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A production inventory model for the deteriorating goods under COVID-19 disruption risk

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Abstract

The rapid onset of the COVID-19 epidemic has brought the manufacturing process to a halt. The problem is especially serious for deteriorating products because demand for these items is not consistent and the product's worth has diminished with time. Many deteriorating product industries are now looking for an appropriate and effective disruption recovery plan to help them recover. However, a survey of the literature suggests that there has been little research done on developing an effective inventory production model for deteriorating products exposed to COVID-19 pandemic risks. This research intends to develop a disruption recovery model that considers demand as a time-dependent quadratic function to find out the optimum number of orders. Two different heuristic algorithms named: Genetic Algorithm (GA) and Whale Optimization Algorithm (WOA) have been employed to solve the model and it has been found that WOA performs better in terms of convergence. The numerical findings indicate that the price inclination rate for the component price and selling price played a pivotal role to maximize net profit. It is expected that by employing the proposed model of this research, the industry managers will be greatly benefitted to obtain quick recovery from the COVID-19 disruption risk for the deteriorating goods and retain financial stability.

Keywords: Disruption risk; COVID-19; Quadratic demand; EOQ model; Heuristics; Deterioration

1. Introduction

COVID-19 supply and production disruptions of deteriorating products have resulted in a huge profit loss and interrupted the UN's achievement of SDG 8 (decent work and economic growth) and SDG 12 (consumption and production) [1]. Following the outbreak of the deadliest COVID-19 pandemic, numerous lockdowns and shutdowns were imposed, obstructing the transit and distribution of perishable commodities and, as a result, affecting their consumption patterns [2]. Restrictions on people's or these goods' movement result in considerable quality loss and increased product waste. A suitable recovery mechanism may help the deteriorating product industries in promptly resolving the situation and overcoming supply chain weaknesses [3].

One of the most pressing difficulties for the industries is determining when and how much to order in order to maximize the overall profit connected with the inventory production system. This becomes more paramount as the inventory deteriorates or decays. Change, impairment, decay, spoiling, obsolescence, and loss of use or actual worth in a product that results in decreased usefulness from the distinctive one, are all examples of deterioration [4]. Furthermore, when products decay, it is assumed that their nominal or original worth has decreased [5]. Crops and vegetables, volatile liquids, dairy products, medicine, and other commodities are all examples of deteriorating items [6]. Since the stock of these products is now at stake amid the COVID-19 pandemic, choosing the best inventory production system for the deteriorating products has become a prominent concern.

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Although industries across the world are now working to improve resiliency in their supply chain networks to fight adverse effects of the COVID-19 disruptions [7-8], there is hardly any effective recovery policy for the deteriorating commodities. However, most of the deteriorating products are fast selling commodities and so distortion in the production or distribution of these goods can lead to countrywide shortage or price hike. Given the vulnerabilities that the deteriorating goods are undergoing [9], it is high time to develop a disruption recovery model to prevent shipment delays or market stockout situations.

In this research, an economic order quantity (EOQ) model has been formulated where a quadratic demand function has been utilized along with the cost of the components and product selling price for the deteriorating items. The logarithmic scale for component cost and selling price was employed to align the model with the real-world situation. Backorder costs and lost sales are two significant cost components that have been included due to the occurrence of disruptions by the COVID-19 pandemic. Besides, a constant deterioration unit cost has been considered here which is also a new addition to the works of contemporary literature. The following research objectives have been targeted to accomplish through our research.

- To construct an inventory production model for the deteriorating products subject to constant deterioration rate and COVID-19 disruption risks.
- To maximize the net profit for the optimal number of orders that should be placed to minimize the COVID-19 pandemic disruption effects for both the supplier and the seller.
- To identify the most sensitive model parameters that can alter the overall profit of the industry through sensitivity analysis.

The contents of this article are outlined as follows. In Section 2, a brief overview of relevant literature has been presented followed by the description of the problem along with the notations and assumptions in Section 3. In Section 4, the model formulation of the proposed inventory system has been illustrated with suitable explanations. Next, the model has been solved and the findings have been discussed in Section 5. Sensitivity analysis is discussed in Section 6 followed by the managerial implications in Section 7. Finally, the conclusions have been provided in Section 8 along with guidelines that can be included in future research.

2. Literature Review

In this section, a comprehensive literature review has been presented on the inventory production model that has been utilized in this research followed by previous works on disruption recovery and production deteriorations. Potential research gaps have been discovered as a result of these findings, which we plan to address through our study.

2.1. Economic Order Quantity (EOQ) Model

Over the years, inventory production systems have become a significant area of interest to many researchers. A fundamental and mostly used inventory production model is the Economic Order Quantity (EOQ) to determine when to order and how much to order [10]. A traditional EOQ model considers the demand from the consumer and then calculates the ordering costs, holding costs to determine the overall costs of the inventory. The target is to achieve the optimal order quantity at the minimal inventory cost [11]. For the past few decades, researchers have formulated their EOQ model under unchanging demand which means that most of the models were constructed assuming the demand rate as constant. For instance, [12] developed an EOQ model with fixed demand while considering backlog and shortage. [13] Suggested an EOQ model with a constant demand for a powdered drink production unit to minimize the total inventory costs. Nonetheless, demand can fluctuate with time and so consideration of time-dependent demand has gotten significant attention from contemporary researchers and academicians. To incorporate the fluctuating nature of demand, some models have been developed to extend the idea of considering demand as a varying function of time. For example, some research works have been performed assuming a linear trend of demand [14-15]. Later various types of time-dependent demand such as exponential demands were considered in the EOQ models [16-17].

