applied to large-scale problems. On the other hand, Goodarzian et al. (2020) took a novel approach of hybridizing two meta-heuristics, particle swarm optimization, and genetic algorithms, to achieve Pareto solutions for their sustainable medical SC network. Their study demonstrated better efficiency than applying the original GA and PSO algorithms to solve complex MILP problems. The established model presented in the current study involves a large number of variables and is highly complex—this has led to the use of multi-objective metaheuristic approaches. MOSEO and MOFEPSO, as newly formed approaches, have made only a limited contribution to the extant literature, especially in VSC application. Mousavi et al. (2021) used MOSEO to solve a blood SC network problem. The MOSEO approach has also been applied in closed-loop SC network optimizations (Abdolazimi et al., 2021; Babaeinessami et al., 2021). Goodarzian et al. (2021a) developed a self-adaptive SEO algorithm to solve home healthcare (HHC) logistics problems toward optimizing time and cost by considering route balancing. This SEO improvement (versus the privately developed FireFly (FF) and Artificial Bee Colony (ABC) algorithms) led to superior performance in solving complex NP-hard problems. Simultaneously, Fathollahi-Fard et al. (2020) developed a modified multi-objective version of SEO using an adaptive memory strategy to address HHC scheduling and routing problems in a fuzzy environment with large-scale instances. Moreover, the suitability of MOFEPSO was demonstrated by Hervani et al. (2022) through their use of the algorithm to solve a classical gear-train optimization problem.
et al., 2021b) and sustainable medical SC (Goodarzian et al., 2021b). Only a few studies, however, have contributed knowledge toward VSC in the COVID-19 pandemic scenario (Abbasi et al., 2020; Guttierez et al., 2021). More importantly, little effort has been given to devising mathematical modeling and decision-making framework for COVID-19 VSCs (Georgiadis and Georgiadis, 2021; Goodarzian et al., 2021a,b; Rastegar et al., 2021). Whereas a few recent studies focused on pharmaceutical SC to solve vehicle routing problems (Goodarzian et al., 2021a,b; Kramer et al., 2019), the perishability of products (Savadkoohi et al., 2018), and inventory location and scheduling (Jankauskaus et al., 2019). A little contribution has been observed in developing an integrated approach to design a VSC that considers the shelf-life of vaccines and uncertainty in demand, distribution, and cost parameters in the context of a pandemic. Moreover, there is still a research gap on modeling a VSC in the context of an emerging economy that ensures economic sustainability and considers environmental and social sustainability.

Hence, the current study aims to fill the gap in the existing literature by establishing a VSC that, in the context of a developing country, does not only provide economic sustainability by minimizing the overall SCN cost, but also ensures environmental sustainability in the SC operations by minimizing GHG emissions. Additionally, the study also focused on social sustainability in the VSC by creating job opportunities in the entire network.

Furthermore, the study contributes to the novel application of recent metaheuristics, namely MOSEO and MOFEPSO, by using them to solve the MIP model for the VSC. Even though MOSEO and MOFEPSO have been previously applied to solve manufacturing and closed-loop SCN problems (Mousavi et al., 2021; Abdolazimi et al., 2021; Babaei-Nesami et al., 2021; Hasanoglu and Dolen, 2018), this study utilizes their superior efficiency compared to traditional GA and PSO algorithms in solving a VSC problem.

Finally, the study integrated an MCDM approach—namely, TOPSIS—into the optimization model to determine the best solution from a set of NDSs from the Pareto-front, which uses input from decision-makers to prioritize environmental sustainability. This integration gives the optimization model a decision-aid for the practitioners in prioritizing an optimal solution. A list of literature relevant to the study is presented in Table 1 to demonstrate the research gap.

### 3. Formulation of a sustainable VSC

In order to design an efficient SCN for vaccine distribution in Bangladesh, a four-echelon SC is considered for this study. From the upper to lower stream, the echelons are classified as suppliers, global assembly centers (GACs), local distribution centers (LDCs), and vaccination centers (VCs). For this problem, to avoid the complexity of considering confidential vaccine raw materials, manufactured vaccines are considered one of the raw materials, along with the packaging and labeling of vaccines. Considering the available vaccines in Bangladesh (DGHS, 2022), the GACs source from a set of manufacturing countries. Fig. 2 represents the SCN for vaccine distribution in Bangladesh, where each GAC receives the raw materials from its suppliers. These materials are then processed and assembled in the GACs as full vaccine packages. The vaccines are then transported to LDCs, where they are preserved in a perishable-goods friendly environment and then transported to the VCs.

Table 2 contains the scale of SCs considered for this problem. The VSC of a major city, ‘X’ has been used as the case study for this problem. ‘X’, the largest city with the highest population density in Bangladesh, has many barriers to establishing an efficient VSC. The existing VCs are unable to cater to a major portion of Bangladeshi citizens needing immediate vaccination to ensure their health against the virus. Hence, expanding the VSC by establishing VCs that consider environmental and social sustainability has become essential amidst the pandemic. Thus, for this problem, the selection of ‘X’ provides a systematic solution that can also be applied to other areas of the country, considering sustainable aspects. Furthermore, to address the scalability of the VSC, the problem has been categorized into three sizes. For small-scale (SS) problems, packaged vaccines are sourced from four GACs located in four different countries. With the expansion of SCN to accelerate the vaccination process, medium-scale (MS) and large-scale (LS) problems are also proposed where multiple GACs are considered within a country as sources for the packaged vaccines and new facilities (i.e., LDCs, VCs) are established in the SCN to increase the overall capacity of vaccine storage in the centers. The problem scales are presented in Table 2.

The following assumptions were made for the problem formulation.

- A quantity discount is offered to the GACs by each supplier;
- Vaccines are perishable with constrained shelf lives;
- Each stage in the SCN has capacity restrictions;
- Capacity levels can be altered to utilize the assembling and holding capacity of the GACs and LDCs;
- Backlogging of orders is included in the SCN, and partial backlogging is allowed;
- Demands for the vaccine in each VC carry uncertainty and follow a probability distribution; and
- Vehicles are heterogenous in each of the echelons according to their capacities.

### 3.1. Designing the multi-objective VSC with an appropriate configuration

The study aims to design a sustainable vaccine SCN by considering several important decisions on the location and size of the GACs and LDCs and the operational and tactical decisions on the distribution of vaccines throughout the network. The study additionally aims to decide the capacity of facilities towards ensuring sustainability and plan for sourcing, distribution, inventory, and vehicle routing. Further, the aim also addresses environmental sustainability within the SC. A multi-objective formulation with multi-echelon, multi-period, and multi-vaccine-type SCN has been considered to meet the abovementioned objectives.
Table 2
Problem scale of the SCN.

| Problem instance | Sets | Suppliers | GACs | LDCs | VCs to be established | Periods | Vaccine Type |
|------------------|------|-----------|------|------|-----------------------|---------|--------------|
| SS1              | 8    | 4         | 6    | 40   | 2                     | 4       |              |
| SS2              | 8    | 4         | 6    | 60   | 2                     | 4       |              |
| MS1              | 16   | 8         | 10   | 100  | 2                     | 4       |              |
| MS2              | 16   | 8         | 10   | 120  | 2                     | 4       |              |
| LS1              | 20   | 10        | 14   | 150  | 2                     | 4       |              |
| LS2              | 24   | 12        | 14   | 150  | 2                     | 4       |              |

Notations
The notations of the proposed model, including a set of indices, parameters, and decision variables, are given as follows.

