SUSTAINABLE SUPPLY CHAIN NETWORK DESIGN

A supply chain disruption risk mitigation model to manage COVID-19 pandemic risk

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Abstract

This study develops a mathematical model to mitigate disruptions in a three-stage (i.e., supplier, manufacturer, retailer) supply chain network subject to a natural disaster like COVID-19 pandemic. This optimization model aims to manage supply chain disruptions for a pandemic situation where disruptions can occur to both the supplier and the retailer. This study proposes an inventory policy using the renewal reward theory for maximizing profit for the manufacturer under study. Tested using two heuristics algorithms, namely the genetic algorithm (GA) and pattern search (PS), the proposed inventory-based disruption risk mitigation model provides the manufacturer with an optimum decision to maximize profits in a production cycle. A sensitivity analysis was offered to ensure the applicability of the model in practical settings. Results reveal that the PS algorithm performed better for such model than a heuristic method like GA. The ordering quantity and reordering point were also lower in PS than GA. Overall, it was evident that PS is more suited for this problem. Supply chain managers need to employ appropriate inventory policies to deal with several uncertain conditions, for example, uncertainties arising due to the COVID-19 pandemic. This model can help managers establish and redesign an inventory policy to maximize the profit by considering probable disruptions in the supply chain network.

Keywords Supply chain disruption · Supply chain resiliency · COVID-19 · Genetic algorithm · Pattern search algorithm · Inventory policy · Supply chain mitigation

Introduction

Today, every organization in a supply chain experiences disruptions from manmade and natural disasters. For example, the recent novel coronavirus (SARS-CoV-2) as disruption risk is creating complexity in supply chain operations since November 2019 (Lopes de Sousa Jabbour et al. 2020). This pandemic outbreak destroys the whole supply chain activities by making restrictions in air transportation facilities, border closure, unavailability of raw material supply, and entire shutdown of manufacturing activities (Paul and Chowdhury 2020a; Chowdhury et al. 2020; Paul and Chowdhury 2020b; Rowan and Galanakis 2020). Also, the recent estimated data confirmed that the recent pandemic outbreak is a rare case of supply chain disruption that is impacting the global economy dramatically (Majumdar et al. 2020; Karmaker et al. 2020; Taqi et al. 2020). For example, the United Nations Conference on Trade and Development (UNCTAD) mentioned that the global income will be a shortfall of USD 2 trillion due to the COVID-19 pandemic (UNCTAD Report 2020). Another report conducted by the World Trade Organization (WTO) confirmed that world trade will decline between 13 and 32% in the year 2020 (WTO 2020). Therefore, to reduce the impact of disruptions caused by such a disaster, it is essential to develop a model to manage supply chain disruptions (Chang et al. 2015).

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Accordingly, this study develops an inventory system for mitigating such disruptions in a supply chain. A manufacturer with one supplier and one retailer is considered. It is assumed that the supplier and retailer are unavailable for a random period due to disruptions caused by disaster (say COVID-19, for example). Also, the reliability of the manufacturer (the ability of a production process to produce good-quality products) and the reliability of the supplier (the ability of a supplier to consistently supply good-quality raw material at the required time) are considered to address defective units produced in the said supply chain system (Abdi et al. 2019).

Motivation

An uninterrupted supply chain network is critical to the success of firms in this competitive era of business. However, the supply chain network is often disrupted due to unavoidable natural (e.g., coronavirus) or manmade disasters (Coelho et al. 2017; Karampour et al. 2020). To ensure the continuity of the supply of products, a manufacturer needs to consider supply chain disruptions caused by a disaster like COVID-19 that may take place at the supplier and/or the retailer's end. Most of the previous studies considered disruptions at the supplier (e.g., Konstantaras et al. 2019; Paul et al. 2018) or retailer's end (e.g., Paul et al. 2018; Sarkar et al. 2017). This study expands such studies by integrating disruptions at the supplier and the retailer's end of a supply chain considering the recent COVID-19 pandemic. In real-world settings, decision-makers also need to consider the defective units produced across the supply chain as those defective units hamper the ability of a supply chain to meet customer demand (Mehranfar et al. 2019; Nezhadroshan et al. 2020). Therefore, there is a need to include such an important issue to aid supply chain managers in their decision-making for supply chain disruption management.

Related works and contributions

Research on supply chain disruption risks gained a lot of attraction in recent years (Govindan et al. 2020; Ivanov 2020; Jabbarzadeh et al. 2018; Al Masud et al. 2014; Pal et al. 2014; Paul et al. 2017; Revilla and Saenz 2017; Sawik 2019; Shokrani et al. 2020; Yoon et al. 2020). The risks resulting from disruptions can be segregated into two categories, risk arising from the mismatch between demand and supply and risk arising from disruptions in routine activities (Kleindorfer and Saad 2009; Schmitt and Singh 2012). Generally, disruptions can be explained as unanticipated incidents that incapacitate the supply chain network of a company (Fathollahi-Fard et al. 2018; Hajiaghaei-Keshteli and Fathollahi Fard 2019; Fathollahi-Fard et al. 2020a; Fathollahi-Fard et al. 2020b; Fathollahi-Fard et al. 2020c; Fathollahi-Fard et al. 2020d). Disruptions in routine activities of a supply chain can be caused by either natural events (e.g., hurricane Cindy during 2017 in the USA) or intentional acts (ships attacked by the Somalian pirates, cargo theft, sanctions imposed by the US government on Iran and other different countries) or accidents (2015 Tianjin explosion in China) or pandemics (the COVID-19 outbreak in China and other countries). These disruptions can drastically hamper the supply chain performance as well as can incur huge losses in terms of productivity loss, revenue loss, and damage to the brand's reputation (Tian et al. 2019a, b). Over the last few years, supply chain disruption management has become a significant interest of research (Ambulkar et al. 2015; Amelkin and Vohra 2019; Ivanov et al. 2016; Pavlov et al. 2018; Sawik 2019; Islam et al. 2020).

At present, to survive and to be profitable, a manufacturer needs to ensure the continuous circulation of its products (Tumpa et al. 2019; Kumar et al. 2020; Mehrbakhsh and Ghezavati 2020). Thus, the disruption at the supplier's end as well as the disruption at the retailer's end can result in a heavy penalty for the manufacturer in terms of losing customers and reputation, which ultimately results in losing market share. Interestingly, it is shown from the recent pandemic situation that both disruptions occurred in the supply chain. Also, from the observation of recent literature, we can see that most of the studies considered disruptions only at one end. Researchers like Ahmed et al. (2017), J. Chen et al. (2012), Hishamuddin et al. (2012), Konstantaras et al. (2019), Paul et al. (2018), and Snyder et al. (2016) discussed models considering disruptions only at the supplier's end. On the other hand, disruptions only at the retailer's end were considered in the models by Baghalian et al. (2013), Paul et al. (2018), Sarkar et al. (2017), and Rahman et al. (2018).

