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Inventory decisions on the transportation system and carbon emissions under COVID-19 effects: A sensitivity analysis

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**Abstract:** The COVID-19 pandemic has created multiple problems in the existing transportation system. The contribution of this study is to guide logistics managers as they make ordering decisions within a disrupted transportation system. In the overall supply chain system, inventory decisions have been either compromised or challenged. Traditional inventory decisions that consider preplanned transportation facilities (and speeds) are currently becoming obsolete, predominantly in post-COVID times due to delays in the delivery of products and higher delivery costs. Therefore, businesses such as retailers must align ordering and pricing decisions to maintain a sustainable profit. To address this issue, this study investigates optimum inventory decisions under the pandemic’s effects while considering the transportation cost as proportional to COVID-19 intensity. This study also considers product deterioration, time-dependent holding costs, price-dependent demands, and carbon emissions from vehicle operation and intends to establish a harmonious relationship among these attributes. The optimization of green technology investment is studied to reduce emissions due to transportation. Some theoretical derivations and numerical examples are given, and they are followed by a sensitivity analysis to extract important managerial insights into the effect of COVID-19. The manager can set an optimal selling price and the cycle length by carefully planning the number of trips in considering the rate of the outbreak and its effect on the increasing transportation cost.

1. Introduction

Inventory decisions are centered on the number and timing of orders, and they consider various costs and supply chain constraints. Inventory decisions affect company profits and are important regarding stock availability to secure consumer needs. These decisions are influenced by various transportation systems and their characteristics, such as availability, reliability, and cost. Among the many detrimental effects of COVID-19 on human health and the economy, COVID-19 has had an undeniable effect on overall supply chain problems and, more specifically, on transportation systems. Due to unexpected and unplanned lockdowns, the usual logistics and distribution activities have been profoundly disrupted. Twinn et al. (2020) showed some impacts, such as delivery delays, backlogs at container ports, shortages of truck drivers, and uncertain demand, especially for small trucking businesses, while Mogaji (2020) indicated an increase in tariffs in developing countries. Prior studies lack adaptations to these disruptions with respect to inventory and supply chain decisions (Ivanov and Das, 2020). Consequently, overall product availability has been challenged or compromised, which ultimately affects customers, such as in food and grocery markets (Mahajan & Tomar, 2020; Singh et al., 2020). Loske (2020) showed the changing volume and capacity in road transport due to panic buying in the early stage of the pandemic. This study argues that when disruption occurs, the transportation cost is proportional to
COVID-19 intensity. Therefore, the inventory decision model must consider the effect of variability in these costs.

The COVID-19 pandemic has been disrupting business systems such that supply, and demand are difficult to match, as the numbers of infections are still fluctuating (Poursoltan et al., 2021; Singh et al., 2020). The effect has continued after one year, and it is not known when it will end. Consequently, making optimal forecasts and decisions is still challenging for logistics managers. Jabbour et al. (2020) suggested managers focus on building smarter and more resilient systems to make a sustainable supply chain. Queiroz et al. (2020) proposed adaptation, digitalization, preparedness, recovery, ripple effects, and sustainability for supply chain operations to sustain the business during the COVID-19 pandemic, while Choi (2021) emphasized the importance of risk analysis in logistics systems to propose innovative solutions and strategies during the pandemic. Ivanov and Das (2020) discussed the existing resilient supply chain practices such as holding more inventory or having subcontracting facilities require further extensions because the COVID-19 pandemic is not limited to a region and time. The length of the pandemic, the likelihood that the transmission rate will re-increase, and the effects on businesses and finances are unknown. Many studies have identified new approaches and models as operational solutions for overcoming logistics disruptions. Alkahtani et al. (2021) investigated a variable production rate as a solution for manufacturers in a supply chain with disrupted demand during the COVID-19 pandemic. Recently, Mashud et al. (2021a) studied the optimum selling price and order decision in a supply chain under the COVID-19 pandemic by suggesting a hybrid payment to deal with any financial crisis that may occur.

Transportation activities, including the transportation of materials and products in the supply chain, are major carbon emitters. Emission levels are influenced by inventory decisions (Tiwari et al., 2018); for example, they may be related to the frequency of transportation and truckloads. Various studies have identified the optimum inventory decisions to minimize these emissions (Tiwari et al., 2019; Taleizadeh et al., 2020; Yu et al., 2020, etc.). Other studies have also involved decisions for green technology investment (Toptal et al., 2014; Mashud et al., 2020b; Mishra et al., 2021; etc.). Sarkis (2020) hoped that the economic recovery after the COVID-19 pandemic will not ignore the regulations and concerns for the environment that have been built so far. Therefore, in line with Sarkis (2020), this study links the effects of pandemics and efforts to reduce carbon emissions in inventory decisions.

Queiroz et al. (2020), Ivanov and Das (2020), and Choi (2021) suggested innovative solutions to deal with the logistics disruption during the COVID-19 pandemic. Recent studies from Alkahtani et al. (2021) and Mashud et al. (2021a) developed new inventory models to respond to the disruption in customer demand and financial difficulties of supply chain parties during the pandemic. However, they did not specifically consider the effect of the disrupted transportation system during the COVID-19 pandemic. This study aims to consider the practical influence of the COVID-19 pandemic on the transportation system and proposes an inventory decision model with increasing transportation costs under a pandemic rate function. This study considers a case in which truck drivers are unwilling to drive vehicles during the pandemic or request additional benefits. This situation depends on the rate of outbreaks of COVID-19. If the infectious rate is low, the drivers are willing to go on trips. If the risk is high, then the drivers claim additional payments are owed for their safety, hence, the total transportation cost increases. With this important criterion in mind, a pandemic function is included in the transportation cost, which will regulate the total cost. Further, the pandemic rate is affected by the vaccination program. Hence, how should the logistics manager adjust the ordering and pricing decisions considering the additional cost function? Given the desire to reduce carbon emission levels, how will these decisions affect the required green technology investments? In the end, how do the model parameters affect the total profit? A sensitivity analysis is needed to extract some important managerial insights about the effects of COVID-19 and changes in other parameters on green technology investments and profits. Fig. 1 illustrates the inventory problem of this study, under the transportation disruption during a pandemic.

This study contributes guidance to logistics managers of retailers in making ordering decisions given a disrupted transportation system. Simultaneously, managers can specify the optimum price by considering the variable transportation cost, the effect of deterioration, and an opportunity to reduce carbon emissions. This study links the disruption and green issues in the second model. The proposed models can be considered until the end of the COVID-19 pandemic and in similar situations in the future, which cannot be predicted. The major contributions are as follows:

- The synergy between pricing strategies and the inventory cycle of deteriorating products has been investigated since the flow of products fluctuates depending on the pandemic outbreak rate and impact of vaccination.
- A brief, clear view of the pandemic’s effect on the transportation system is illustrated by constructing a realistic pandemic function linked to the carbon emissions of the system. The pandemic function comprises the relation of infected and vaccinated populations.
- A flexible, environmentally sustainable system is presented that can control carbon emissions through green technology investments during the pandemic.

Fig. 1. Inventory problem under the transportation disruption, price-dependent demand, product deterioration, and green technology investment.
• Important managerial implications have been extracted from the experimental results, which will help any future practitioners and researchers.

In this study, Section 2 discusses the existing literature on logistics and supply chain systems during the COVID-19 pandemic, inventory decisions with pricing and deterioration effects, and green logistics that minimize carbon emissions. Section 3 describes the scope of the problem and the assumptions made in solving it. Sections 4 and 5 present the proposed mathematical model together with some theoretical derivations. Sections 6 and 7 study the system with some numerical examples and sensitivity analysis. Then, Section 8 identifies the managerial insights, and Section 9 provides the research conclusion.

2. Literature review

The COVID-19 pandemic, which has lasted more than a year and continues to disrupt logistics systems and supply chains in all countries, raises the need for fine-tuning managerial decisions (Kim, 2021; Pour-soltan et al., 2021). Through a literature study, Chowdhury et al. (2021) identified four main topics related to logistics systems in response to this pandemic, namely, the impact of the pandemic, strategies for responding to adversity, the role of technology, and the sustainability of the supply chain. Chen et al. (2020) studied the vehicle routing problem for serving some closed gated communities in a certain area. The study focused on food distribution services with contactless service due to communities’ isolation during the COVID-19 pandemic, and it optimized the routing to satisfy customers and reduce contact among the couriers. Choi (2020) analyzed mobile service operations to bring services near customers’ homes, and he suggested a government subsidy to make the distribution system financially viable. Patriarca et al. (2020) studied order quantity decisions given uncertain demand during a pandemic, and they assumed time-dependent and inventory rate-dependent demand and a variable deterioration rate. The study focused on the effect of demand uncertainty and showed the ability to identify optimum quantity ranges. However, the proposed model did not consider the disruption of transportation. Alkahtani et al. (2021) also investigated the disruption of supply chain demand during the COVID-19 pandemic from the manufacturer’s perspective. These authors assumed that the demand depends on the level of emergency or outbreak and proposed a variable production rate as a solution. Mashud et al. (2021a) focused on the financial problems that may occur in the supplier-retailer supply chain. Hence, the study suggested a hybrid payment system as the solution. However, the proposed model also lacks the consideration of different transportation costs from different levels of the outbreak.

