



Sustainable production-inventory system for perishables under dynamic fuel pricing and preservation technology investment

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Abstract

In the production and inventory management of perishables, environmental considerations are gaining prominence. By reducing carbon emissions from various supply chain processes, such as production, transportation, warehousing, and waste disposal of perishable items, the present study aims to minimize the overall cost to the manufacturer through an optimized investment in green technology. Additionally, cycle time and preservation technology investment are optimized to decrease deterioration and revenue loss in order to minimize cost. The originality of the present research lies in the following considerations. Due to an increase in fuel price, the transportation cost of every subsequent order will also increase, thus resulting in an increase of average delivery cost in a production cycle. We investigate the impact of changes in fuel prices on transportation costs and production inventory model policies due to the volatile nature of fuel prices. The function of transportation cost can be used to calculate transport costs in the future. The deterioration rate is a random variable with a double triangular distribution. Precisely, the demand for any product depends on the product's price; therefore, linear price-dependent demand is considered. Per unit production cost is a function of direct material cost, tooling cost, and manpower cost. Taking into account all the aforementioned parameters, this paper simultaneously optimizes green technology investment, preservation investment, and cycle time. To achieve the solution of the proposed sustainable production system, an optimization technique for the nonlinear function is employed. Finally, numerical experiments are conducted to validate the model. A special case of a numerical example demonstrates that the expected value of the total average cost is reduced by 10.723% when investments are made in both green and preservation technology, whereas investments in green technology alone result in a cost reduction of only 2.15%. Then, managerial implications and a discussion of findings are proposed after a sensitivity analysis that examines the model's response to key parameter variation. The study concludes with a discussion of the limitations of current work and possible future scopes.

Keywords Production inventory model · Sustainable · Green investment · Preservation technology · Dynamic fuel pricing · Carbon tax · Perishable

Introduction

Global warming is caused primarily by carbon emissions. Researchers and world leaders are pursuing control measures to reduce emissions amid alarming global climate change. Due to government rules and regulations and growing environmental consciousness of consumers, most businesses

are eager to go green. The emission of carbon from various sources, such as industries, transportation, and warehousing, among others, is one of the major determinants of the environmental problems facing the world today, according to research (Jaber et al. 2013; Tang et al. 2018; Rout et al. 2020; Sepehri et al. 2021). Recently, Kharaji Manouchehrabadi and Yaghoubi (2022) described the use of fossil fuels as damaging to the environment. They also emphasized using solar energy instead of fossil fuel in the supply chain. In the same year, Manteghi et al. (2022) identified the food supply chain as a major source of greenhouse gas (CHG) emissions and urged all the stakeholders to implement measures to reduce CHG emissions. As per the literature, the first inventory model based on emission was given by Hua et al. (2011), who proposed a carbon cap and tax policy and considered

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ordering and warehousing operations as a source of emission. After 1 year, Bouchery et al. (2012) revealed only a handful of quantitative inventory model is available that consider sustainability, so they modified the classical inventory model taking environmental concern into account. Later, Taleizadeh et al. (2018) highlighted the drawbacks of basic EOQ and EPQ models because these models ignore many actual issues and insisted on giving equal importance to both economic and environmental concerns. Following this, Mishra et al. (2020a, b) identified supply chain activities as an important source of emission and emphasized the development of an emission-reducing inventory model. An attempt to rectify the drawback of fundamental EOQ and EPQ models has been made by Sahoo et al. (2022). They included carbon emission in the EOQ model because carbon emission is the primary cause of global warming and climate change. Recently, Mashud et al. (2022a, b) mentioned various activities of supply chain and logistics like production, storage, transportation, and waste disposal are also responsible for carbon emissions. After that, Zhang and Qin (2022), for a three-echelon supply chain consisting of the manufacturer, transporter, and retailer, described the manufacturer's production process and transportation process as emission sources.

Researchers have discussed methods for reducing carbon emissions, such as Pan et al. (2020) mentioned carbon emitted from business activities can be reduced by investing in green technologies. They also cited carbon cap and trade and carbon offset as crucial policies for lowering emissions. Afterward, Yadav and Khanna (2021) developed sustainable inventory models for perishable items having expiration dates and mentioned deterioration, warehousing, and transshipment as a source of carbon emissions as well as carbon tax policy as an effective tool to diminish emissions. As we invest in green technology to reduce emissions, cost increases. Moving one step further, Soleimani et al. (2021) claimed that a comprehensive model is required to deal with competing objectives like simultaneous reduction of cost and carbon emission because as we invest in green technology to reduce emissions, the cost rises. Consequently, the present study develops an inventory model that simultaneously reduces deterioration-related waste, carbon emissions from various stages of the supply chain, and the total cost of the inventory system.

When perishables are stored for a longer duration, losses due to deterioration aggravate. Any product can maintain freshness and usefulness for a limited period (Soni and Suthar 2019). The profit of any firm can be increased by slowing down the pace of deterioration by optimizing cycle time. By optimizing cycle time, Sarkar et al. (2018) attempted to enhance the performance of inventory management. The deterioration phenomenon is observed in real life on inventory items such as fruits, vegetables, pharmaceuticals, volatile liquids, and others (Dye 2013). Optimizing cycle time alone is insufficient to maintain the freshness of perishables; a suitable environment

is also required. Utilizing efficient preservation technology (processes and equipment) to create a suitable environment, such as refrigeration, prevents microbial spoilage and chemical deterioration. Proper packaging, along with preservation, is highly effective in slowing down the deterioration of packed food Fang et al. (2017). The spoilage rate of deteriorating items can be controlled through investment in preservation technologies (Yang et al. 2015). From the aforementioned works of literature, deterioration issues are a major concern, but they can be controlled by investing in preservation technologies. According to Mashud et al. (2021), the simultaneous use of green investment to reduce emissions and preservation investment to reduce waste is extremely rare in the literature. As the deterioration of products results in revenue loss and its disposal harms the environment, businesses are utilizing preservation technologies to extend product life and reduce deterioration-related waste. Therefore, all these issues have been simultaneously addressed in the present study. A carbon tax policy is implemented and investments are made in green technologies in order to control emissions. To prevent deterioration-related waste, investments are made in preservation technologies, and the cycle time for replenishment is optimized. By simultaneously optimizing green technology investment, preservation technology investment, and replenishment cycle time, the overall cost to the manufacturer is minimized.

Figure 1 is a visual representation of how various stages of the supply chain, such as production, storage, and transportation, contribute to carbon emissions and the associated costs at various stages. At the manufacturing unit, the manufacturer incurs costs for setup, production, and emissions due to the manufacturing process. Due to warehouse operations, the manufacturer incurs deterioration costs, holding costs, screening costs, waste disposal costs, and emission costs. Another significant expense incurred by the manufacturer is the cost of transporting the product to the distributor. Green technology is invested in reducing emissions, and preservation technology is invested in minimizing waste.

The aim of this paper is three-fold: the first one is to develop a mathematical model for a sustainable inventory problem involving perishable products when items cannot be reworked. Generally, the deterioration rate is not constant; it varies between a maximum under the worst condition and a minimum under the most favorable condition; hence in this paper, it is assumed that the deterioration rate follows double triangular probability distribution. Unit production cost is variable, and it is a function of production rate, cost of raw materials, tooling cost, and manpower cost. The demand rate is price dependent as the demand for perishables is greatly dependent on price. Transportation cost is a function of distance travelled by the vehicle, load carried by the vehicle, and fuel price variation with time, so the transportation cost function used in this study can also calculate future transportation cost if fuel price varies. The second is to optimize the decision variables investment

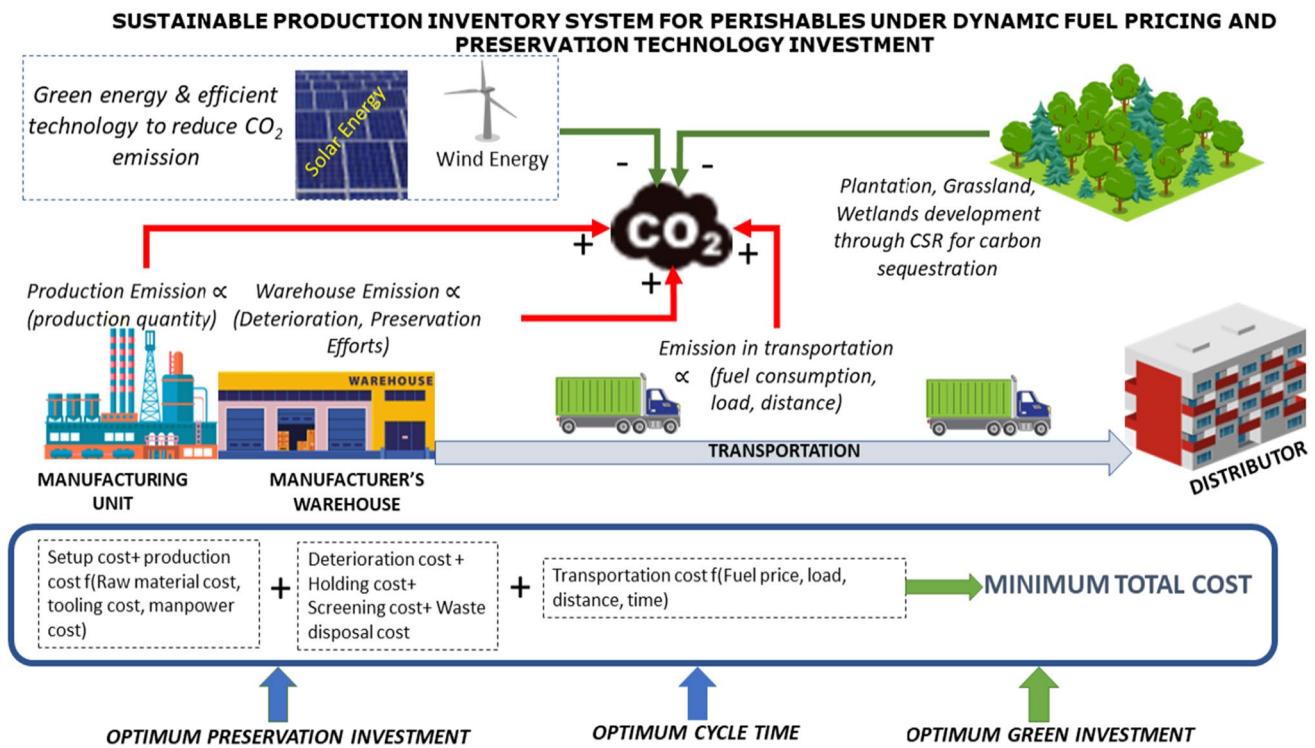


Fig. 1 Graphical illustration of the environmental impact of a production inventory system

in green technology, investment in preservation technology, and replenishment cycle time to minimize the total cost. The third is to identify the key parameters by performing sensitivity analysis and suggest some insights for the industry. The proposed sustainable inventory model considers all these issues to answer the following research questions.

- What are the implications of investment in green technologies and preservation technologies on total average cost and inventory decisions?
- What is the optimum replenishment cycle time to restart the production process so that the total average cost can be minimized?
- What is the influence of key parameters on total average cost and inventory decisions?

The rest of the paper is organized as follows. In the “Literature review” section, literature review is mentioned. The “Assumption and notations” section consists of assumptions and notations used in the paper. Furthermore, the “Problem description” section deals with problem description and derivations. The “Numerical experiments” section covers numerical examples and algorithms to solve the problem. Furthermore, the “Sensitivity analysis, theoretical implications, and discussion of findings” section presents sensitivity analysis, theoretical implications, and a discussion of findings. The “Insights for industry” section proposes insights

into the industry. Finally, in the “Conclusion, limitation, and future scope” section, conclusions, limitations, and future scopes are mentioned.

Literature review

In this section, previous studies and fundamental theories supporting this model have been written. Inventory models related to deteriorating items and preservation technology investment and carbon emission are mentioned.

Inventory models for deteriorating items

For the past many years, various studies have incorporated the influence of deterioration rate on inventory decisions. A significant amount of study was carried out by many researchers (He et al. 2010; Lee and Dye 2012; Bhunia et al. 2018; Tiwari et al. 2018a, b; Khakzad and Gholamian 2020). Another paper investigated the inventory model for deteriorating items presented by Rana et al. (2021a). They examined the impact of demand disruption on deteriorating items in a two-warehouse system with time-dependent demand and a two-parameter Weibull distribution deterioration rate with an objective to minimize the cost of the retailer in the event of sudden demand disruption. Afterward, Rout et al. (2021) proposed a production inventory model for deteriorating

items with constant demand and deterioration rate with piecewise constant demand during stock-out condition with a goal to minimize the cost of the manufacturer. Later, Dai and Wang (2022) proposed an inventory model for deteriorating items considering stochastic demand; by optimizing order quantity and the number of shipments, they maximized the profit of the retailer. In the same year, Anil Kumar and Paikray (2022) proposed an inventory model for deteriorating items considering trapezoidal demand, completely backlogged shortage, and constant deterioration to minimize the cost of the retailer. Murmu et al. (2022b) proposed a production inventory model for perishable items during pandemics. Although significant studies have been done in the case of deteriorating inventory, none of the above has considered double triangular probability distributed deterioration with price-dependent demand and variable production cost, which depends on raw material cost, production rate, tooling cost, and manpower cost, variable fuel price, and optimization of preservation technology investment.