The reliability of the production process is another essential factor that can affect the capability of a manufacturer to satisfy customer demand (Sarkar 2012; Nujoom et al. 2018; Ilyas et al. 2020). Konstantaras et al. (2019) developed an economic order quantity (EOQ) model where the supplier's reliability follows an independent Bernoulli process and allows backorder to fulfill demand. Analyzing the reliability of the process for a production inventory model, some literature considered the demand as a fuzzy set and incorporated opportunity cost with non-repairable defective productions (Chang 2004; Chen and Chang 2008). Furthermore, we observed that many models considered imperfect production process with reliability-dependent production period and unit production cost (Tripathy et al. 2011; Al Masud et al. 2014). For an in-depth investigation of the existing literature, we have reviewed the current literature also to clarify the novelty of the study. In the recent study, we have observed that lack of studies has focused on the COVID-19 pandemic to manage the disruption in the supply chain. The findings of the recent studies are reflected in Table 1.

This study recognizes that for a manufacturer, disruption at the supplier and the retailer's end and the reliability of its

Table 1 Recent studies of risk mitigation

Authors	Research contribution	Nature of disruption	Model	Solution	Focused COVID-19?
Islam et al. (2020)	The authors proposed a mathematical model to minimize the disruption that occurred due to the unavailability of suppliers	Supplier disruption	Optimization model	GA and simulated annealing algorithm	No
Xu et al. (2020)	The authors proposed a mathematical framework for perishable products that optimize operational decisions like inventory allocation and vehicle routing	Network and production	A mathematical framework	Optimization algorithms	No
El Baz and Ruel (2020)	Authors demonstrated the role risk management in supply chain to mitigate the disruption in the context of COVID-19 outbreak	Supply chain	Structural equation modeling	No	Yes
Fattahi (2020)	A data-driven two-stage stochastic programming model was proposed along with a social life cycle assessment (SLCA) to manage the disruption in the supply chain	Network	Two-stage stochastic programming	Benders' decomposition algorithm	No
Nguyen et al. (2020)	In this study, an optimization model based on equivalent integer programming is utilized to manage supply chain disruption focusing an earthquake	Network	Equivalent integer programming	Optimization algorithms	No
Ivanov (2019)	In this study, authors investigated the disruptions on production and distribution networks using an optimization model	Production and network distribution	Discrete-event simulation-based optimization	Simulation	No
Paul et al. (2018)	To reduce the disruption risk in a three-tier supply chain network, authors proposed a quantitative mathematical model	Supply	Constrained mathematical programming	Heuristic and PA algorithm	No
Darom et al. (2018)	To focus the environmental sustainability, authors proposed a recovery model for a two-stage supply chain with a disruption	Supply	Constrained integer nonlinear programming	Branch and bound algorithm	No

production are of high significance in the time of the recent pandemic. Also, the reliability of the supplier is an important factor in addressing demand. This research develops a model for recovering disruptions for a manufacturer's supply chain comprising a single supplier and a single retailer motivated from the recent COVID-19 pandemic situation. We also consider that the supplier's capacity follows an exponential distribution. Also, due to the COVID-19 pandemic, the supplier and the retailer both can get disrupted and may not be available during the time cycles. Also, the reliability of the supplier and the manufacturer is considered. In this study, the average profit per cycle is formulated as the objective function. This study contributes to supply chain disruption risk management literature in several ways. First, we include the disruption risk at the supplier and the retailer's end along with the reliability of the supplier and the manufacturer's production system motivated by the COVID-19 pandemic situation. Second, we consider randomness in the capacities of the supplier and the retailer to tackle disruptions risk associated with the level of inventory of real-word supply chains. Considering randomness in capacities is important as they influence many supply chain decisions.

The rest of this paper is arranged as follows: "Problem description" presents the problem description followed by the model formulation in "Disruption risk mitigation model." Numerical investigations are illustrated in "Numerical investigations." "Sensitivity analysis" offers a sensitivity analysis. "Managerial and practical implications" presents the managerial insights of the model. "Conclusions and recommendations for future research" concludes this paper.

Problem description

In this study, we consider a manufacturer who has a single supplier and a single retailer. The supplier and the retailer can get disrupted due to various reasons, e.g., for the recent COVID-19 pandemic. This disruption is considered to happen at random times. Also, both the supplier and retailer can remain unavailable for a random length of time. The available state is denoted as an ON state and the unavailable state is denoted as an OFF state. Also, we considered the supplier to have a random capacity; as a result, there will be a disparity in his/her capacity to supply the amount ordered. For the supplier, the reliability is also considered. The reliability of the manufacturer is also considered in the inventory building process. The reliability of the manufacturing process is also considered for the depreciation cost. The manufacturer needs an inventory model considering these facts and also formalizes an ordering policy that will maximize his average profit to avoid the impact of the COVID-19 pandemic. The model allows the manufacturer to back-order in case of not meeting the

demand. The following are some assumptions made for this model:

- A single type of product is manufactured by the manufacturer.
- One raw material is used to produce one final product.
- Production lot size is equal to the ordering lot size.
- A lower markup than acceptable products is considered for faulty products.
- Holding cost is directly related to process reliability.
- The ON and OFF states of both the supplier and retailer are unknown to the manufacturer in advance. Such an availability and unavailability of the supplier and retailer are obvious in a situation like the COVID-19 pandemic risk. Due to the lockdown of areas and isolation of people, these two supply chain agents are not always available to execute the promised supply chain functions.
- Lengths of availability and unavailability for the supplier and retailer are exponential random variables where the demand generation follows the Poisson process.
- Manufacturer can order when both the supplier and retailer are available.
- The lead time for delivery is zero.
- Capacity of the supplier follows an exponential distribution.

Using these assumptions and modifying the work of Parlar and Perry (1995), the disruption risk mitigation model is formulated in the next section.

Disruption risk mitigation model

The notations used for the disruption risk mitigation model are given in Appendix A. The model developed here consists of one supplier and one retailer. In this model, at random times, the supplier and retailer can be available and unavailable. The availability is indicated by ON and unavailability is indicated by OFF. The length of duration of the ON and OFF periods is considered to be exponentially distributed for both the supplier and the retailer. The parameter for the length of ON and OFF periods for the supplier and the retailer is given below:

	Parameter for length of ON period	Parameter for length of OFF period
Supplier	λ	μ
Retailer	α	β

Renewal reward theory is the part of probability theory that is used to generalize the Poisson process for random interarrival times (Ross 1995). In a renewal reward process, each interarrival time is associated with a random variable that is commonly thought of as the reward connected with the interarrival time. Concept from renewal reward process is used to identify the regenerative cycle and thereby develop average objective functions for this model.

In this model, depending on the ON and OFF states of the supplier and retailer, there can be four different states. These states are shown below:

State 0: Supplier – ON, Retailer – ON
State 1: Supplier – ON, Retailer – OFF
State 2: Supplier – OFF, Retailer – ON
State 3: Supplier – OFF, Retailer – OFF

In state 0, we can see that both the supplier and retailer are available. In states 1 and 2, either the supplier or the retailer is available. Also, in state 3, both of them are unavailable at the same time. In this model, we considered that order can be placed in state 0 as both the supplier and the retailer are available and it can be reached to the end customers. In state 0, the reordering quantity is r. In the remaining three states, either the supplier or the retailer remains unavailable. In those states, the product cannot reach the customers. As a result, there is only one order quantity (q_0), which will be at state 0. As the state of both the supplier and retailer can change, the transient probabilities are considered. The transient probabilities are stated as $X_{ij}(t) =$ probability (being in state j at time t starting at state i at time 0), $i, j = 0, 1, 2, 3$. Now, the problem resembles four-state continuous-time Markov chain (CTMC). Based on the assumptions made earlier, the supplier has a random capacity and it follows an exponential distribution with parameter having distribution function $F(x)$ where $F(x) = 1 - e^{-\theta x}$. This means whenever he/she received an order of q units, the amount he/she delivered will be either q or less than that (whichever applicable) and depends on the values of its distribution function, density function, and the amount ordered. From now on, the amount delivered by the supplier is going to be denoted as $E(q)$ throughout the following parts.