Optimum order quantities and replenishment cycles have been considered the main decisions in inventory management. This field considers basic costs such as ordering, purchasing, holding, and transportation costs. According to Swenseth & Godfrey (2002), transportation costs can account for 50% of the total logistic costs. Rahman et al. (2016) incorporated the transportation cost as a function of the shipping weight and distance. The model considered a less-than-truckload transportation mode. Wangsa & Wee (2018, 2020) considered freight forwarding services that accumulate products during distribution. Recently, many authors have incorporated carbon emissions from transportation activities to develop green inventory models. The emissions from fuel combustion depend on several factors, such as the delivery distance, shipping quantity, product weight, and fuel efficiency (Tiwari et al., 2018; Daryanto et al., 2019; Wei & Daryanto, 2020; Daryanto & Wei, 2021). Moreover, a cold chain supply chain emits higher emissions from temperature-controlled vehicles and warehouses (Bozorgi et al., 2014; Hariga et al., 2018; Babagolzadeh et al., 2020). Similar to these studies, the proposed model incorporates carbon tax regulation to include the emission cost from transportation in the logistics costs.

The economic order quantity (EOQ) model with environmental concern has been studied for several years. Due to climate change, most of the studies incorporate carbon emission reduction. Bonney & Jaber (2011) and Hua et al. (2011) initiated the study by adding emission costs into the traditional EOQ model. The studies considered several emission sources, such as warehousing, transportation, and obsolete items. Hua et al. (2016), Tiwari et al. (2019), Shi et al. (2020), and Mishra et al. (2020) studied EOQ models with carbon emissions for deterioration products. Taleizadeh et al. (2020) and Yu et al. (2020) integrated order quantity and price decisions under the effect of carbon emissions. Recently, several researchers have boosted emission reductions by investing in green technology such as energy-efficient equipment and the use of renewable energy (Tiptal et al., 2014; Mashud et al., 2020b; Mishra et al., 2020; Mishra et al., 2021; Poursoltan et al., 2021). Lin (2018) focused on emission reduction from transportation activities to create a sustainable EOQ model. This study involves emission reductions through green technology investments by optimizing the investment cost per replenishment cycle.

Before the COVID-19 pandemic, researchers developed inventory models that consider disruptions in terms of supply, demand, and transportation (Wilson, 2007; Hishamuddin et al., 2013; Azad et al., 2014; Snyder, 2014; Paul et al., 2016; Taleizadeh, 2017). For example, Wilson (2007) studied a transportation disruption and investigated the impact on the different echelons of the supply chain using a system dynamic approach. This research focused on the transportation capacity, inventory fluctuation, and unfilled customer demand. Hishamuddin et al. (2013) and Azad et al. (2014) assumed a single disruption and considered the recovery time for production and distribution. The studies do not fit the COVID-19-caused disruption, as none of them considers the increasing transportation cost due to lockdowns and health protocols during a pandemic. Those studies are lacked consideration of the variability of transportation costs in different locations with different outbreak levels.

In a situation where the customer demand is price-dependent, the manager also needs to determine the optimal selling price. Naturally, the demand rate decreases with increasing price (Sana, 2011; Teksan & Geunes, 2016). Hence, the demand rate may follow a linear function with a decreasing price coefficient, as in Hasan, Mashud, Daryanto, & Wee, 2021. Another important factor in an inventory system is the deterioration rate. By nature, the quality and quantity of some products, such as fruits and vegetables, decrease over time (Wee, 1999; Widyadana et al., 2011). These losses should not be ignored, and many researchers have sought to reduce them (Hsu et al., 2010; Mashud et al., 2020a). Other researchers have investigated inventory decisions under the effects of both price-dependent demand and product deterioration (Hasan, Mashud, Daryanto, & Wee, 2021; Mashud, Hasan, Wee, & Daryanto, 2020a; Sana, 2011). This study considers both factors, together with the effects of transportation disruptions and emission reductions.

In summary, this study meets the challenges of inventory decisions under a transportation disruption, such as during the COVID-19 pandemic. COVID-19 has spread all over the world with different outbreak levels in different areas and affected logistics operations. Although many have studied logistics decisions to deal with the COVID-19 pandemic’s impact, these studies investigated inventory decisions and were challenging. Recent studies from Patriarca et al. (2020), Alkahtani et al. (2021) and Mashud et al. (2021a) proposed inventory decision models to address the effect or disruption caused by this pandemic. However, none of them considers the increase and variability of transportation costs. Queiroz et al. (2020) found that distribution (including transportation) has emerged as one of the main challenges during the pandemic. Considering the variability of transportation costs due to lockdowns and health protocols, this study investigates the optimum replenishment cycle and selling price. Furthermore, we provide a second case in which green investment is optimized to make the inventory model sustainable. Sarkis (2020) argued that the pandemic has
shown that sustainability with its three concerns (i.e., the economic profit and cost, social safety and health, and environment) is indivisible.

3. Problem definition, assumptions and notations

The effect of COVID-19 on the transportation system and inventory decision model is presented in terms of problem descriptions and assumptions. The associated notations are also given.

3.1. Problem definition

The supplier-retailer-customer supply chain of deteriorating items is discussed in this study. This study involves a retailer that purchases products from a supplier such that the transportation cost becomes the retailer’s responsibility. During the COVID-19 pandemic, the transportation system has experienced difficulties due to lockdowns and health protocols. Hence, for transporting products to its warehouse, the retailer needs to pay extra money, which depends on the outbreak level and impact of vaccination.

When transporting products, carbon emissions are produced by the vehicle. Hence, green technology investment is considered to reduce carbon emissions. Two cases of systems with and without green investment are investigated to study the effect on the total profit. Furthermore, when certain products are stored in a warehouse, their freshness decreases due to deterioration. Due to the covid pandemic, the transportation cost increases depending on the infection rate. In contrast, the influence of the vaccination process reduces the disruption. The customer demand for the products depends on the selling price such that if the retailer raises the selling price of the product, demand decreases. Therefore, the retailer also tries to increase profit by optimizing the selling price. Considering the total inventory costs and demand characteristics, the order quantity is specified by optimizing the cycle time.

3.2. Assumptions

The model was developed based on the following assumptions and notations:

\( a \) The demand rate \( D_m = \alpha - \beta P_0 \) is a linear function of the selling price \( P_0 \) with \( \alpha \) and \( \beta \), and this rate is the constant part and price coefficient of the demand function \( (\alpha > 0 \text{ and } \beta > 0) \), which is similar to Hasan, Mashud, Daryanto, & Wee, 2021.

\( b \) The lead time is negligible or zero.

\( c \) The transportation costs consist of variable and fixed parts with additional emission costs, and this setup is similar to Daryanto & Wee (2021). Additionally, carbon tax pricing is applied.

\( d \) A constant deterioration rate is applied, and no replacement or repair of deteriorated items is allowed during the period of the replenishment cycle \( [0, T] \).

\( e \) Shortages are not allowed.

\( f \) The rate of intensity of COVID-19 outbreaks is considered constant during a cycle.

\( g \) The effectiveness of the vaccine is 100%. Initial vaccinated people must be less than the total people i.e., \( V_r < P \). The infection rate \( r \) lies in \( [0, 1] \) and the vaccination rate \( V_r \) is positive i.e., \( V_r > 0 \). No one will be infected if there are no infected people.