Inventory models with preservation technology investment

Wastage of perishable items is a serious issue that needs to be addressed. Based on producer prices, the direct economic cost of food wastage of agricultural products (excluding fish and seafood) is roughly USD 750 billion, equivalent to Switzerland's GDP (FAO, 2013). Researchers have paid considerable attention to the reduction of food waste throughout the supply chain's various stages. Such as Hsu et al. (2010), in their inventory model, first used preservation technology investment to reduce deterioration. Then, Tsao (2016) designed a supply chain network under preservation effort and trade credit and mentioned that perishable goods such as medicine, vegetables, and volatile items quantity decrease due to deterioration. Yang et al. (2019) introduced the concept of cross perishability, in which the storage of different items together shortens the shelf life of other products, necessitating the need for continuous screening to remove the deteriorated product. Later, Yang et al. (2020), in their research work, mentioned that the deterioration rate is the main characteristic of perishable inventory and it is unavoidable; however, there are ways to reduce it. Furthermore, Saha et al. (2021) optimized preservation technology investment for seasonable or fashionable products. But in the above-mentioned literature, preservation technology investment has not been optimized with green technology investment and cycle time in a production inventory model.

Inventory model with carbon emission

A sustainable supply chain has received significant attention from academicians and companies such as Seuring

and Müller (2008), Jaber et al. (2013), Jauhari et al. (2022), and Tang et al. 2018. According to Yadav et al. (2021), carbon emission is responsible for environmental degradation, and at the same time, wastage due to deterioration affects the ecosystem significantly. In the same line, Sarkar et al. (2021) insisted on sustainable energy generation due to the rising demand for energy and greenhouse gas emissions. Later, Thomas and Mishra (2022) also emphasized emission reduction and waste minimization in the plastic forming industry in their inventory model and urged to invest in green technology to minimize emissions. Later, Rana et al. (2022) considered emissions from various supply chain activities and used carbon cap and carbon tax policy to curb carbon emissions. After going through the available literature and observing the facts highlighted by the researchers, like environmental degradation due to carbon emission and ill effects of the deteriorated product on our ecosystem motivated to develop an inventory model that can simultaneously control these issues.

Research gaps and contribution of the study

These research gaps have been identified after a comprehensive literature review of numerous inventory models (Table 1). It has been found that various supply chain activities, from production to consumption, emit carbon. However, the majority of research work ignores the consideration of investment in green technology and carbon tax policy to reduce carbon emissions. On the contrary, a significant investment in green technologies significantly raises the cost of the manufacturer; as a result, optimization of investment in green technologies is crucial to reduce emissions as well as the overall cost of the manufacturer. Therefore, the current research work optimizes green technology investment and considers carbon tax policy to reduce emissions. Moreover, a large number of studies has considered the deterioration rate as constant, but in reality, it is not so, and in the case of perishable inventory, we cannot let it deteriorate at a normal rate because the deterioration rate is very high, so it is vital to slow down the deterioration rate; despite its importance, very few have investigated the influence of investment in preservation technology. Again, a large investment in preservation technologies increases the cost of the manufacturer; therefore, a manufacturer must optimize their investment in preservation technologies to reduce both cost and emissions due to the disposal of deteriorated products. So, the current work is focused on optimizing investment in preservation technologies. Despite adopting preservation facilities, perishable inventory remains fresh for a limited time; therefore, it is crucial to sell perishable products within a specific time frame, and another more significant challenge is to determine when to restart the production process.

Table 1 Comparison between the past contributions and research gap identification

Authors contribution	Demand rate	Deterioration rate	Production inventory model	Preservation technology investment	Green technology investment	Screening cost	Solution methodology	Time-dependent transportation cost
Cárdenas-Barrón et al. (2013)	Constant	✗	✗	✗	✗	✗	Algebraic method	✗
Sarkar et al. (2014)	Constant	✗	✓	✗	✗	✗	Classical optimization technique	✗
Tayyab and Sarkar (2016)	Constant	✗	✓	✗	✗	✗	Classical optimization technique	✗
Tsao (2016)	Constant	Preservation dependent	✗	✗	✗	✗	Piecewise nonlinear optimisation	✗
Tiwari et al. (2018a, b)	Constant	Constant	✓	✗	✗	✗	Classical optimization technique	✗
Mashud et al. (2020)	Constant	Non-instantaneous constant	✗	✓	✗	✗	Classical optimization technique	✗
Rout et al. (2020)	Constant	Constant	✓	✗	✗	✗	Non-dominated sorting technique	✗
Lin (2021)	Uncertain	Constant	✓	✗	✗	✗	Classical optimization technique	✗
Ruidas et al. (2021)	Price dependent	✗	✓	✗	✗	✗	Quantum-behaved particle swarm Optimization	✗
Mashud et al. (2021)	Price dependent	Non-instantaneous constant	✓	✓	✓	✗	Classical optimization technique	✗
Das et al. (2021)	Price and displayed stock dependent	Non-instantaneous constant	✗	✓	✗	✗	Particle swarm optimization	✗
Rana et al. (2021a, b)	Price and freshness dependent	Constant	✗	✗	✗	✗	Local optimization	✗
Mashud et al. (2022a, b)	Constant	Constant	✗	✗	✓	✗	Classical optimization technique	✗
Lee and Hussain (2022)	Constant	Constant	✗	✗	✓	✗	Simulation model	✗
Thomas and Mishra (2022)	Function of Circularity index	✗	✗	✓	✓	✗	Karush–Kuhn–Tucker optimization technique	✗
Gautam et al. (2022)	Green degree and price dependent	✗	✓	✗	✓	✓	Classical optimization technique	✗
Sebatjane (2022)	Constant	Constant	✗	✓	✗	✗	Classical optimization technique	✗
Murmu et al. (2022a)	Quality and price-dependent demand	Constant	✗	✗	✓	✗	Local optimization	✗

Table 1 (continued)

Authors contribution	Demand rate	Deterioration rate	Production inventory model	Preservation technology investment	Green technology investment	Screening cost	Solution methodology	Time-dependent transportation cost
Mahapatra et al. (2022)	Promotion dependent demand	Time dependent	✗	✓	✗	✗	Classical optimization technique	✗
This paper	Price dependent	Random	✓	✓	✓	✓	Classical optimization technique	✓

Optimizing cycle time simultaneously addresses these two concerns. Consequently, the present study simultaneously optimizes three crucial parameters: green technology investment, preservation technology investment, and cycle time. Most literature has assumed that the unit production cost is constant, but it is actually a complex function of direct material cost, tooling cost, and labor cost. Very few pieces of literature have considered the transportation cost of the manufacturer in delivering goods to the retailers, and those who have taken transportation cost into account viewed fuel price as constant, but it is varying if we observe data of the fuel price from a base year till now. Due to an increase in fuel price, the transportation cost of every subsequent order will also rise, thus resulting in a surge of average delivery cost in a production cycle. We investigate the impact of changes in fuel prices on transportation costs and production inventory model policies due to the volatile nature of fuel prices, and this variation in fuel price is only observed by Gurtu et al. (2015) in the basic EOQ model. The transportation costs function is able to evaluate transportation cost in future if fuel price changes. In general, the rate of deterioration of perishables is not constant; it varies depending on the ambiance; therefore, in the current study, the rate of deterioration is treated as a double triangular random variable. Cross perishability can increase the rate of deterioration, so continuous screening of perishables is necessary to prevent further deterioration of fresh items from ethylene emitted by a deteriorated product; thus, screening is included in the present study. In this study, the demand rate is considered to be a function of the selling price because the demand for perishables is highly price-sensitive.

To the author's knowledge, no research study to date has taken into account all these plausible phenomena in an inventory model for the manufacturer. Consequently, in the current research, an effort has been made to create an integrated production inventory model that is sustainable and minimizes the manufacturer's overall cost by simultaneously optimizing cycle time, green technology investment, and preservation technology investment.

Assumption and notations

Notations

A list of notations used to formulate this model is given below with proper units.

Decision variables

G : investment in green technology to reduce carbon emission (\$)

ξ : investment in preservation technology to reduce deterioration of product (\$)

T : cycle time (unit of time)

Parameters

P : production rate (units/time)

T_m : production time at which available inventory becomes maximum (unit of time)

v : indicates the efficiency of green technology implemented

λ : indicates efficiency of preservation techniques used to reduce deterioration

$E(\theta)$: expected value of deterioration rate of on-hand inventory (units)

c_h : it is holding cost per unit product per cycle (\$)

X : being the time in years between first order since 1990 (unit of time)

d : distance travelled by the vehicle to deliver product (km)

l : fuel consumed by the vehicle (liter)

α : fuel price (\$)

f_{ca} : additional fuel consumption by the vehicle (per kg of payload/km)

x : vehicle emission standard (kg CO₂/liter fuel)

w : weight of a single product in (kg)

β : annual increment in fuel price (\$)

γ : conversion factor for oil from liters to per barrel US

f_{tc} : fixed transportation cost (\$)

σ : screening time (min/unit)

ψ : a positive constant

n : trip or shipment number being sent by the manufacturer

Q : lot size (units)

β_o : a positive constant

W_d : weight of waste produced from one unit (kg/unit)

E_q : carbon emitted due to inventory carried out by the vehicle (kg/unit)

E_p : carbon emitted from the production process (kg/unit)

E_{wd} : carbon emitted from waste disposal process (kg/unit)

E_h : carbon emitted from warehousing operations (kg/unit)

δ : carbon tax per cycle (\$/kg)

Function and expression

TC: total average cost (\$)

$D(s)$: selling price dependent demand rate (units/ time)

$f(G)$: carbon emission reduction function

$\omega(\xi)$: deterioration reduction function

A_0 : transportation cost at the start of an order point (\$)

A_1 : annual incremental increase in transportation cost (\$)

$Q_1(t)$: inventory level at any time t during the time interval $0 \leq t \leq T_m$ (units)

$Q_2(t)$: inventory level at any time t during the time interval $T_m \leq t \leq T$ (units)

Assumptions

Following assumptions are made while developing this model.

- a. Demand rate is deterministic and linear decreasing function of price $D(s) = D_o - bs$, where D_o and b are constant greater than zero and s is the selling price per unit of product.
- b. Per unit production cost is given by $C_p = c + \frac{J}{P} + kP$, where c is the unit cost of raw material, P is the production rate and assumed constant, J represents per unit cost components that reduce as the production rate increases (manpower cost), and k represents the unit cost component that increases with production rate (tooling cost).
- c. Fuel price is changing with time.
- d. Manufacturer invests in green technology to make the production system more sustainable. The fraction of carbon reduction after making the green investment is given by the continuously differentiable function $f(G) = \phi (1 - e^{-vG})$, where v is the efficiency of green technology. $f(G)$ tends to zero when $G=0$, and when $G \rightarrow \infty$, $f(G)$ tends to ϕ (Sepehri et al. (2021)). Figure 2 shows as the investment in green technology increases, the fraction of carbon reduction rises, but after a certain limit curve becomes almost asymptotic.
- e. Manufacturer invests in preservation technology to minimize waste. Fraction of deterioration reduction after making preservation technology investment is given by continuously differentiable function $\omega(\xi) = (1 - e^{-\lambda\xi})$, where λ is the efficiency of preservation technology. $\omega(\xi)$ tends to zero when $\xi=0$, and when $\xi \rightarrow \infty$, $\omega(\xi)$ tends to 1, (Mashud et al. (2022)). From Fig. 3, we can observe as the investment in green technology increases, the fraction of carbon reduction rises, but after a certain limit, curve becomes almost asymptotic.
- f. The deterioration rate is uncertain, follows the double triangular probability distribution where $\theta \in [a, c]$ and $a < b < c$, and the expected value is given by $E(\theta) = \frac{a+4b+c}{6}$, where a is the deterioration rate under the most optimistic condition, c is the deterioration rate under the most pessimistic condition, and b is the most likely value of the deterioration rate (Sarkar et al. (2020)).
- g. The shortage is not allowed.
- h. The production rate is known and greater than price dependent demand rate.

Problem description

In this section, a sustainable economic production quantity model for deteriorating items is developed where the deterioration rate is uncertain and follows the double

triangular distribution. Various sources of carbon emission at different stages of the supply chain are outlined, and relevant costs are calculated.

Mathematical model

The inventory level is zero at time $t=0$. When the buyer places an order, production process starts from $t=0$, and simultaneous production and demand fulfillment takes place; it is assumed that the production rate is greater than demand, so a gradual build-up of inventory takes place. At $t = T_m$ inventory level reaches a maximum value, and the production process stops. After time $t=T_m$, inventory depletes due to the combined effect of demand and deterioration (Fig. 4).

For the time period $0 < t < T_m$, inventory is being produced with a production rate P and depleting due to the combined effect of demand and deterioration, the governing differential equation is given by,

$$\frac{dQ_1(t)}{dt} + E(\theta)e^{-\lambda\xi}Q_1(t) = P - D \tag{1}$$

The deterioration rate is uncertain and follows double triangular distribution, and it is being controlled by investing in preservation technology let $\omega(\xi)$.