Indices

| i | j | s | r | p | t | f | n |
|---|---|---|---|---|---|---|---|
|   |   |   |   |   |   |   |   |

Parameters

| Parameter | Description |
|-----------|-------------|
| k_{p}   | a penalty paid to VC v due to a backlog of vaccine type p |
| c_{v}   | cost of opening a VC i ∈ (A ∪ D) with capacity level c |
| h_{i}   | inventory holding cost of each unit of raw material r per unit time in GAC a |
| h_{i}   | inventory holding cost of each unit of packaged vaccine p per unit time in LDC d |
| a_{i}   | unit assembly cost of packaged vaccine p in GAC a |
| c_{p}   | period operating cost for LDC d with capacity level c |
| r_{n}   | unit price of raw material r within interval n of discount schedule that is offered by supplier s |
| t_{a}   | transportation cost of one unit of packaged vaccines from source node i to destination node j |
| e_{v}   | environmental impacts of VC i ∈ (A ∪ D) with capacity level c |
| e_{p}   | environmental impacts of each unit of packaged vaccine p in GAC a |
| e_{h}   | environmental impacts of handling each unit of packaged vaccine p in LDC d |
| e_{s}   | environmental impacts of transporting one unit of each packaged vaccine from source node i to destination node j |
| j_{c}   | number of job creation if VC i ∈ (A ∪ D) is opened with capacity level c |

Fig. 2. Schematic drawing of sustainable vaccine SCN in Bangladesh.

(continued)

| Indices | Description |
|---------|-------------|
| w_{r}  | unemployment ratio in the region of VC v ∈ (A ∪ D) |
| q_{p}v  | quantity of packaged vaccine p is demanded by VC v in time period t |
| c_{c}v  | VC capacity i ∈ (A ∪ D) with capacity level c |
| s_{r}v  | supplier capacity s in supplying raw material r per period |
| c_{f}  | capacity of vehicle f |
| k_{n}  | lower bound of interval n of discount schedule for raw material r offered by supplier s |
| u_{n}  | upper bound of interval n of discount schedule for raw material r offered by supplier s |
| A_{max} | a limitation on the number of established GACs |
| P_{max} | a limitation on the number of established LDCs |
| c_{1}v  | shelf-life of raw material r |
| c_{2}v  | shelf-life of packaged vaccine p |
| c_{3}v  | the required amount of raw material r for producing a unit of packaged vaccine p |
| g_{1}v  | weight of the long-term costs |
| g_{2}v  | weight of the mid-term costs |
| g_{3}v  | a sufficiently large number |

Decision Variables

| Variable | Description |
|----------|-------------|
| V_{i}   | 1 if center i ∈ (A ∪ D) with capacity level c is established; 0 otherwise |
| X_{i}   | 1 if raw material r is provided to GAC a by supplier s in period t; 0 otherwise |
| X_{i}   | 1 if LDC d receives packaged vaccine p from GAC a during time period t; 0 otherwise |
| X_{i}   | 1 if VC v receives packaged vaccine p from distribution center d during time period t; 0 otherwise |
| Y_{sr}  | 1 if order quantity of GAC a for raw material r falls within interval n of the discount schedule of supplier s in time period t; 0 otherwise |
| Z_{i}   | 1 if link i − j is a part of the route of vehicle f for delivering packaged vaccine p in time period t; 0 otherwise |
| P_{s}   | inventory quantity of raw material r in assembly center a at the end of period t |
| F_{p}   | inventory quantity of packaged vaccine p in LDC d at the end of period t |
| W_{i}   | quantity of order for raw material r that is released from GAC a to supplier s in time period t |
| W_{i}   | quantity of order for packaged vaccine p that is released from LDC d to assembly center a in time period t |
| M_{f}   | a fraction of the order for packaged vaccine p by VC v that can be satisfied by distribution center d in time period t |
| Q_{i}   | a fraction of the order for packaged vaccine p by VC v that cannot be satisfied by distribution center d in time period t |
| G_{f}   | an auxiliary non-negative variable used for sub-tour elimination |

3.1.1. Formulation
The formulation aims to optimize three objective functions, as
The objective function $f_1$ in Equation (1) contributes to minimizing the entire network's cost, including VC foundation cost, raw material procurement cost, distribution and assembling cost, inventory storage cost, logistics cost, and order backlogging cost, all calculated in US dollars ($). The objective function $f_2$ in Equation (2) addresses the environmental efficacy of the transportation network. The objective primarily assesses the effects of the environment on the VC foundation, assembling, and distribution activities, as well as minimizing the total environmental impact caused by the VSC. $f_2$ is calculated using metric tons carbon equivalent (MTCE).

The objective function $f_3$ in Equation (3) attempts to intensify social sustainability by minimizing the negative value of employment—that is, it maximizes the total social sustainability of the VSC. Finally, $f_3$ is calculated using the number of persons.

\[
\begin{align*}
\text{Min } & f_1(x) = \gamma_1 \sum_{i \in (\bar{A} \cup \bar{D}) \cap C} c_{iV} V_i + \sum_{r \in R} \sum_{c \in C} c_{rn} W_{ sr} Y_{max} \\
& + \sum_{p \in P} \sum_{f \in F} \sum_{a \in A} \sum_{d \in D} \sum_{r \in R} a_{pf} W_{alp} Y_{max} \\
& + \sum_{r \in R} \sum_{c \in C} c_{rn} W_{sr} Y_{max}
\end{align*}
\]

\[
\begin{align*}
\text{Min } & f_2(x) = \gamma_2 \sum_{i \in (\bar{A} \cup \bar{D}) \cap C} c_{iV} V_i + \sum_{r \in R} \sum_{c \in C} c_{rn} W_{sr} Y_{max} \\
& + \sum_{p \in P} \sum_{f \in F} \sum_{a \in A} \sum_{d \in D} \sum_{r \in R} a_{pf} W_{alp} Y_{max} \\
& + \sum_{r \in R} \sum_{c \in C} c_{rn} W_{sr} Y_{max}
\end{align*}
\]

\[
\text{Max } f_3(x) = \sum_{c \in C} \sum_{t \in T} X_{ct} U_c V_c
\]

\[
\sum_{c \in C} V_c \leq 1; \forall i \in (\bar{A} \cup \bar{D})
\]

Constraint (4) indicates the level of capacity of newly developed VCs. The variable will decide whether a particular VC will be considered in the VSC based on a specified capacity level $c$.

\[
\sum_{c \in C} V_c \leq A_{max}
\]

\[
\sum_{c \in C} V_c \leq D_{max}
\]

Constraints (5) and (6) restrict the number of established GACs and LDCs in the VSC, respectively. The number of GACs must not exceed a specified maximum limit $A_{max}$, and the number of LDCs must not exceed a specified maximum limit $D_{max}$.