2.2. Inventory Model for Deteriorating Products

Many relevant research works have been identified for multi-echelon inventory production systems of deteriorating products. A few studies have been developed to consider the deterioration effect in the EOQ inventory model such as an EOQ model with payment delays and unpredictable deteriorate rate [18], a deterministic EOQ model with payment delays and changing deterioration rate [19], an EOQ model considering production shortage under ramp type demand [20]. Later some recent works have also been explored to analyze the deteriorating products inventory with emerging techniques such as two warehouse production systems for deteriorating inventory items with fuzzy demands [21], mitigating deterioration risks for the medicines with the application of Blockchain philosophy [22], etc. Some works have also been performed considering different economic conditions such as establishing a multi-layer supply chain system for deteriorating goods facing partial backorder and inflations [23], developing an inventory model for the deteriorating products with seasonal demands [24], a probabilistic model for deteriorating products inventory with Ramp Type Demand Rate under Inflation [25], an integrated production model for deteriorating items considering price-dependent demand for two-level trade policy [26], etc.

2.3. Disruption Risks and Recovery Strategies

Disruption risks are often considered the primary impediments that raise an imbalance between an efficient inventory system and total production costs. Disruptive events are defined as uncertain and unprecedented occurrences such as natural calamities, labor strikes, machine breakdowns, process interruption, etc. that hinder the conventional flow of value propositions within a supply chain [27]. Disruption sources can be classified into five categories such as (i) demand disruptions (ii) supply disruptions (iii) legislative disruptions (iv) infrastructural disruptions (v) catastrophes [28-29]. When there is any disruption in the production system, the production rate becomes lower than the demand rate which creates a shortage in the production system.

In order to recover from disruption risks, many researchers come up with the idea of establishing a resilient supply chain system. A resilient supply chain can anticipate the possibility of a production mishap and take appropriate actions to counter it. In this regard, many researchers have proposed suitable recovery strategies to mitigate the effects of disruptions. For example, [30] had proposed a recovery model for an imperfect single-stage production system. Besides, suitable recovery plans for two-stage and three-stage inventory production systems were also developed by the researchers [31-32]. Recently, many researchers have tried to configure a resilient supply chain to recover from the COVID-19 pandemic risks. For instance, [33] developed an inventory production model with the help of an integer programming approach to make the profit maximum amid the COVID-19 outbreak. [34] Designed a sustainable and resilient closed-loop supply chain network to incorporate responsiveness in the supply chain configuration during the pandemic.

After analyzing the pertinent contemporary literature, the following research gaps have been identified.

- There is hardly any study that addressed the recovery plan from the COVID-19 pandemic disruptions for the deteriorating products.
- The cost of the individual component and the selling price of the deteriorating products vary with time in the practical scenario which is often overlooked by many researchers.
- Most of the existing researches is confined to developing a linear programming model for proposing an effective recovery mechanism whereas a complex non-linear model may capture the practical scenario more accurately.

This research aims to cover all these research gaps and propose a suitable recovery plan for the deteriorating products amid the COVID-19 pandemic situation.

3. Problem description

In this section, the details of the formulated problem have been discussed. We are considering the time-dependent quadratic demand of a deteriorating product that is undergoing COVID-19 disruption risk. This inventory problem aims to determine the optimal order quantity to maximize the total net profit as much as possible. The structure of the production model for a finite time zone is depicted in Figure 1 below.

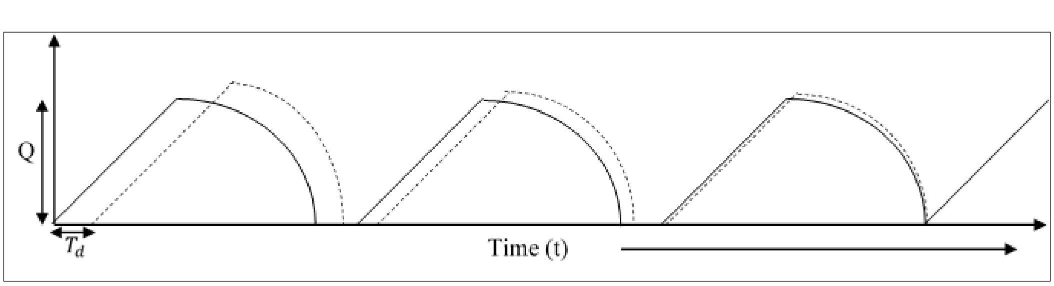

Figure 1 An inventory system after a single disruption

Due to the sudden occurrence of the COVID-19 pandemic, the global supply chain system has been paused for a while, the production system of the deteriorating products also undergoes the disruption effect. The production system fails to function properly for a certain amount of time. The production again starts after the disruption effect has been recovered by developing a resilient supply chain configuration. Nonetheless, the system encounters backorder and lost sales cost owing to the disruption effects. In order to fight against the COVID-19 disruption effect, a revised ordering policy has been suggested to recover the production in the disruption period, as demonstrated by the dashed line in Figure 1. The pre-disruption production plan is also shown using the solid line. As we can see after a certain time, the production system returns to its original state. The current stock level gradually reaches zero as shown in the above figure. The production process is continuous, so the decision variable (order) is changed with the disruption scenario. In a real situation, the production system can face a single disruption or a series of disruptions. However, a resilient supply chain system should establish adequate facilities to prevent further losses amid COVID-19 effects. In this connection, only a single-stage production system with COVID-19 disruption is considered. The production system is assumed to be reliable and no inflation has occurred in this entire time horizon.