Solving the above differential equation and using the boundary conditions at $t=0$, $Q_1(t) = 0$,

$$Q_1(t) = \frac{P - D}{E(\theta)\omega(\xi)} (1 - e^{-E(\theta)\omega(\xi)t}) \tag{2}$$

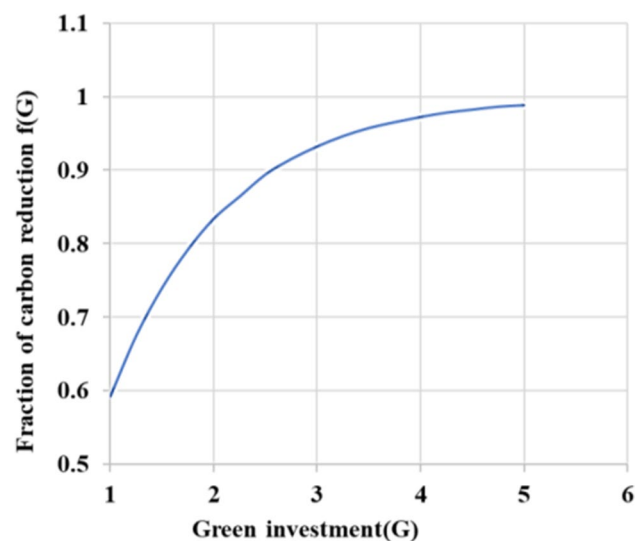


Fig. 2 A variation of the fraction of carbon reduction $f(G)$ with green investment G

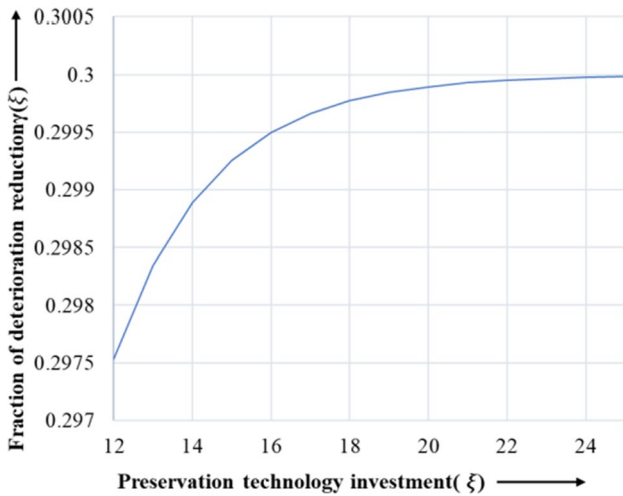


Fig. 3 Variation of the fraction of deterioration reduction $\omega(\xi)$ with preservation technology investment ξ

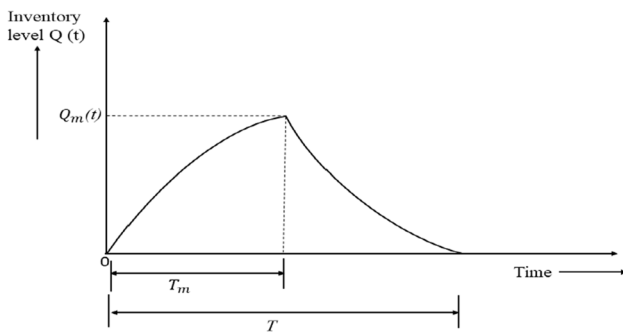


Fig. 4 Graphical illustration of production inventory model

For the interval $T_m \leq t \leq T$, governing differential equation is given by

$$\frac{dQ_2(t)}{dt} + E(\theta)e^{-\lambda\xi}Q_2(t) = -D \tag{3}$$

Applying boundary conditions at $t = T, Q_2(t) = 0$

$$Q_2(t) = \frac{D}{E(\theta)\omega(\xi)}(e^{E(\theta)\omega(\xi)(T-t)} - 1) \tag{4}$$

Cost estimation Various costs associated with the vendor are discussed as follows:

Setup cost (SC) is the cost required to prepare equipment for making products of different batches. This includes the downtime losses and consumables etc.

$$SC = \frac{C_{st}}{T}$$

Production cost is the cost required to manufacture a product. It depends on the quantity to be produced. It includes a material cost (raw material), labor cost, and tool die cost. If C_p is the cost required to produce a single product and is given by $C_p = C + \frac{J}{P} + KP$, where C =unit cost of raw material, $\frac{J}{P}$ is the cost component that decreases with the production rate (labor cost), and KP is the unit cost component that increases with the production rate (tooling cost).

$$\text{Total production cost } TP = \frac{PT_m C_p}{T} \tag{5}$$

Holding cost (HC) is the cost incurred of storing and maintaining the unsold, finished, and semifinished product in the warehouse. It depends on the holding time and quantity of products in the warehouse. It includes rent and insurance of the warehouse, wages for the labor, etc. If C_h is the holding cost per unit, then the holding cost per cycle is given by HC.

$$HC = \frac{C_h}{T} \left[\int_0^{T_m} Q_1(t)dt + \int_{T_m}^T Q_2(t)dt \right] \tag{6}$$

$$HC = \frac{C_h}{T} \left[\frac{P-D}{E(\theta)\omega(\xi)} \left(T_m + \frac{1}{E(\theta)\omega(\xi)} (e^{-E(\theta)\omega(\xi)T_m} - 1) \right) + \frac{D}{E(\theta)\omega(\xi)} \left(\left(\frac{1}{E(\theta)\omega(\xi)} (e^{E(\theta)\omega(\xi)(T-T_m)} - 1) \right) - (T - T_m) \right) \right] \tag{7}$$

Waste disposal cost (WC) is the cost related to disposing of the waste produced during the production process, and it is a fixed cost.

$$WC = \frac{C_{wd}}{T}$$

There is a deterioration of products at different stages like production and storage in the warehouse. So, a certain amount of money is invested by the vendor to reduce the deterioration rate called preservation technology investment cost (PIC) or waste minimization technique cost; preservation technology investment cost per cycle is given by

$$PIC = \frac{\xi T}{T}$$

Vendors have to hold the product in their warehouse after production. To get rid of ripening hormones and fungus in the warehouse, the deteriorated product needs to be screened out. When the vendors do not have enough budget, the temporary staff inspects products from time to time manually.

$$\text{Associated screening cost per unit is calculated as follows } SC = \beta_o(e^{\psi\sigma} - 1) \tag{8}$$

In *transportation cost*, vendors deliver the product to their distributor as an order placed by them, so a certain cost is incurred in delivering the product to distributors. Variation of transportation cost with time is calculated as mentioned by Gurtu et al. (2015).

From Fig. 5, we can observe world oil demand has been increasing every year since 2016 except in 2020, when demand decreased but again increased in 2021. An increase in demand for oil is one of the main reasons for the increment in price with time.

Another reason for the fuel price hike is taxation, as a huge tax is imposed on crude oil by the governments, as shown in Fig. 6. Thus, the cost of transportation increases with time due to the surge in fuel prices. So, the cost of transportation for a particular cycle varies dynamically. Therefore, it is important to consider the variation in transportation costs with time.

$$TR = \frac{f_{ic} + B_i}{T}$$

$$B_i = B_o + B_1(i - 1)\frac{Q}{D}$$

$$B_o = 2dl\alpha + d\alpha f_{ac}wQ$$

where α is the fuel price, the oil price has been steadily increasing over the years. The form $\alpha = 2.8917X + 11.802$ is the best curve for the price of oil per barrel in US dollars, where X is the number of years counting from 1990. $\alpha = \frac{2.8917X + 11.802}{\gamma}$, where γ is equal to 159 L per barrel US.

$$B_1 = 2dl\beta, \text{ where } \beta = \frac{2.8917}{\gamma}$$

$$TR = \frac{f_{ic} + 2dl\alpha + d\alpha f_{ac}wQ + B_1(i - 1)\frac{Q}{D}}{T}$$

In *Green technology investment*, carbon emission costs, various supply chains activities like production, storage, transportation, wastage, and consumption emit a large amount of CO₂. Emissions due to the production process depend on production time, whereas emission due to transportation depends on distance travelled and fuel consumption. Carbon emission due to waste disposal depends on the amount of solid waste produced. Emissions from warehousing operations depend on the quantity stored in the warehouse as well as holding time in the warehouse; various sources of carbon emission during warehousing operation are energy consumption for lightening, some items require

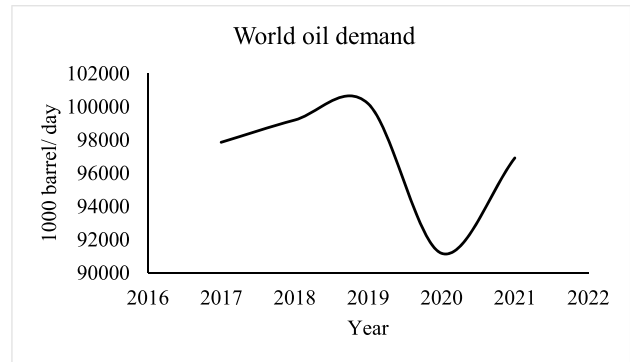


Fig. 5 The world oil demand in 1000 barrels/day (2022 OPEC Annual Statistical Bulletin 57th Edition, 2022)

hot ambiance, whereas some require cold ambiance, so heating or cooling is also a source of carbon emissions.

Emissions due to transportation $E_T = 2ndIV_e$. It is emission due to distance covered by the vehicle, two is used for round trip

Additional carbon emission during transportation due to the load carried by the vehicle

$$= E_Q = wdQf_{ca}V_e$$

So total carbon emission during transportation is $E_T + E_Q = 2ndIV_e + wQdf_{ca}V_e$

Emissions due to the production process $e_p = E_pPT_m$

Emissions due to waste disposal $e_{wd} = W_dQE_{wd}$

Emission from warehousing operation

$$e_h = E_h \left\{ \int_0^{T_m} Q_1(t)dt + \int_{T_m}^T Q_2(t)dt \right\}$$

Total carbon emission

$$TCE = 1 - \phi(1 - e^{-vG})(E_T + E_Q + e_p + e_{wd} + e_h).$$

Total cost due to carbon emission

$$TCEC = \delta \{ 1 - \phi(1 - e^{-vG})(E_T + E_Q + e_p + e_{wd} + e_h) \}$$

The green technology investment cost is the cost incurred to reduce the carbon emission from various stages of the supply chain.

$$\text{Green technology investment cost } GIC = \frac{GT}{T}$$

Therefore, the expected value of the total average cost of the inventory system for a cycle time T can be written as follows:

$$E[TC(T, G, \xi)] = \text{Set up cost} + \text{Production cost} + \text{Holding cost}$$

$$+ \text{waste disposal cost} + \text{preservation investment cost}$$

$$+ \text{Green investment cost} + \text{Screening cost}$$

$$+ \text{Transportation cost} + \text{total cost due to carbon emission} \tag{9}$$

$$E[TC(T, G, \xi)] = \frac{C_{st}}{T} + \frac{PT_m c_p}{T} + \frac{C_h}{T}$$

$$\left[\frac{P - D}{E(\theta)\omega(\xi)} \left(T_m + \frac{1}{E(\theta)\omega(\xi)} (e^{-E(\theta)\omega(\xi)T_m} - 1) \right) + \frac{D}{E(\theta)\omega(\xi)} \left(\left(\frac{1}{E(\theta)\omega(\xi)} (e^{E(\theta)\omega(\xi)(T - T_m)} - 1) \right) - (T - T_m) \right) \right]$$

$$+ \frac{C_{wd}}{T} + \frac{\xi T}{T} + \frac{\xi G}{T} + \beta_o(e^{w\sigma} - 1) + \frac{2dl\alpha + d\alpha f_{ac}wQ + B_1(i - 1)\frac{Q}{D}}{T} + \delta \{ 1 - \phi(1 - e^{-vG})(E_T + E_Q + e_p + e_{wd} + e_h) \}$$

Fig. 6 The distribution of crude price, industry margin, and tax on the price of crude oil (2022 OPEC Annual Statistical Bulletin 57th Edition, 2022)



It is very difficult to show the convexity of $E [TC (T, G, \xi)]$ due to highly complicated equations, but it can be shown for a fixed value of ξ .

Lemma 1 $E [TC (T, G, \xi)]$ provides a minimum value in green investment G when investment in preservation technology ξ and cycle time T is fixed.

Proof: Appendix 1

Corollary 1 For a fixed value of ξ and T if the term $-1 + e^{-e^{-\lambda_2 m \theta}} > 0$ & $m - T + \frac{e^{\lambda_2 (-1 + e^{-\lambda_2 (-m + T \theta)})}}{\theta} > 0$, then minimum exists at $E [TC (T, G, \xi)]$.

Proof: Appendix 2

Figure 7 shows that as the green investment increases, the total cost reduces and becomes minimum at $G = G^*$ and further increment in green investment causes an increase in total cost. To plot Fig. 7, values are considered from the data mentioned in the numerical experiment.

Lemma 2 $E [TC (T, G, \xi)]$ provides a minimum value in cycle time T when investment in preservation technology ξ and green investment G is fixed.

Proof: Appendix 3

Figure 8 shows that as the cycle time rises, the total cost diminishes and becomes minimum at $T = T^*$ and further increment in cycle time causes an increase in total

cost. To plot Fig. 8, values are considered from the data mentioned in the numerical experiment.

Lemma 3 The principal minors of $E [TC (T, G, \xi)]$ are positive definite at the optimal values (T^*, G^*, ξ^*) for a given value of ξ .

Proof: Appendix 4

Numerical experiments

In this section, numerical examples are solved with the proposed algorithm to validate the model, and the convexity of the total average cost function has been proved.

An illustrative case study Values for the validation of the model are adopted from Mashud et al. (2022) and modified according to our elaboration, which is a case study Taiwanese greenhouse flower production company. Values pertaining to fuel prices are obtained from (OPEC Annual Statistical Bulletin 57th Edition 2022) and Gurtu et al. (2015). However, the unavailability of real-time data for all the parameters which is mentioned in the conclusion is one of the limitations.