\[
\begin{align*}
\sum_{i \in M} X_{iV} &= \sum_{c \in C} V_i; \forall m \in M, r \in R, t \in T \\
\sum_{a \in A} X_{alp} &= \sum_{c \in C} V_i; \forall d \in D, p \in P, t \in T \\
\sum_{v \in V} X_{v} &= 1; \forall v \in V, p \in P, t \in T
\end{align*}
\]

Constraints (7) to (9) are added to the model to justify the single-sourcing strategy signifying the flow of vaccines through the VSC. Decision variables $X_{iV}$, $X_{alp}$, $X_{v}$ are considered if raw material $r$ is provided to a, packaged vaccine $p$ provided to $d$ and $v$ within a time period $t$ respectively.

\[
X_{alp} \leq \sum_{c \in C} V_i; \forall d \in D, v \in V, p \in P, t \in T
\]

Constraint (10) depicts assigning vaccine centers to LDCs. According to this, each VCs of the VSC is assigned to one LDCs. That means, a VC receives packaged vaccine $p$ from a LDC within time $t$.

\[
\sum_{j \in J} Z_{ijpv} = 1; \forall j \in V, p \in P, t \in T
\]

Constraint (11) indicates that a VC is served once at a time. A decision variable $Z_{ijpv}$ denotes it concerning the route of the vehicle.

\[
\sum_{j \in J} Z_{ijpv} - Z_{ijpv} = 0; \forall i \in D, f \in F, p \in P, t \in T
\]

Constraints (12) and (13) define each vehicle must begin and stops its travels at the same LDC. It assures that each vehicle must complete the route obeying the abovementioned condition. Constraint (12) make sure if a particular route $Z_{ijpv}$ is considered for the vaccine distribution and constraint (13) checks if the route $i$ to $j$ and $j$ to $i$ are equal.

\[
\sum_{j \in J} Z_{ijpv} = 0; \forall i \in V, p \in P, f \in F, t \in T
\]

Constraint (14) confirms that a vehicle must leave again each time it arrives at a VC considering LDC and VC.

\[
\sum_{j \in J} Z_{ijpv} + \sum_{j \in J} Z_{ijpv} - X_{alp} \leq 1; \forall i \in V, i \notin D, p \in P, f \in F, t \in T
\]

Constraint (15) connects the decision variables regarding routing and allocation. It connects the decision variable $X_{alp}$ with routing variable $Z_{ijpv}$.

\[
G_{ijpv} - G_{ijpv} + |Z_{ijpv} - 1| - 1; \forall i \in V, i \notin D, p \in P, f \in F, t \in T
\]

Constraint (16) is incorporated within the model to omit sub-touring employing non-negative variable $G_{ijpv}$ and $G_{ijpv}$ for route $i$ to $j$. It eliminates all the solutions containing sub-tours, as for every subset of nodes by forbidding the number of selected routes within $V$ to be equal to or larger than the number of nodes in $V$.

\[
\sum_{p \in P} \sum_{f \in F} \sum_{i \in (\bar{A} \cup \bar{D})} \sum_{j \in J} \sum_{t \in T} \left( q_{ijpv} Z_{ijpv} - \sum_{p \in P} \sum_{f \in F} \sum_{i \in (\bar{A} \cup \bar{D})} M_{ijpv} + \sum_{p \in P} \sum_{f \in F} M_{ij(p-1)} \right) \leq c_{ij}; \forall f \in F, t \in T
\]
As this model includes a non-linear term, constraints (37) and (39) exclude the non-linearity in the objective function (1) caused by \( W_{\text{opt}} \) and \( Y_{\text{opt}} \) and convert it into a mixed-integer linear programming model.

4. Solution framework

To address the optimization problem, selecting an algorithm to handle a large number of variables, probability distribution for the uncertain parameters, and selecting the best solution from a Pareto-front is important. The following discussions highlight the framework for the solution approach.

4.1. Addressing uncertainties of parameters

To address the uncertainties associated with real-life fluctuations, some parameters, such as the demands in VCs, number of job creations, and shelf-life of vaccines, have been considered probabilistic and defined with a uniform probability distribution. The probabilistic distribution of the parameters is specified in Table A1 (see Appendix A).

![Flowchart of the MOSEO methodology (Fathollahi-Fard et al., 2018).](image-url)
The distributions have been used to simulate the parameters of the test problems.

### 4.2. Suggested metaheuristics

In the current study, we propose the use of two-meta heuristics. The established model in this study involves a large number of variables and is highly complex, which drives the utilization of multi-objective metaheuristic approaches. Two metaheuristics, namely the MOSEO and MOFEPSO methods, are proposed in the current study toward confronting the multi-objective optimization problem.

Fathollahi-Fard et al. (2018) demonstrated that MOSEO performs very well compared with other well-known metaheuristic algorithms, such as GA, SA, and the red deer algorithm (RDA). The performance of MOFEPSO has been evaluated against many different multi-objective solution algorithms and has proven superior (Hasanoglu and Dolen, 2018). Several works have successfully utilized these methods.

#### 4.2.1. Multi-objective social engineering optimization (MOSEO)

In the MOSEO algorithm, each solution is equivalent to a person along with their personality traits in the search space. The algorithm is a single-solution metaheuristic in which two main phases, attacker and defender, are controlled. An attacker attacks a defender, and this attack follows a four-step cycle. To better visualize this approach, a flowchart of it is presented in Fig. 3. The steps of the procedure are described below (Fathollahi-Fard et al., 2018).

**Step 1: Initialization of the attacker and defender**

In this step, two random solutions are selected. One is the attacker, which represents the superior solution, and another is the defender. They are considered two persons with N traits, each as mentioned in equation (39). The objective function (OF) is represented in Equation (40).

\[
person = [X_1, X_2, \ldots, X_N] \quad \text{(39)}
\]

\[
OF = f(person) = f(X_1, X_2, \ldots, X_N) \quad \text{(40)}
\]

**Step 2: The training and retraining of the attacker from the defender**

The attacker examines each trait of the defender and replaces the most efficient trait, as shown in Equation (41).

\[
N_{\text{train}} = \text{round} (\alpha, N) \quad \text{(41)}
\]

Here, \(\alpha\) represents the percentage of traits replaced, and \(N_{\text{train}}\) is the number of traits replaced.

**Step 3: Spotting an attack from the attacker to the defender**

This is an approach taken to locate the defender in a feasible search space. This approach constitutes four techniques, as follows in equation (42–46); Fathollahi-Fard et al. (2019).

**i. Obtaining technique:**

\[
D_{\text{new}} = D_{\text{old}} \times (1 - \sin \beta \times U(0, 1)) + \left( \frac{D_{\text{old}} + A}{2} \right) \times \sin \beta \times U(0, 1) \quad \text{(42)}
\]

**ii. Phishing technique:**

\[
D_{\text{new}} = D_{\text{old}} \times \left(1 - \sin \left(\frac{\pi}{2} - \beta\right) \times U(0, 1)\right) + \left(\frac{D_{\text{old}} + A}{2}\right) \times \sin \left(\frac{\pi}{2} - \beta\right) \times U(0, 1) \quad \text{(43)}
\]

**iii. Diversion theft technique:**

\[
D_{\text{new}} = D_{\text{old}} \times \left(1 - \sin \beta \times U(0, 1)\right) + \left(\frac{D_{\text{old}} + A}{2}\right) \times \sin \beta \times U(0, 1) \quad \text{(44)}
\]

**iv. Pretext technique:**

\[
D_{\text{new}} = D_{\text{old}} \times \left(1 - \sin \beta \times U(0, 1)\right) + \left(\frac{D_{\text{old}} + A}{2}\right) \times \sin \beta \times U(0, 1) \quad \text{(45)}
\]

Here, \(D_{\text{old}}/D_{\text{new}}\) = Current/new position of the defender.

\[A = \text{Attacker position}\]

\[\beta = \text{Rate of spotting an attack}\]

\[U(0, 1) = \text{Random distribution}\]

**Step 4: Creating a new defender in response to a attack**

After each attack, the positions of the defender and the attacker are interchanged. Thus, a new defender is created. This process continues until a suitable stopping criterion is met.