3.1. Notation

In order to formulate the mathematical model, the following notations have been utilized.

n	Optimal number of orders which is an integer decision variable for this problem
C	Capacity of the production system in the entire planning horizon, known to the system
Q_{j-1}	Lot size during j^{th} cycle, j $= 1, 2\ \dots .$ n
$I(t)$	Inventory level at time t.
Tj	The time when the inventory level of j^{th} cycle reaches zero
P	Replenish interval length
U	Production rate (units/time)
$d(t)$	Demand rate (units/ time), $d(t)\ = a + bt + ct^2;\ a, b, c > 0$
A	Component cost ($), where $A = A_0(1 + C_c)t$, A_0 is the fixed component cost at $t = 0$
R	Selling price ($), where $R\ = R_0(1 + S_r)t$, R_0 is the fixed selling price at $t = 0$
C_c	Component cost inclination rate ($/units/unit time)
S_r	Selling price inclination rate ($/units/unit time)
E	Production interval length
M	Ordering cost ($/order)
HC	Holding cost ($/units/unit time)
ψ	Deterioration rate assumed to be a constant and $0 <\ \psi < 1$
T_d	Disruption (shortage) period, assumed to be a constant.
I_t	Total idle time for the system
Dc	Total set up time for the system
S_t	Deteriorating cost ($/units/unit time)
ω	Weightage contributing to the backorder cost
B	Backorder cost ($/order)
L	Lost sales cost ($/order)

3.2. Assumptions of the model

The proposed mathematical model is based on some assumptions which are listed below.

- The production rate U is finite.
- Both component cost and selling price of the deteriorating product incline at a continuous rate per unit time to the end consumer and inclination rate is constant for that entire planning horizon.
- The deteriorating cost per item must be different from the per-unit component cost.
- Demand $d(t)$, follows the quadratic nature of an expression and it can be written as $d(t)\ = a + bt + ct^2;\ a, b, c > 0$
- The total planning horizon is finite.
- No shortage is allowed in the pre-disruption period.
- Lead time is not changing with each cycle.
- Deterioration rate, ψ is known and fixed.
- Return or replacement policies are not considered for deteriorating products.

4. Model formulation

Here, a fixed replenishment interval has been considered. It is aimed to obtain the optimal number of orders, n to maximize the total amount of profit. The production system has been started at the time, $t = 0$ and the production system has been stopped due to the presence of the disruption for the disruption period T_d. The overall production starts when the lot size is Q_0. With the progress of time, the inventory level is depleted to fill the consumer demands. At the time $t = t_j$, the inventory level of the system in j^{th} cycle depletes to zero. The inventory level of the system at any time, t can be described by the following differential equations

$$\frac{d(t)}{dt} + \psi^* d(t) = U; P \leq t \leq jP \tag{1}$$

Which can be written as

$$\frac{d(t)}{dt} = U - \psi^*(a + bt + ct^2); P \leq t \leq jP \tag{2}$$

The time period can be expressed as

$$\mathrm{T} = \mathrm{E/n} \tag{3}$$

$$t_k = kP, k = 1,2,3 \ldots . n \tag{4}$$

From the boundary rule, $I(t) = 0$ at $t = kP$ and Eq. (2) becomes

$$I(t) = (U - \psi a)(t - kP) - \frac{b\psi}{2}(t^2 + P^2) - \frac{c\psi}{3}(t^3 + kP^3) \tag{5}$$

The lot size during the k^{th} cycle is $I(t)$ at $t = (k-1)P$ and we get

$$Q_{k-1} = (\psi a - U)P - \frac{b\psi}{2}(1 - 2k)P^2 - \frac{c\psi}{3}(2 + 3k)P^3 \tag{6}$$

With the help of Eq. (5) and Eq. (6), total inventory cost can be determined as expressed in Eq. (7).

Total holding cost

$$HC(n) = \frac{A_O * Hc}{\psi}[\frac{C}{n\psi}(\exp^{\psi nP} - 1) - \{ap - \frac{bP^2}{2} - \frac{2cP^3}{3} + \frac{1}{2}n(n+1)(bP^2 - cP^3)\}] \tag{7}$$

Total component cost can be obtained by utilizing Eq. (8).

Total component cost

$$\mathrm{PC}(n) = \mathrm{A_O}(\frac{P((1 - Cc)^{nP} - 1)(\psi a - U)}{2((1 - Cc)^P - 1)} - \frac{b\psi P^2}{2}(\frac{(1 - Cc)^{nP} - 1}{((1 - Cc)^P - 1)} - \frac{2}{(Cc)^{2P}}) - \frac{(\psi c P^3)}{3}(\frac{2((1 - Cc)^{nP} - 1)}{(1 - Cc)^P - 1} + \frac{3}{(Cc)^{2P}})) \tag{8}$$

The deterioration costs of the products can be expressed by using Eq. **Error! Reference source not found.**.