In this model, the manufacturer has a single supplier from whom it replenishes its inventory and keeps production running from the raw material inventory. When the supplier gets disrupted for a random period, the manufacturer faces random disruptions in supply. On the other hand, the retailer can remain unavailable for random times. The ordering policy for the manufacturer is that it will order q_0 units after reaching the reordering point, with the state being 0. When either the supplier or the retailer is not available, he has to wait for the time when both of them become available again. Upon receiving

the supply from the supplier, the inventory level becomes $E(q_i) + r$; $i = 0, 1, 2$.

So, the objective function for profit is

$$\text{AP}(q0, r, n_s, n_m) = \frac{X_{00}}{T_{00}} = \frac{E[\text{profit per cycle}]}{E[\text{length per cycle}]} \quad (1)$$

The profit can be calculated as the difference between the revenue generated and the cost incurred in a cycle. After computing the revenue generated per cycle R_{00}, cost per cycle C_{00}, and the cycle length T_{00} (see Eqs. (24)–(34) in Appendix B), the final objective function can be written as below:

$$\text{AP}(q, r, n_s, n_m) = \frac{X_{00}}{T_{00}} = \frac{R_{00} - C_{00}}{T_{00}} = \frac{P \times m_1 \times E(q) \times n_m + P \times m_2 \times E(q) \times (1 - n_m) - X_{00}A_0 - X\sigma_1 - X_{02}\sigma_2 - X_{03}\left(\overline{C} + \rho_1\sigma_1 + \rho_2\sigma_2\right)}{\frac{E(q)}{\gamma} + XT_{10} + X_{02}T_{20} + X_{03}\left(\overline{T} + \chi_1\rho_1 + \chi_2\rho_2\right)}$$

$$(2)$$

Equation (2), the final objective function, is a nonlinear and unconstrained function. Here, we have four decision variables: quantity ordered, reliability of the supplier, reliability of the manufacturer, and reordering points. A decision-maker (the manufacturer here) seeks to maximize the objective function by optimizing the decision variables. To optimize the objective function, this study uses the genetic algorithm (GA) and pattern search (PS) technique due to the following advantages:

- GA is an advanced optimization method that can search parallel from a population of points, whereas traditional optimization models can search from a single point (Fu et al. 2019).
- GA follows probabilistic selection rules, whereas traditional models follow deterministic rules.
- GA can operate on the Chromosome, which is an encoded version of the potential solution parameter, rather than the parameters themselves.
- GA is a powerful optimization tool that can manage fitness scores without considering auxiliary information (Sahebjamnia et al. 2018).
- PS is another dynamic numerical optimization methods that can perform without a gradient. Therefore, it can be used on functions that are not continuous or differentiable (Malik and Sarkar 2020).
- PS optimization method can perform better to search for solutions in a multidimensional analysis space of possibilities environment with the lowest error value (Paul et al. 2015).

Numerical investigations

Our model builds the inventory system of a manufacturer considering Poisson demand with uncertainty of the supplier and retailer along with the random capacity of the supplier and the reliability of the supplier. We consider quantity ordered, reliability of the supplier, reliability of the manufacturer, and reordering points as the decision variables. The values of the different parameters used in the model are given in Table 2. We also used the cost of interest and depreciation, in the form used by Cheng (1989), as we have shown in the model development section. Here, we used $a = 1000$, $b = 0.8$, and $c = 0.75$.

Here, we are considering a modified (Q, r, n_s, n_m) policy formed in this model for a manufacturer with one retailer and one supplier. The goal is to maximize the value of the objective function by optimizing the decision variables.

We used the GA and the PS algorithms to solve the model. In the next section, we are going to discuss the results.

Results

For the GA algorithm, stall generation (G) has been varied to have a better assessment of the result. For each number of generations, the algorithm was run 15 times, and the best value was taken. Now, let us look at the different relationships between the profit and the decision variables as presented in Table 3 and Figs. 1 and 2.

Table 2 Parameter values used in maximizing the function

Parameter	Value	Parameter	Value
h_s	2	K	10
h_m	3.5	S	12
m_1	3	π	25
m_2	0.2	π'	2.5
e_1	0.05	λ	0.25
e_2	0.08	μ	2.0
c_1	5	α	1
c_2	8	β	0.5
P	15	ψ	0.020
P_P	10	γ	80

In Fig. 1, as the reliability of the supplier improves, the average profit also increases. We can observe the profit to be negative at lower reliability, which can be caused by higher holding cost as well as high inspection and rejection cost. The average profit increased with reliability. Maximization occurs just after crossing the 0.9, and then, the profit shows a decrease again. From Fig. 2, we can see that when the reliability of the manufacturer increases, the average profit also increases. Maximization of profit occurs just when the reliability of the manufacturer crosses the value of 0.7, and then, the profit shows a decrease again.

From Fig. 3, we can see that with the increase in ordered quantity, the profit increases up to a certain ordering quantity nearing 100 units. Initially, for a lower ordering quantity, the ordering cost is higher than the holding cost. However, the increase in the holding cost due to increased ordering quantity affects the total profit after that point.

Figure 4 describes the variation in profit concerning the reordering point. In the beginning, the increased reordering point increased the profit up to the optimum point. The underlying reason is that a higher reordering point can significantly improve the shortage problem as well as the backlog orders. This results in a decrease in their cost, which in turn results in a higher profit margin. However, a higher reordering point beyond the optimal point results in higher safety stock. Subsequently, the holding cost increases and rapidly reduces profit.

We also used the PS algorithm to optimize the values of the decision variable to get the maximum profit in a cycle. There are three results summarized in Table 4, which are obtained through the PS algorithm. Maximum number of iterations (M) has been varied to have a better assessment of the result. From the result, we can see that the result remains almost the same for the change in the iteration number. With the increase in iteration number, the profit increased by a small margin, and after 400 iterations, the result becomes static with insignificant change.

Now, using the pattern search algorithm, we look at the different relationships between the profit and the decision variables, presented in graphs. Figure 5 reveals the almost similar result as we have seen from the GA. The average profit increased with an increase in the supplier's reliability. Initially, when the reliability of the supplier is less than 0.3, the profit is
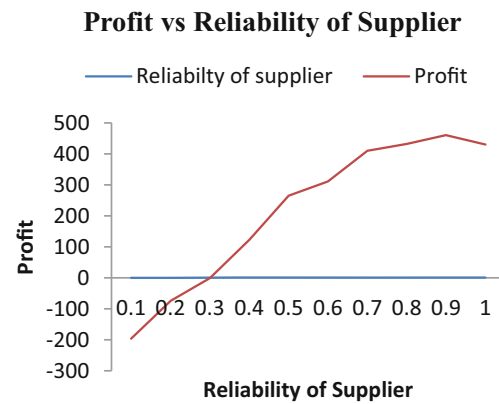

Fig. 1 Average profit vs reliability of the supplier for GA

negative. However, the profit increases with an increase in reliability. Profit maximization occurs just after crossing the 0.8, and then, the profit shows a decrease again. Figure 6 reveals the influence of the manufacturer's reliability on the profit. From the graph, we can see that when the reliability increases, the average profit also increases. The gradient is maximum between the ranges of 0.4 and 0.5. The profit becomes maximum just after crossing the 0.7, and then, the profit shows a decrease again. This indicates that trying to achieve a high level of reliability results in more cost than actually increasing profit.