#### 4.2.2. Multi-objective feasibility enhanced particle swarm optimization (MOFEPSO)

The MOFEPSO algorithm can be used to efficiently and feasibly solve optimization problems with a variety of constraints. Notably, it does not need a feasible position for initialization. MOFEPSO does not calculate objective function for an infeasible position. To better visualize this, a flowchart of the approach is presented in Fig. 4. The steps of the procedure are demonstrated as follows.

**Step 1: Initializing routine**

Initially, the position (X) and velocity (V) matrices are initialized. For every feasible position, the objective function is analyzed with respect to the best global and local positions. Here, non-dominated positions are judged.

**Step 2: Updating velocity**

Velocity is differentially updated for both feasible and infeasible particles. If ith particle offers an infeasible solution, the modified velocity can be given as
On the other hand, feasible particles are attracted to both the best global and local positions. Therefore, the velocity is updated as follows:

\[
v_{i,n} = s_{m,n}[Ev_{i,n} + c_1r_{1,n}(x_{G_i}^c - x_{i,n})] + c_2r_{2,n}(x_{P_i}^c - x_{i,n})
\]

(47)

Here, \(s_{m,n}\) = Sensitivity of the \(m\) constraint.

\(E\) = Inertia factor  
\(c_1, c_2\) = Acceleration coefficients  
\(r_{1,n}, r_{2,n}\) = Uniformly distributed random numbers

For a given position, constraints are inspected. If the current best position violates any unviolated constraints, the velocity is set as zero, and the particle position \(x_{i,*}^c\) is updated using a limit violation rate \((w)\).

\[
w = \max\left[\max_n \frac{x_{L_i}^c - x_{i,n}}{x_{L_i}^c - x_{U_i}^c}, \max_n \frac{x_{U_i}^c - x_{i,n}}{x_{U_i}^c - x_{L_i}^c}\right]
\]

(49)
\[ x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (50) \]

**Step 4: Post-flight operations**

For an infeasible particle position, the constraint priorities are changed. The objective function is then updated for each feasible particle position.

### 4.3. Selecting an optimal solution from the pareto-optimal front using MCDM approach

Since the problem is solved using a multi-objective approach, it is not possible to directly obtain an optimal solution from a set of NDSs. Different techniques exist in the extant literature that can be used to achieve the optimal solution from the decision-makers’ opinions. This, in turn, can assist in the trade-off analysis. In the current study, we have used a MCDM approach referred to as TOPSIS. This approach considers the best-ranked value as the optimal solution.

The steps in obtaining the optimal value from the TOPSIS method are given as follows.

**Step 1:** Establishing a normalized decision matrix \( X = \frac{x_i}{\sum_{j=1}^{n} r_j} \) based on an initial decision matrix given by the decision-makers for a set of non-dominated solutions.

**Step 2:** Calculating a normalized weighted matrix, \( V_i = X_i \times W_i \) here, \( W_i \) is the weight of the criteria for all \( j \). They can be presented as \( W_i = (W_1, W_2, W_3, \ldots, W_q) \).

In addition, the normalization of the weight matrix is defined as \( V_i = W_i \times r_i \).

**Step 3:** Determining the ideal solution matrix for the positive and negative ideal solution using equations (51) and (52), as follows:

\[
V^+ = \{ (\max v_{ij} \mid j \in J), (\min v_{ij} \mid j \in J), i = 1, 2, 3, \ldots, m \} \\
V^- = \{ (\min v_{ij} \mid j \in J), (\max v_{ij} \mid j \in J), i = 1, 2, 3, \ldots, m \} 
\]

**Step 4:** Calculating the Euclidian distance from ideal best and worst using equations (53) and (54).

\[
S_i^+ = \left[ \sum_{j=1}^{m} \left( V_{ij} - V^+_{ij} \right)^2 \right]^{\frac{1}{2}} \quad (53)
\]

\[
S_i^- = \left[ \sum_{j=1}^{m} \left( V_{ij} - V^-_{ij} \right)^2 \right]^{\frac{1}{2}} \quad (54)
\]

**Step 5:** Calculating performance best \( P_i = \frac{S_i^+}{S_i^- + S_i^+} \)

**Step 6:** Denoting rank based on the performance value and selecting the best-ranked value as the optimal solution.

### 5. Computational results

The optimization model has been solved using a computer program, and the results obtained from the solution are discussed in this section.

#### 5.1. Assigning instances of the problem

The formulation of VSC in a multi-objective optimization problem involved some datasets that are not found as standard benchmarks in the existing literature. Hence, some values have been generated randomly to represent a real-life scenario in practice. However, critical data related to the case study have been used from a real-time source (DGHS, 2022). Random instances can help validate the usability of the proposed model and the metaheuristics used in the current study. Furthermore, the random instances can be replaced as per the availability of data from real-time sources.

#### 5.2. Numerical illustrations

The problem is programmed in MATLAB 2019a software to achieve the formulation results. The specification of the device used to code the problem includes a 2.3 GHz Dual-Core i5 CPU with 8 GB 2133 MHz RAM. To address the robustness of the solution due to handling uncertain parameters, each test problem—SS, MS, and LS—has been run 20 times, and the average results have been recorded for discussion. It is worth noting that, for the solutions, the maximum iteration has been considered 100 for both metaheuristics. The metaheuristic parameters for MOSEO and MOFEPSO are given in Table 3.

Fig. 5 presents the Pareto-front obtained for the small-scale problem SS1 for both metaheuristics, MOSEO and MOFEPSO. In Fig. 5, the x-axis maps the maximized value of the objective function \( f_3 \). The y and z axes map the values of the minimized values of \( f_1 \) and \( f_2 \), respectively. The points marked in red in the figure present the NDSs obtained from the MOSEO algorithm, whereas those marked in blue are the NDSs obtained from the MOFEPSO algorithm.

From Fig. 5, it is quite evident that both the metaheuristics perform equivalently for the problems in the small-scale scenario. However, the results obtained using MOSEO is more reliable for the case study, as some of the NDSs in the Pareto-front for MOFEPSO are not optimal. This is because the results reflect that with the increase in the size of the problems, the average deviation from the optimal solution is greater for MOFEPSO than MOSEO (see Figures A1 and A2 in Appendix A). The performance of MOFEPSO can also be explained via a comparison between the convergence behaviors of the two metaheuristics. Fig. 6(a) illustrates that the convergence for MOFEPSO is stuck at the 42nd iteration in a locally optimal solution for \( f_3 \) for instance SS1. Whereas for MOSEO, the convergence continues until the 84th iteration, with the best solution identified for \( f_3 \) in problem SS1. A similar phenomenon in the convergence behavior can also be seen for \( f_2 \) and \( f_3 \), in Fig. 6(b) and (c), respectively. Thus, we can be certain that MOSEO, compared with MOFEPSO, performed better in optimizing the problem under the study.