Total cost from product deterioration

$$\mathrm{DC}(n) = \mathrm{Dc}[\frac{C}{n\psi}(\exp^{\psi nP} - 1) - \{ap - \frac{bP^2}{2} - \frac{2cP^3}{3} + \frac{1}{2}n(n+1)(bP^2 - cP^3)\}] \tag{9}$$

Because of the COVID-19 disruptions, the shortage may create in the inventory which will be adjusted by the backorder and lost sales quantities. The cost components for the adjustments are indicated by Eq. (10) and Eq.(11).

Total backorder cost

$$BC(n) = \frac{C\omega}{n} B * (T_d + nS_t - 0.01(n-1)) \tag{10}$$

Total lost sales cost

$$LC(n) = \frac{C(1-\omega)}{n} L * (T_d + nS_t - 0.01(n-1)) \tag{11}$$

Total ordering cost can be computed by multiplying number of orders with cost per order as expressed in Eq. (12).

Total ordering cost

$$OC(n) = Mn \tag{12}$$

The total amount of revenue that would be generated by considering the logarithmic selling price per unit is written in Eq. (13).

Total sales revenue

$$SR(n) = \frac{n((R_o(S_r+1)^{nP})(na + bnp - \frac{b}{\log(S_r+1)} - \frac{2ncP * e^P}{\log(S_r+1)+1} - \frac{2c * e^P}{\log(S_r+1)}))}{-\frac{aS_r}{\log(S_r+1)}} \tag{13}$$

Net profit is a function of n, so it is needed to find out the interdependency between the independent variable n and the dependent output Net Profit (NP). The objective function of this model is to maximize NP expressed as:

Net Profit (NP) = Sales revenue – holding cost – procurement cost – deteriorating cost – ordering cost – backorder cost – lost sales cost

$$NP = SR - HC - PC - DC - OC - BC - LC$$

$$\begin{aligned} = & \frac{n((R_o(S_r+1)^{nP})(na + bnP - \frac{b}{\log(S_r+1)} - \frac{2cP * e^P}{\log(S_r+1)+1} - \frac{2c * e^P}{\{\log(S_r+1)+1\}^2}))}{-\frac{log(S_r+1)}{\log(S_r+1)} - \frac{A_0 * Hc}{\psi}[\frac{C}{n\psi}(e^{\psi nP}-1) - \{ap - \frac{bP^2}{2} - \frac{2cP^3}{3} + \frac{1}{2}n(n+1)(bP^2 - cP^3)\}]} \\ & -A_0(\frac{P((1-Cc)^{nP}-1)(\psi a - U)}{2((1-Cc)^P-1)} - \frac{b\psi P^2}{2}(\frac{(1-Cc)^{nP}-1}{((1-Cc)^P-1)} - \frac{2}{(Cc)^{2P}}) \\ & - \frac{(\psi cP^3)}{3}(\frac{2((1-Cc)^{nP}-1)}{(1-Cc)^P-1} + \frac{3}{(Cc)^{2P}})) - Dc[\frac{C}{n\psi}(e^{4nP}-1) - \{ap - \frac{bP^2}{2} - \frac{2cP^3}{3} + \frac{1}{2}n(n \\ & +1)(bP^2 - cP^3)\}] - \frac{C\omega}{n}B * (T_d + nSt - It(n-1)) - \frac{C(1-\omega)}{n}L(T_d + nSt - It(n-1)) \\ & -Mn \end{aligned} \tag{14}$$

Eq. (14) is the net profit expression that is maximized in this study for the optimal number of orders.

5. Numerical Analysis

In this section, the formulated mathematical model is solved and analyzed with the help of three case studies. To obtain the values of model parameters, we rely on the extant literature (e.g., [27], [35]). The mathematical model was coded in MATLAB 2018a by using the default settings. The Intel Core i3 processor with 8.00 GB RAM and a 3.40 GHz CPU was chosen to run the code smoothly.

5.1. Solution Approach

Since the final objective function is non-linear, we need to utilize heuristic algorithms to obtain the optimal solutions. For the proposed mathematical model, we have employed two different heuristics named the Genetic Algorithm (GA) and the Whale Optimization Algorithm (WOA). Although GA is an old and popular nature-inspired heuristic method to solve a non-linear optimization problem [36], it has a slow convergence rate in some test problems to reach the optimal solution which limits the fruitfulness of this algorithm. On the contrary, the WOA is a recently evolved heuristic approach that shows competitive performance compared to other nature-inspired algorithms [37]. In this research, we would solve the model by employing both approaches and then compare their performances.