From Fig. 7, we can observe that the profit increases with the ordering quantity until it reaches the saturation point at the mark around 90. This increase in profit is due to the lowering of ordering cost, which is more prominent than the holding cost for small ordering quantity, though increased ordering quantity after the optimum ordering point increases the total cost. This is reflected in the profit. Figure 8 reveals the variation in profit concerning the reordering point. In the beginning, the increased reordering point increased the profit up to the optimum point. However, the higher reordering point
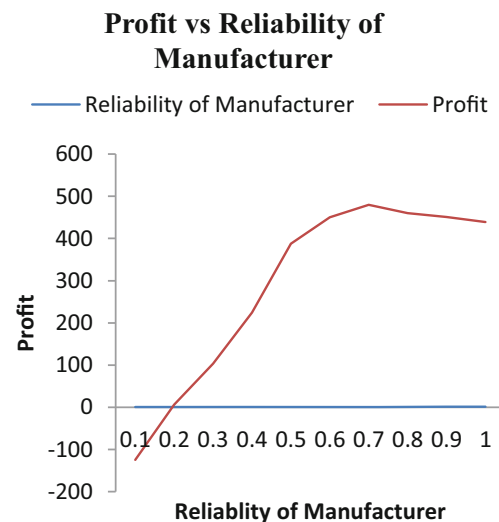

Fig. 2 Average profit vs reliability of the manufacturer for GA

Table 3 Optimization using GA

Generation	q (units)	r (units)	n_s	n_m	Profit
100	99.81	69.2	90.1%	71.4%	475.16
150	99.78	68.8	89.4%	71.5%	475.45
200	99.64	69.1	90.7%	72.9%	475.25
250	99.81	69.1	90.7%	71.4%	474.38

Profit vs Ordering Quantity
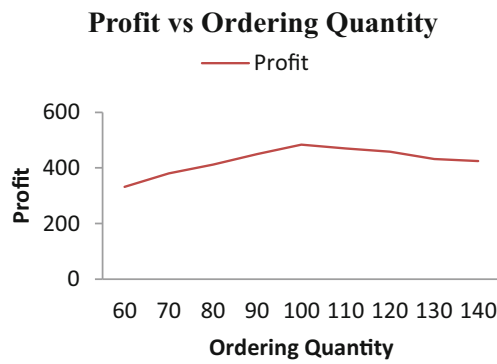
Fig. 3 Average profit vs ordering quantity for GA

Table 4 Optimization using pattern search

Max Iteration (M)	q (units)	r (units)	n_s	n_m	Profit
100	90.35	57.4	84.2%	71.4%	496.72
200	99.37	57.4	84.1%	71.5%	495.16
300	90.18	57.6	84.6%	72.9%	497.35
400	90.31	57.5	84.6%	71.4%	498.56

beyond the optimal point results in higher holding costs of increased safety stock and rapidly reduces the profit.

We optimized the model using two algorithms – the GA and PS. For the GA, we checked the model by increasing the stall generation at 50 iterations starting from 100. For each generation number, we ran the algorithm 15 times and selected the best among the results. We continued this up to 600 iterations. On the other hand, for the pattern search, we started with 100 iterations. Then, we increased the iteration by 100 at each step. The optimization finally terminates after 1018 iterations.

From the results, we find that both GA and PS give almost identical results, but PS produced better results than GA in most cases. The reason may underlie in the working procedure of these two algorithms. For GA, which is a stochastic search process, sometimes, it converges to local optima or even arbitrary points rather than the global optimum of the problem. In contrast, PS finds a certain search direction, which helps it to perform better than many search-based algorithms.

Sensitivity analysis

To study the effects of the parameters of the model, a sensitivity analysis is performed with the illustrative example described earlier. In Table 5, the basic value of the parameters as considered in the example is represented in level 1. In the following columns, level 2 represents the values at + 20% of
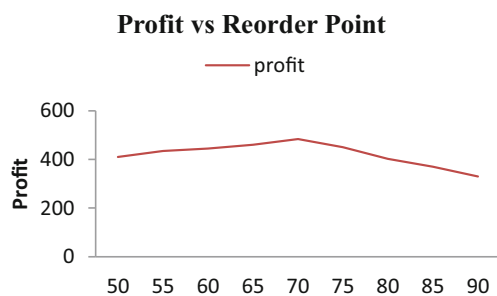
the basic level, whereas level 3 represents + 40%. For each of these parameters, we run both the GA and the PS to solve the model. The result from the sensitivity analysis is shown in Table 6.

From the sensitivity analysis, we have identified that our most sensitive parameters for this model are h_s, h_m, P, m_1, and γ. For these parameters, we then checked the variation in profit by increasing them by 10%, 20%, 30%, and 40% and showed them in Table 7.

For h_s, sensitivity analysis reveals the fact that when raw material holding cost is increased, both ordering quantity and reordering point decrease. It reflects that if the holding cost is high, the material should be ordered in a lower quantity. Besides, to keep the safety stock at minimal, the reordering point should be set at a lower point accordingly.

For h_m, it is seen that when the finished material holding cost is increased, it affects the ordering quantity as well as the reordering point. They both decrease. The profit level also decreases. For P, which is the purchasing cost, increasing it affects the profit by a significantly large margin. It also increases the requirement of the manufacturer's reliability by a large amount.

For m_1, an increase in m_1 influences the profit positively by directly increasing the selling price. However, increase in m_1 requires proper market analysis, as it can impact the product sales directly. From the analysis, it can be said that m_1 is a comparatively more sensitive parameter as any increase in m_1 reduces the value of the quantity ordered.
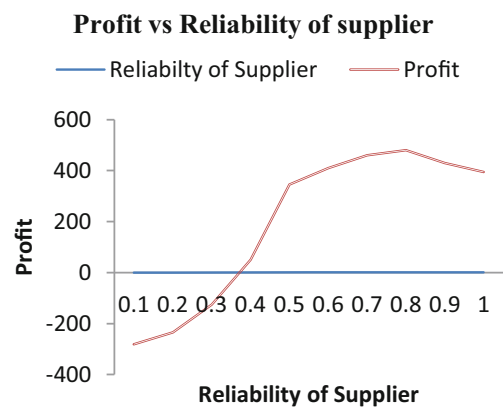
Profit vs Reorder Point

Fig. 4 Average profit vs reordering point for GA

Profit vs Reliability of supplier

Fig. 5 Average profit vs reliability of the supplier for PS

Profit vs Reliability of Manufacturer
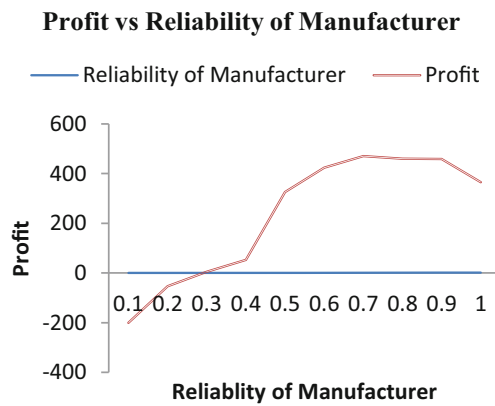
Fig. 6 Average profit vs reliability of the manufacturer for PS

Profit vs Reorder Point

Fig. 8 Average profit vs reordering point for PS

For γ, we found that the ordering quantity as well as the reorder quantity is readily influenced by the change in demand rate. Both increase rapidly with the increase in demand rate. The demand rate also highly influences the average profit value. So, we should be careful while changing the circumstances that can affect the profit maximization objective.