\( h \) To hold products in a retailing house, the retailer always seeks a fixed arrangement of holding facilities, and variable facilities

Table 1

| Notations | Description |
|-----------|-------------|
| \( t \) | the vehicle fuel consumption when empty |
| \( c_t \) | fixed transportation cost |
| \( c_f \) | fuel consumption per ton of payload |
| \( d_s \) | delivery distance to the retailer warehouse |
| \( c_r \) | carbon emission cost per unit distance of delivery |
| \( e_r \) | carbon emission cost per unit item per unit distance of delivery |
| \( E \) | the efficiency of greener technology for emission reduction, \( E \geq 0 \) |
| \( f_p \) | the fuel price |
| \( b_h \) | per unit holding cost |
| \( M \) | Maximum carbon emission reduction from the green technology investment, \( 0 < M < 1 \) |
| \( O_z \) | ordering cost |
| \( P_u \) | unit purchase cost |
| \( r \) | the rate of intensity of COVID-19 outbreaks |
| \( \beta \) | rate of change of vaccination acceleration |
| \( w \) | product weight |
| \( \epsilon \) | deterioration rate |
| \( \eta \) | number of trips |

Fig. 2. Research methodology.
depend on the quantity of products that must be held. Thus, a realistic holding cost is considered here. This cost has two parts, where one is constant, and the other variable is similar to Mashud et al. (2021c). The complete list of notations is provided in Table 1.

(i) The cycle will be repeated over an infinite planning horizon as similar to the work of (Tiwari et al. 2019; Mishra et al. 2021).

4. Mathematical models

This paper considers the increasing transportation costs as the effect of the COVID-19 outbreak and investigates two different cases. Whereas the first case only involves the impact of the COVID-19 outbreak on transportation, the second case incorporates green technology investment, as the retailer is willing to be environmentally friendly. The research methodology is presented in Fig. 2. The following sections provide the corresponding mathematical models and discussion for the two cases.

4.1. Case I (Considering the effect of COVID-19 on transportation)

During the inventory cycle [0, T], the level of stock at any time \( t \) is given by the function \( I(t) \), as shown in Fig. 3. The rate of the inventory level decreases in accordance with the demand rate (\( D_{m} \)) and the deterioration rate (\( \epsilon \)) of the available inventory level. At the beginning of the cycle (\( t = 0 \)), the inventory level is equal to the order quantity (\( N \)). At the end of the replenishment cycle (\( t = T \)), the inventory level is zero. Therefore, the inventory level at time \( t \) is governed by the following differential equation:

\[
\frac{dI(t)}{dt} = -(D_{m} + \epsilon I(t)), \quad 0 \leq t \leq T
\]

where \( D_{m} = \alpha - \beta p_{p} \) and the boundary conditions are \( I(0) = N \) and \( I(T) = 0 \).

Considering the boundaries, Eq. (1) becomes

\[
\frac{dI(t)}{dt} + \epsilon I(t) = -D_{m}, \quad 0 \leq t \leq T
\]

The solution of differential Eq. (2) is

\[
I(t) = -\frac{D_{m}}{\epsilon} + Ce^{-\epsilon t}
\]

As \( I(0) = N \), Eq. (3) becomes

\[
C = N + \frac{D_{m}}{\epsilon}
\]

By substituting the value of \( C \) into Eq. (3), we obtain

\[
I(t) = -\frac{D_{m}}{\epsilon} + \frac{D_{m}}{\epsilon} e^{-\epsilon t}
\]

Again, using the boundary condition \( I(T) = 0 \), we derive

\[
N = \frac{D_{m}}{\epsilon} (e^{\epsilon T} - 1)
\]

Substituting the value of \( N \) into Eq. (5) and simplify, one can get

\[
I(t) = \frac{D_{m}}{\epsilon} (e^{\epsilon T} - 1)
\]

The profit function of the system depends on the following costs and revenue component:

(1) Cost for ordering (OC). The cost of placing an order per cycle is \( OC = O \).

(2) Purchase cost (PC). The purchasing cost per cycle is

\[
PC = P_{c} N = \frac{P_{c} D_{m}}{\epsilon} (e^{\epsilon T} - 1)
\]

(3) Holding cost (HC). The holding cost depends on the inventory level and varies over time. If \( h_{u} \) is known and \( g \) and \( h \) are the respective constant part and time-reliant part of the holding cost, then the holding cost per cycle is

\[
HC = h_{u} \int_{0}^{T} (g + h t) I(t) \, dt
\]

\[
= \frac{h_{u} D_{m}}{2\epsilon^{2}} \left[ 2e^{\epsilon T}(h + g \epsilon) - 2g \epsilon (1 + T \epsilon) - h(2 + T \epsilon) (2 + T \epsilon) \right]
\]

(4) Transportation cost (TC). The transportation cost consists of a fixed transportation cost (\( c_{f} \)), variable transport costs, and a carbon emission cost. The travel distance (\( 2d_{s} \)) by the truck is counted with the incoming and outgoing travels. The variable transport cost is the total fuel consumption (\( 2d_{s} c_{f} \)) multiplied by the fuel price (\( f_{p} \)). Additional fuel consumption occurs based on the truckload. Hence, a one-way distance (\( d_{s} \)) multiplied by the fuel consumption per ton of payload (\( c_{f} \)), product weight (\( w \)), order quantity (\( N \)), and \( f_{p} \). The carbon emission cost is the travel distance (\( 2d_{s} \)) multiplied by the unit carbon cost and carbon emission cost from the truckload. Therefore, with \( \eta \) trips per cycle
as like the work of Sultana et al. (2022) the total transportation cost per cycle is

\[
TC = \eta \left[ \left( \frac{d_e c_e N_w}{\eta} \right) + \left( \frac{2d_e c_e N}{\eta} \right) \right] = \left[ \left( \frac{c_m}{\eta} + \frac{2d_m}{\eta} \right) \right] + \left( \frac{d_m}{\eta} \right) \left( e^{eT} - 1 \right)
\]

(11)

However, due to COVID-19 being around the globe, most places are partially or completely locked down. This circumstance increases transportation and logistics costs. This study considers the situation in which the effect depends on the rate of the COVID-19 outbreaks.

\[
\omega(S_p, T) = \frac{1}{T} (SR - OC - PC - HC - TC)
\]

(16)

In a town the total population is \( P \). The covid spreads among these people with an infection rate \( r \). However, the vaccination process is continued; the rate of change of vaccination acceleration is \( \eta \). Then the developed covid function \( I_p(t) \) with initial infected people \( b \) and initial vaccinated people \( V_0 \) is the Eq. (12). The details are discussed in Appendix A.

\[
I_p(t) = \frac{b e^r P (P - V_0)}{P (P - V_0) + (v \pi T + P) (be^r - b)}
\]

(12)

For example, for total population \( P = 1000 \); infected rate \( r = 0.3 \); the rate of change of vaccination acceleration \( \eta = 0.5 \); initial infected people \( b = 100 \); and initial vaccinated people \( V_0 = 200 \) the infected function Eq. (12) is represented in Fig. 4.

Normalized covid infected function \( \phi(T) \) is as follows

\[
\phi(T) = \frac{I_p(T)}{P} = \frac{b e^r (P - V_0)}{P (P - V_0) + (v \pi T + P) (be^r - b)}
\]

(13)

The normalized covid indicator function is \( \phi(T) \). Taking this important criterion in mind, the transportation cost increases \( M_\phi \phi \) times of the original transportation cost that is \( TC = TC \times (1 + M_\phi \phi) \). This transportation cost becomes highest when the covid indicator function is at peak. Therefore, the complete transportation cost is

\[
TC = \left[ \left( \frac{c_m}{\eta} + \frac{2d_m}{\eta} \right) \right] + \left( \frac{d_m}{\eta} \right) \left( e^{eT} - 1 \right) + \left( \frac{d_m}{\eta} \right) \left( e^{eT} - 1 \right)
\]

(14)

4.2. Case II (Considering the effect of COVID-19 on transportation and green investment)

Although the rush of the transportation system has declined during the pandemic, \( CO_2 \) is still emitted by transport vehicles, and this gas damages the balance of the environment. To curb \( CO_2 \) emissions from transportation, green technology is implemented in this case. To implement this technology, capital investment is needed. A fraction of the emission reduction \( H = M(1 - e^{-G_1}) \) is considered in a similar manner to Mashud et al. (2021b). The value of \( H = 0 \) when there is no green investment \( G_1 = 0 \) and equals \( M \) when \( G_1 \rightarrow \infty \). The investment cost function \( H(G_i) \) is continuously differentiable with \( H'(G_i) > 0 \) and \( H'(G_i) < 0 \).