The optimal number of orders has been determined and associated net profit is also been calculated. The integer value of n has been used to determine the optimum profit which is indicated by $n*$. The overall model needs to be solved by employing an integer programming approach. However, the feasibility and optimality of the model will not be hampered since this is an unconstrained optimization problem. Substituting the value of $n*$ in $NP\ (n*)$, maximized net profit has been obtained. The solution obtained here would provide the maximum in the entire planning horizon. So, the solution is both a local and global optimum solution. However, before employing the proposed heuristics, we need to test the optimality condition of the developed problem. For a high-order non-linear problem, we know that both the first-order necessary condition and second-order sufficient condition must be met. Mathematically, the requirements can be expressed by using Eq. (15) and Eq. (16) as shown below.

$$\frac{d(NP)}{dn^*} = 0 \quad (15)$$

$$\frac{d^2(NP)}{dn^{*2}} < 0 \quad (16)$$

5.2. Numerical Examples

We have solved the proposed mathematical model by taking appropriate values for each model parameter. At first, we find out the range of the model parameters as depicted in Table 1. The range of the model parameters has been collected with the help of relevant researchers. Next, three case problems have been conducted to analyze the solutions properly. For the first case study, we picked up suitable values of the parameters from Table 1 and then utilize them to solve the model. The values of the parameters for the first case study are summarized in Table 2. The parameters for the second and third case studies are placed in Table A.1 and Table A.2 under Appendix A. The parameters for the GA and WOA are presented in Table 3.

Table 1 Range of the model parameters

Parameter	Value	Parameter	Value
A	1-10	E	2-8
C_c	0.01-0.9	H_C	0.0001-0.005
S_t	0.001-0.1	I_t	0.01
R_0	0.1-0.9	ψ	0.05-0.7
S_r	0.5-8	B	400-800
a	600-1200	L	200-600
b	300-650	U	400-1000
c	0.1-0.9	T_d	0.1-0.8

Table 2 Selected values of the parameters for the first case study

Parameter	Value	Parameter	Value
A	2.2	E	4
C_c	0.04	H_C	0.0002
S_t	0.05	I_t	0.01
R_0	0.8	ψ	0.1
S_r	1.1	B	600
a	800	L	400
b	450	U	900 units/week
c	0.5	T_d	0.1

Table 3 Parameters of GA and WOA

Heuristics	Parameters		
	Notation	**Details**	**Value**
GA	*Npop*	Number of populations	150
	MR	Mutation rate	0.4
	CR	Crossover rate	0.5
	Fun. Tol.	Function tolerance	1×10^{-6}
WOA	*Npop*	Number of populations	150
	a	Convergence factor	1
	T_{max}	Maximum number of iterations	200
	$B.D$	Step size	0.6

Table 4 Solutions obtained from Genetic Algorithm (GA)

Case	n	NP	CPU run time (milliseconds)
1.	5	75546	23450
2.	6	78341	26200
3.	4	67211	24230

Table 5 Solutions obtained from Whale Optimization Algorithm (WOA)

Case	n	NP	CPU run time (milliseconds)
1.	5	75546	18630
2.	6	78341	21410
3.	4	67211	20770

For the first case study, the optimal value of profit is obtained at n = 5. For this solution both Eq. (15) and Eq. (16) are satisfied. Similarly, for the second and third cases, optimal solutions have been recorded. Identical solutions have been obtained from both GA and EOA as summarized in Table 4 and Table 5. However, in terms of CPU elapsed time to converge to the optimal solution, EOA takes less time than GA. Therefore, for the proposed mathematical model, it can be stated that the EOA performs better than GA in terms of convergence.

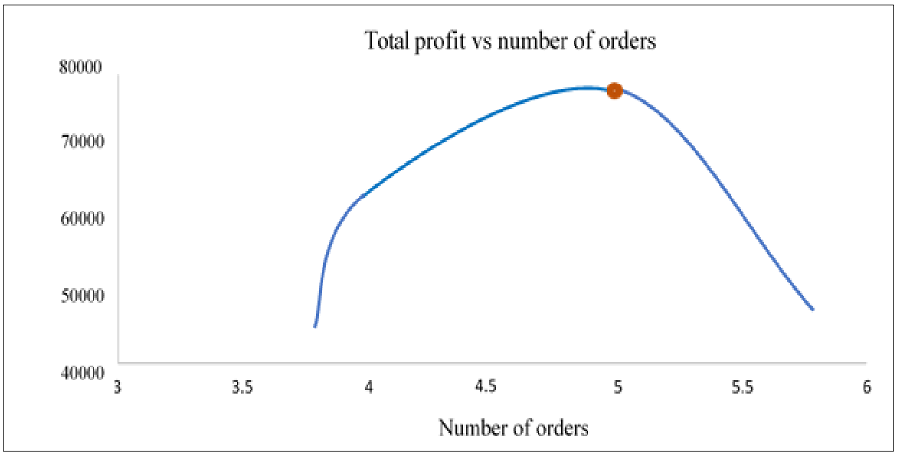

Figure 2 Total net profit vs number of orders

For the first case study, the change of the optimal solution with the change of the number of orders has been illustrated graphically in Figure 2. It can be observed from Figure 2 that, with the increase of the order number, NP increases until it reaches the optimal solution. However, after the optimal point, NP decreases drastically with the increase of orders. Therefore, we can say that the solution found from this model is both a local and global optimum solution.

6. Sensitivity Analysis

Sensitivity analysis plays a pivotal role to analyze a mathematical model [38]. In this study, different model parameters have been utilized, and changing the value of these parameters will result in an alteration of the value of total profit. Although the net profit varied with the fluctuation of all the model parameters, some parameters change the total profit very significantly, which are discussed in this section. In order to inspect the changes, 5% increase and 5% decrease of the model parameters have been considered as shown in Table 6. The corresponding change of the net profit is also shown in Table 6.