Managerial and practical implications

The model developed in this study can help managers to deal with disruptions in the supply chain while maintaining profitability in the context of COVID-19 pandemic. The COVID-19 pandemic is creating complexity in the supply chain operations by making unavailability of suppliers. This unavailability of suppliers can create randomness in its capacity and reliability. Therefore, this study considered randomness in the capacity for the supplier along with its reliability to capture the real-life situations. Also, the reliability of the manufacturing process is introduced, as it influences the ability of the manufacturer to supply with acceptable products to sell in the sudden disruption condition. The managerial implications of the model in the context of COVID-19 are presented below:
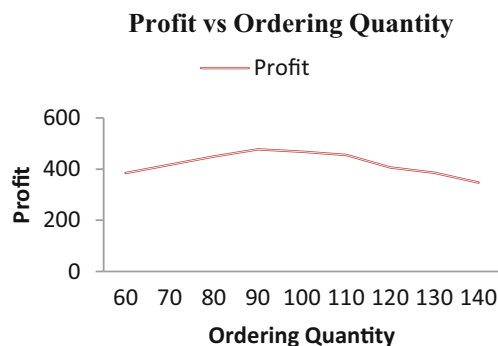
- *Supplier reliability and random capacity*

Randomness in capacity in the current pandemic situation is a common occurrence for suppliers in real life. Though it is the responsibility of the supplier to supply the amount ordered, in the pandemic situation, the managers of the manufacturing entity should take into account the randomness of the capacity of the supplier while sourcing. Also, the supplier's reliability is another important concern for supply chain operations. Managers need to take the reliability of the supplier into account to offset its effect. This can assist the managers to make a revised plan for the alleviation of disruption risk of a supply chain caused by the COVID-19 pandemic by considering these factors while making decisions.

Table 5 Experimental data set for sensitivity analysis

Parameter	Level 1	Level 2(+ 20%)	Level 3(+ 40%)
hs	2	2.4	2.8
hm	3.5	4.2	4.9
$m1$	3	3.6	4.2
$m2$	0.2	0.24	0.28
e1	0.05	0.06	0.07
e2	0.08	0.096	0.112
$c1$	5	6	7
$c2$	8	9.6	11.2
P	15	18	21
Pp	10	12	14
k	10	12	14
S	12	14.4	16.8
τ	25	30	35
τ'	2.5	3	3.5
λ	0.25	0.3	0.35
μ	2	2.4	2.88
α	1	1.2	1.4
β	0.5	0.6	0.72
ψ	0.025	0.024	0.0288
γ	80	96	112

Profit vs Ordering Quantity

Fig. 7 Average profit vs ordering quantity for PS

Table 6 Results from sensitivity analysis

Case	Parameter	Level	q (units)		r (units)		n_s		n_m		Profit($)	
			For GA	For PS	For GA	For PS	For GA	For PS	For GA	For PS	For GA	For PS
1	basic modelmodelmodel	1	99.81	95.79	69.14	57.53	0.907	0.846	0.714	0.714	474.38	498.56
2	h_s	2	91.56	92.46	59.82	59.85	0.944	0.854	0.575	0.685	408.71	401.71
3	h_s	3	88.62	81.62	55.41	48.45	0.951	0.901	0.623	0.793	350.46	312.46
4	h_m	2	93.47	86.47	63.25	51.27	0.922	0.873	0.657	0.614	412.66	423.66
5	h_m	3	90.53	83.53	58.57	46.61	0.933	0.866	0.514	0.523	386.74	352.74
6	m_1	2	69.64	71.64	54.83	54.82	0.813	0.813	0.645	0.645	724.32	818.32
7	m_1	3	67.2	65.28	42.08	45.05	0.784	0.784	0.623	0.623	819.45	1051.45
8	m_2	2	92.97	88.95	66.75	55.15	0.841	0.792	0.668	0.657	491.75	527.95
9	m_2	3	83.34	82.43	66.83	52.83	0.798	0.755	0.642	0.635	515.78	535.68
10	e_1	2	104.34	99.34	66.33	54.73	0.926	0.881	0.745	0.732	467.21	449.81
11	e_1	3	109.24	105.22	66.71	55.40	0.941	0.851	0.757	0.778	450.41	450.41
12	e_2	2	108.94	103.34	66.88	52.68	0.942	0.862	0.746	0.762	449.42	435.42
13	e_2	3	111.86	105.48	71.94	48.31	0.968	0.898	0.779	0.789	421.84	431.94
14	c_1	2	106.22	99.22	66.63	54.43	0.967	0.907	0.810	0.825	448.73	455.93
15	c_1	3	117.38	107.38	71.94	65.44	0.977	0.817	0.883	0.834	421.84	427.84
16	c_2	2	112.51	105.51	67.93	59.93	0.961	0.902	0.821	0.833	445.21	442.71
17	c_2	3	119.79	111.68	69.35	58.67	0.979	0.897	0.889	0.879	417.62	317.94
18	P	2	129.55	119.55	67.24	53.64	0.981	0.886	0.812	0.781	301.67	338.67
19	P	3	138.64	125.64	68.68	76.78	0.994	0.874	0.905	0.955	242.86	265.93
20	P_p	2	100.67	96.67	70.87	59.77	0.928	0.908	0.775	0.782	469.98	466.98
21	P_p	3	119.23	107.53	71.77	62.42	0.955	0.885	0.782	0.762	444.62	456.39
22	k	2	101.76	101.76	70.44	60.15	0.921	0.874	0.739	0.779	466.79	456.49
23	k	3	121.15	109.19	65.34	61.23	0.934	0.894	0.751	0.753	434.61	394.61
24	S	2	108.73	103.76	64.34	51.34	0.914	0.914	0.753	0.763	421.62	429.63
25	S	3	114.95	110.52	69.25	59.25	0.925	0.835	0.841	0.811	411.56	403.66
26	π	2	135.55	119.55	68.74	55.79	0.968	0.908	0.778	0.758	416.55	427.92
27	π	3	144.37	145.37	76.82	65.68	0.993	0.913	0.798	0.772	379.19	319.22
28	π'	2	107.66	97.66	66.73	68.73	0.923	0.923	0.739	0.749	426.92	426.92
29	π'	3	107.87	104.78	66.98	66.98	0.925	0.925	0.743	0.761	369.18	379.18
30	λ	2	71.01	112.75	57.33	60.95	0.854	0.848	0.687	0.719	443.89	454.16
31	λ	3	59.27	144.54	50.43	66.72	0.823	0.834	0.661	0.778	413.37	439.09
32	μ	2	123.25	76.95	65.95	57.33	0.938	0.854	0.749	0.687	495.10	518.89
33	μ	3	138.95	51.56	65.62	50.43	0.944	0.823	0.758	0.671	503.09	548.37
34	α	2	88.29	97.31	62.72	64.33	0.901	0.881	0.724	0.742	485.78	613.82
35	α	3	79.72	132.88	60.73	63.13	0.856	0.902	0.687	0.736	497.35	689.38
36	β	2	107.51	81.72	74.63	52.94	0.941	0.891	0.756	0.724	500.74	335.68
37	β	3	137.48	71.32	73.73	59.36	0.943	0.856	0.763	0.689	511.66	309.35
38	ψ	2	101.97	95.27	66.88	51.48	0.898	0.838	0.722	0.722	469.82	469.82
39	ψ	3	99.74	97.74	66.52	54.32	0.895	0.815	0.719	0.726	424.75	471.75
40	γ	2	111.66	101.56	90.01	70.01	0.898	0.868	0.722	0.719	575.28	625.98