The retailer optimizes \( G_i \) to reduce the emissions. The Green Technology cost (GTC) is

\[
GTC = G_i T
\]

(17)

Considering the reduction in transportation carbon emissions, one can rewrite the transportation cost as

\[
SR = S_p \int_0^T D_w dt = S_p D_w T
\]

(15)

Finally, the total profit per unit of time can be written as follows:
Theoretical derivations

This section presents some theoretical derivations for the proposed two cases. Then, the solution algorithms are developed.

\[
TCG = \left[ \frac{c_i \eta + 2d_i c_i f_i \eta + D_m d_i c_i w_i f_p (e^{T_1} - 1)}{e^{T_1}} \right] + (1 - H) \left[ \frac{2d_i c_i f_i \eta + D_m d_i c_i w_i f_p (e^{T_1} - 1)}{e^{T_1}} \right] \left( 1 + \frac{M_p b e^{T_1} (P - V_0)}{P(P - V_0) + (v_i T + P) (be^{T_1} - b)} \right)
\]

(18)

Then, the total profit function becomes

\[
\omega(S_p, T, G) = \frac{1}{T} \left( SR - OC - GTC - PC - HC - TCG \right)
\]

(19)

5. Theoretical derivations

This section presents some theoretical derivations for the proposed two cases. Then, the solution algorithms are developed.

Proposition 1. The profit function \(\omega(S_p, T)\) in Eq. (16) is concave in terms of selling price \(S_p\) when replenishment cycle \(T\) is considered constant with \(\beta > 0\) and the optimal \(S_p^*\) is as follows:

(a)

\[
S_p^* = \frac{1}{T} \left[ \frac{2a}{\beta} + \left( \frac{2e^{T_1} (h + g e) - 2g e (1 + T e) - h (2 + T e (2 + T e))}{Te^{T_1}} \right) h_a + \frac{2(-1 + e^{T_1}) P_n}{Te^{T_1}} \right]
\]

5.1. For Case 1 (Considering the effect of COVID-19 on transportation without green investment)

The following propositions confirms the profit maximization of this

(b) The solution \(S_p^*\) in (a) satisfies the sufficient condition for the retailer’s maximum profit.
Proof. The retailer profit function from Eq. (16) can be written as:

\[
\omega(S_p, T) = \frac{1}{T} \left[ S_p D_m T - O_s - \frac{P D_m}{e} (e^T - 1) - \frac{h S_p^2}{2e} \left[ 2e^{T_s} (h + g \epsilon) - 2g \epsilon (1 + T \epsilon) \right] - h(2 + T \epsilon (2 + T \epsilon)) \right] - \frac{h P s}{e (e^T - 1)} \left( d, \epsilon + wc \right) \left( 1 + \frac{M_p b e^{T_s} (P - V_0)}{h (-1 + e^{T_s}) (P + T^3 v_1) + P (P - V_0)} \right)
\]  

(20)

where \( D_m = \alpha - \beta S_p \).

After differentiating Eq. (20) with respect to \( S_p \), we obtain.

\[
\frac{d\omega}{dS_p} = \left[ \frac{h \beta}{2T \epsilon} \left( 2e^{T_s} (h + g \epsilon) - 2g \epsilon (1 + T \epsilon) - h(2 + T \epsilon (2 + T \epsilon)) \right) + \frac{\beta P}{T \epsilon} (e^{T_s} - 1) \right] \left( a - 2S_p \beta + \frac{\beta d \epsilon}{T \epsilon} (e^{T_s} - 1) \right) (e_s + wc \beta) \left( 1 + \frac{b e^{T_s} M_p (P - V_0)}{h (-1 + e^{T_s}) (P + T^3 v_1) + P (P - V_0)} \right)
\]  

(21)

By setting the above equation equal to zero, one can find the critical value as

\[
S_p = \frac{1}{4} \left[ \frac{2a}{\beta} + \frac{2e^{T_s} (h + g \epsilon) - 2g \epsilon (1 + T \epsilon) - h(2 + T \epsilon (2 + T \epsilon))}{T \epsilon} \frac{h_s}{e_s + wc \beta} + \frac{2(-1 + e^{T_s}) P_s}{T \epsilon} \right] + \frac{b e^{T_s} M_p (P - V_0)}{h (-1 + e^{T_s}) (P + T^3 v_1) + P (P - V_0)} \left( a - 2S_p \beta + \frac{\beta d \epsilon}{T \epsilon} (e^{T_s} - 1) \right) (e_s + wc \beta) \left( 1 + \frac{b e^{T_s} M_p (P - V_0)}{h (-1 + e^{T_s}) (P + T^3 v_1) + P (P - V_0)} \right)
\]  

(22)

Again, by differentiating Eq. (21) with respect to \( S_p \), we obtain

\[
\frac{d^2\phi}{dS_p^2} = -2\beta
\]  

(23)

If \( \beta > 0 \), then the second derivative of the profit function \( \omega(S_p, T) \) becomes negative, which implies that for the critical point \( S_p \), we obtain a maximum value of \( \omega(S_p, T) \). The critical point \( S_p \) becomes the optimal point or a saddle point, which proves part (a) of the proposition.

By substituting for the value of \( S_p \) in Eq. (23) with any value of \( \beta \), we obtain

\[
\left[ \frac{d^2\phi}{dS_p^2} \right]_{S_p=S_p^*} = -2\beta < 0
\]

Since \( \beta > 0 \), the above second-order derivative is negative, so at the point \( S_p = S_p^* \) we have a maximum value of the profit function \( \omega(S_p, T) \). This fact proves the second part (b) of the proposition. □.

Proposition 2. For any fixed value \( S_p \), the retailer profit function \( \omega(S_p, T) \) is concave down. Hence, there exists an optimum point \( T = T^* \), which is found by the following equation.
\[
\frac{h_0}{2e^\epsilon} (a - S_0) \left[ (e^{\epsilon s} (h + g\epsilon) (1 - \epsilon T) - 2g\epsilon + h(T^2 \epsilon^2 - 2) \right] + O_\epsilon + \frac{P_a}{\epsilon} (a - S_0) \left( e^{\epsilon s} - T e^{\epsilon s} - 1 \right) + \\
\left( \eta c_1 + 2\eta d_1 c_1 + 2\eta d_1 c_1 f_1 - T e^{\epsilon s} (a - S_0) (d_1 e_1 + wc d_1 f_1) \right) \left( 1 + \frac{\beta e^{\epsilon T} e_2}{(be^{\epsilon T} - b)(P + T^2 \epsilon) + P(P - V_0)} \right) \\
+ T \left( \frac{1}{\epsilon} (e^{\epsilon s} - 1) (a - S_0) (d_1 e_1 + wc d_1 f_1) \right) \left( \frac{3 (be^{\epsilon T} - b) T^2 \epsilon + rb (P + T^2 \epsilon) - rP (P - V_0)}{(be^{\epsilon T} - b)(P + T^2 \epsilon) + P(P - V_0)^2} \right) = 0
\]

(24)

**Proof.** This proof is similar to that of Proposition 1. To avoid redundancy, the same solution procedures are omitted in this theoretical derivation. □

**Proposition 3.** The profit function \(\omega(S_0, T)\) is concave with respect to \(S_0\) and \(T\).

**Proof.** The retailer’s profit function from Eq. (16) is

\[
\omega(S_0, T) = \frac{1}{T} \left[ S_0 D_0 T - O_\epsilon - \frac{P_a}{\epsilon} (a - \beta S_0) (e^{\epsilon T} - 1) - \frac{h_0 D_0}{2e^\epsilon} \left( 2e^{\epsilon s} (h + g\epsilon) - 2g\epsilon (1 + T\epsilon) \right) - h(2 + T\epsilon (2 + T\epsilon)) \right] \\
\left( \frac{P_a}{\epsilon} (e^{\epsilon s} - 1) (d_1 e_1 + wc d_1 f_1) \right) \left( 1 + \frac{M_b e^{\epsilon T} (P - V_0)}{P(P - V_0) + (\nu, T^2 + P)(be^{\epsilon T} - b)} \right)
\]

(25)

where

\[
D_m = a - \beta S_0.
\]

By inserting the values \(D_m = a - \beta S_0\) in Eq. (25), we obtain

\[
\omega(S_0, T) = \frac{1}{T} \left[ S_0 T (a - \beta S_0) - O_\epsilon - \frac{P_a}{\epsilon} (a - \beta S_0) (e^{\epsilon T} - 1) - \frac{h_0}{2e^\epsilon} (a - \beta S_0) \left( 2e^{\epsilon s} (h + g\epsilon) - 2g\epsilon (1 + T\epsilon) \right) - h(2 + T\epsilon (2 + T\epsilon)) \right] \\
\left( \frac{P_a}{\epsilon} (e^{\epsilon s} - 1) (d_1 e_1 + wc d_1 f_1) \right) \left( 1 + \frac{M_b e^{\epsilon T} (P - V_0)}{P(P - V_0) + (\nu, T^2 + P)(be^{\epsilon T} - b)} \right)
\]

(26)

Here, \(\Omega_1, \Omega_2, \Omega_3, \Omega_4, \Omega_5\) are positive.

