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A Deterministic Optimization Framework for O2O Supply Chains under Manufacturing Unreliability, Transportation Hazards, and SSMUID Delivery Structures

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Abstract

This paper presents a deterministic optimization framework for a two-echelon Online-to-Offline (O2O) supply chain composed of an unreliable manufacturer and a reliable retailer. Customer demand is modeled as a function of selling price, green investment, and service-improvement investment. The manufacturer produces at a controllable rate but only a fraction of output is usable due to unreliability; shipments are further subject to transportation hazards that damage a fraction of each delivery. The retailer employs a single-setup–multi-unequal-increasing-delivery (SSMUID) policy, parameterized by a geometric ratio, to reduce average inventory at the expense of increased shipment frequency, emission and transport costs. We derive closed-form expressions for SSMUID shipment sizes and average inventory, present the joint total cost (manufacturer + retailer), and reduce the decision problem via substitution. First-order optimality conditions for price, investments, shipment shape and cycle time are obtained and a full 5×5 Hessian matrix is constructed to provide a sufficient Hessian-based global-optimality certificate under interpretable parameter conditions. Numerical experiments compare single-delivery, equal-multi-delivery and SSMUID policies and provide sensitivity analysis on reliability and hazard parameters. Results show that SSMUID reduces joint cost under typical ranges and that manufacturing reliability and transportation hazards are the dominant cost drivers.

Keywords: Online-to-Offline (O2O) supply chain; unreliable manufacturer; transportation hazard; SSMUID delivery policy; green investment; deterministic optimization

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1. Introduction

In recent years, Online-to-Offline (O2O) retailing has transformed global supply chains by integrating online purchasing with offline fulfilment. This hybrid structure enables customers to search, compare, and order products online while receiving physical delivery through offline logistics networks. The O2O model is increasingly preferred due to convenience, faster response time, and omnichannel service experience. However, these advantages also introduce stringent requirements on delivery reliability, fulfilment speed, and consistency across both online and offline channels. Even minor disruptions in upstream production or downstream transportation can lead to delayed fulfilment, customer dissatisfaction, and long-term reputation loss. As consumer expectations continue to rise, robust O2O supply-chain strategies have become vital for competitive success.

Manufacturing unreliability represents a significant challenge in O2O supply chains. Real-world production processes are prone to machine breakdowns, quality inconsistency, work-in-process delays, and other operational disturbances, resulting in the generation of defective or unusable items. Prior research has highlighted the adverse effects of imperfect production systems and the importance of designing replenishment strategies that mitigate such disruptions (Hota, 2020; Hota et al., 2024, 2022b). When unreliable output interacts with the stringent delivery-performance expectations of O2O retailing, the consequences can be particularly severe, leading to shortages, loss of goodwill, and increased reliance on costly emergency replenishments.

Transportation hazards introduce another major source of risk. During shipment, products may be damaged, delayed, or lost due to uncertain environmental conditions, improper handling, or inadequate logistics coordination. Such hazards not only reduce the quantity of usable items reaching the retailer but also contribute to service deterioration, especially in O2O systems where customers value speed and reliability. As shown in Hota et al. (2022b), transportation losses can significantly distort inventory availability and complicate replenishment planning. Designing shipment structures that both minimise risk exposure and reduce inventory cost is therefore an essential component of O2O supply-chain management.

Environmental sustainability further influences consumer choices and supply-chain design. Customers increasingly prefer products with lower environmental impact, prompting firms to invest in green technologies, cleaner production processes, and low-emission logistics (Mishra et al., 2020). At the same time, customer satisfaction in O2O settings is strongly shaped by service quality, including delivery convenience, responsiveness, and communication. Prior empirical evidence shows that home delivery, in-store pickup, and service-tier choices have considerable impact on purchasing behaviour (Dey and Others, 2023; Choi et al., 2023). These findings motivate the incorporation of both green investment and service-improvement investment into the demand structure of modern supply-chain models.