- ***Reliability of the manufacturer***

The reliability of the manufacturer plays a vital role in the profitability of the manufacturer. Although the ideal situation dictates for a reliability level of a hundred percent, in real life, due to various reasons like the COVID-19 pandemic, this is not achievable. Furthermore, it is also seen that in the COVID-19 pandemic, situation increasing the reliability of the manufacturing system is financially prohibitive in proportion with the return on investment. Thus, the optimum reliability of

Table 7 Change in profit for different levels of parameters

Parameter	Algorithm	Basic model	+10%	+20%	+30%	+40%
h_s	GA	474.38	445.65	408.71	367.98	350.46
	PS	498.56	438.74	401.71	363.87	312.45
h_m	GA	474.38	457.65	412.66	398.87	386.74
	PS	498.56	443.27	423.66	388.48	352.63
P	GA	474.38	414.26	301.67	269.92	242.86
	PS	498.56	394.33	338.92	283.13	265.93
m_1	GA	474.38	626.18	724.32	779.01	819.45
	PS	498.56	667.41	818.32	912.78	1051.45
γ	GA	474.38	538.42	575.28	594.39	615.27
	PS	498.56	586.56	625.98	656.75	694.35

the manufacturing process considering the COVID-19 pandemic to stay profitable in the face of disruption in the supply chain is an important decision factor for supply chain managers.

- ***Inventory management policy***

Developing efficient inventory management policies considering the current pandemic COVID-19 situation is crucial for business organizations to satisfy customers and maximize profit. Therefore, supply chain managers need to reduce the cost related to the inventory, like warehousing and ordering cost, and they need to make sure that the production process runs smoothly with sufficient raw material at hand. However, the COVID-19 pandemic situation is creating trouble to manage sufficient raw material supply. Therefore, this model can help managers to establish a revised model and make changes to the inventory policy to maximize the profit by guiding their purchasing decision.

Conclusions and recommendations for future research

This study offered an inventory model to manage supply chain disruption risks. The model maximizes the profit of the manufacturer as a function of order quantity, reordering point, and manufacturer and supplier reliability. This model indicates the optimum level of reliability required to maintain profitability for a manufacturer. As a faulty manufacturing system produces defective products, process reliability is a major concern to increase the profit. However, increasing process reliability comes with an added cost of operation, which can reduce the profit margin. In developing countries, smaller manufacturing industries frequently lack any rigorous inventory policy to address any kind of uncertainty in their supply chain.

Manufacturing industries, especially where the defective product can be recycled like soap industry and plastic industry, often ignore their manufacturing process reliability, which can impact their ability to stay profitable when faced with disruption in their supply chain during the COVID-19 pandemic. A single product is often manufactured from a concert of many items. Disruption in the supply of a single item due to COVID-19 can potentially delay the whole production process, which is now seen in the ready-made garments (RMG) sector. Considering the reliability of the supplier during the purchasing policy can alleviate this problem to a large extent. There are also other sources of disruptions like epidemic outbreak, accidents, natural calamities, strikes, trade embargo, and even holiday at the sourcing country. For example, in recent times, we have seen the sudden catastrophic impact of COVID-19 on the global supply chain. As one of the biggest raw material suppliers for almost all industries, the closure of China due to the pandemic resulted in the shutdown of production in manufacturing industries globally. This pandemic is impacting the global supply chain terribly by creating uncertainty in supply, manufacturing, and demand. Therefore, this model can help to address such disruptions from the unavailability of suppliers, which are random practical settings.

Besides, in most of the recent studies, it is assumed that the supplier will always be able to supply the amount ordered, which is not the case in real-life scenarios, especially in the COVID-19 situation. This model considered limited capacity for the supplier to make it more realistic. The generation of demand is considered to follow the Poisson process, and the availability and the unavailability period of the supplier as well as the retailer are considered to follow an exponential distribution. The objective function of this model is formulated by using concepts from the renewal reward theorem, which is a function of average cycle profit. We used the GA and the PS to maximize the function. We got a better result from PS for this particular model. Lastly, we conducted a sensitivity analysis to investigate the implication of the parameters and their relationship with the decision variable and influence on the average profit. In summary, the model considered capacity randomness along with reliability in conjunction with disruption at both the retailer and the supplier due to a disruption like the COVID-19 pandemic to have a better apprehension of the real operating conditions.

In this research, we considered the reliability as a decision variable that is non-integer by value and deterministic. In future research, reliability can be considered as probabilistic to modify the model. A manufacturer may have multiple suppliers. In this study, only a single supplier was considered for the manufacturer. Therefore, the work can be extended by considering multiple suppliers for the manufacturer considering the epidemic outbreak. In this research, zero lead time has been considered, although in reality, there is always a finite lead time associated with the orders. Hence, lead time may be

introduced in the model. Furthermore, instead of a continuous-time Markov chain (CTMC), a semi-Markov chain can be used for transient probabilities.

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Notations used in the study

In this study, the following notations are used.

P:	Purchasing cost of per unit product
P_p:	Production cost per unit
m_1:	Markup factor for acceptable unit price
m_2:	Markup factor for faulty unit price
e_1:	Inspection cost of raw material (as a percentage of the purchasing cost)
e_2:	Inspection cost of finished goods (as a percentage of the production cost)
c_1:	Rejection cost per unit for raw material
c_2:	Rejection cost per unit for finished product
h_s:	Holding cost for raw material (per unit time)
h_p:	Holding cost per unit time for finished product (per unit time)
K:	Cost per order
S:	Setup cost per cycle
τ:	Per unit back-order cost
τ':	Back-order cost per unit per time

(continued)