$D_o = 10,000$ unit/year, $b = 1$, $s = 60$ \$, $P = 12,000$ unit/year, $k = 0.0009$, $J = 100$, $c = 30$ \$, $a = 0.02$, $b = 0.04$, $c = 0.06$, $T_m = 2.5$ unit time, $c_{st} = 100$ \$ per setup, $c_{wd} = 60$ \$, $Q = 100$ units, $\beta_o = 0.3$, $\sigma = 0.2$ min/unit, $\psi = 1$, $n = 3$, $v = 0.9$, $\phi = 0.4$, $\lambda = 0.9$, $c_h = 2$ \$/unit time, $X = 32$ years, $d = 10$ km, $l = 1$ L, δ

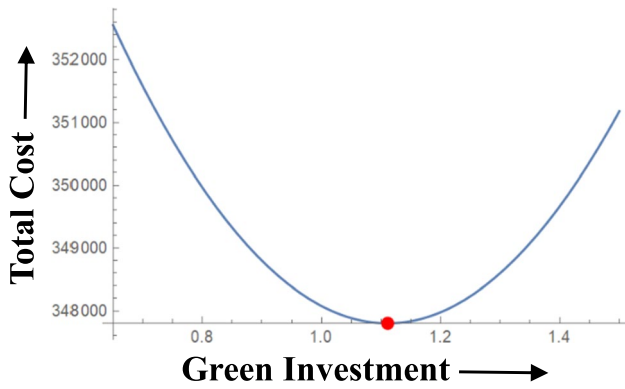


Fig. 7 Convexity of total cost w.r.t green investment G

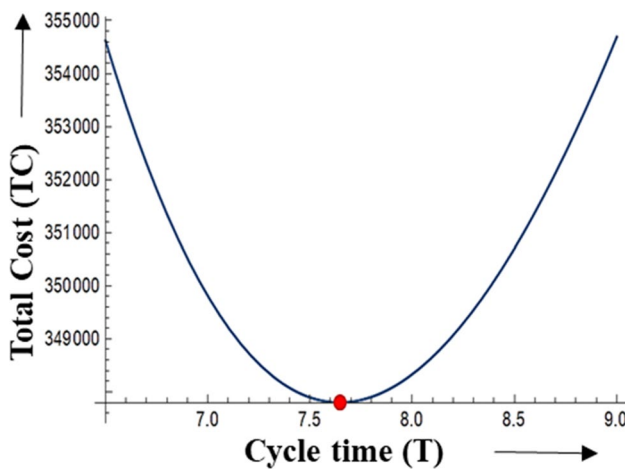


Fig. 8 Convexity of total cost w.r.t cycle time T

$= 5 \text{ \$/kg}$, $E_w = 1.2 \text{ kg CO}_2/\text{unit}$, $E_p = 1.2 \text{ kg CO}_2/\text{unit}$, $f_{ca} = 1 \text{ L/unit km}$, $E_{wd} = 0.24 \text{ kg CO}_2/\text{kg waste}$, $V_e = 3 \text{ kg CO}_2/\text{L fuel}$, $F = 100\text{\$}$, $W_d = 0.2 \text{ kg/unit}$, $w = 3 \text{ kg/unit}$. For the given condition, the objective is to find the optimum expected total average cost per cycle TC^* , optimum investment in waste minimization ξ^* , optimum investment in green technology G^* , and optimum cycle time T^* .

Algorithm The objective of this algorithm is to get the optimum value of total average cost $E[TC(T, G, \xi)]$ and the corresponding optimal value of preservation technology investment (ξ), green technology investment (G), and cycle time (T). The given production inventory model is solved

with the help of Mathematica software and the steps are mentioned below.

- Step 1: assign the values to the parameters
- Step 2: set the value of $\xi = n$ where $n = 0, 1, 2, 3, \dots$
- Step 3: for $n = 0$, find the optimal value of (G^*, T^*) by equating the first derivative of the total average cost function with respect to G and T equal to 0
- Step 4: compute the total average cost with the help of G^* and T^* and the value of the parameter set in step 1
- Step 5: set the value of $n = 1$, repeat steps 3 and 4
- Step 6: continue the steps 3 and step 4 until the total cost starts to increase, reach a negative value for any variable or a non-real value
- Step 7: the values of ξ , G , and T corresponding to the lowest value of the total cost function is the optimal value of preservation technology investment ξ^* , green technology investment G^* and cycle time T^*
- Step 8: end

As per the result obtained in Table 2, considering no investment in waste minimization technique, the total average cost obtained $E[TC] = 355,308.8875$, cycle time $T = 7.272$, and investment in green technology $G = 1.111$. From the above-mentioned algorithm, as the ξ increases and converges to optimal cycle time $T^* = 7.6454$, optimal investment in green technology $G^* = 1.111$, and optimal investment in waste minimization technique $\xi^* = 10$, with the total average cost $E[TC^*] = 347,799.9214$. The 3D plot of the total average cost with respect to cycle time (T) and investment in green technology (G) is given in Fig. 9 below.

Convexity conditions (Fig. 10) are held by

$$\text{Hessian matrix, } H = \begin{bmatrix} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T \partial G} \\ \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} \end{bmatrix}$$

If the leading minors of H are

$$H_1 = \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} > 0, \quad \& \quad H_2 = \begin{bmatrix} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T \partial G} \\ \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} \end{bmatrix} > 0,$$

then minimum exists for the function $E[TC(T, G, \xi)]$ at T^* & G^*

$$H_1 = \frac{\partial^2 TC(T,G)}{\partial G^2} = 44,669.2 > 0$$

$$\frac{\partial^2 TC(T,G)}{\partial T^2} = 8841.86 > 0$$

$$\frac{\partial^2 TC(T,G)}{\partial G \partial T} = \frac{\partial^2 TC(T,G)}{\partial T \partial G} = -0.0795$$

Therefore, the determinant of the above matrix $|H_2| = 394958812.7 > 0$.

A contour plot is also presented to show the convergence of the total average cost function TC w.r.t T and G .

Table 2 Solution algorithm to find the optimal value of ξ

Optimal values for all the cases			
ξ	T	G	E[TC]
0	7.272	1.111	355308.8875
1	7.4842	1.111	350922.2508
2	7.5782	1.111	349077.4839
3	7.6178	1.111	348317.2356
4	7.6341	1.111	348006.9050
5	7.6408	1.111	347881.0220
6	7.6435	1.111	347830.3845
7	7.6445	1.111	347810.3817
8	7.6452	1.111	347802.8405
9	7.6453	1.111	347800.3626
10	7.6454	1.111	347799.9214 (Min E[TC]) (Optimum value of Decision Parameters)
11	7.6454	1.111	347800.1089
12	7.6555	1.111	347800.1392

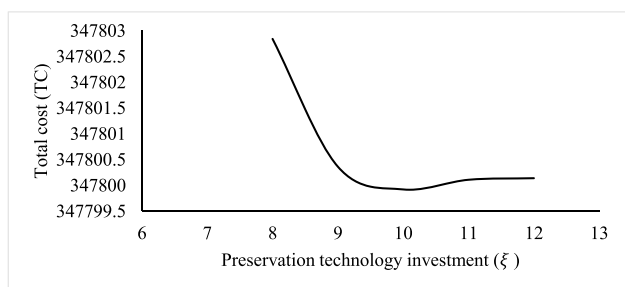


Fig. 9 Convexity of the total cost (TC) w.r.t. preservation investment (ξ)

Special case study of the numerical example

In this section, we study some special cases (Fig. 11) that arise and reveal some very useful facts:

Case 1: for a given value of cycle time $T=7.6454$, and other parameters remain constant as mentioned in the above numerical example, but investment in green technology $G=0$, and investment in preservation technology $\xi=0$, total average cost $E[TC]=385,095.005$.

Case 2: $\xi=0, T=T^*=7.6454, G=G^*=1.111$, total expected average cost $E[TC^*]=355,308.8875$.

Case 3: when $\xi=\xi^*=10$, total expected average cost $E[TC]=347,799.9214$. So, we can see total average cost is minimum when we are investing in both green and waste minimization techniques and maximum when investment in green and waste minimization techniques is zero. So, it is beneficial to invest in green and waste minimization techniques.

Sensitivity analysis, theoretical implications, and discussion of findings

Sensitivity analysis is conducted to study the influence of different parameters on total average cost function (TC) and decision variables (G, T, ξ). The sensitivity analysis is conducted by changing one variable from -20 to $+20\%$ while keeping other parameters constant.

Results mentioned in Table 3 and Fig. 12 reveal the effect of production rate, appraised by changing production rate on both sides while other parameter remains unchanged. The data obtained show that the production rate (P) is highly sensitive to the total average cost (TC), as well as cycle time (T), and has a positive impact on total average cost (TC). The linear relationship between the production rate and the total average cost is shown in Eq. 9 of total average cost $TC(T, G, \xi)$, which is also confirmed by Fig. 12; if the production rate increases uniformly, total average cost rises linearly. The first reason behind the nonlinear increment in total average cost is the high tooling cost because the wear rate intensifies as the production rate rises, and the second reason is high stock available because for a given demand rate, an increase in production rate results in large available inventory, which in turn causes high holding cost. The reason for the large cycle time is more time required to dispatch large accumulated inventory, but the production rate does not influence green technology investment.

The influence of production time can be realized from the data revealed in Table 4 and Fig. 13, and it has been observed that the production time has a positive impact on total average cost (TC) and increases cycle time (T). The reason behind the increment in cost is the high manufacturing cost and also significant manufacturing time results in a large inventory stock which requires more time to deplete, causes rise in holding and deterioration cost. The total average cost varies nonlinearly with production time; demonstrated in Eq. 9 of total average cost and Fig. 13, we observe that total average cost flattens at low production time and becomes rather steep as the production time rises which may be due to the accumulation of large inventory stock. The influence on green technology investment (G) is significantly less, but it rises with production time.

From Table 5 and Fig. 14, a surge in total average cost (TC) and replenishment cycle time can be perceived with the rise in direct material cost. The relationship between total average cost and direct material cost is linear shown in Eq. 9 of total average cost and Fig. 14. In real conditions, more direct material is required as production volume increases, and the requirement of the material rises linearly with production volume as each product requires an equal amount of material, resulting in a linear increase of total average cost.

Results of Table 6 and Fig. 15 show the same impact of manpower cost on total average cost (TC) and cycle (T) as

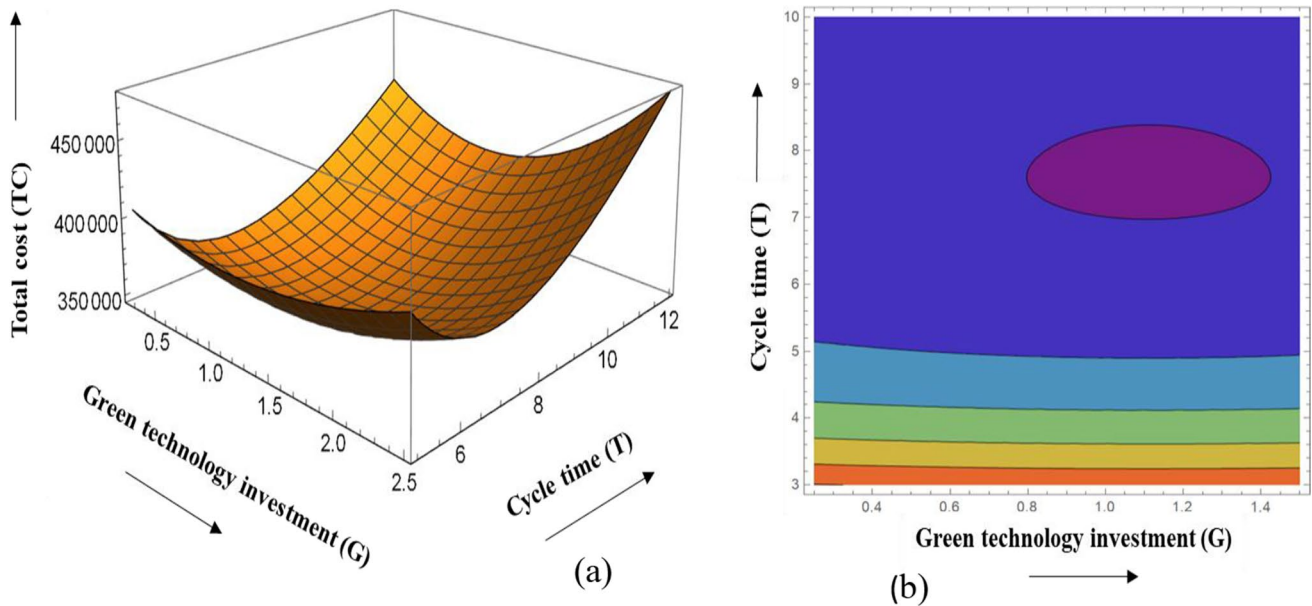


Fig. 10 **a** Convexity of total cost (TC) w.r.t cycle time (T) and green technology investment (G). **b** Contour plot showing the convergence of total average cost function (TC) w.r.t green technology investment (G) and cycle time (T)

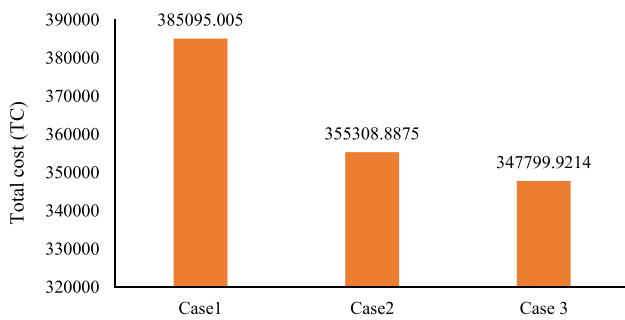


Fig. 11 Variation of TC for different conditions case1: when $G=0$ and $\xi=0$, case2: when $G=1.111$ and $\xi=0$, case3: when $G=1.111$ and $\xi=10$

the direct material cost, and the reason behind the surge in total average cost (TC) and cycle (T) is also the same. The relationship between total average cost and manpower cost is linear as demonstrated in Eq. 9 of total average cost and Fig. 15. Manpower cost increases linearly with workforce number, therefore increasing manufacturing cost in the same manner and so does the total average cost.

Data mentioned in Table 7 and Fig. 16 shows the same impact of tooling cost (k) on total average cost (TC) and cycle (T) as direct material (c) and manpower costs (J). Since large tooling cost means a high production rate which results in large inventory and it will increase the other associated cost. The relationship between total average cost and tooling cost is linear as shown in Eq. 9 of total average cost and Fig. 16. As the tooling cost increases, manufacturing cost rises linearly so does the total average cost.

From Table 8 and Fig. 17, varying holding cost per unit on both sides while keeping other parameters constant, as the holding cost rises, total average cost upsurges whereas cycle time (T) reduces because longer cycle time will cause more holding cost, so warehouse should be evacuated on optimum cycle time. In contrast, it does not influence green investment (G). Total average cost varies linearly with holding cost per unit, as holding cost of each unit is the same, so rise in holding cost per unit will cause linear increase in total average cost, and it can be confirmed from Eq. 9 and Fig. 17.