First, to compare the computational performance of the two metaheuristics for each problem in Table 2, an optimal solution has been chosen using the TOPSIS method described in section 4.2. Table A2 presents the rank obtained for each of the NDSs in problem SS1 for MOSEO using the weightage normalized matrix in TOPSIS. Similarly, the ranks are determined for all other problems, and the best solutions for MOSEO Rate of collecting data, \( \alpha \)  0.8
Rate of connecting attacker, \( \beta \)  0.5
Number of connections, \( NC \)  200
MOFEPSO Population size, \( n_{\text{pop}} \)  200
Inertia weight, \( E \)  0.6
Global acceleration coefficient, \( c_1 \)  1.2
Individual acceleration coefficient, \( c_2 \)  2.5
Inflation rate, \( \mu \)  0.1
Mutation rate, \( \mu \)  0.1

Table 3

| Metaheuristic | Parameter | Value |
|---------------|-----------|-------|
| MOSEO         | Rate of collecting data, \( \alpha \) | 0.8   |
|               | Rate of connecting attacker, \( \beta \) | 0.5   |
|               | Number of connections, \( NC \) | 200   |
| MOFEPSO       | Population size, \( n_{\text{pop}} \) | 200   |
|               | Inertia weight, \( E \) | 0.6   |
|               | Global acceleration coefficient, \( c_1 \) | 1.2   |
|               | Individual acceleration coefficient, \( c_2 \) | 2.5   |
|               | Inflation rate, \( \mu \) | 0.1   |
|               | Mutation rate, \( \mu \) | 0.1   |
are selected to prioritize environmental sustainability. Table 4 presents the best optimal solutions for each problem, with a computation time of 100 iterations for both metaheuristics (with their defined parameters; see Table 3). The objective function $f_1$ minimizes overall costs of the VSC calculated in US dollars ($), $f_2$ minimizes overall GHG emissions in metric tons carbon equivalent (MTCE), $f_3$ maximizes the number of persons employed in the VSC.

The results revealed that the deviation of the number of NDSs increases between MOFEPSO and MOSEO, with the scale of the problem moving from small-to large-scale instances. To elaborate, the results shown in Table 4 make it evident that MOSEO achieves a better result of overall SCN cost for all scales of problems. For small-scale instances, MOSEO results in 24.06% lower optimal SCN costs for SS1 than MOFEPSO ($3866017 and $5091499, respectively for MOSEO and MOFEPSO). Even though the difference in optimal SCN costs lowers with an increase in the problem scale for the two methods, MOSEO achieves an average of 4.01% and 9.6% lower optimal SCN costs for medium and large scale instances, respectively. In case of minimizing overall GHG emissions ($f_2$) in MTCE, MOSEO still performs better than MOFEPSO. The difference in achieving the optimal value is as low as 3.4% for small-scale instances (5413 MTCE and 5608 MTCE for MOSEO).

![Fig. 5. Pareto-front for problem SS1.](image)

![Fig. 6.](image)

Fig. 5. Pareto-front for problem SS1.

Fig. 6. (a) Convergence behavior of $f_1$ for instance SS1; (b) convergence behavior of $f_2$ for instance SS1; and (c) convergence behavior of $f_3$ for instance SS1.
and MOFEPSO, respectively). However, with the increase in the problem scale, MOSEO outperforms MOFEPSO and achieves an average of 14.9% lower GHG emissions for large-scale instances. Finally, to maximize the number of persons employed in the VSC ($f_3$), MOSEO generates 8.08% (average) more employment with the same resources than MOFEPSO. Table 4 also shows that MOSEO can generate 10.81% more NDS than MOFEPSO.

A similar phenomenon is observed in the computational time for both metaheuristics. Fig. 7 shows that when the problem is small-to-medium in size, both algorithms are subjected to a computational time with a small deviation. However, when the problem scale is large, MOSEO can handle the problem better, with a computational time that is substantially lower than that for MOFEPSO.

Moreover, for the comparative performance of the proposed

| Problem instance | Objective function | MOSEO | MOFEPSO |
|------------------|--------------------|--------|----------|
|                  | Optimal solution   | T(s)   | NDS      |
| SS1              | $f_1$ ($)          | 3,866,017 | 18.3415  | 5,091,499 | 21.8157 |
|                  | $f_2$ (MTCE)       | 5031   | 2921     |
|                  | $f_3$ (Persons)    | 5413   | 22.2471  | 7,774,019 | 25.3875 |
| SS2              | $f_1$ ($)          | 4,658,934 | 22.2471  | 5,674,826 | 25.3875 |
|                  | $f_2$ (MTCE)       | 3351   | 2921     |
|                  | $f_3$ (Persons)    | 8871   | 25.1419  | 7,774,019 | 25.3875 |
| MS1              | $f_1$ ($)          | 7,522,336 | 29.4358  | 7,774,019 | 25.3875 |
|                  | $f_2$ (MTCE)       | 8399   | 29.4358  |
|                  | $f_3$ (Persons)    | 8996   | 7990     |
| MS2              | $f_1$ ($)          | 9,162,302 | 35.0863  | 9,666,230 | 45.4219 |
|                  | $f_2$ (MTCE)       | 8059   | 35.0863  |
|                  | $f_3$ (Persons)    | 8996   | 45.4219  |
| LS1              | $f_1$ ($)          | 10,529,269 | 59.5091  | 11,194,701 | 81.0981 |
|                  | $f_2$ (MTCE)       | 12,105 | 59.5091  |
|                  | $f_3$ (Persons)    | 11,456 | 81.0981  |
| LS2              | $f_1$ ($)          | 13,662,302 | 65.9371  | 15,752,823 | 93.1853 |
|                  | $f_2$ (MTCE)       | 14,319 | 65.9371  |
|                  | $f_3$ (Persons)    | 11,456 | 93.1853  | 11,479   | 93.1853 |

Fig. 7. Comparison of computational time for proposed algorithms.

Fig. 8. Values of achieving $f_1$

Fig. 9. Values of achieving $f_2$

Fig. 10. Values of achieving $f_3$
algorithms, Figs. 8–10 show that both the algorithms achieved comparable solutions toward minimizing overall cost and GHG emissions and maximizing employment. However, as the size of the problem increases, it can be observed that MOFEPSO begins to fall short in obtaining the global optimum and gets stuck in locally optimal solutions. In contrast, it can be seen that MOSEO, in all cases, achieves better solutions and serves as a superior algorithm for implementing a sustainable VSC.