λ:	Length of ON period for supplier
μ:	Length of OFF period for supplier
α:	Length of ON period for retailer
β:	Length of OFF period for retailer
ψ:	Exponential distribution parameter of supplier's capacity
γ:	Poisson distribution parameter for demand
q:	Ordering quantity to supplier
$E(q)$:	Expected quantity to receive from supplier
r:	Reordering point
AP:	Objective function of average profit
C_{00}:	Cost incurred in a cycle
T_{00}:	Total cycle length
$X_{ij}(t)$:	Probability of going to state j with initially in state i
P_i:	Steady-state probability of state i
Φ:	Rate of leaving from any state
$X'(t)$:	Kolmogorov differential equation system for $X(t)$
Q:	Generator matrix
ω:	Eigenvalues of matrix $\boldsymbol{Q}$
U:	Eigenvector matrix of matrix $\boldsymbol{Q}$
U^{-1}:	Inverse of U matrix
H:	Diagonal matrix
$Y(t)$:	Solved matrix from spectral analysis
Q_{i0}:	Cost at the start of the next cycle from the time when inventory level drops to r at state $i = 0, 1, 2, 3$ and q units are ordered in case of state 0
$\overline{C}$:	Expected cost from the time inventory level drops to r until both supplier and retailer become available
δ:	Departure rate from the state when both retailer and supplier are unavailable
T_{i0}:	Time to the beginning of the next cycle from the time when inventory level drops to r at state $i = 0, 1, 2, 3$ and q units are ordered in case of state 0
$\overline{T}$:	Expected time until both supplier and retailer become available after inventory level reaches reordering point
A_i:	Total cost for state i
n_s:	Reliability of the supplier
n_m:	Reliability of the manufacturer

Transient probability calculation

Let $X(t) = (X_{ij}(t))$, $t \geq 0$, $i,j = 0, 1, 2, 3$ be the 4×4 matrix of transition functions for the CTMC. We can use the Kolmogorov forward equations (Kolmogoroff 1931), which is a system of ordinary differential equations, to derive the transient probabilities from the matrix. A generic form of the equation is given below:

$$X'_{ij}(t) = -\varphi(j)X_{ij}(t) + \Sigma_{k \neq j}X_{iy}(t)\varphi(k,j) \tag{3}$$

Here, the k represents an intermediate state in between the state i and j. The rate out of any state is denoted by φ. In the same manner, other differential equations can be derived. As there are four states, there are 16 Kolmogorov equations. They can be put in a matrix differential form, which is more convenient. The matrix is given below:

$$X'(t) = X(t)Q \tag{4}$$

where Q is
$$\begin{bmatrix} -(\lambda+\alpha) & \alpha & \lambda & 0 \\ \beta & -(\lambda+\beta) & 0 & \lambda \\ \mu & 0 & -(\alpha+\mu) & \alpha \\ 0 & \mu & \beta & -(\mu+\beta) \end{bmatrix}.$$

Here, Q is the generator matrix of the Markov chain. The solution for the matrix differential equation can be defined as $X(t) = e^{Qt}$. Here, e^{Qt} is defined as

$$e^{Qt} = \sum_0^\infty \frac{t^n Q^n}{n!} \tag{5}$$

It is the matrix exponent. Now, from the spectral theory of the matrices (Hilderbrand)

$$Q = UHU^- \tag{6}$$

where U is the nonsingular matrix formed with the right eigenvectors of Q and H is the diagonal matrix. To find the eigenvectors of Q, we first find the eigenvalues

$$det\ (Q-\omega I) = 0 \tag{7}$$

Solving Eq. A5 gives $\omega_0 = 0$, $\omega_I = -(\lambda+\mu)$, $\omega_2 = -(\alpha+\beta)$, and $\omega_3 = -(\lambda+\mu+\alpha+\beta)$.

The eigenvectors can be determined by using the eigenvalues above, and the matrix U is formed as follows:

$$U = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -\beta/\alpha & -\beta/\alpha \\ 1 & -\mu/\lambda & 1 & -\mu/\lambda \\ 1 & -\mu/\lambda & -\beta/\alpha & \mu\beta/\lambda\alpha \end{bmatrix} \tag{8}$$

If $Q = UHU^{-1}$, then $Q^n = (UH^nU^{-1})$ \hfill (9)

Therefore, the final equation for determining the transient probability can be obtained by substituting the value Q:

$$X(t) = \sum_{n=0}^\infty \frac{(UH^n U^{-1})}{n!} = UA(t)U^{-1} \tag{10}$$

where

$$Y(t) = \begin{bmatrix} e^{\omega_1 t} & 0 & 0 & 0 \\ 0 & e^{\omega_1 t} & 0 & 0 \\ 0 & 0 & e^{\omega_2 t} & 0 \\ 0 & 0 & 0 & e^{\omega_3 t} \end{bmatrix} \tag{11}$$

Consumption of the order quantity received in state 0 follows the Erlang distribution. The Y_{11} will be derived from the following equation when the received quantity is $E(q_0)$ in state 0:

$$Y11 = \frac{\frac{\gamma}{\Gamma E(q)} \int_0^\infty \left[e^{-(\lambda+\mu)x}\right](\gamma x)^{E(q-1)} e^{-\gamma x} dx}{= \left(\frac{\gamma}{\gamma+\lambda+\mu}\right)^{E(q)}} \tag{12}$$

Similarly,

$$Y22 = \left(\frac{\gamma}{\gamma+\alpha+\beta}\right)^{E(q)} \tag{13}$$

And

$$Y33 = \left(\frac{\gamma}{\gamma+\lambda+\mu+\alpha+\beta}\right)^{E(q)} \tag{14}$$

Therefore, the transition probability from state 0 to the other three states can be calculated from the following matrix.

$$Y(t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \left(\frac{\gamma}{\gamma+\lambda+\mu}\right)^{E(q)} & 0 & 0 \\ 0 & 0 & \left(\frac{\gamma}{\gamma+\alpha+\beta}\right)^{E(q)} & 0 \\ 0 & 0 & 0 & \left(\frac{\gamma}{\gamma+\lambda+\mu+\alpha+\beta}\right)^{E(q)} \end{bmatrix} \tag{15}$$

The value of transition probabilities can be generated by using the eigenvector matrix (U) and its inverse (U^{-1}) of the generator matrix Q. Based on the quantity received, which will be consumed, the matrix $Y(t)$ can be one of the three matrices as derived. This received order quantities are also state-dependent.

Cycle profit calculation

Profit is defined as the difference between total revenues and total costs. Here, for a production cycle, we considered the cost components as holding cost (for raw material and finished product), ordering cost, setup cost, purchasing cost, inspection cost (for raw material and finished product), rejection cost (for raw material and finished product), production cost, and cost of interest and depreciation. Now, orders can be placed to supplier for raw material in case of state 0 only when both the supplier and retailer are available. For other states, the different cost is incurred.

Total cost incurred per production cycle = holding cost + ordering cost + setup cost + purchasing cost + inspection cost + rejection cost + production cost + cost of interest and depreciation

Now, the expressions of different cost components are given below:

- Holding cost $= \frac{h_s E(q)}{\gamma} \times \frac{E(q)+2r}{2n_s} + \frac{h_m E(q)}{\gamma} \times E(q) \times n_m = \frac{h_s E(q^2)}{2\gamma n_s}$
  $+ \frac{h_s E(q) r}{\gamma n_s} + \frac{h_m E(q^2) n_m}{\gamma}$
- Purchasing cost $= P \times \frac{E(q)}{n_s}$
- Inspection cost $= P \times e_1 \times \frac{E(q)}{n_s} + P \times e_2 \times E(q)$
- Rejection cost $= C_1 \times E(q) \times \frac{(1-n_s)}{n_s} + C_2 \times E(q) \times (1-n_m)$

- Production cost $= E(q) \times P_p$
- Cost of interest and depreciation $= a(S)^{-b}(n_m)^c$

Thus, the total cost incurred per production cycle

$$= \frac{h_s E(q2)}{2\gamma n_s} + \frac{h_s E(q) r}{\gamma n_s} + \frac{h_m E(q2) n_m}{\gamma} + k + S + P$$

$$\times \frac{E(q)}{n_s} + P \times e_1 \times \frac{E(q)}{n_s} + P \times e_2 \times E(q) + C_1$$

$$\times E(q) \times \frac{(1-n_s)}{n_s} + C_2 \times E(q) \times (1-n_m) + E(q)$$

$$\times P_p + a(S)^{-b}(n_m)^c \tag{16}$$

where

$E(q) = \frac{1}{\psi} \times \left(1 - e^{-\psi q}\right)$ and $E(q2) = \frac{2}{\psi^2} \times \left\{1 - (1 + \psi q)e^{-\psi q}\right\}$.