To maximize the total profit function \(\omega(S_0, T)\), we can calculate first-order partial derivatives of \(\omega(S_0, T)\) from Eq. (27) with respect to \(S_0\) and

\[
\omega(S_0, T) = \frac{1}{T} \left[ S_0 T (a - \beta S_0) - (a - S_0) (e^{\epsilon s} - T\epsilon e^\epsilon + 1) (\Omega_5 - \frac{h_0}{2e^\epsilon} (a - S_0) (e^{\epsilon s} - 1) (a - S_0) P_a) \right] \\
\left( \frac{P_a}{\epsilon} (e^{\epsilon s} - 1) (a - S_0) \Omega_1 \right) \left( 1 + \frac{\epsilon^T \Omega_1}{be^{\epsilon T} (P + T^2 \epsilon) + P(P - V_0) + \Omega_1} \right) - O_e
\]

(27)
Then set these partial derivatives equal to zero. Hence, we obtain

\[
\frac{\partial \omega}{\partial S_p} = \left[ \frac{(e^\psi - 1)\beta P_p}{2e^\psi} + \frac{\beta e^\psi (e^\psi - 1)}{2e^\psi} \left( 1 + \frac{e^\psi \Omega_1}{2e^\psi} \right) \right] + \alpha - 2S_p\beta - \frac{\beta h_0}{2Te^\psi} (2T^2 e^\psi + (1 - e^\psi + Te^\psi) \Omega_1)
\]

(29)

The Hessian matrix of the profit function is

\[
\frac{\partial^2 \omega}{\partial S_p^2} = \left[ \frac{h_0 (\alpha - S_p\beta) (be^\psi T^2 + (e^\psi - 1) \Omega_1) + (e^\psi \varepsilon T e^\psi - 1) (\alpha - S_p\beta) P_p}{2e^\psi} \right] + \left( \Omega_1 + \frac{\Omega_2}{\varepsilon} (\alpha - S_p\beta) (e^\psi - 1 - \varepsilon T e^\psi) \right) \left( 1 + \frac{e^\psi \Omega_1}{2e^\psi} \right) - 2Te^\psi (e^\psi - 1 - \varepsilon T e^\psi)^2
\]

(30)

By solving \( \frac{\partial \omega}{\partial S_p} = 0 \) and \( \frac{\partial \omega}{\partial T} = 0 \) simultaneously from Eqs. (29) and (30), we obtain the critical points of \( S_p \) and \( T \), which are denoted by \( S_p^* \) and \( T^* \), respectively.

After finding the second derivative of the profit function from Eq. (27), we obtain

\[
\frac{\partial^2 \omega}{\partial S_p^2} = -2\beta
\]

(31)

By solving \( \frac{\partial \omega}{\partial S_p} = 0 \) and \( \frac{\partial \omega}{\partial T} = 0 \) simultaneously from Eqs. (29) and (30), we obtain the critical points of \( S_p \) and \( T \), which are denoted by \( S_p^* \) and \( T^* \), respectively.

The first principal minor is

\[ |H_{11}| = -2\beta \]

where \( \beta \) is the coefficient of the price in the demand rate, which is always greater than 0. Hence, \( |H_{11}| < 0 \). Additionally, the second principal minor is

\[
\frac{\partial^2 \omega}{\partial T^2} = \left[ \frac{2e^\psi (1 + e^\psi (e^\psi - 1)) P_p - h_0 (hT e^\psi + (1 - Te^\psi) \Omega_1)}{2h_1} \right] - 2\frac{\varepsilon T e^\psi (e^\psi - 1 - \varepsilon T e^\psi)^2}{h_1 e^\psi}
\]

(32)

\[
\frac{\partial^2 \omega}{\partial T \partial S_p} = \left[ \frac{2e\Omega_1 + D_\alpha h_1 h_3 P_p + \frac{(2e\Omega_1 + \Omega_1 D_\alpha h_1)(h_1 + \Omega_1 e^\psi)}{h_1} + \frac{\Omega_1 e^\psi h_1 h_3 + \Omega_1 h_1 h_3}{h_1} + \frac{D_\alpha h_1 h_3 \Omega_1}{2e^\psi}}{h_1} \right] - \frac{e^\psi \Omega_1}{h_1} \left[ \frac{3hT e^\psi (1 - Te^\psi (2 + rT)) (h_1 + \varepsilon T e^\psi D_\alpha \Omega_1) h_1 + h_1 h_3 + h_1 h_3}{h_1} \right]
\]

(33)

where

\[
D_\alpha = \alpha - S_p\beta
\]

\[
h_1 = be^\psi P + b(e^\psi - 1) T^3 v_i + \Omega_4
\]
The Hessian matrix for \( \omega(S_p, T) \) will be negative definite if the second principal minor is \( |H_{22}| > 0 \). For these the condition arises as follows

\[
\begin{align*}
|H_{22}| & = \frac{\beta}{4T^6} \left[ 2\epsilon_0 + \frac{2\epsilon \Omega_1 + \epsilon \Omega_2 \tilde{h}_1 H_1}{h_1} + \frac{\epsilon \Omega_2 \tilde{h}_2}{h_1'} + \frac{D_a \tilde{h}_1 H_1}{2\epsilon^2} + \right. \\
& \quad \left. \frac{\epsilon^2 T \Omega_2}{h_1'} \right] \\
& = \frac{\beta}{4T^6} \left[ 2\epsilon_0 (1 + \epsilon^2 (T - 1)) p - h_1 (h^T \epsilon^2 + (\epsilon^2 (1 - T \epsilon) - 1) \Omega_1) - \\
& \quad 2\epsilon \Omega_1 \epsilon^2 T \epsilon^2 (\epsilon^2 - 1) h_2^2 - 2\epsilon \Omega_1 \epsilon^2 (\epsilon^2 - 1) \left( \frac{\epsilon^2 \Omega_1}{h_1} \right) \right]^2
\end{align*}
\]

Considering the condition in Eq. (34), the Hessian matrix for \( \omega(S_p, T) \) is negative definite, one can easily conclude that the profit function \( \omega(S_p, T) \) is a strictly concave function with respect to \( S_p \) and \( T \). This

\[
\begin{align*}
\begin{align*}
& = \frac{\beta}{4T^6} \left[ 2\epsilon_0 (1 + \epsilon^2 (T - 1)) p - h_1 (h^T \epsilon^2 + (\epsilon^2 (1 - T \epsilon) - 1) \Omega_1) - \\
& \quad 2\epsilon \Omega_1 \epsilon^2 T \epsilon^2 (\epsilon^2 - 1) h_2^2 - 2\epsilon \Omega_1 \epsilon^2 (\epsilon^2 - 1) \left( \frac{\epsilon^2 \Omega_1}{h_1} \right) \right]^2
\end{align*}
\end{align*}
\]

Fig. 5. A situation during the pandemic at a truck station.
implies that there are only one critical point \((S_p, T)\) which is optimal point \((S_p^*, T^*)\). Hence, our objective function \(\mathcal{w}(S_p, T)\) reaches the global maximum value at point \((S_p^*, T^*)\). □.

5.2. For Case II (Considering the effect of COVID-19 on transportation with green investment)

The challenges of COVID-19 on transportation system are consid-

\[
\xi_1 = Md_1e^{-EG} (e^{EG} - 1) (e_sD_s (1 + e^{EG} (T \xi - 1)) - 2e\eta e_s) - D_s (1 + e^{EG} (T \xi - 1)) \Omega_2
\]
\[
\xi_2 = Md_1 (e^{EG} - 1) \left( D_s e_s (e^{EG} - 1) + 2e\eta e_s \right) - e^{\delta T} (e\Omega_1 + D_s \Omega_1 (e^{\delta T} - 1))
\]
\[
\xi_3 = \alpha - \beta S_p
\]

\[\Omega_1, \Omega_2, \Omega_3, \Omega_4, \Omega_5\] are describe in Eq. (28).

**Proposition 4.** The profit function \(\mathcal{w}(S_p, T, G_i)\) in Eq. (19) is concave in terms of selling price \(S_p\), replenishment cycle \(T\), and green investment \(G_i\). There exists a unique optimal point \((S_p^*, T^*, G_i^*)\) which is find by solving the following system of equation:

\[
\frac{d\mathcal{w}(S_p, T, G_i)}{dS_p} = 0
\]

\[
\frac{d\mathcal{w}(S_p, T, G_i)}{dT} = 0
\]

\[
\frac{d\mathcal{w}(S_p, T, G_i)}{dG_i} = 0
\]

**Proof.** Using Eq. (19), we see that the objective function for Case II is highly nonlinear. Indeed, this function is very similar to Eq. (16). Thus, to avoid the redundancy of the same solution procedures (i.e., theories and their corresponding proofs), we have omitted the theoretical derivations. □.
5.3. Algorithms

For numerically optimize of profit function \( \omega \) one can use the following algorithm.