Table 6 Sensitivity Analysis for model parameters

Parameters	Change in %	Change of NP in %
R_0	+5%	+29.33%
	-5%	-31.36%
A_0	+5%	-0.70%
	-5%	+0.72%
M	+5%	-0.28%
	-5%	+0.29%
U	+5%	+0.23%
	-5%	-0.23%
C_c	+5%	+1.45%
	-5%	-1.59%
S_r	+5%	+49.66%

	-5%	-44.84%
B	+5%	-4.17%
	-5%	+4.16%
L	+5%	-0.003%
	-5%	+0.0029%

Some key decisions regarding sensitivity analysis can be made for the model parameters after analyzing Table 6. For instance, the net profit (NP) will be increased if we increase the selling price per unit (R_0). However, NP will be decreased if the component cost (A_0) increases. Similarly, a trade-off relationship has been found between the cost per order and the profit. Nonetheless, with the increase of the production rate U, it will increase the value of NP.

While considering the change of net profit with respect to the incline rate of component cost (C_c) and selling price (S_r), it has been found that an increasing inclination rate will increase the volume of profits. As the backorder cost per order increases, the net profit (NP) will be decreased. The increasing value of lost sales cost per order will decrease the value of net profit (NP). On the basis of the above table, it can be clearly stated that lost sales and backorder costs due to COVID-19 disruptions have an important contribution to determining the optimum number of orders in order to maximize profit.

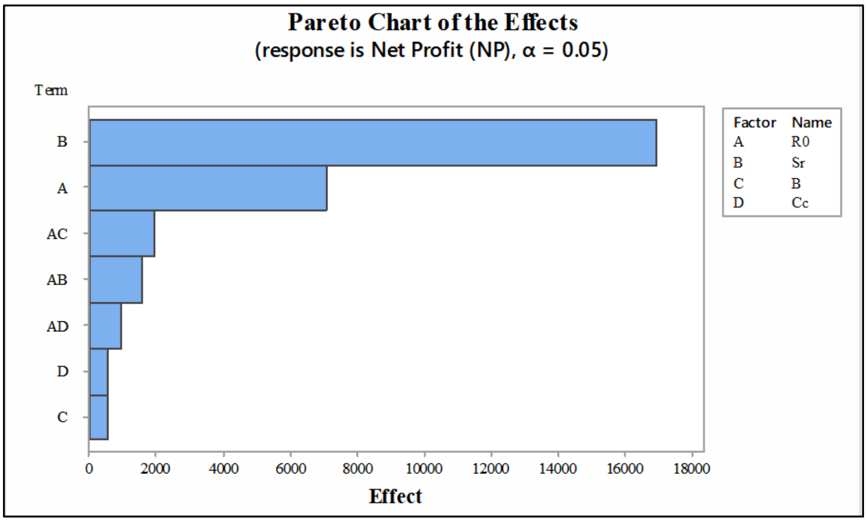

Figure 3 Individual and Interaction effects from ½ factor factorial analysis

Table 7 Findings from the ½ factor factorial analysis

Parameters	Effect	*F* value	*P* value
R_0	6860	8.11	0.00001
S_r	17352	17.36	0.00000
B	468	0.27	0.6250
C_c	512	0.59	0.5210
$R_0 * S_r$	1890	3.46	0.0150
$R_0 * C_c$	938	1.28	0.1356
$R_0 * B$	2017	4.29	0.0050

It is apparent from Table 6 that $\boldsymbol{R_0}$, $\boldsymbol{S_r}$, $\boldsymbol{B}$, and $\boldsymbol{C_c}$ are the most crucial parameters to vary the value of the objective function significantly than other model parameters. Therefore, the proposed mathematical model is highly sensitive to these model parameters and their effects need to be investigated properly. To analyze their effects, a ½ factor factorial analysis has been conducted and the findings have been presented in Table 7 and Figure 3. It is evident from Table 7 and Figure 3 that S_r has the highest contribution to the change in the value of the objective function. Nonetheless, the interaction effect between S_r and R_0 is also found significant which symbolizes that the model can be altered tremendously if both the inclination rate and original value of the selling price are changed in the same direction.

7. Managerial Implications

The research has several implications in terms of managerial perspectives which are discussed below.

- Configuring a resilient supply chain network: The COVID-19 pandemic is a global crisis that gives a clear message to the industries to be proactive rather than reactive. In this study, we discovered that due to COVID-19 pandemic disruptions, a significant amount of backorder and lost sales costs have been incurred which reduce the supply chain surplus of an industry. In this connection, a resilient supply chain configuration should be established which will be able to anticipate the further occurrence of any risks in the future and act accordingly.
- Paying special attention to component cost and selling price: Due to the COVID-19 pandemic, consumers' economic condition has been changed significantly and this also influences their buying decisions. The component cost and selling price of the deteriorating products have become one of the most significant deciding factors to enhance the sales of these products that have been established from this research. Therefore, the industry managers of the deteriorating products should pay attention to selling price and component cost.
- Avoiding placing orders abruptly: This study establishes a strong relationship between numbers of orders and total net profit and discovers that placing lower or higher than the optimal number of orders will drastically reduce the net revenue of the organization. So, the industry needs to find out the optimal number of orders for their production inventory system of the deteriorating products amid COVID-19 disruption risk