Now, revenue generated per cycle = selling price of acceptable units + selling price of faulty units

Therefore, revenue generated per cycle

$$= P \times m_1 \times E(q) \times n_m + P \times m_1 \times E(q) \times (1-n_m) \tag{17}$$

Consequently,

$$AP(E(q), r, n_s, n_m) = P \times m_1 \times E(q) \times n_m + P \times m_1 \times E(q) \times (1-n_m) \tag{18}$$

$$-\frac{h_s E(q2)}{2\gamma n_s} - \frac{h_s E(q) r}{\gamma n_s} - \frac{h_m E(q2) n_m}{\gamma} - k - S - P \times \frac{E(q)}{n_s} - P \times e_1 \times \frac{E(q)}{n_s}$$

$$-P \times e_2 \times E(q) - C_1 \times E(q) \times \frac{(1-n_s)}{n_s} - C_2 \times E(q) \times (1-n_m) - E(q)$$

$$\times P_p - a(S)^{-b}(n_m)^c$$

Transition cost, C_{i0}, is defined as the cost of reaching state 0 starting from state i. Again, other states can be reached before reaching state 0. Subsequently, values of those elements (C_{10}, C_{20}, C_{30}) are evaluated.

$$C_{00} = X_{00}(E(q))A\big(E(q), r, n_s, n_m\big) + \sum_{j=1}^{3} P_{ij}(E(q))\big[\, C_{j0}\big]; i = 0, 1, 2 \tag{19}$$

The above equation signifies that after receiving the expected quantity from the supplier, the new inventory level will be $E(q)+r$. After the $E(q)$ unit is finished, the manufacturer will find him/her either in state 0, 1, 2, or 3 with respective probability of $X_{00}(E(q)), X_{01}(E(q)), X_{02}(E(q)),$ and $X_{03}(E(q))$.

So, we find

$$C_{00} = X_{00}A_0 + X_{01}C_{10} + X_{02}C_{20} + X_{03}C_{30} \tag{20}$$

For C_{10}, we can write

$$C_{10} = X_{10}\overline{C}_{10} + X_{11}C_{10} + X_{12}C_{20} + X_{13}C_{30} \tag{21}$$

For C_{20}, we can write

$$C_{20} = X_{20}\overline{C}_{20} + X_{21}C_{10} + X_{22}C_{20} + X_{23}C_{30} \tag{22}$$

But C_{30} has a different expression.

$$C_{30} = (\overline{C} + C_{10})\rho_1 + (\overline{C} + C_{20})\rho_2$$

$$= \overline{C} + C_{10}\rho_1 + C_{20}\rho_2 \tag{23}$$

where

$$\rho_1 = \frac{\mu}{\mu + \beta} \quad \text{and} \quad \rho_2 = \frac{\beta}{\mu + \beta}$$

Then, we evaluate the value of $\overline{C}, \overline{C}_{10},$ and $\overline{C}_{20}$.

Therefore, $C_{00} = X_{00}A_0 + X_{01}\sigma_1 + X_{02}\sigma_2$

$$+ X_{03}\left(\overline{C} + \rho_1\sigma_1 + \rho_2\sigma_2\right) \tag{24}$$

where $[\sigma_1\ \sigma_2]' = [C_{10}\ C_{20}]'$.

Cycle length calculation

Now, we define the length of cycle T_{00}. From the research of Ahmed et al. (2017), we can define $T_{i0} = E$ (time at the beginning of the next cycle from the time when inventory drops to r at state $i = 0, 1, 2, 3$ and q units are ordered in case of state 0).

Then,

$$T_{i0} = X_{i0}(E(q_i)) \times \frac{E(q_i)}{\gamma} + \sum_{j=1}^{3} X_{ij}(E(q_i))\left[\frac{E(q_i)}{\gamma} + T_{j0}\right]; i = 0, 1, 2 \tag{25}$$

Cycle length T_{00} can be derived from the equation above:

$$T_{00} = X_{00}(E(q_i)) \times \frac{E(q_0)}{\gamma} + \sum_{j=1}^{3} X_{0j}(E(q_0))\left[\frac{E(q_0)}{\gamma} + T_{j0}\right] \tag{26}$$

The above equation signifies that after receiving the expected quantity from the supplier, the new inventory level will be $E(q)+r$. After the $E(q)$ unit is finished, the manufacturer will find him either in state 0, 1, 2, or 3 with respective probability of $X_{00}(E(q)), X_{01}(E(q)), X_{02}(E(q)),$ and $X_{03}(E(q))$.

Here,

$$T_{00} = \frac{E(q)}{\gamma} + X_{01}T_{10} + X_{02}T_{20} + X_{03}T_{30} \tag{27}$$

For T_{10}, we can write

$$T_{10} = X_{10}\overline{T}_{10} + X_{11}T_{10} + X_{12}T_{20} + X_{13}T_{30} \tag{28}$$

For T_{20}, we can write

$$T_{20} = X_{20}\overline{T}_{20} + X_{21}T_{10} + X_{22}T_{20} + X_{23}T_{30} \tag{29}$$

And the equation of T_{30} is obtained as follows:

$$T_{30} = \overline{T} + \frac{\mu}{\delta} T_{10} + \frac{\beta}{\delta} T_{20} \tag{30}$$

where $\delta = \mu + \beta$.

So, $T_{00} = \dfrac{E(q)}{\gamma} + X_{01} T_{10} + X_{02} T_{20} + X_{03}\left(\overline{T} + \chi_1 \rho_1 + \chi_2 \rho_2\right)$
$$\tag{31}$$

where $[\chi_1\ \chi_2]' = [T_{10}\ T_{20}]'$

Cycle revenue calculation

Now, we define the revenue generated in a cycle, R_{00}. Let us define $R_{i0} = E$ (revenue to the beginning of the next cycle from the time when inventory drops to r at state $i = 0, 1, 2, 3$ and q units are ordered in case of state 0).

Then,

$$
\begin{aligned}
R_{i0} &= X_{i0}(E(q_i)) \times Z_{i0}(E(q_i), n_m) \\
&\quad + \sum_{j=1}^{3} X_{ij}(E(q_i)) Z_{j0}(E(q_i), n_m); i \\
&= 0, 1, 2
\end{aligned}
\tag{32}
$$

From this equation, R_{00} can be defined as

$$R_{00} = X_{00}(E(q_i)) \times Z_{00} + \sum_{j=1}^{3} X_{0j}(E(q_0)) Z_{i0} \tag{33}$$

Here, revenue is generated when state transits from state 0 to state 0.

$$R_{00} = P \times m_1 \times E(q) \times n_m + P \times m_2 \times E(q) \times (1 - n_m) \tag{34}$$

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