5.3. Sustainability performance analysis

As the problem involves the implementation of a sustainable VSC in Bangladesh that ensures the scalability of the SCN using a multi-objective formulation, the proposed metaheuristics were focused on obtaining the best set of results with conflicting objectives. Furthermore, TOPSIS has been integrated to analyze a set of NDSs and select the best solution. In the current study, the economic performance of the VSC has been determined using minimized cost, whereas environmental sustainability has been addressed by minimizing GHG emissions in different operational and tactical activities. In addition, sustainability is measured using the growth of employment in the SCN. While selecting the best trade-off in conflicting objectives using TOPSIS, the decision-makers have concentrated on the environmental sustainability of the VSC. Let’s take a closer look at the normalized values for all of the solutions obtained for problem SS1 in MOSEO, the preferred algorithm for this case study. We can see the conflicting nature between the objectives for economic performance and environmental sustainability (see Table A2 in Appendix A). With an increase in costs for the entire SCN, the solutions reduce the total GHG emissions. From Fig. 11, it can be seen that for the 9th solution (3,866,017 \( f_1 \), 5031.041 \( f_2 \), 2921 \( f_3 \)), with a slight increase in the overall SCN costs, the overall GHG emissions significantly decrease, representing 11.3% less than the average decrease of all solutions. Furthermore, the selection of the best solution in TOPSIS also reveals a reduction in the overall GHG emissions in the entire network, with a 14.44% improved sustainability performance from the second-best solution (4,058,341 \( f_1 \), 4397 \( f_2 \), 3063 \( f_3 \)).

A detailed breakdown of the solutions also reveals that the decision made to establish and locate facilities greatly affects the sustainability of the SCs. Consequently, while selecting the optimal solution using TOPSIS, solutions that involve decentralized LDCs are prioritized to enhance the sustainability of the SCN. The selection of decentralized LDCs has promoted a reduction in transportation effort and GHG emissions, improving overall sustainability. The results also reveal that when economic performance is more focused on the problem (i.e., facilities are established with more capacity without a focus on other factors), the environmental sustainability of the solution overall decreases. Fig. 12 indicates that if we benchmark a conventional economic performance-focused SC where environmental sustainability is not considered, the best solution obtained in TOPSIS for MOSEO has 13.25% lower average capacities and a 10.13% lower average distance between facilities, making it more environmentally sustainable through its resulting lower amount of GHG emissions.

6. Discussions

From the results illustrated in Section 5, it is evident that the MOSEO results in a computationally better solution by achieving better convergence for the optimal solutions. MOSEO algorithm has been compared with other algorithms, including MOPSO, and the results from MOSEO were better (Fathollahi-Fard et al., 2018). For example, Baliarsingh et al. (2019) used a hybrid SEO algorithm for data classification and showed that SEO performed better than PSO in terms of the number of iterations. Furthermore, with the increase in the size of the problem, MOSEO performs better than MOFEPSO, as shown in our model (Table 4 and Fig. 5). It is obvious that for solving a VSC model in other settings with different parameters, MOSEO can be applied effectively. Furthermore, the sustainability analyses in our model also reveal that the MOSEO model performed better in obtaining sustainable objectives than MOFEPSO in all scales of problems (Figs. 11 and 12). The results also highlight the importance of embedding the TOPSIS model for choosing the best optimal solution based on the priority of objectives. Nevertheless, sensitivity analyses on the most crucial design parameters reveal insights into the results obtained from the model. Table 5 shows that change in the holding cost effect marginally affects other cost parameters. However, a change in the transportation costs significantly affects the opening costs of facilities. However, MOSEO shows more robustness in all cases by reducing changes than MOFEPSO.

Based on the discussion, solutions from MOSEO-TOPSIS are suggested to the policy-makers in developing a VSC. Moreover, the study’s key findings in creating a scalable and sustainable VSC are as follows.

- The optimization model developed in can significantly help practitioners in defining sustainable objectives.
- The model has effectively addressed uncertainties of different parameters a VSC can face in a developing economy.
- The solutions from MOSEO algorithms can provide policy-makers with substantially better optimal inventory and routing policies when the scale of the model is significant. This can be obtained with limited resources by minimizing the overall SC costs.
Sensitivity analysis of parameters.

| Inventory holding cost 50% | Transportation cost 50% |
|----------------------------|-------------------------|
| Increased                  | Increased               |
| Inventory holding cost     | Transportation cost     |
| 50%                        | 50%                     |
| Opening cost ($c_{oi}$)    | MOSEO                   | MOFEPSO                 |
| 0%                         | 1.215%                  | 21.456%                 |
| MOFOEPO                    | 1.341%                  | -19.504%                |
| Periodic operating cost    | MOSEO                   | MOFEPSO                 |
| 1.816%                     | -3.245%                 | -1.216%                 |
| MOFEPSO                    | -3.543%                 | 2.415%                  |
| Transportation cost ($c_{ij}$) | MOSEO                   | MOFEPSO                 |
| 1.907%                     | 2.426%                  | -1.971%                 |
| MOFEPSO                    | 2.975%                  | 3.213%                  |
| Assembly cost ($a_{cm}$)   | MOSEO                   | MOFEPSO                 |
| 0.126%                     | -0.512%                 | 0.216%                  |
| MOFEPSO                    | -0.759%                 | -0.212%                 |
| Inventory holding cost     | MOSEO                   | MOFEPSO                 |
| 0%                         | 1.821%                  | -1.241%                 |
| MOFEPSO                    | -1.912%                 | -2.531%                 |

- The solutions from MOSEO algorithms can significantly increase the sustainability of a VSC in a developing economy by minimizing GHG emissions and maximizing job opportunities in a region.
- The MOSEO-TOPSIS approach can guide decision-makers in choosing the best optimal solutions from a set of solutions according to their priority.

7. Research implications

This section addresses the implications of this study which are demonstrated from both theoretical and practical perspectives. This helps SC practitioners and professionals to comprehend the significance of VSC incorporating economic, environmental, and social sustainability.

7.1. Theoretical implications

This study identifies the importance of sustainability in VSC by incorporating economic and social sustainable concerns in the proposed model. The incorporation of minimizing environmental impacts and maximizing social sustainability in the VSC in this study will guide policymakers to concentrate more on environmental and social concerns while minimizing overall network costs with optimal facility location, inventory policies, and the routing plan of transportation. Additionally, comparing the algorithms to determine the best solutions will help SC professionals and decision-makers decide on the appropriate one for their own SC, considering different perspectives. From a theoretical perspective, the MIP model developed in this study can be further utilized, focusing on vaccines and other pharmaceutical products. Since the model addresses the uncertainty of important parameters of VSC (e.g., shelf-life of materials, costs of raw materials, quantity of demand), it can be used to solve SCN problems of related products (such as medicines and perishable foods) under uncertainty. Even though the problem is solved from a developing economy perspective, the model can be utilized to solve VSC problems in other social settings where the costs of establishing facilities ($c_{oi}$), long-term and mid-term costs and other parameters differ from the case study this paper solved. Furthermore, since the model addresses global sourcing by incorporating Global assembly centers (GACs), the model can be used in solving cross-boundary SC problems. This study provides a ground for the researcher to improvise the proposed model further and incorporate more uncertain parameters to ensure robustness and.