This paper integrates these important dimensions into a unified deterministic analytical framework. We study a two-echelon O2O supply chain composed of one unreliable manufacturer and a reliable retailer operating under transportation hazards. The retailer adopts a single-setup–multi-unequal-increasing-delivery (SSMUID) replenishment strategy, where shipment quantities follow a geometric progression. This delivery policy reduces holding cost but increases shipment frequency and hence exposure to transportation hazard and carbon-emission costs. Demand depends jointly on selling price, product greenness, and service investment, reflecting modern O2O shopping behaviour. The total cost includes holding, production, setup, emission, shortage, service-tier, green investment, service improvement, and unreliability costs.

A deterministic classical optimization problem is formulated to minimise the joint total cost of the supply chain. Closed-form expressions are derived for effective production, shipment structure, and SSMUID inventory dynamics. First-order optimality conditions are established for pricing, green investment, service investment, production, shipment ratio, and cycle time. To ensure mathematical validity of the solution, a Hessian-based convexity analysis is conducted to identify conditions guaranteeing global optimality. Through a detailed numerical study, we compare the proposed SSMUID policy with traditional single-delivery and equal-delivery strategies. The results show that SSMUID can substantially reduce overall system cost, particularly under low manufacturing reliability or high transportation hazard.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the problem environment, notation, and assumptions. Section 4 presents the deterministic mathematical model. Section 5 develops the solution methodology and optimality analysis. Section 6 provides a numerical illustration, and Section 7 reports a sensitivity analysis. Section 8 concludes with key insights and directions for future research.

2. Literature review

Research on O2O supply chains, unreliable manufacturing, transportation hazards, green investment, and delivery policies has grown rapidly in recent years. This section synthesizes the existing contributions and identifies the research gaps that motivate the present study (He et al., 2018; Gallino and Moreno, 2014; Cao and Li, 2018).

2.1. O2O retailing, home delivery, and service strategies

The rapid expansion of Online-to-Offline (O2O) retailing has reshaped how customers interact with sellers, requiring firms to deliver high service quality and fulfil orders through multiple channels (Bai et al., 2018; He and Huang, 2019). Empirical studies show that home-delivery convenience significantly affects customer perception and purchasing behaviour (Dey and Others, 2023; Hwang and Kim, 2020). Service quality, fulfilment responsiveness, and delivery reliability have emerged as essential differentiators in O2O competition, and retailers increasingly rely on service investment to enhance customer experience (Li and Li, 2021; Xie and Liang, 2022).

In a related work, Choi et al. (2023) examined servicing strategies under imperfect production conditions within an O2O environment. Their analysis highlights the strong interdependence between service levels, production reliability, and retailer profitability (Yan and Pei, 2020; Zhang et al., 2021). These insights suggest that service-level decisions and production characteristics must be integrated into unified supply-chain models.

2.2. Unreliable manufacturing and imperfect production

Unreliable or imperfect production systems have been widely studied because real-world manufacturing processes frequently generate defective items or experience disruption (Porteus, 1986; Chakraborty and Giri, 2018). Classical models assume a constant defect rate or reliability parameter influencing usable output (Salameh and Jaber, 2000; Cheng and Wang, 2012). Hota (2020) analysed unequal lot-size and variable transportation impacts under unreliable supply, showing that production imperfection significantly increases overall cost.

In a related stream, Hota et al. (2022b) investigated transportation hazards combined with unreliable manufacturing and established that risk during shipment amplifies the effects of unreliable production (Paul et al., 2014). Retail strategies under unequal shipment from imperfect manufacturers were explored in Hota et al. (2024), demonstrating that shipment structure directly influences retailer cost and shortage behaviour (Banerjee and Giri, 2016). Furthermore, reliability enhancement through smart technologies and distribution-robust modelling was examined in Hota et al. (2022a), reinforcing the importance of incorporating manufacturing unreliability explicitly into supply-chain decision models (Ivanov et al., 2021).

These works collectively show that unreliable production is a key factor that must be integrated with logistics, pricing, and demand decisions in modern supply chains (Ketzenberg and Metters, 2015).