5.3.1. Algorithm for Case I with a single decision variable \( S_p \)

Step 1. Input all the parameters value \( \left( O_i, \alpha, \beta, P_i, \lambda_i, g, h, \mu_i, c_{j1}, d_{j1}, w_{j1}, e_{j1}, r_{j1}, V_i, P_i, b, V, M_p \right) \).

Step 2. Evaluate the value of \( S_p \) from Eq. (20) using all the parameters and the value of\( S_{p}^* \).

Step 3. Output the optimal value of \( S_{p}^* \) and \( \omega \).

Step 5. End.

5.3.2. Algorithm for Case I with a single decision variable \( T \)

Step 1. Input all the parameters value \( \left( O_i, \alpha, \beta, P_i, \lambda_i, g, h, \mu_i, c_{j1}, d_{j1}, w_{j1}, e_{j1}, r_{j1}, V_i, P_i, b, V, M_p, T \right) \).

Step 2. Declare \( \psi(T) \) left hand side of the Eq. (24).

Step 3. Take \( T_0 \) where \( T_0 > 0 \) and iterative variable \( i = 0 \).

Step 4. Evaluate \( \psi(T_0) \) using all the parameters and the value of \( T_0 \).

Step 5. IF \( \psi(T_0) \) = 0, Go to Step 3.

Step 6. Set \( T_1 = T_0 - \frac{\psi(T_0)}{\psi'(T_0)} \).

Step 7. IF \( |T_1 - T_0| < \varepsilon \) Go to Step 8 (where \( \varepsilon \) is a small value).

Step 8. Update \( T_0 = T_1 \) and \( i = i + 1 \). Go to Step 5.

Step 9. Calculate \( \omega(S_p, T_1) \) from Eq. (16) using all the parameters.

Step 10. Output the optimal value of \( T_1 \) and optimal profit \( \omega \).

Step 11. End.

5.3.3. Algorithm for Case I with two decision variables \( S_p, T \)

Step 1. Input all the parameters value \( \left( O_i, \alpha, \beta, P_i, \lambda_i, g, h, \mu_i, c_{j1}, d_{j1}, w_{j1}, e_{j1}, r_{j1}, V_i, P_i, b, V, M_p, S_p, T \right) \).

Step 2. Evaluate additional sub equations from Eq. (28) using the parameters.

Step 3. Declare \( \chi(S_p, T) = \frac{\psi}{\psi'} \) and \( \psi(S_p, T) = \frac{\omega}{\omega'} \) from Eqs. (29) and (30).

Step 4. Take \( S_{p0}, T_0 \) where \( S_{p0} > 0, T_0 > 0 \) and iterative variable \( i = 0 \).

Step 5. Evaluate \( D = \begin{bmatrix} \frac{\partial \chi}{\partial S_p} (S_{p0}, T_{0}) & \frac{\partial \chi}{\partial T} (S_{p0}, T_{0}) \\ \frac{\partial \psi}{\partial S_p} (S_{p0}, T_{0}) & \frac{\partial \psi}{\partial T} (S_{p0}, T_{0}) \end{bmatrix} \).

Step 6. IF \( D = 0 \) and \( i = 0 \), Go to Step 3. ELSE IF \( D = 0 \) and \( i \neq 0 \), Go to Step 11.

Step 7. Evaluate \( h = \begin{bmatrix} \frac{\partial \chi}{\partial S_p} (S_{p0}, T_{0}) \frac{\partial \chi}{\partial T} (S_{p0}, T_{0}) \\ \frac{\partial \psi}{\partial S_p} (S_{p0}, T_{0}) \frac{\partial \psi}{\partial T} (S_{p0}, T_{0}) \end{bmatrix} \) and \( k = \)...

\[ \frac{\partial \chi}{\partial S_p} (S_{p0}, T_{0}) \frac{\partial \chi}{\partial T} (S_{p0}, T_{0}) \]
Fig. 9. Profit function ($\omega$) with regard to: (a) selling price ($S_p$) & cycle time ($T$); (b) selling price ($S_p$) & green technology investment ($G$); (c) cycle time ($T$) & green technology investment ($G$).

Fig. 10. COVID-19 effect on profit function Case I and Case II.
Step 8. Set $S_{p1} = S_{p0} - h$ and $T_1 = T_0 - k$.

Step 9. IF $|S_{p1} - S_{p0}| < \sigma$ and $|T_1 - T_0| < \sigma$, Go to Step 11 (where $\sigma$ is small value).

Step 10. Update $S_{p0} = S_{p1}$, $T_0 = T_1$ and $i = i + 1$. Go to Step 5.

Step 11. Check condition from Eq. (34), IF it’s False Go to Step 1.

Step 12. Calculate profit function $\omega(S_{p1}, T_1)$ from Eq. (27).

Step 13. Output the optimal value of $S_{p1}$, $T_1$ and optimal profit $\omega$.

Step 14. End.

6. Case study

This section illustrates the problem with a case study that contains numerical examples.

6.1. Link to a real situation

The anticipated model is based on a transportation company called Volvo Truck Agency, Bangladesh. We talked with the company manager and asked him questions about the transportation system during the pandemic. The manager said that the situation is worse than ever. In as much as most truck drivers and helpers are unwilling to drive trucks, the daily basic transportation system faces some unavoidable scenarios. The drivers demand high wages according to the condition of the place of delivery (a red, yellow, or green zone). If the delivery place is within a red zone, drivers are sometimes unwilling to go or ask a very high price to transport the products. Due to the rapid vaccination rate, the situations rapidly change, resulting in slightly lower transportation wages than the previous fully pandemic situation. Fig. 5 illustrates the situation at a truck station during the pandemic. Based on the importance of this problem, this study was formed. To validate our model, some information is requested from the manager in our query.

6.2. Numerical examples

Example 1. Based on Case I of the study, we assume the following parameters from Mashud et al. (2020a) with some additional parameters when the selling price ($S_p$) is considered the decision variable.

- The initial expense for placing an order $O_c = 400 \$/cycle,
- the constant part of the demand rate $\alpha = 65$,
- the coefficient of the demand rate $\beta = 0.075$,
- the number of trips per cycle $\eta = 15$,
- the cost for purchasing a product $P_u = 200 \$/Unit,
- the deterioration rate $\epsilon = 0.01$,
- the holding cost $h_u = 3 \$/Unit,
- and the constant part of the holding cost $g = 2 \$/Unit.

In addition, the time-reliant part of the holding cost $h = 1.2 \$/Unit, the distance to travel $d_t = 100$ km, the fixed transportation cost $c_f = 3 \$/Trip, the fuel price $f_p = 0.15 \$/Liter, the vehicle fuel consumption

Fig. 11. COVID-19 vaccination effect on profit function Case I and Case II.

Fig. 12. COVID-19 effect on profit and associated cost functions (Case I).
Table 2
Sensitivity analysis without and with green technology investment.