7.2. Managerial implications

The COVID-19 pandemic has caused a global health disaster, putting civilization at great health risk. At the time of writing, vaccination is considered the only way to protect individuals from experiencing a serious, and sometimes fatal, reaction to COVID-19 infection. Consequently, ensuring individuals are vaccinated with as little delay as possible has become a global emergency. However, due to the scarcity in supply and limited distribution capacity, countries like Bangladesh have not yet succeeded in ensuring vaccination coverage for a major portion of their citizens, which has led to a detrimental public health situation for such countries. In comparison to how densely populated such countries are, a lack of adequate and appropriate foundations for LDCs and VCs has caused a huge delay in the vaccination process. The effort of local governments and public sectors in investing huge capital in establishing an effective VSC will be in vain if a strategic plan at the operational and tactical level is not properly designed and implemented. The current study focused on developing a VSC model that could provide decision-makers with a holistic map of the foundation, location, and definition of different facilities, along with transportation and distribution plans that can minimize overall VSC costs. While the conventional formulation of SC would have focused on increasing the overall economic performance of the SC by concentrating on the cost factor involved, the proposed model extends the novelty of VSC by incorporating the sustainable aspects of SC. The case study involved developing a VSC that focuses on establishing decentralized LDCs and VCs in a major city in Bangladesh, the implications of which will not only be able to efficiently manage the sourcing, distribution, and foundation of VCs but will also significantly minimize the environmental impacts of the SC and ensure social sustainability through promoting growth in employment in the city under study. Furthermore, the proposed model can be used as a benchmark to develop a country-wide sustainable VSC.

In addition to what is mentioned above, if applied immediately, the proposed approach could contribute greatly to meeting several important sustainable development goals (SDG), while simultaneously the public’s safety against COVID-19. First, establishing a sustainable VSC can promote SDG 2 (Good Health and Well-being) by expanding the capacity of healthcare SCs in the country. The results presented in Table 4 demonstrate that establishing a sustainable VSC with the solution selected can establish 40 VCs and scale them up to 150 with a minimal increase in the cost of the entire SCN. With the attainment of the environmental sustainability-related objective in the model, the study touches on SDG 12 (Responsible Consumption and Production) by minimizing overall GHG emissions in the SCN. This is evident in the solution presented in Fig. 11, where the solution selected for problem SI
resulted in a VSC that reduces overall GHG emissions in the SCN, with 14.44% improved sustainable performance than the next best solution. Finally, by ensuring social sustainability through maximizing employment in the sustainable SC, the study has also attempted to approach SDG 8 (Decent Work and Economic Growth) as the solution confirmed employment creation representative of 2921 people. Furthermore, this can be expanded to 12,071 people with the expansion of the SCN.

Therefore, the current study can help decision-makers establish and sustain a healthcare SC with commendable milestones. Accordingly, an important implication of the study is that it can help to create scalable, sustainable aid in the wake of this critical global health crisis.

8. Conclusions

Along with other SCs, the healthcare SC (particularly the VSC) continues to encounter the devastating impacts of the COVID-19 pandemic while continuing its production, operation, and transportation. As the abovementioned SC is crucial for the whole world’s recuperation, it carries more weight than other areas. To cater to the healthcare systems upon the emergence and continuation of the COVID-19 pandemic, it has become inevitable for Bangladesh to expand its vaccination capacity to ensure the health and safety of the public. Addressing the current disruption and health crisis caused by COVID-19, the current study has proposed a mathematical approach to establish a VSC that considers economic, environmental, and social sustainability. The VSC is modeled using two metaheuristic algorithms, MOSEO and MOFEPSO. The comparative analysis reveals that the convergence rate and tendency to reach a globally optimal solution is superior in MOSEO, as MOFEPSO often stops at a locally optimal solution. Hence, MOSEO is more reliable than MOFEPSO in solving the VSC problem. The results obtained from MOSEO are then integrated into the TOPSIS model to devise the best solution that considers the minimization of GHG emissions as a major sustainability goal for the VSC. The findings highlight that the obtained solution from MOSEO-TOPSIS has significantly higher environmental while also achieving economic and social goals. Hence, the study proposes this approach to the practitioners of emerging economies in designing a sustainable VSC.

The current study has several limitations, all of which create a considerable avenue for future research to expand on the study’s scope. While conducting this study, some parameters are assumed due to data unavailability. Moreover, only uniform distribution is considered for parameters to address the parameters’ uncertainty.

Finally, this study can be further expanded by comparing the results with other hybrid metaheuristic algorithms and concluding validity based on their comparison. The problem can additionally be solved with a distributionally robust optimization approach, which can offer a more realistic result. In conclusion, the findings of this study can assist SC decision-makers in healthcare in the context of developing countries in implementing an effective VSC network for improving public health outcomes.

CRediT authorship contribution statement

Naimur Rahman Chowdhury: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Writing – original draft, Research Administration, Supervision. Mushaer Ahmed: Conceptualization, Methodology, Formal analysis, Resources, Writing – original draft. Priom Mahmud: Methodology, Software, Validation, Formal analysis, Resources, Writing – original draft. Sanjoy Kumar Paul: Conceptualization, Investigation, Research Administration, Supervision, Writing – review & editing. Sharmine Akther Liza: Visualization, Data curation, Investigation, Writing – original draft.

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.

Data availability

Data used in this study are available from the corresponding author on reasonable request.

Appendix A

Table A1

| Parameter     | Distribution          | Parameter     | Distribution          |
|---------------|-----------------------|---------------|-----------------------|
| $bc_{cr}$     | Uniform [1, 1.7] ($)  | $cv_{d}$      | $10^5$ Uniform [5, 20] ($) |
| $bh_{cr}$     | Uniform [0.1, 0.3] ($) | $bc_{pd}$    | Uniform [0.2, 0.4] ($) |
| $aw_{cr}$     | Uniform [0.3, 0.9] ($) | $ac_{ck}$    | $10^5$ Uniform [15, 30] ($) |
| $rc_{11}$     | Uniform [6, 10] ($) (vaccine type 1) | $ac_{ck}$    | Uniform [15, 30] ($) |
| $rc_{21}$     | Uniform [5, 7] ($) (vaccine type 2) | $ep_{d}$     | Uniform [0.2, 0.8] (MTCE) |
| $rc_{31}$     | Uniform [4, 6] ($) (vaccine type 3) | $ep_{d}$     | Uniform [5, 25] (MTCE) |
| $rc_{41}$     | Uniform [8, 10] ($) (vaccine type 4) | $lp$         | Uniform [0.2, 0.3] (%) |
| $rc_{51}$     | Uniform [2, 6] ($) (packages) | $ep_{d}$     | $10^2$ Uniform [40, 65] (ton) |
| $rc_{61}$     | Uniform [1, 3] ($) (filling material) | $ep_{d}$     | 10 Uniform [5, 11] (ton) |
| $cv_{d}$      | $10^5$ Uniform [0.3, 0.6] (MTCE) | \[\epsilon_{1}, \epsilon_{2}\] | Uniform [1, 4] |
| $\theta_{pd}$ | Uniform [0.1, 0.3] (MTCE) | $lp$         | Uniform [0.1, 3] (pers.) |
| $l_{d}$       | $10^5$ Uniform [1, 5] (pers.) | $lp$         | Uniform [15, 40] (ton) |
| $ct_{d}$      | $10^5$ Uniform [0.8, 6] (ton) | $lp$         | $10^2$ Uniform [2, 6] (ton) |
| $n_{ac} - l_{ac}$ | $10^2$ Uniform [2, 6] (ton) | $lp$         | Uniform [2, 5] (ton) |
Table A2
Rank of solutions for SS1 from weightage normalized matrix in TOPSIS