8. Conclusion

This research proposed a deterministic inventory production system for deteriorating items amid COVID-19 disruption risks and considered the deterioration rate constant. This model has vitalized the concept of the EOQ production model with quadratic demand function and time-varying component cost as well as the selling price. Moreover, the proposed model considered disruption and its effect of it on the production model. Lost sales cost and backorder cost are the two main effects associated with production disruption that are faced due to the COVID-19 Pandemic. These are also considered in this model. The model has become robust by incorporating the non-linear nature of a complex production system.

The formulated problem is then solved with two nature-inspired algorithms named GA and WOA. Both algorithms provide identical solutions for three different cases, however, EOA takes less time to converge in comparison to GA. The findings indicate that the net profit has a strong correlation with the number of orders and without determining the optimal order numbers, the company may face a huge profit loss. The sensitivity analysis has been conducted to identify some crucial parameters that alter the net profit critically. Industry managers may adopt the proposed model for their deteriorating product industry to recover from the COVID-19 disruption risks and make profits.

Recommendations

In the future, the model can be integrated with the concept of a multi-product inventory system under disruptive scenarios. Also, the stochastic nature of the model parameters may be included to deal with the uncertain business environment. Deteriorating products may face multiple disruptions in different stages of an inventory system. Therefore, multiple disruption cases may also be included in this study. Finally, the model should be tested and validated with other recently developed algorithms to justify the applicability of the formulated problem.

Compliance with ethical standards

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Disclosure of conflict of interest

There are no conflicts of interest

References

[1] K. Shulla *et al.*, "Effects of COVID-19 on the Sustainable Development Goals (SDGs)," *Discov. Sustain.* Dec. 2021; 2(1): 15.

[2] AA Cariappa, KK Acharya, CA Adhav, R Sendhil, Ramasundaram. "COVID-19 induced lockdown effects on agricultural commodity prices and consumer behaviour in India – Implications for food loss and waste management," *Socioecon. Plann. Sci.* Sec 2021; 101-160.

[3] Y Kazancoglu, MD Sezer, M Ozbiltekin-Pala, Ç Lafçı, and RS Sarma. "Evaluating resilience in food supply chains during COVID-19," *Int. J. Logist. Res. Appl.* Nov 2021; 1–17.

[4] Y He, H Huang, D Li, "Inventory and pricing decisions for a dual-channel supply chain with deteriorating products," *Oper. Res.* Se 2020 20(3): 1461–1503,

[5] M Sepehri, Z Sazvar. "Multi-objective Sustainable Supply Chain with Deteriorating Products and Transportation Options under Uncertain Demand and Backorder," *Sci. Iran.* Oct. 2016; 23(6): 2977–2994.

[6] S Priyan, Mala. "Multi-echelon Supply Chain Model for Deteriorating Products in a Fuzzy Deterioration Environment," *Fuzzy Inf. Eng.* Jan. 2019; 11(1): 86–104.

[7] ML Pimenta, LO Cezarino, EL Piato, CH da Silva, BG Oliveira, LB Liboni. "Supply chain resilience in a Covid-19 scenario: Mapping capabilities in a systemic framework," *Sustain. Prod. Consum.* Jan. 2022; 29: 649–656.

[8] A Belhadi, S Kamble, CJC Jabbour, A Gunasekaran, NO Ndubisi, M Venkatesh. "Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries," *Technol. Forecast. Soc. Change*. Feb. 2021; 163: 120447.

[9] G Pulighe, F Lupia. "Food First: COVID-19 Outbreak and Cities Lockdown a Booster for a Wider Vision on Urban Agriculture," *Sustainability*. Jun. 2020; 12(12): 5012.

[10] FW Harris. "HOW MANY PARTS TO MAKE AT ONCE," *Int. J. Prod. Econ.* Se 2014; 155: 8–11.

[11] S Senthilnathan. "Economic Order Quantity (EOQ)," *SSRN Electron. J.* 2019.

[12] RT Neha Sang. "EOQ Model for Constant Demand Rate with Completely Backlogged and Shortages," *J. Appl. Comput. Math.* 2012; 1(6).

[13] A. Vania and H. Yolina, "Analysis Inventory Cost Jona Shop with EOQ Model," *Eng. Math. Comput. Sci. J.* Feb. 2021; 3(1): 21–25,

[14] J Mishra, T Singh, H Pattanayak. "An EOQ inventory model for deteriorating items with linear demand, salvage value and partial backlogging," *Int. J. Appl. Eng. Res.* 2016.

[15] R Tripathi, SM Mishra. "EOQ model with linear time dependent demand and different holding cost functions," *Int. J. Math. Oper. Res.* 2016; 9(4): 452.

[16] Y Yaqing, M Yizhong, Z Jianlan, Z Lianyan. "A Robust Simulation for EOQ Model with Exponential Distributed Demand," in *2014 Seventh International Symposium on Computational Intelligence and Design*, Dec. 2014; 486–489.