2.3. Transportation hazards and logistics risks

Transportation risk—including loss, damage, and delay—plays a significant role in determining product availability at the retailer (Sheffi, 2005; Tang, 2006). Transportation hazard modelling has been particularly relevant in perishable-goods logistics, e-commerce fulfilment, and global supply chains (Blackhurst and Dunn, 2011; Snyder and Shen, 2016). As shown in Hota et al. (2022b), hazard-induced losses affect inventory balance, shortage levels, and shipment frequency, thereby influencing the total cost of the system.

However, the interaction between transportation hazards and multi-delivery shipment structures has not been sufficiently addressed in the literature (Chen and Xiao, 2019). Most classical EOQ-type and lot-sizing models assume hazard-free logistics, which does not reflect real O2O environments where shipments are frequent and demand variability is high (Giri and Bardhan, 2017).

2.4. Green investment and sustainable operations

Growing environmental consciousness has shifted consumer preference toward greener products (Chen, 2011). Green production and emission-conscious logistics are now strategic priorities in manufacturing and retailing (Benjaafar et al., 2013). Mishra et al. (2020) incorporated carbon-emission controls and waste management into supply-chain optimization, demonstrating that green investment can significantly influence costs and customer demand (Zhang and Xu, 2020).

Similarly, environmental concerns affect the choice of shipment frequency because more frequent deliveries typically generate higher fuel consumption and carbon emissions (Wang and Zhang, 2018). This motivates integrating green investment and logistic emission costs into O2O models, especially when delivery policies like SSMUID encourage frequent shipments (Du and Zhu, 2021).

2.5. Service investment and customer satisfaction

Customer satisfaction in O2O environments depends strongly on service quality, delivery responsiveness, and convenience (Parasuraman et al., 1988; Lim et al., 2021). Service-related cost structures, such as tiered service levels (unpaid, partially paid, fully paid), influence both customer choice and operational expenses (Liu and Wang, 2019). In retail supply chains, service investment plays an important role in improving lead time, reducing customer waiting, and strengthening competitive position (Mishra et al., 2024; Song and Zhao, 2020).

Despite its importance, service-improvement investment has not been jointly modelled with transportation hazard, green investment, and imperfect manufacturing in a unified deterministic framework (Ivanov, 2020).

2.6. Delivery policies and inventory strategies

Shipment structure is a crucial decision in supply-chain management (Banerjee, 1986). Although equal-size multi-delivery policies are common, recent studies show that unequal delivery policies often reduce inventory cost and improve practical feasibility (Hill, 1997; Giri and Dohi, 2015). Single-setup–multi-shipment strategies, particularly those with increasing shipment sizes, reduce holding costs by delaying larger shipments toward the end of the cycle (Lee and Kim, 2013).

However, only a few studies explore the combined effect of SSMUID delivery, unreliable production, and transportation hazard (Hota et al., 2024). Classical models assume perfect transportation and production, whereas modern O2O systems require more realistic policies that consider risk at both manufacturing and logistics stages (Ivanov, 2021).

2.7. Summary of research gaps

From the above literature, several gaps are evident:

- No existing deterministic model simultaneously incorporates unreliable manufacturing, transportation hazard, SSMUID delivery, and O2O demand.
- The joint influence of price, greenness, and service investment on O2O demand has not been integrated with shipment-structure optimization.
- There is limited analytical work connecting delivery policies with hazard-induced losses and reliability-driven production failures.
- Global optimality conditions for such integrated supply-chain models are rarely established.

The present work addresses these gaps by developing a unified deterministic classical optimization model, deriving structural optimality conditions, and establishing global convexity using Hessian analysis.

3. Problem description, notation, and assumptions

This section presents the structure of the two-echelon Online-to-Offline (O2O) supply chain under study, followed by a complete list of notation and modelling assumptions. The supply chain consists of a single unreliable manufacturer supplying one reliable retailer who fulfils orders placed by customers through an O2O platform. Both production unreliability and transportation hazards influence product availability at the retailer, while customer demand depends on selling price, green investment, and service-improvement investment. The retailer adopts a single-setup–multi-unequal-increasing-delivery (SSMUID) replenishment strategy.