| NDS point number in MOSEO | $f_1(\$)$ | $f_2$(MTCE) | $f_3$(persons) | Rank |
|---------------------------|------------|------------|----------------|------|
| 1  | 3,000,561  | 6953.12    | 2183           | 14   |
| 2  | 3,049,758  | 6756.9129  | 2348           | 15   |
| 3  | 3,105,750  | 6743.4624  | 2458           | 16   |
| 4  | 3,434,155  | 6611.20239 | 2551           | 8    |
| 5  | 3,547,812  | 6604.59779 | 2596           | 11   |
| 6  | 3,609,143  | 6230.75263 | 2641           | 3    |
| 7  | 3,619,212  | 6218.316   | 2795           | 6    |
| 8  | 3,790,121  | 6037.2     | 2799           | 5    |
| 9  | 3,866,017  | 5031.041   | 2921           | 1    |
| 10 | 4,058,341  | 4397.094   | 3063           | 2    |
| 11 | 4,161,792  | 4001.35554 | 3066           | 7    |
| 12 | 4,358,945  | 3881.31487 | 3128           | 4    |
| 13 | 4,773,917  | 3531.99654 | 3165           | 9    |
| 14 | 4,978,889  | 3249.43681 | 3436           | 13   |
| 15 | 5,153,614  | 2989.48187 | 3762           | 10   |
Liu, Y., Sandmann, F.G., Barnard, R.C., Pearson, C.A.B., Pastore, R., Pebody, R., Flashe, S., Jit, M., 2022. Optimising health and economic impacts of COVID-19 vaccine prioritisation strategies in the WHO European Region: a mathematical modelling study. The Lancet Regional Health - Europe 12, 100267. https://doi.org/10.1016/j.lanepe.2021.100267.

Liza, S.A., Chowdhury, N.R., Paul, S.K., Morshed, M., Morshed, S.M., Bhuiyan, M.A.T., Rahim, M.A., 2022. Barriers to achieving sustainability in pharmaceutical supply chains in the post-COVID-19 era. Int. J. Emerg. Mark. https://doi.org/10.1080/17410982.2021.1160380 (in press).

Mousavi, R., Salehi-Amiri, A., Zadeh, A., Hajighahre-Keshhtii, M., 2021. Designing a supply chain network for blood decomposition by utilizing social and environmental factor. Comput. Ind. Eng. 160, 107501. https://doi.org/10.1016/j.cie.2021.107501.

Mukherjee, S., Baral, M.M., Chittipaka, V., Pal, S.K., Nagarjir, R., 2022. Investigating sustainable development for the COVID-19 vaccine supply chain: a structural equation modelling approach. J. Humanit. Logist. Supply Chain Manag. https://doi.org/10.1080/JHSLCM-08-2021-00709 (in press).

Nasrollahi, M., Razmi, J., 2021. A mathematical model for designing an integrated pharmaceutical supply chain with maximum expected coverage under uncertainty. Operational Research 21 (1), 525–552. https://doi.org/10.1007/s12351-019-00450-3.

Ni, J., 2020. How China Can Rebuild Global Supply Chain Resilience after COVID-19, p. 2020. Retrieved April 4.

Nishanith, B., Priyanka, S., Kannan, V., Muhammad Raheel Basha, A., Dinesh, J., Muhammad Raheel Basha, A., Muruganandham, R., Harish, V., Muruganandham, R., 2020. Mathematical modelling of supply chain under current COVID-19 business scenario with the review study on the fuzzy logic based supply chains. European Journal of Molecular and Clinical Medicine 7 (2), 4972–4981. https://www.embase.com/search/results?subaction=viewrecord&id=L201048992&from=export.

Ocampo, L., Yamagishi, K., 2020. Modeling the lockdown relaxation protocols of the Philippine government in response to the COVID-19 pandemic: an intuitionistic fuzzy DEMATEL analysis. Soc. Econ. Plann. Sci. 72, 100911. https://doi.org/10.1016/j.seps.2020.100911.

Paul, S.K., Chowdhury, P., 2021. A production recovery plan in manufacturing supply chains for a high demand item during COVID-19. Int. J. Phys. Distrib. Logist. Manag. 51 (2), 104–125.

Paul, S.K., Chowdhury, P., Moktadir, M.A., Lau, K.H., 2021a. Supply chain recovery strategies in the wake of the COVID-19 pandemic. Comput. Ind. Eng. 158, 107401. https://doi.org/10.1016/j.cie.2021.107406.

Rahman, T., Taghikhah, F., Paul, S.K., Shukla, N., Agarwal, R., 2021b. An agent-based model for multi-period perishable pharmaceutical supply chain network design. J. Bus. Res. 136, 316–329. https://doi.org/10.1016/j.jbusres.2020.12.022.

Yadav, A.K., Kumar, D., 2022. A fuzzy decision framework of lean-agile-green (LAG) practices for sustainable vaccine supply chain. Int. J. Prod. Perform. Manag. https://doi.org/10.1108/IJPCC-08-2021-0079 (in press).

Zhong, N.S., Zheng, B.J., Li, Y.M., Poon, L.L.M., Xie, Z.H., Chan, K.H., Li, P.H., Tan, S.Y., Yu, D.E.C., Razon, L.F., Tan, R.R., 2020. Can global pharmaceutical supply chains scale from Bangladesh perspective. In: 2021 International Conference on Electronics, Communications and Information Technology (ICECIT) 14–16 September 2021, pp. 1–4. https://doi.org/10.1109/ICECIT49545.19.

Rahman, A., Islam, J., Karim, R., Kundu, D., Kabir, S., 2021a. An intelligent vaccine distribution process in COVID-19 pandemic through blockchain-SDN framework from Bangladesh perspective. In: 2021 International Conference on Electronics, Communications and Information Technology (ICECIT) 14–16 September 2021, pp. 1–4. https://doi.org/10.1109/ICECIT49545.19.

Rele, S., 2021. COVID-19 vaccine development during pandemic: gap analysis, opportunities, and impact on future emerging infectious disease development strategies. Hum. Vaccines Immunother. 17 (4), 1122–1126. https://doi.org/10.1089/hvim.2021.05990 (in press).

Rume, T., Islam, S.M.D.U., 2020. Environmental effects of COVID-19 pandemic and potential strategies of sustainability. Heliyon 6 (9), e04965. https://doi.org/10.1016/heliyon.2020.e04965.

Sandee Kumar, M., Maheshwari, V., Prabhj, J., Prasanna, M., Jayalakshmi, P., Suganya, P., Benjula Anbu Malar, M.B., Jothikumar, R., 2020. Social economic impact of COVID-19 outbreak in India. Int. J. Pervasive Comput. Commun. 16 (4), 309–319. https://doi.org/10.1016/j.fpcc.2020.06.0053.

Savadkhoohi, E., Moussazadeh, M., Torabi, S.A., 2018. A possibilistic location-inventory model for multi-period perishable pharmaceutical supply chain network design. Chem. Eng. Res. Des. 138, 490–505. https://doi.org/10.1016/j.cherd.2018.09.008.