From the results mentioned in Table 9 and Fig. 18, we can see for a given investment in preservation technology, the rise in preservation technology efficiency has a diminishing

Table 3 Effect of production rate (P)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
P	-20	9600	6.8799	1.111	10	295,962.2654
	-10	10,800	7.2659	1.111	10	322,119.1644
	10	13,200	8.0198	1.111	10	373,072.2087
	20	14,400	8.8873	1.111	10	397,990.6519

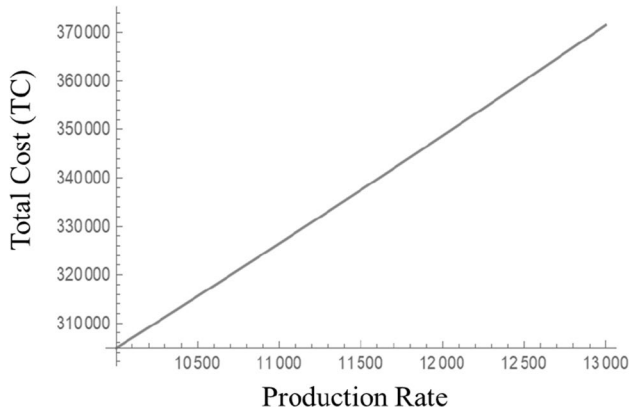


Fig. 12 Influence of increasing production rate on total cost

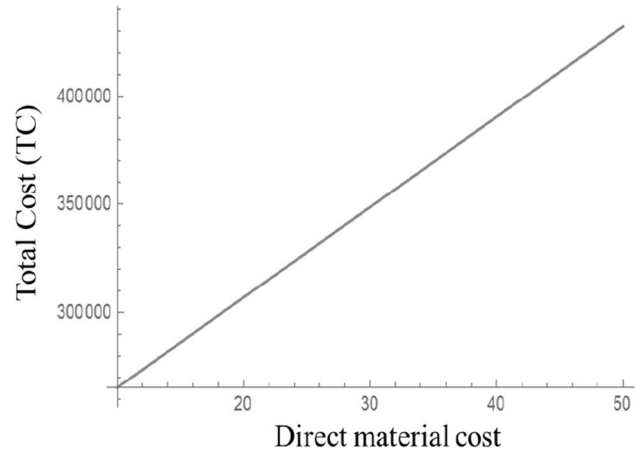


Fig. 14 Influence of increasing direct material cost on total cost

Table 4 Effect of production time (T_m)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
T_m	-20	2	6.9009	1.1110	10	331,353.5159
	-10	2.25	7.2770	1.1116	10	339,867.8591
	10	2.75	8.0069	1.1118	10	355,229.9006
	20	3	8.3589	1.1119	10	362,222.6013

Table 6 Effect of manpower cost (J)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
J	-20	80	7.6437	1.1111	10	347,793.3926
	-10	90	7.6437	1.1111	10	347,796.6602
	10	110	7.6453	1.1111	10	347,803.1920
	20	120	7.6456	1.1111	10	347,806.4646

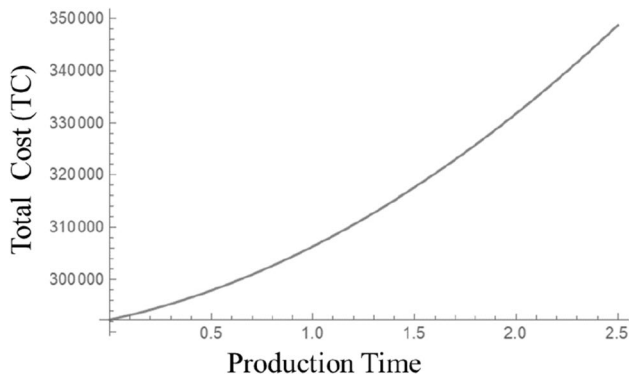


Fig. 13 Influence of increasing production time on total cost

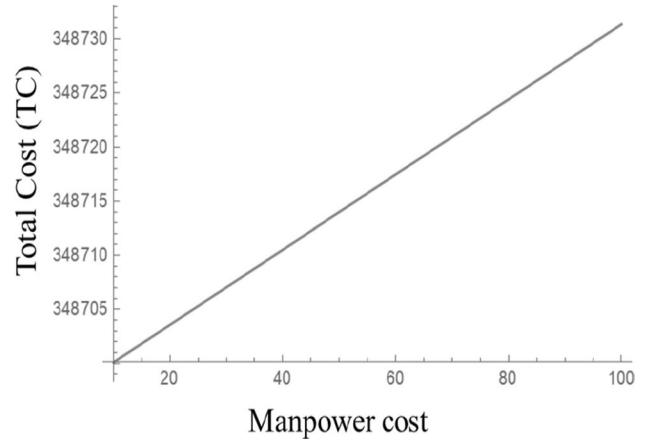


Fig. 15 Influence of increasing manpower cost on total cost

Table 5 Effect of direct material cost (c)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
c	-20	24	7.2887	1.1111	10	323,693.9605
	-10	27	7.4704	1.1110	10	335,890.8460
	10	33	7.8170	1.1111	10	35,440.6782
	20	36	7.9846	1.1110	10	370,830.4731

Table 7 Effect of tooling cost (k)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
k	-20	0.00072	7.5177	1.1111	10	339,253.5209
	-10	0.00081	7.5816	1.1111	10	343,544.5341
	10	0.00099	7.7077	1.1111	10	352,020.5544
	20	0.00108	7.7697	1.1111	10	356,207.2741

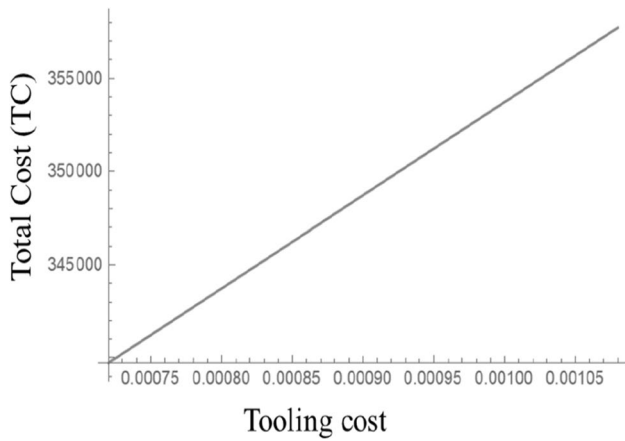


Fig. 16 Influence of increasing tooling cost on total cost

Table 8 Effect of holding cost per unit (c_h)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
c_h	-20	1.6	7.8506	1.111	10	340,403.5464
	-10	1.8	7.7453	1.111	10	344,146.3261
	10	2.2	7.5496	1.111	10	351,368.7195
	20	2.4	7.4586	1.111	10	354,856.8023

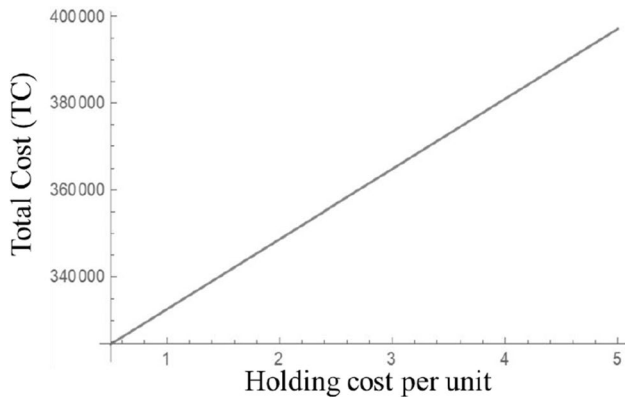


Fig. 17 Influence of increasing holding cost per unit on total cost

Table 9 Effect of preservation technology efficiency (λ)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
λ	-20	0.72	7.6452	1.111	10	347,804.8405
	-10	0.81	7.6452	1.111	10	347,801.3626
	10	0.99	7.6444	1.111	10	347,799.1811
	20	1.08	7.6555	1.111	10	347,798.1392

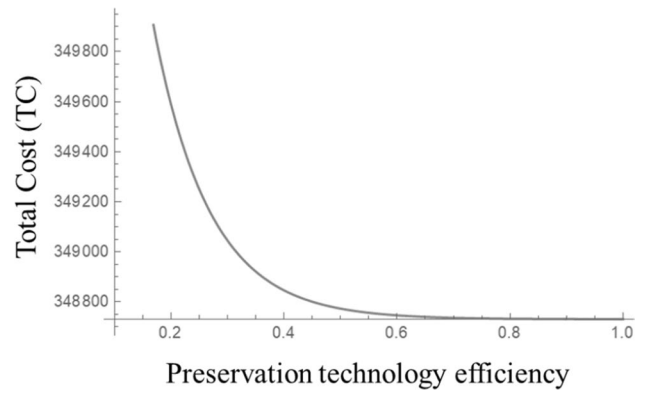


Fig. 18 Influence of increasing preservation technology efficiency on total cost

Table 10 Effect of deterioration rate $E(\theta)$

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
$E(\theta)$	-20	0.032	7.6454	1.111	10	347,799.7063
	-10	0.036	7.6456	1.110	10	347,799.8174
	10	0.044	7.6444	1.111	10	347,800.0225
	20	0.048	7.6459	1.110	10	347,800.1276

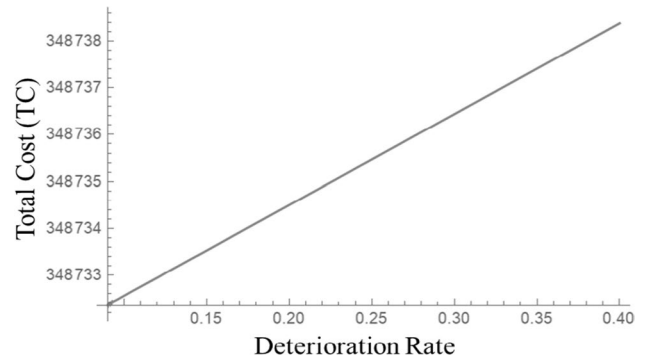


Fig. 19 Influence of increasing deterioration rate on total cost

Table 11 Effect of lot size (Q)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
Q	-20	80	7.5090	1.111	10	338,587.2335
	-10	90	7.5782	1.111	10	343,214.2925
	10	110	7.7116	1.111	10	352,345.2180
	20	120	7.7793	1.111	10	356,851.2218

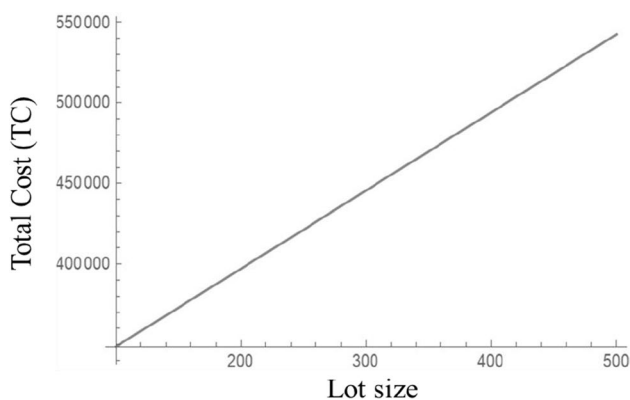


Fig. 20 Influence of rise in lot size on total cost

Table 12 Effect of screening time (σ)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
σ	-20	0.16	7.6456	1.111	10	347,799.7370
	-10	0.18	7.6456	1.111	10	347,799.8300
	10	0.22	7.6456	1.111	10	347,800.0217
	20	0.24	7.6456	1.111	10	347,800.1205

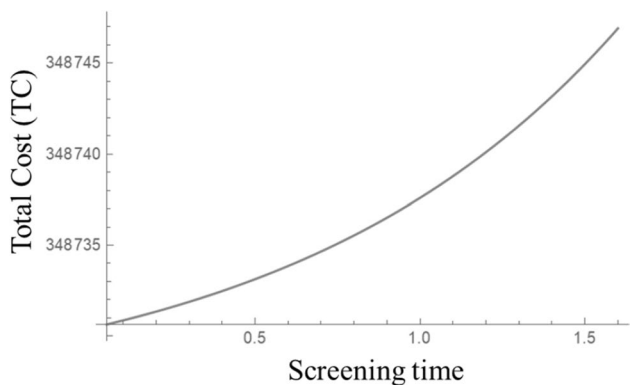


Fig. 21 Influence of increasing screening time on total cost

Table 13 Effect of time in years between first order since 1990 (X)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
X	-20	25.6	7.5353	1.111	10	340,437.0439
	-10	28.8	7.5919	1.111	10	344,131.6890
	10	35.2	7.7001	1.111	10	351,442.3037
	20	38.4	7.7527	1.111	10	355,059.3593

effect on total average cost (TC) and an increment in cycle time (T) has been noticed. This happens because the rise in preservation technology efficiency results in the reduction of deterioration rate so the vendor can sell the product for a longer period of time. However, it does not influence green technology investment. Preservation technology efficiency has a nonlinear relationship with total cost as shown in Eq. 9 of total average cost and in real condition, also cost will not decrease uniformly with the rise in efficiency of preservation system.

From the results of Table 10 and Fig. 19, it can be perceived changing the deterioration rate on both sides and keeping other parameters constant, the deterioration rate has a positive influence on total average cost (TC) because with a surge in deterioration rate, wastage as well as emission cost due to deterioration upsurges. Total cost varies linearly as well as nonlinearly with deterioration rate and it can be seen from Eq. 9. The influence of linear term for the chosen value may be more dominating, so the total average cost seems to vary linearly with the deterioration rate.

We can see from the data in Table 11 and Fig. 20 that as the distributor orders a larger quantity in a lot, the total cost incurred to the vendor rises. At the same time, it does not influence green investment (G) but increases cycle duration (T). Total cost varies linearly with lot size and it can be seen from Eq. 9 as well as Fig. 20. As the lot size increases, the transportation and other associated cost rises linearly and so does the total cost.