| Parameter (Base) | Change in % | Changed Value | Case I | Case II |
|------------------|-------------|---------------|--------|--------|
|                   |             |               | $\eta'$ | $\tau'$ |
| $O_2$ (400)      | 20%         | 480           | 64.541 | 6.121  |
|                  | 10%         | 440           | 64.141 | 6.045  |
|                  | 5%          | 365           | 64.375 | 5.969  |
|                  | -20%        | 320           | 64.998 | 5.831  |
| $\sigma$ (65)    | 20%         | 78.0          | 719.358 | 4.147  |
|                  | 10%         | 71.5          | 679.799 | 4.724  |
|                  | 5%          | 58.5          | 612.952 | 4.192  |
|                  | -20%        | 52.0          | 576.115 | 10.261 |
| $\rho$ (0.075)   | 20%         | 0.090         | 584.284 | 8.765  |
|                  | 10%         | 0.083         | 612.044 | 7.559  |
|                  | -20%        | 0.068         | 687.600 | 5.211  |
| $P_e$ (200)      | 20%         | 240           | 760.237 | 7.125  |
|                  | 10%         | 195           | 745.086 | 4.771  |
|                  | -20%        | 140           | 706.571 | 4.477  |
| $h_0$ (3)        | 10%         | 1.0           | 640.999 | 4.969  |
|                  | -10%        | 0.9           | 641.770 | 5.320  |
|                  | 20%         | 1.8           | 654.591 | 5.315  |
|                  | -20%        | 0.1           | 654.366 | 5.207  |
| $\epsilon$ (0.01)| 10%         | 0.1           | 643.313 | 5.782  |
|                  | -10%        | 0.011         | 654.600 | 5.275  |
|                  | 20%         | 0.11          | 641.770 | 5.320  |
|                  | -20%        | 0.012         | 642.982 | 5.623  |
| $q$ (2)          | 10%         | 0.8           | 640.999 | 4.969  |
|                  | -10%        | 0.7           | 641.770 | 5.320  |
|                  | 20%         | 3.6           | 640.999 | 4.969  |
|                  | -20%        | 3.5           | 641.770 | 5.320  |
| $h$ (15)         | 10%         | 1.3           | 641.850 | 5.465  |
|                  | -10%        | 1.0           | 644.591 | 5.315  |
|                  | 20%         | 1.0           | 641.770 | 5.320  |
|                  | -20%        | 0.9           | 642.982 | 5.623  |
| $f$ (0.15)       | 10%         | 0.9           | 652.868 | 8.125  |
|                  | -10%        | 0.8           | 654.591 | 5.315  |
|                  | 20%         | 0.8           | 652.868 | 8.125  |
|                  | -20%        | 0.7           | 654.366 | 5.207  |
| $\omega$ (3)     | 10%         | 1.0           | 637.748 | 4.930  |
|                  | -10%        | 0.9           | 656.142 | 8.677  |
|                  | 20%         | 0.9           | 656.142 | 8.677  |
|                  | -20%        | 0.8           | 654.591 | 5.315  |
| $w$ (3)          | 10%         | 0.9           | 656.142 | 8.677  |
|                  | -10%        | 0.8           | 654.591 | 5.315  |
|                  | 20%         | 0.8           | 654.591 | 5.315  |
|                  | -20%        | 0.7           | 652.868 | 8.125  |
| $d_e$ (100)      | 10%         | 0.9           | 765.588 | 8.877  |
|                  | -10%        | 0.8           | 765.588 | 8.877  |
|                  | 20%         | 0.8           | 765.588 | 8.877  |
|                  | -20%        | 0.7           | 763.989 | 8.827  |
| $e_a$ (0.3)      | 10%         | 0.9           | 656.924 | 5.372  |
|                  | -10%        | 0.8           | 654.591 | 5.315  |
|                  | 20%         | 0.8           | 654.591 | 5.315  |
|                  | -20%        | 0.7           | 652.868 | 8.125  |
| $M$ (0.6)        | 20%         | 0.7           | 619.875 | 3.902  |
|                  | -10%        | 0.6           | 621.539 | 4.014  |
|                  | 20%         | 0.6           | 621.539 | 4.014  |
|                  | -20%        | 0.5           | 624.945 | 4.250  |
| $F$ (4.5)        | 20%         | 0.4           | 626.697 | 4.377  |
|                  | -10%        | 0.4           | 626.697 | 4.377  |

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A.H.M. Mashud et al.

we will solve for two decision variables: the selling price (S) and replenishment cycle (T). We obtain the optimal solutions: the selling price \(S_p = 643.75 \$/Unit\), cycle time \(T = 5.97\) months, order quantity \(N = 102.85\) units and total profit per unit time \(\omega = 2706.908\) . Fig. 9 illustrates the concavity of the retailer’s profit function \((\omega)\). 

After the purchase cost, the impacts of the ordering cost are also notable, the rate of change of COVID-19 on the purchase cost produces a significant increase with an increased rate of COVID. The extra vehicle fuel consumption brings greater profit. However, without any carbon emissions, while a higher COVID rate brings a decrease in profit in all cases.

The effect of the rate of change of vaccination acceleration on the total profits of the chain is presented in Fig. 11. The total profit increases with increasing rate of change of vaccination acceleration. The rapid vaccination process provides a higher profit in all cases. The total profit is significant when no green investment is implemented, while a green investment slows the fluctuations in profit. A slightly higher profit has been achieved without any carbon emissions, while a higher COVID rate brings a decline in profit in all cases.

Example 3. Based on Case II of the study, we assume the following parameters when only one variable is decision variable other as constant. All of the values of the parameters are the same as in Example 1 with the maximum reduced amount of carbon emissions \(M = 0.6\) and the efficiency of green technology \(E = 4.5\).

Then we obtain the optimal selling price \(S_p = 623.23\) , optimal cycle time \(T = 4.13\) months, optimal green technology investment \(G_i = 1.80 \$/month\). Fig. 8 shows the concavity of the retailer’s profit function \((\omega)\).

In this section, let us consider that the COVID-19 outbreak rate \(r\) varies for both Case I and Case II; hence, the profit also varies. A graphical representation of the effects of the COVID-19 outbreak rate on the total profit function is illustrated in Fig. 10. When the effects of the COVID-19 outbreak rate increase, the total profit decreases exponentially. The effect of COVID-19 on the total profit is significant when no green investment is implemented, while a green investment slows the fluctuations in profit. A slightly higher profit has been achieved without any carbon emissions, while a higher COVID rate brings a decline in profit in all cases.

| Parameter (Base) | Change in % | Changed Value | Case I | Case II |
|-----------------|-------------|---------------|--------|--------|
| \(S_p\)         | 10%         | 4.95          | 623.23 | 623.23 |
| \(T\)           | -10%        | 4.05          | 623.23 | 623.23 |
| \(N\)           | -20%        | 3.60          | 623.23 | 623.23 |
| \(\omega\)      |             |               | 4.13   | 4.13   |
| \(c_e\)         | 2            | Liter/Ton     | 1.80   | 1.80   |
| \(w\)           | 3            | kg            | 0.38   | 0.38   |
| \(c_w\)         | 75           | dollars       | 1.00   | 1.00   |
| \(c_c\)         | 623.23       | dollars       | 1.80   | 1.80   |
| \(G_i\)         | 10%          | 5.5           | 623.23 | 623.23 |
| \(T\)           | -10%         | 4.5           | 623.23 | 623.23 |
| \(N\)           | -20%         | 4             | 623.23 | 623.23 |
| \(\omega\)      |             |               | 4.13   | 4.13   |
| \(c_e\)         | 2            | Liter/Ton     | 1.80   | 1.80   |
| \(w\)           | 3            | kg            | 0.38   | 0.38   |
| \(c_w\)         | 75           | dollars       | 1.00   | 1.00   |
| \(c_c\)         | 623.23       | dollars       | 1.80   | 1.80   |
| \(G_i\)         | 10%          | 5.5           | 623.23 | 623.23 |
| \(T\)           | -10%         | 4.5           | 623.23 | 623.23 |
| \(N\)           | -20%         | 4             | 623.23 | 623.23 |
| \(\omega\)      |             |               | 4.13   | 4.13   |
| \(c_e\)         | 2            | Liter/Ton     | 1.80   | 1.80   |
| \(w\)           | 3            | kg            | 0.38   | 0.38   |
| \(c_w\)         | 75           | dollars       | 1.00   | 1.00   |
| \(c_c\)         | 623.23       | dollars       | 1.80   | 1.80   |
| \(G_i\)         | 10%          | 5.5           | 623.23 | 623.23 |
| \(T\)           | -10%         | 4.5           | 623.23 | 623.23 |
| \(N\)           | -20%         | 4             | 623.23 | 623.23 |
| \(\omega\)      |             |               | 4.13   | 4.13   |

N.B. (−) means infeasible solution or invalid.

When empty \(c_e = 2\) Liter/Ton, the product weight \(w = 3\) kg, the carbon emission cost \(c_w = 0.38\) /Trip, the additional carbon emission cost \(c_c = 0.15\) /Unit. Consider in a city, total population \(P = 1000\), a variant of covid affected people \(b = 300\) meanwhile already vaccinated people \(V = 500\) of the same type of variant of covid, the rate of the intensity of covid variant outbreaks \(r = 0.30\), rate of change of vaccination acceleration \(v_t = 0.5\) and peak cost of transportation due to cvd \(M_p = 5\).

When replenishment cycle is constant \(T = 5.97\) months. We obtain the optimal solutions: the selling price \(S_p = 643.75\) /Unit, order quantity \(N = 102.85\) units and total profit per unit time \(\omega = 2706.908\) . Fig. 6 (a) shows the concavity of the retailer’s profit function \((\omega)\) regarding the individual decision variables of \(S_p\).