[17] HS Pandey, R Tripathi. "Comprehensive Economic Order Quantity (EOQ) Model for Weibull decline with Negative Exponential Demand under trade credits," *Int. J. Math. Oper. Res.* 2020; 1(1).

[18] B. Sarkar, "An EOQ model with delay in payments and time varying deterioration rate," *Math. Comput. Model.* Feb. 2012; 553–4, 367–377.

[19] S Ting, KJ Chung. "Some formulations for optimal solutions with delays in payment and price-discount offers in the supply chain system," *Appl. Math. Comput.* Mar. 2014; 230: 180–192.

[20] T Singh, J Mishra, H Pattanayak. "An EOQ inventory model for deteriorating items with time-dependent deterioration rate, ramp-type demand rate and shortages," *Int. J. Math. Oper. Res.* 2018; 12(4): 423.

[21] B Anil Kumar, SK Paikray, H Dutta, "Cost optimization model for items having fuzzy demand and deterioration with two-warehouse facility under the trade credit financing," *AIMS Math.* 2020; 5(2): 1603–1620.

[22] A Singh Yadav, G Pandey, T Kumar Arora, Kumar Chaubey. "Block-chain application Based Economic impact of Coronavirus pandemic on Medicine industry inventory System for Deteriorating objects with two-warehouse and wastewater treatment using PSO," *Mater. Today Proc.* 2021.

[23] A Shastri, SR Singh, D Yadav, S Gupta. "Multi-Echelon Supply Chain Management for Deteriorating items with Partial Backordering under Inflationary Environment," *Procedia Technol.* 2013.

[24] S Tayal, SR Singh, R Sharma. "An inventory model for deteriorating items with seasonal products and an option of an alternative market," *Uncertain Supply Chain Manag.* 2015; 3(1):69–86.

[25] S Kumar, US Rajput, "A Probabilistic Inventory Model for Deteriorating Items with Ramp Type Demand Rate under Inflation," *Am. J. Oper. Res.* 2016; 6(1): 16–31.

[26] M Rameswari, R Uthayakumar. "An integrated inventory model for deteriorating items with price-dependent demand under two-level trade credit policy," *Int. J. Syst. Sci. Oper. Logist.* Jul. 2018; 5(3): 253–267.

[27] NA Darom, H Hishamuddin, R Ramli, Z Mat Nopiah. "An inventory model of supply chain disruption recovery with safety stock and carbon emission consideration," *J. Clean. Prod.* Oct. 2018; 197: 1011–1021.

[28] SM Wagner, C Bode. "AN EMPIRICAL EXAMINATION OF SUPPLY CHAIN PERFORMANCE ALONG SEVERAL DIMENSIONS OF RISK," *J. Bus. Logist.* 2008.

[29] S Zhao, Q Zhu. "A risk-averse marketing strategy and its effect on coordination activities in a remanufacturing supply chain under market fluctuation," *J. Clean. Prod.* Jan. 2018; 171: 1290–1299.

[30] SK Paul, R Sarker, D Essam. "Managing disruption in an imperfect production-inventory system," *Comput. Ind. Eng.* 2015.

[31] SK Paul, R Sarker, D Essam. "Real time disruption management for a two-stage batch production–inventory system with reliability considerations," *Eur. J. Oper. Res.* Aug. 2014; 237(1): 113–128.

[32] SK Paul, R Sarker, D Essam. "A disruption recovery plan in a three-stage production-inventory system," *Comput. Oper. Res.* 2015,

[33] J Chen, H Wang, RY Zhong. "A supply chain disruption recovery strategy considering product change under COVID-19," *J. Manuf. Syst.* Jul. 2021; 60: 920–927.

[34] MM Vali-Siar, E Roghanian. "Sustainable, resilient and responsive mixed supply chain network design under hybrid uncertainty with considering COVID-19 pandemic disruption," *Sustain. Prod. Consum.* Mar. 2022; 30: 278–300, ,

[35] H Hishamuddiin, R Sarker, D Essam. "A simulation model of a three echelon supply chain system with multiple suppliers subject to supply and transportation disruptions," in *IFAC-PapersOnLine*, 2015; 28(3): 2036–2040.

[36] M Gen, R Cheng, *Genetic Algorithms and Engineering Optimization*. 1999.

[37] S Mirjalili, A Lewis. "The Whale Optimization Algorithm," *Adv. Eng. Softw.* May 2016; 95: 51–67.

[38] G Qian, A Mahdi. "Sensitivity analysis methods in the biomedical sciences," *Math. Biosci.* May 2020; 323: 108306.

Appendix A

Table A.1: Selected values of the parameters for second case study

Parameter	Value	Parameter	Value
A	2.0	E	5
C_c	0.05	H_C	0.0005
S_t	0.06	I_t	0.05
R_0	0.6	ψ	0.2
S_r	1.2	B	650
a	900	L	420
b	550	U	900 units/week
c	0.7	T_d	0.2

Table A.2: Selected values of the parameters for third case study

Parameter	Value	Parameter	Value
A	1.8	E	3
C_c	0.06	H_C	0.0003
S_t	0.04	I_t	0.03
R_0	0.7	ψ	0.15
S_r	1.0	B	550
a	850	L	350
b	580	U	900 units/week
c	0.9	T_d	0.15