Results mentioned in Table 12 and Fig. 21 demonstrate that screening time positively impacts the total average cost (TC) because the manufacturer needs an extra person to employ for the screening purpose. Total cost varies nonlinearly with screening time and it can be seen from Eq. 9 as well as Fig. 21. As the screening time increases, the screening cost rises nonlinearly and so does the total cost.

Data mentioned in Table 13 and Fig. 22 shows as the fuel price is growing every year, it positively impacts the transportation cost incurred in delivering the product by the vendor, resulting in increased total average cost (TC). Cycle time (T) also rises, but green investment (G) remains unaffected. Total cost varies linearly with time and it can be seen from Eq. 9 as well as Fig. 22. As the time increases, the transportation cost varies linearly and so does the total cost.

From Table 14 and Fig. 23, the distance travelled by the vehicle has a rising influence on total average cost (TC) and cycle time (T). There are two reasons for the increment in total average cost. First, as the distance travelled by the vehicle increases, the vehicle consumes more fuel, resulting in high transportation costs, and at the same time, vehicle emits more carbon if it travels more distance, so carbon emission cost also surges, which leads to a negative influence on total average

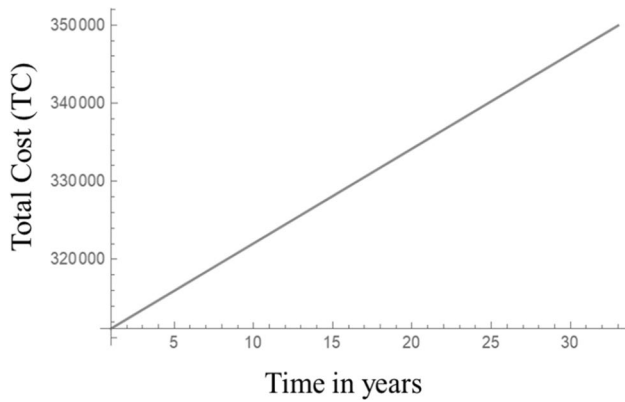


Fig. 22 Influence of increasing time in years on total cost

Table 14 Effect of distance travelled by the vehicle (d)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^{**}]$
d	-20	8	7.5079	1.111	10	338,513.0770
	-10	9	7.5763	1.111	10	343,177.5529
	10	11	7.7129	1.111	10	352,381.3138
	20	12	7.7803	1.111	10	356,922.7951

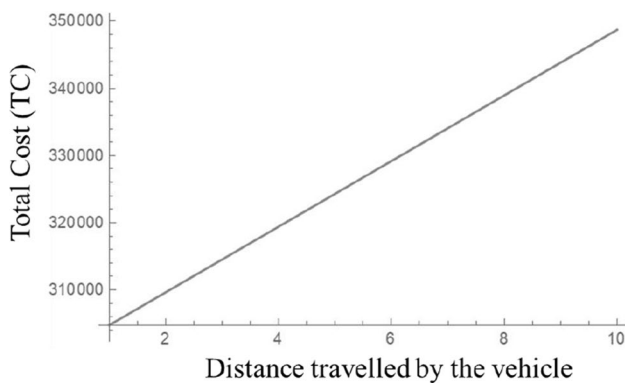


Fig. 23 Influence of increasing distance travelled by the vehicle on total cost

Table 15 Effect of fuel consumption (l)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^{**}]$
l	-20	0.8	7.6430	1.111	10	347,726.4963
	-10	0.9	7.6435	1.111	10	347,763.2141
	10	1.1	7.6457	1.111	10	347,836.6295
	20	1.2	7.6468	1.111	10	347,873.3378

cost. Cycle time also increases because if the vehicle takes more time to deliver the product, cycle time is likely to be longer. Total average cost varies linearly with distance travelled by the vehicle and it can be seen from Eq. 9 as well as Fig. 23. As the distance travelled by the vehicle increases, the transportation cost varies linearly and so does the total cost.

Results of Table 15 and Fig. 24 show as the vehicle consumes more fuel, transportation cost increases, and vehicles emit more carbon when travelling large distances, so carbon emission cost also rises; as a result, the total cost per cycle increases. Total average cost varies linearly with fuel consumption and it can be seen from Eq. 9 as well as Fig. 24. As the fuel consumption increases, the transportation cost varies linearly and so does the total average cost.

Results of Table 16 and Fig. 25 show the positive influence of additional fuel consumption (f_{ca}) on total average cost (TC). Total cost varies linearly with additional fuel consumption and it can be seen from Eq. 9 as well as Fig. 25. As the additional fuel consumption increases, the transportation cost varies linearly and so does the total average cost.

From Table 17 and Fig. 26, as the vendor sends shipments to the distributor, it becomes costlier because of the rising trends in fuel price, so transportation costs increase. Total average cost varies linearly with the shipment number and it can be seen from Eq. 9 as well as Fig. 26. As the shipment number increases, the transportation cost varies linearly and so does the total cost.

The results of Table 18 and Fig. 27 show a rise in total average cost (TC) with the carbon tax imposed to curb emissions and reduce cycle time because if the cycle time is longer, the vendor must pay more tax. Total average cost varies linearly with carbon tax per cycle and it can be seen from Eq. 9 as well as Fig. 27.

Data mentioned in Table 19 and Fig. 28 demonstrates a rise in total cost per cycle with emission from warehousing operations because the tax paid by the vendor will be more, so it is suggested to keep cycle duration smaller so that total carbon emitted in a production cycle can be minimized. Vendors should judiciously invest in green technology like solar technology to reduce emissions. Total average cost varies linearly with carbon emission due to the warehousing operations and it can be seen from Eq. 9 as well as Fig. 28 because as the emission from warehousing operations rises, emission cost increases linearly and hence the total cost.

Results of Table 20 and Fig. 29 show that total average cost (TC) upsurges with emissions from the production process because vendors have to pay more tax, and investment in green technology also increases to curb emissions. Total average cost varies linearly with carbon emission due to the production process and it can be seen from Eq. 9 as well as Fig. 29 because as the emission from the production process rises, emission cost rises linearly and hence in the same way the total cost increases.

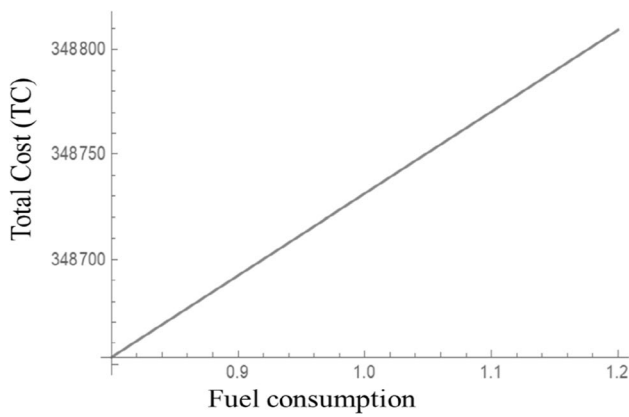


Fig. 24 Influence of increase in fuel consumption on total cost

Table 16 Effect of additional fuel consumption due to transportation of Q units (f_{ca})

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
f_{ca}	-20	0.8	7.5097	1.1106	10	338,587.8436
	-10	0.9	7.5782	1.1112	10	343,214.5914
	10	1.1	7.7116	1.1109	10	352,344.9243
	20	1.2	7.7792	1.1110	10	356,850.6387

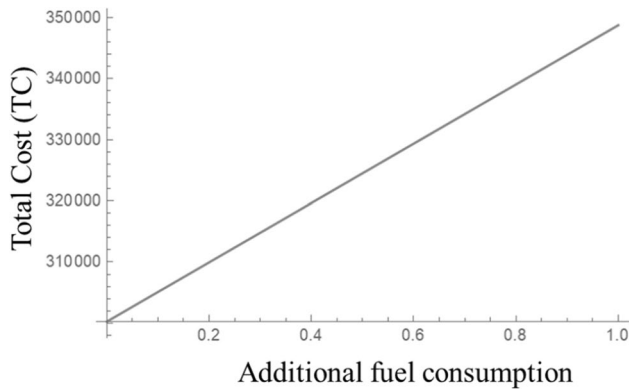


Fig. 25 Influence of surge in additional fuel consumption on total cost

Table 17 Effect of the trip or shipment number being sent by the manufacturer (n)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
n	-20	2.4	7.6428	1.111	10	347,781.1069
	-10	2.7	7.6437	1.111	10	347,790.514
	10	3.3	7.6456	1.111	10	347,809.3422
	20	3.6	7.6458	1.111	10	347,818.7533

From the above data mentioned in Table 21 and Fig. 30, as the carbon emission from waste disposal rises, the total average cost (TC) surges, but its influence is less as compared to other kinds of emissions. Total average cost varies linearly with carbon emission from waste disposal and it can be seen from Eq. 9 as well as Fig. 30. Because if carbon emission will increase linearly and hence the emission cost due to waste disposal and total cost will also rise in the same manner.

From the data mentioned in Table 22 and Fig. 31, a positive impact of vehicle standard emission (x) on total average cost (TC) can be perceived. If the vehicle carrying inventories emits more carbon vendor has to pay more tax, so they should use a vehicle having less carbon emission potential to deliver the goods, or the vendor should shift to the electric vehicle. Total average cost varies linearly with vehicle standard emission and it can be seen from Eq. 9 as well as Fig. 31.

From Table 23 and Fig. 32, it can be noted that a rise in green technology efficiency has a diminishing impact on total average cost (TC) because it reduces carbon emissions as well as investment in green technology. However, it has very less influence on cycle time. Green technology efficiency has a nonlinear relationship with total average cost as shown in Eq. 9 of total average cost and in real condition, also cost will not decrease uniformly with the rise in green technology efficiency.

Discussion of findings

In this section, the present study is compared with the existing literature. However, it is not possible to compare with the existing literature as all the parameters are not the same. Some of the most important insights gained from data analysis are highlighted below.

- Simultaneous optimization of cycle time, green technology investment, and preservation technology investment is helpful in reducing the cost incurred by the manufacturer. Similar observations have been shown by Mashud et al. (2022) in their inventory model for the manufacturer. They maximized the profit of the manufacturer; however, they considered constant demand, production rate, deterioration rate, and fuel price.
- The results of the special case of the numerical example make it abundantly clear that investments in both waste minimization and green technology would produce superior results compared to the situation in which neither preservation technology nor green technology is invested in. This observation aligns with Mashud et al. (2022).

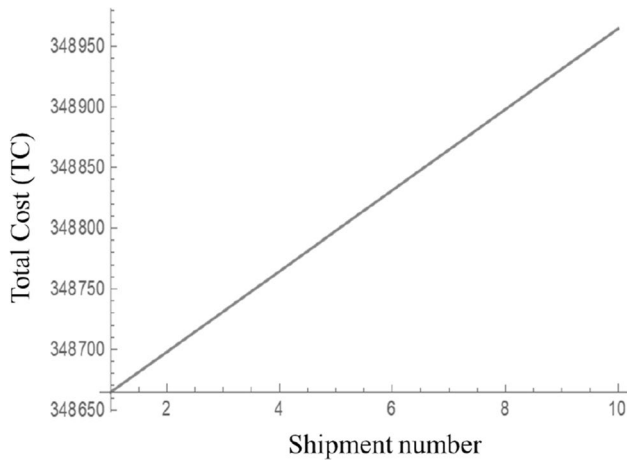


Fig. 26 Influence of shipment number on total cost

Table 18 Effect of carbon tax per cycle (δ)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
δ	-20	4	8.0981	1.110	10	324,964.438
	-10	4.5	7.8579	1.111	10	336,585.6094
	10	5.5	7.4561	1.111	10	358,659.7250
	20	6	7.2847	1.111	10	369,208.1622

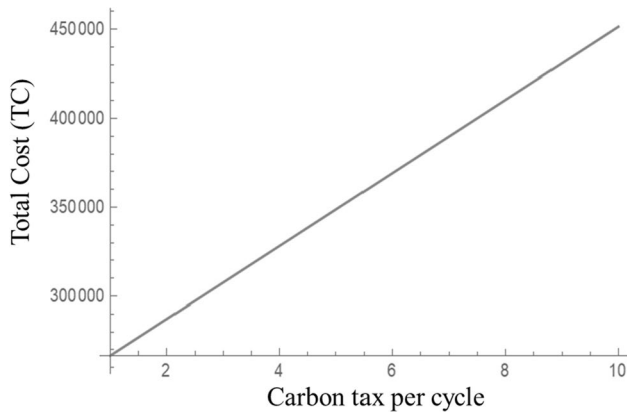


Fig. 27 Impact of carbon tax per cycle on total cost

Table 19 Effect of carbon emission due to warehousing operations (E_h)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
E_h	-20	0.96	8.1743	1.1110	10	329,407.2836
	-10	1.08	7.8941	1.1112	10	338,880.4120
	10	1.32	7.4229	1.1111	10	356,230.2767
	20	1.44	7.2219	1.1109	10	364,225.1152

- A high production rate increases the manufacturer’s overall costs, and this observation is consistent with Sepehri et al. (2021). This might be brought on by an increase in tooling costs, significant wear and tear, and high holding costs brought on by a massive build-up of inventory. Therefore, a manufacturer should select their production rate carefully. However, Sepehri et al. (2021) considered constant demand, production rate, and deterioration rate, whereas no discussion of transportation cost and fuel price. They also optimized different parameters in their profit maximization problem.
- Emissions from various sources and significant carbon tax increase the cost of the manufacturer. This observation is consistent with Ruidas et al. (2021), so a manufacturer should invest in green technologies to reduce the cost of emissions from various activities. But large investment in green technologies again leads to a rise in cost, so an optimum investment is recommended.
- As the efficiency of green technology increases, green technology investment reduces, which results in the reduction of the overall cost of the manufacturer, this result is inline with Mishra et al. (2020a).
- As the preservation technology efficiency rises total cost reduces, this result is consistent with Hsu et al. (2010).
- As the holding cost per unit cost increases, total cost of the manufacturer surges Hsu et al. (2010).