When selling price is constant \(S_p = 643.75\) /Unit. We obtain the optimal solutions: the replenishment cycle \(T = 5.97\) months, order quantity \(N = 102.85\) units and total profit per unit time \(\omega = 2706.908\) . Fig. 6 (b) shows the concavity of the retailer’s profit function \((\omega)\) regarding the individual decision variables of \(T\).
7. Sensitivity analysis

We present a sensitivity analysis to study the impacts of different parameters on the optimal values of the total profit ($\omega$), cycle length ($T$), selling price ($S_p$), order quantity ($N$), and green investment ($G_i$) for the case with green technology. For this purpose, the parameter value is changed by $-20\%$ to $+20\%$, and the remaining values are fixed.

Based on the obtained results of the sensitivity analysis outlined in Table 2, the following observations can be made:

(a) When the ordering cost ($O_i$) increases, the retailer needs to increase the selling price ($S_p$). As the retailer needs to invest more in ordering a product, it always tries to sell the product at an increased price. Consequently, the cycle time ($T$) and the number of ordering quantities ($N$) also increase, but the total profit ($\omega$) decreases. When considering green technology, the total profit ($\omega$) and green investment ($G_i$) decrease with increasing ordering cost.

(b) When the number of trips ($\eta$) increases, the selling price, ordering quantity and cycle time also increase. However, the total profit decreases because an increasing number of trips means increases to the transportation cost.

(c) When the purchasing cost per unit ($P_u$) increases, the order quantity and total profit decrease because the retailer always has limited capital. As a result, the retailer will have fine-tuned the selling price to avoid losses, which causes the selling price to increase.

(d) With increases of the outbreak COVID-19 rate ($\tau$), deterioration ($\epsilon$), and holding cost per unit time ($h_o$), the total profit, cycle time and ordering quantity decrease.

(e) When the fixed transportation cost ($c_T$), product weight ($w$), fuel price ($f_c$), quantity of fuel consumed when the transport is empty ($c_e$), additional fuel consumption per ton ($c_l$) and traveled distance increase, the transportation cost increases. For this reason, the retailer raises the selling price to prevent any losses. However, the total profit decreases with higher transportation expenses.

(f) When the emission cost per unit distance ($e_d$) and the additional emission cost ($e_a$) increase, the total carbon cost also increases, and for this reason, the total profit decreases. To raise profits, green investment ($G_i$) is applied to reduce emissions.

(g) When the maximum reduced carbon emissions ($M$) are increased, the profit from green technology increases. Additionally, green investment increases. In a similar manner, when the efficiency of green technology ($E$) increases, the total profit also increases.

8. Managerial insights

This study provides some insights for managers to respond to disruptions in transportation systems that can be implemented in the supply chain during a pandemic. A retailer’s manager can consider some critical decisions as follows:

(a) By implementing this model, a retailer can discover the optimal cycle length and order quantity by responding to the increasing transportation cost after considering the rate of the outbreak. The manager must carefully plan the number of trips, as this number affects the transportation costs, hence, it decreases the total profit.

(b) Proper management of carbon emissions can be achieved through the use of green technology, and managers need to know how much to invest to curb emissions.

(c) A manager can make decisions in which the optimal price will result in maximum profit by considering the whole cost increase in the transportation system and technology investment.

9. Concluding remarks

The effect of COVID-19 on transportation systems has been illustrated with considerations of the environmental impacts. The proposed model introduces a cost factor in the transportation cost of the inventory model. This model considers a realistic transportation cost that hinges on the rate of the COVID-19 outbreak under price-sensitive demand. This research shows that the intensification of the COVID-19 rate decreases the retailer’s profit. Further study reveals some realistic results, such as:

- A retailer can decide what extra expense he needs to provide to the driver to transport products to higher-risk areas.
- This model allows decisions on how green technology efficiently works within a limited budget under some regulations.
- Some pricing strategies with simultaneous investments in emissions reduction that directly impact profit-making decisions have been suggested for deteriorating items.

This study has certain limitations; hence, further research to extend the proposed model can be performed in the future. This study failed to show how COVID-19 affects customers’ purchases instead of the effects on the transportation system. Therefore, a variable time-varying demand may be considered because the pandemic may influence customer demand. This type of work could be a great extension of this study. Furthermore, the limitations of employing a carbon emission reduction process, such as cap-and-trade and carbon offsets, were missing from this study.

CRediT authorship contribution statement

Abu Hashan Md Mashud: Conceptualization, Writing-original draft, Writing-review & editing. Sujan Miah: Conceptualization, Writing-original draft, Writing-review & editing. Yosef Daryanto: Conceptualization, Writing-original draft, Writing-review & editing. Ripon K. Chakrabortty: Conceptualization, Writing-original draft, Writing-review & editing. S.M. Mahmudul Hasan: Conceptualization, Writing-original draft, Writing-review & editing. Ming-Lang Tseng: Conceptualization, Writing-original draft, Writing-review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Appendix A. Constructive COVID infected function

Suppose $I_p(t)$ covid infected function, $r$ is covid infection rate and $A$ is carrying capacity. Since change of infected people is proportion to the infected people, one can write.

$$\frac{dI_p(t)}{dt} \propto I_p(t)$$

(A1)

Incorporating the carrying capacity, $A$, the Equation (A1) can be modified as Equation (A2). The Equation (A2) becomes similar as Equation (A1) when there is no infected people. Also, if the total infected population becomes as the carrying capacity then one can observe no change to infected people.

$$\frac{dI_p(t)}{dt} = rI_p(t) \left(1 - \frac{I_p(t)}{A}\right)$$

(A2)

At the beginning the number of infected people is say, $b$. After solving the differential equation with initial condition $I_p(0) = b$, one can obtain Equation (A3).

$$I_p(t) = \frac{Abe^{rt}}{A - b + be^{rt}}$$

(A3)

Fig. A1 represents the function Equation (A3) graphically.

The effort of scientists to invent the vaccine helps to decrease the infected population. Suppose the rate of change of vaccination acceleration (i.e., jerk) is constant.

$$\frac{d^3V}{dt^3} = v_r$$

(A4)

where $v_r$ is the rate of change of vaccination acceleration.

By solving the differential equation with $V(0) = V'(0) = V''(0) = 0$, one can write.

$$V(t) = v_r t^3$$

(A5)

Fig. A2 shows the increasing vaccination people for higher time. But, there is a necessity to set range of vaccinated people. Considering maximum population as upper boundary and already vaccinated people parameters, the vaccination functions, $V(t)$ can be written as.
\[ V(t) = \frac{P(v_t^3 + V_0)}{v_t^3 + P} \]  \hspace{1cm} (A6)

where, \( P \) is total population, \( V_0 \) is initial vaccinated people.

Fig. A3 shows that the number of vaccinated people is increasing with increasing time for total population of 1000.

In this model, it is assumed that the effectiveness of vaccine is 100%. Thus, if someone is vaccinated then there is possibility to infected again. Only those people may be infected newly who do not take any vaccine. Therefore, vaccinated free people are target people to be infected. The vaccination free function, \( V_f(t) \) can be obtained by subtracting the vaccinated population, \( V(t) \) from total population, \( P \).

\[ V_f(t) = P - \frac{P(v_t^3 + V_0)}{v_t^3 + P} = \frac{P(P - V_0)}{v_t^3 + P} \]  \hspace{1cm} (A7)

Fig. A4 shows that the number of vaccinated free people approaching to zero as time is increasing for total population of 1000.

Now, the carrying capacity (A) can be replaced with the vaccination free function \( V_f(t) \) in Equation (A3) of the covid infected people.

\[ I(t) = \frac{be^\rho P(P - V_0)}{P(P - V_0) + (v_t^3 + P) [be^\rho - b]} \]  \hspace{1cm} (A8)

Fig. A5 represents the effect of vaccination. The blue line represents the vaccinated free people of Equation (A7). After vaccination the modified infected function Equation (A8) is represented by the red line. It is observed that as the vaccination free population is decreasing with time increasing the infected people is also decreasing which confirms the effect of vaccination. Since no people will be newly infected if once he/she takes the vaccine.
Fig. A4. Vaccinated free people in different time for total population $P = 1000$; vaccinated rate $V_r = 0.5$; and initial vaccinated people (b) $V_0 = 0$ and (c) $V_0 = 200$.

Fig. A5. Infected and vaccinated free people in different time for total population $P = 1000$; infected rate $I_r = 0.3$; the rate of change of vaccination acceleration $= 0.5$; initial infected people $I_0 = 100$; and initial vaccinated people $V_0 = 200$.

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