Insights for industry

The industrial benefits of this paper are discussed in this section as follows. This paper may assist the managers in taking operational and tactical level decisions, including cycle time, green technology investment, and preservation technology investment, as described below.

- This study considers dynamic fuel pricing while taking decisions. As the fuel prices are increasing aggressively, so transportation cost is rising every year, and manufacturers must incur more cost in delivering the product to the customer. Whereas fuel consumption is affected by the distance travelled by the vehicle as well as the load carried by the vehicle which in turn affects the cost and adds more carbon to the environment. So, from a manufacturer, a paradigm shift from conventional vehicles to modern electric vehicles is required to deliver the product to the distributor to reduce dependency on fuel. Moreover, this novel step taken by the manufacturer will help to diminish the huge carbon emission to the environment and conserve fuel.
- Optimal cycle time, investment in green technology and investment in waste minimization techniques help the

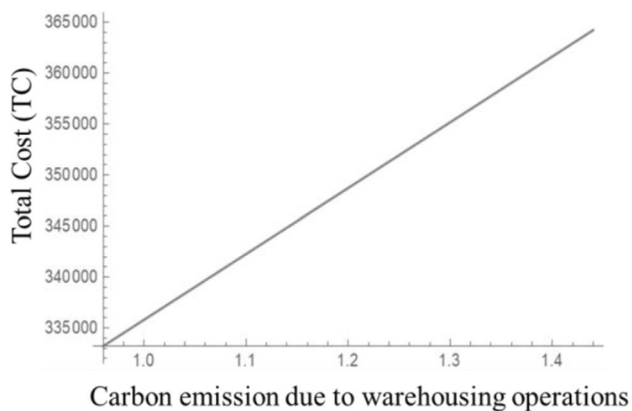


Fig. 28 Impact of emission due to warehousing operations the on total cost

Table 20 Effect of carbon emission due to the production process (E_p)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
E_p	-20	0.96	7.5886	1.1107	10	344,019.984
	-10	1.08	7.6167	1.1112	10	345,912.9780
	10	1.32	7.3957	1.1113	10	354,286.7539
	20	1.44	7.4749	1.1113	10	360,096.4130

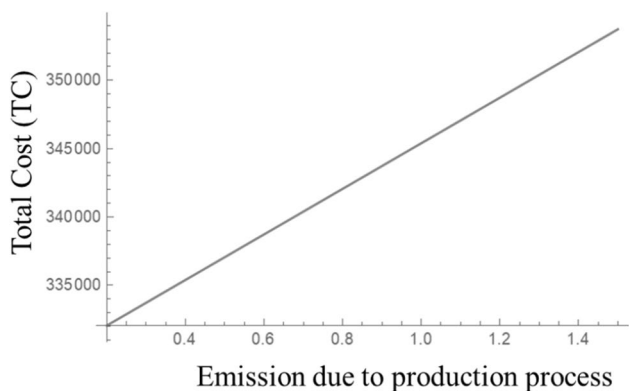


Fig. 29 Impact of emission due to the production process on total cost

Table 21 Effect of carbon emission due to waste disposal (E_{wd})

Param- eters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
E_{wd}	-20	0.16	7.6453	1.11108	10	347,799.5062
	-10	0.18	7.6453	1.11108	10	347,799.7105
	10	0.22	7.6456	1.11159	10	347,800.1342
	20	0.24	7.6456	1.11159	10	347,800.3439

industry to make their decision on how much to invest in these technologies, what would be the cost incurred, what should be the cycle time to restart the production process, and if cycle time is longer, it can increase various costs whereas if it is too small, it can lead to selling loss. Through this study, the industry can minimize its cost.

- c. Through sensitivity analysis, many significant parameters like production rate and fuel consumption have been identified; even a small change in these parameters affects the cost of the manufacturer significantly. As we have seen from the data mentioned in Table 6, a very high production rate does not necessarily reduce cost; instead, it surges tooling cost, deterioration cost, and holding cost, so the manufacturer should judiciously control the production rate likewise other parameters are also consequential and needs special attention.
- d. From the special case discussed in the numerical example, it has been observed that when a manufacturer simultaneously invests in green and waste minimization techniques, total average cost is minimum. So, the industry will be surely benefited by making optimal investments in green technology like solar energy in place of non-renewable fuel sources, and its benefit is two-fold. First, it reduces cost as it is cheap and readily available and also helps in conserving conventional fuels. Some perishable products require refrigerated space, whereas others require warm conditions to stay fresh, so a manufacturer should make arrangements accordingly.

Conclusion, limitation, and future scope

There are two bigger challenges before any sustainable perishable product supply chain deterioration or wastage and emission from various stages. The deterioration of inventory poses a huge cost to any company dealing with deteriorating items. Moreover, emissions from various sources at different stages are a matter of concern and need to be minimized. The main aim of this study is to simultaneously solve these issues. To solve the first problem of wastage, investment is made in preservation technology, but too much investment can lead to higher cost, so keeping this issue in view, investments in preservation technology has been optimized. Carbon emission can take place due to production, transportation, warehousing, and waste disposal, so with a target of achieving zero emissions and making the supply chain more sustainable, investment in green technology is made. With the goal to minimize the total cost, the cycle time to restart the manufacturing process has been optimized, as too longer cycle time can lead to more deterioration cost, holding cost, carbon emission cost due to warehousing operations and shortage, and too

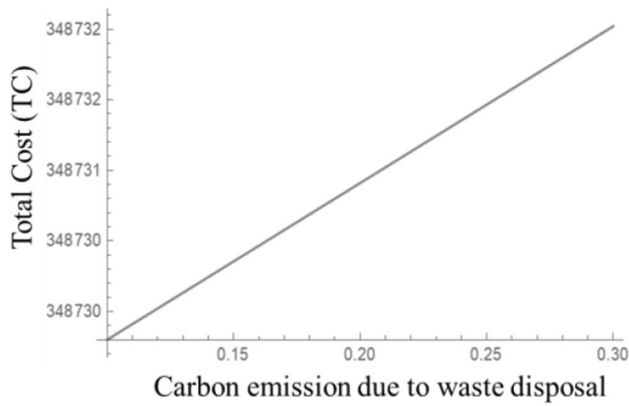


Fig. 30 Impact of increase in carbon emission due to waste disposal on total cost

Table 22 Effect of vehicle standard emission (V_e)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
V_e	-20	2.4	7.6311	1.11110	10	346,838.4429
	-10	2.7	7.6383	1.11091	10	347,319.4043
	10	3.3	7.6535	1.11141	10	348,279.9958
	20	3.6	7.6607	1.11091	10	348,759.6211

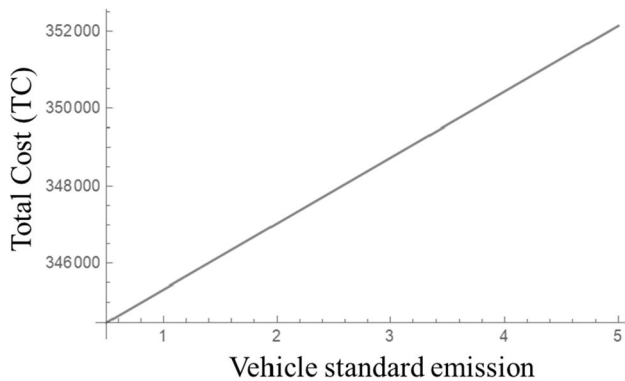


Fig. 31 Impact of changes in vehicle standard emission on total cost

Table 23 Effect of green technology efficiency (v)

Parameters	% Change	New value	T^*	G^*	ξ^*	$E[TC^*]$
v	-20	0.72	7.6445	1.3886	10	347,800.1996
	-10	0.81	7.6445	1.2345	10	347,800.0427
	10	0.99	7.6461	1.0103	10	347,799.8222
	20	1.00	7.6453	0.9259	10	347,799.7395

short a cycle time can lead to revenue e loss. An algorithm is proposed to obtain the optimum solution. A numerical experiment is done to validate the model, and the convexity of the total cost function has been proved. The purpose of sensitivity analysis is to identify significant parameters that have a huge impact on the cost of the manufacturer; some of the most important insights gained from data analysis are highlighted below. Simultaneous optimization of cycle time, green technology investment, and preservation technology investment is helpful in reducing the cost incurred by the manufacturer. Similar observations have been shown by Mashud et al. (2022). A high production rate increases the manufacturer’s overall costs, and this observation is consistent with Sepehri et al. (2021). This might be brought on by an increase in tooling costs, significant wear and tear, and high holding costs brought on by a massive build-up of inventory. Therefore, a manufacturer should select their production rate carefully.

Though an extensive study has been done yet, it has certain limitations and ample scope for future extension of the model. As the reworking process has not been considered in this model, so it is applicable for those items which cannot be reworked; this is the main limitation of this model, but the same model with little modification can be used for the items that can be reworked. This paper did not consider backlogging, which is a natural extension of the present model. The present study can be further extended by considering the time-dependent deterioration rate, which is more realistic. As the preservation technology is being used, it will surely affect the freshness of the product, so the freshness-dependent demand is a very relevant extension of the present study. Deterministic price-dependent demand can be replaced with stochastic demand, or other deterministic demand like stock-dependent demand, price, and stock-dependent demand are other possible extensions of the present study. Demand fluctuation due to supply chain disruptions can also be considered. However, the unavailability of real-time data for all the parameters is one of the limitations.

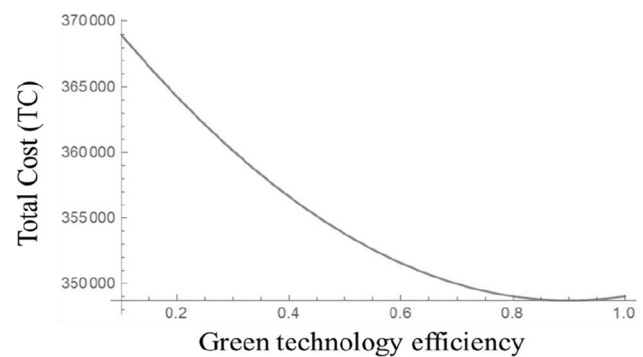


Fig. 32 Influence of increasing green technology efficiency on total cost

Appendix 1

Proof of Lemma 1

To determine the optimal values of G , calculate the first and second-order derivatives of $E [TC (T, G, \xi)]$ with respect to G . First-order derivatives are given below.

$$\begin{aligned} & \frac{\partial E[TC(T,G,\xi)]}{\partial G} \\ &= \{T - \delta(\vartheta - G\vartheta^2)\phi(T_m P E_p \\ & \quad e^{\lambda\xi(P+bs-a)} \left(T_m + \frac{e^{\lambda\xi} (e^{-\lambda\xi} T_m E(\theta) - 1)}{E(\theta)} \right) \\ & + E_h \left(\frac{E(\theta)}{e^{\lambda\xi} (a-bs)} \left(T_m - T + \frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)\theta - 1)}{E(\theta)} \right) \right) \\ & + \frac{2d \ln V_e + dQw_{fca} V_e}{E(\theta)} + W_d Q E_{wd} \} / T \end{aligned}$$

$$\frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} = \frac{\left\{ \delta\vartheta^2 \phi \left(T_m P E_p + E_h \left(\frac{e^{\lambda\xi} (P+bs-a)}{E(\theta)} \left(T_m + \frac{e^{\lambda\xi} (e^{-\lambda\xi} T_m E(\theta) - 1)}{E(\theta)} \right) + \frac{e^{\lambda\xi} (a-bs)}{E(\theta)} \left(T_m - T + \frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)\theta - 1)}{E(\theta)} \right) \right) \right) + 2d \ln V_e + dQw_{fca} V_e + W_d Q E_{wd} \right\}}{T} > 0$$

Appendix 2

Proof of corollary 1

For a given value of ξ and $P > a - bs$, and $a - bs = D$, from the above expression we can observe possible negative terms are

$$e^{-\lambda\xi} T_m E(\theta) - 1 \text{ and } \frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)E(\theta) - 1)}{E(\theta)}$$

Definitely $e^{-\lambda\xi} (T-T_m)E(\theta) > 1$ and also $\frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)E(\theta) - 1)}{E(\theta)} > (T_m - T)$
 so $e^{\lambda\xi} (a - bs) \left(T_m - T + \frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)E(\theta) - 1)}{E(\theta)} \right)$ is a very large positive

To determine the minimum cost of the production inventory system, the above-mentioned partial differentiation should satisfy the necessary condition, i.e., $\frac{\partial E[TC(T,G,\xi)]}{\partial G} = 0$; from this condition, we can find the optimum value of the decision variable G .

Moreover, to satisfy optimality, i.e., convexity conditions, the sufficient condition must be satisfied, i.e., the corresponding principal minor should be positive definite.

$$\text{Hessian matrix, } H = \begin{bmatrix} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T \partial G} \\ \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} \end{bmatrix}$$

$$\text{If the leading minors of } H \text{ are } H_1 = \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} > 0$$

value. $e^{-\lambda\xi} T_m E(\theta) < -1$, but $e^{\lambda\xi} (a - bs) \left(T_m - T + \frac{e^{\lambda\xi} (e^{-\lambda\xi} (T-T_m)E(\theta) - 1)}{E(\theta)} \right)$ is very large as compared to $e^{\lambda\xi} (P + bs - a) \left(T_m + \frac{e^{\lambda\xi} (e^{-\lambda\xi} T_m E(\theta) - 1)}{E(\theta)} \right)$ so since $H_1 > 0$, corollary 1 is satisfied one can conclude $\frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} > 0$, therefore, $E [TC (T, G, \xi)]$ is convex in G and a unique minimum solution exists at G^* hence corollary 1 is proved.

Appendix 3

Proof of Lemma 2

To determine the optimal values of T , calculate the first and second-order derivatives of $E [TC (T, G, \xi)]$ with respect to T . First-order derivatives are given below.

$$\begin{aligned} & \frac{\partial TC E [TC(T, G, \xi)]}{\partial T} \\ &= \frac{G + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1) C_h (a - bs)}{E(\theta)} + \xi + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1) (a - bs) E_h \delta (1 - (G\theta - \frac{G^2 \theta^2}{2}) \phi)}{E(\theta)}}{E(\theta)} \\ & - \frac{1}{T^2} (A + F + T_m P (c + \frac{J}{p} + kP) + GT + W + 2d\alpha + Q\beta_o (e^{\sigma \psi} - 1) + \frac{2dl(n-1)Q\beta}{a-bs}) \\ & + \frac{e^{\lambda \xi} C_h (P + bs - a) (T_m + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1)}{E(\theta)})}{E(\theta)} + \frac{e^{\lambda \xi} C_h (a - bs) (T_m - T + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1)}{E(\theta)})}{E(\theta)} + T\xi \\ & + dQw\alpha f_{ca} + \delta (1 - (G\theta - \frac{G^2 \theta^2}{2}) \phi) (T_m P E_p + E_h (\frac{e^{\lambda \xi} (P + bs - a) (T_m + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1)}{E(\theta)})}{E(\theta)} \\ & + \frac{e^{\lambda \xi} (a - bs) (T_m - T + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1)}{E(\theta)})}{E(\theta)}) + 2d\ln V_e + dQw\alpha f_{ca} V_e + W_d Q E_{wd})) \end{aligned}$$

To determine the minimum cost of the production inventory system, the above-mentioned partial differentiation should satisfy the necessary condition, i.e., $\frac{\partial E [TC(T, G, \xi)]}{\partial T} = 0$; from this condition, we can find the optimum value of the decision variable T .

Moreover, to satisfy optimality, i.e., convexity conditions, the sufficient condition must be satisfied, i.e., the corresponding principal minor should be positive definite.

$$\text{Hessian matrix, } H = \begin{bmatrix} \frac{\partial^2 E [TC(T, G, \xi)]}{\partial G^2} & \frac{\partial^2 E [TC(T, G, \xi)]}{\partial T \partial G} \\ \frac{\partial^2 E [TC(T, G, \xi)]}{\partial G \partial T} & \frac{\partial^2 E [TC(T, G, \xi)]}{\partial T^2} \end{bmatrix}$$

If the leading minors of H are $H_1 = \frac{\partial^2 E [TC(T, G, \xi)]}{\partial T^2} > 0$

$$\begin{aligned} & \frac{\partial^2 E [TC(T, G, \xi)]}{\partial T^2} = \frac{e^{-\lambda \xi} (T - T_m) E(\theta) C_h (a - bs) + e^{-\lambda \xi} (T - T_m) E(\theta) (a - bs) E_h \delta (1 - (G\theta - \frac{G^2 \theta^2}{2}) \phi)}{T^2} \\ & 2 \left(G + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1) C_h (a - bs)}{E(\theta)} + \xi + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1) (a - bs) E_h \delta (1 - (G\theta - \frac{G^2 \theta^2}{2}) \phi)}{E(\theta)} \right) \\ & + \frac{1}{T^3} 2(A + F + T_m P (c + \frac{J}{p} + kP) + GT + W + 2d\alpha + Q\beta_o (e^{\sigma \psi} - 1) + \frac{2dl(n-1)Q\beta}{a-bs}) \\ & + \frac{e^{\lambda \xi} C_h (P + bs - a) \left(T_m + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T - T_m) E(\theta) - 1)}{E(\theta)} \right) + e^{\lambda \xi} C_h (a - bs) \left(T_m - T + \frac{e^{\lambda \xi} (-1 + e^{-\lambda \xi} (T - T_m) E(\theta))}{E(\theta)} \right)}{E(\theta)} + T\xi + dQw\alpha f_{ca} + \\ & \delta \left(1 - (G\theta - \frac{G^2 \theta^2}{2}) \phi \right) \left(T_m P E_p + E_h \left(\frac{e^{\lambda \xi} (P + bs - a) \left(T_m + \frac{e^{\lambda \xi} (-1 + e^{-\lambda \xi} (T - T_m) E(\theta))}{E(\theta)} \right)}{E(\theta)} \right) + \right. \\ & \left. \frac{e^{\lambda \xi} (a - bs) \left(T_m - T + \frac{e^{\lambda \xi} (-1 + e^{-\lambda \xi} (T - T_m) E(\theta))}{E(\theta)} \right)}{E(\theta)} \right) + 2d\ln V_e + dQw\alpha f_{ca} V_e + W_d Q E_{wd} \Bigg) \geq 0 \end{aligned}$$

Appendix 4

Proof of Lemma 3

To determine the optimal values of T and G , calculate the first- and second-order derivative of $E [TC (T, G, \xi)]$ with respect to T and G . First-order derivatives are given below.

$$\begin{aligned} & \frac{\partial E[TC(T,G,\xi)]}{\partial G} \\ = & \left\{ T - \delta(G - G^2) \phi(T_m P E_p \right. \\ & \left. + E_h \left(\frac{e^{\lambda \xi} (P+bs-a) \left(T_m + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} T_m E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right) \right. \\ & \left. + \frac{e^{\lambda \xi} (a-bs) \left(T_m - T + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} (T-T_m) E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right) \right\} + 2d \ln V_e + dQw f_{ca} V_e \\ & + \frac{W_d Q E_{wd}}{\frac{\partial E[TC(T,G,\xi)]}{\partial T}} \\ = & \frac{G + \frac{e^{\lambda \xi} (e^{-\lambda \xi} (T-T_m) E(\theta) - 1) C_h(a-bs)}{E(\theta)} + \xi + \frac{\frac{\partial T}{\partial G} \left(e^{-\lambda \xi} (e^{-\lambda \xi} (T-T_m) E(\theta) - 1) (a-bs) E_h \delta \left(1 - \left(G - \frac{G^2}{2} \right) \phi \right) \right)}{E(\theta)}}{T} \\ & - \frac{1}{T^2} \left(A + F + T_m P \left(c + \frac{J}{P} + kP \right) + GT + W + 2d\alpha + Q\beta_o (e^{\sigma\psi} - 1) + \frac{2d(n-1)Q\beta}{a-bs} \right. \\ & \left. + \frac{e^{\lambda \xi} C_h(P+bs-a) \left(T_m + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} T_m E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right. \\ & \left. + \frac{e^{\lambda \xi} C_h(a-bs) \left(T_m - T + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} (T-T_m) E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right) + T\xi + dQw a f_{ca} \\ & + \delta \left(1 - \left(G - \frac{G^2}{2} \right) \phi \right) \left(T_m P E_p \right. \\ & \left. + E_h \left(\frac{e^{\lambda \xi} (P+bs-a) \left(T_m + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} T_m E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right) \right. \\ & \left. + \frac{e^{\lambda \xi} (a-bs) \left(T_m - T + \frac{e^{-\lambda \xi} (e^{-\lambda \xi} (T-T_m) E(\theta) - 1)}{E(\theta)} \right)}{E(\theta)} \right) \right) + 2d \ln V_e + dQw f_{ca} V_e + W_d Q E_{wd} \end{aligned}$$

To determine the minimum cost of the production inventory system, the above-mentioned partial differentiation should satisfy the necessary condition, i.e., $\frac{\partial E[TC(T,G,\xi)]}{\partial T} = 0$, $\frac{\partial E[TC(T,G,\xi)]}{\partial G} = 0$, from this condition, we can find the optimum value of decision variables.

Moreover, to satisfy optimality, i.e., convexity conditions, the sufficient condition must be satisfied, i.e., the corresponding principal minors should be positive definite.

$$\text{Hessianmatrix, } H = \begin{bmatrix} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} \\ \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} \end{bmatrix}$$

If the leading minors of H are $H_1 = \frac{\partial^2 TC(T,G,\xi)}{\partial G^2} > 0$, $\& H_2 = \begin{vmatrix} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T \partial G} \\ \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} & \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} \end{vmatrix} = \frac{\partial^2 E[TC(T,G,\xi)]}{\partial G^2} \frac{\partial^2 E[TC(T,G,\xi)]}{\partial T^2} - \left(\frac{\partial^2 E[TC(T,G,\xi)]}{\partial G \partial T} \right)^2 > 0$ then minimum exists for the function $E[TC(T, G, \xi)]$ at T^* & G^*

To calculate the principal minors, second-order derivatives are given as follows

$$\begin{aligned} & \frac{\partial^2 E[TC(T, G, \xi)]}{\partial G^2} \\ &= \left\{ \delta \vartheta^2 \phi(T_m P E_p + E_h \left(\frac{e^{\lambda \xi} (P + bs - a) \left(T_m + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} T_m E(\theta) - 1})}{E(\theta)} \right)}{E(\theta)} \right) \right. \right. \\ & \quad \left. \left. + \frac{e^{\lambda \xi} (a - bs) \left(T_m - T + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - m) E(\theta) - 1})}{E(\theta)} \right)}{E(\theta)} \right) + 2 \ln V_e \right. \\ & \quad \left. + dQw f_{ca} V_e + W_d Q E_{wd} \right\} / T \\ & \quad \frac{\partial^2 TCE[TC(T, G, \xi)]}{\partial T^2} \\ &= \frac{e^{-\lambda \xi (T - T_m) E(\theta)} C_h (a - bs) + e^{-\lambda \xi (T - T_m) E(\theta)} (a - bs) E_h \delta (1 - (G \vartheta - \frac{G^2 \vartheta^2}{2}) \phi)}{2 \left(G + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - T_m) E(\theta) - 1}) C_h (a - bs)}{E(\theta)} + \xi + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - T_m) E(\theta) - 1}) (a - bs) E_h \delta (1 - (G \vartheta - \frac{G^2 \vartheta^2}{2}) \phi)}{E(\theta)} \right)} \\ & \quad + \frac{1}{T^3} 2(A + F + T_m P (c + \frac{J}{P} + kP) + GT + W + 2d\alpha + Q\beta_o (e^{\sigma\psi} - 1) + \frac{2d(n-1)Q\beta}{a-bs} \\ & \quad + \frac{e^{\lambda \xi} C_h (P + bs - a) (T_m + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} T_m E(\theta) - 1})}{E(\theta)})}{E(\theta)} + \frac{e^{\lambda \xi} C_h (a - bs) (T_m - T + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - m) E(\theta) - 1})}{E(\theta)})}{E(\theta)} \\ & \quad + T\xi + dQw\alpha f_{ca} + \delta (1 - (G\vartheta - \frac{G^2\vartheta^2}{2})\phi) (T_m P E_p + E_h \left(\frac{e^{\lambda \xi} (P + bs - a) (T_m + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} T_m E(\theta) - 1})}{E(\theta)})}{E(\theta)} \right) \\ & \quad + \frac{e^{\lambda \xi} (a - bs) (T_m - T + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - m) E(\theta) - 1})}{E(\theta)})}{E(\theta)} \Big) + 2 \ln V_e + dQw f_{ca} V_e + W_d Q E_{wd} \Big) \\ & \quad \frac{\partial^2 E[TC(T, G, \xi)]}{\partial T \partial G} = \frac{\partial^2 E[TC(T, G, \xi)]}{\partial G \partial T} \\ &= \frac{1 - \delta \left(\frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - T_m) E(\theta) - 1}) (a - bs) \xi}{E(\theta)} \right) (\vartheta - G \vartheta^2) \phi}{T} - \frac{1}{T^2} (T - \delta (\vartheta - G \vartheta^2) \phi) (T_m P E_p \\ & \quad + E_h \left(\frac{e^{\lambda \xi} (P + bs - a) (T_m + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} T_m E(\theta) - 1})}{E(\theta)})}{E(\theta)} \right) \\ & \quad + \frac{e^{\lambda \xi} (a - bs) (T_m - T + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - m) E(\theta) - 1})}{E(\theta)})}{E(\theta)} \Big) + 2 \ln V_e + dQw f_{ca} V_e \\ & \quad + W_d Q E_{wd} \end{aligned}$$

Sufficient condition for $E[TC(T, G, \xi)]$ to be convex for a fixed value of ξ is principal minors should be positive definite at the optimal values of (T, G) is shown below

$$\begin{aligned} H_1 &= \frac{\partial^2 TC(T, G, \xi)}{\partial G^2} \\ &= \left\{ \delta \vartheta^2 \phi(T_m P E_p + E_h \left(\frac{e^{\lambda \xi} (P + bs - a) \left(T_m + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} T_m E(\theta) - 1})}{E(\theta)} \right)}{E(\theta)} \right) \right. \\ & \quad \left. + \frac{e^{\lambda \xi} (a - bs) \left(T_m - T + \frac{e^{\lambda \xi} (e^{-e^{-\lambda \xi} (T - m) E(\theta) - 1})}{E(\theta)} \right)}{E(\theta)} \right) + 2 \ln V_e + dQw f_{ca} V_e \\ & \quad + W_d Q E_{wd} \Big\} / T \geq 0 \\ H_2 &= \left| \begin{array}{cc} \frac{\partial^2 E[TC(T, G, \xi)]}{\partial G^2} & \frac{\partial^2 E[TC(T, G, \xi)]}{\partial T \partial G} \\ \frac{\partial^2 E[TC(T, G, \xi)]}{\partial T \partial G} & \frac{\partial^2 E[TC(T, G, \xi)]}{\partial T^2} \end{array} \right| \\ &= \frac{\partial^2 E[TC(T, G, \xi)]}{\partial G^2} \frac{\partial^2 E[TC(T, G, \xi)]}{\partial T^2} - \frac{\partial^2 E[TC(T, G, \xi)]}{\partial G \partial T} > 0 \end{aligned}$$

Hence, we ensure that the total average cost function $E[TC(T, G, \xi)]$ is convex for a fixed value of ξ .

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