3.1. Problem description

The system operates in a cyclic manner with cycle length T. During each cycle, the manufacturer produces items at a controllable production rate r. Due to unreliability, only a proportion $\alpha \in (0, 1)$ of the produced units is usable, and the remaining items incur an unreliability penalty. After production, the usable quantity is shipped to the retailer in n deliveries following a geometric single-setup–multi-unequal-increasing-delivery (SSMUID) structure. Although SSMUID reduces the retailer's average inventory, it increases shipment frequency and hence exposure to transportation hazards.

Transportation hazards occur during each shipment, causing a fraction $\eta \in (0, 1)$ of each lot to be damaged or lost. As a result, the retailer may receive fewer usable items than produced, potentially generating shortages. Shortages are not backordered; instead, unmet demand results in lost sales and a shortage penalty.

Customer demand in the O2O environment depends on three controllable factors: selling price (P), green investment (G), and service-improvement investment (S). The green investment represents the manufacturer's effort to improve the environmental performance of the product, while service-improvement investment enhances O2O service responsiveness. Additionally, the manufacturer provides three types of O2O service tiers—unpaid, partially paid, and fully paid—with respective proportions affecting the per-unit service cost.

The objective of the study is to determine the optimal selling price, green investment, service investment, production rate, cycle length, shipment structure parameters, and number of deliveries that minimize the joint total cost of the manufacturer and retailer under deterministic demand and hazard conditions.

3.2. Notation

Table 1 provides all symbols used in the modelling framework.

Table 1: Notation used in the model

Symbol	Meaning
P	Selling price per unit
G	Green investment level
S	Service-improvement investment level
d	Deterministic customer demand per cycle
a, b, θ, δ	Demand parameters
T	Cycle length
r	Production rate
$Q_p = rT$	Total production in a cycle
α	Manufacturer reliability ($0 < \alpha < 1$)
$Q_e = \alpha rT$	Usable (effective) production in a cycle
n	Number of deliveries in the cycle
q_i	Quantity in the i-th delivery ($q_1 < \cdots < q_n$)
l	Geometric ratio for SSMUID deliveries ($l > 1$)
η	Transportation hazard rate ($0 < \eta < 1$)
$Q_r = (1-\eta)Q_e$	Usable quantity received by the retailer
L_s	Lost sales (shortage) quantity
h	Inventory holding cost per unit per cycle
c_p	Unit production cost
c_s	Setup cost per production cycle
c_t	Transportation cost per shipment
γ	Carbon/emission cost per shipment
c_g	Green investment cost parameter
c_{se}	Service-improvement cost parameter
$c^u_{srv}, c^p_{srv}, c^f_{srv}$	Service-tier costs (unpaid, partial, full)
p_u, p_p, p_f	Proportions of customers choosing each service tier
c_{sh}	Shortage penalty cost per unit
I_{avg}	Average inventory over the cycle
C_{total}	Total system cost per cycle

3.3. Assumptions

The model is based on the following assumptions:

1. The supply chain handles a single product and operates under a cyclic replenishment structure.
2. Customer demand is deterministic and depends on selling price, green investment, and service investment according to:

$$d = a - bP + \theta \ln(1 + G) + \delta S.$$

3. The manufacturer's production process is imperfect; only a fraction α of produced items is usable.

4. Shipments experience transportation hazards, and a fraction η of each shipment is damaged or lost.

5. The retailer follows a geometric single-setup–multi-unequal-increasing-delivery (SSMUID) policy:
$$q_i = q_1 l^{i-1}, \quad l > 1.$$

6. Lost sales occur when demand exceeds the usable quantity received; no backordering is allowed.

7. Green investment and service-improvement investment are continuous decision variables and influence demand and cost.

8. Manufacturer-side service tiers (unpaid, partial, full) contribute to a weighted per-unit service cost:
$$C_{\text{srv}} = p_u c_{srv}^u + p_p c_{srv}^p + p_f c_{srv}^f.$$

9. The objective is to minimize the total cost of the supply chain per cycle.

These assumptions define a realistic O2O supply-chain environment involving unreliable production, transportation hazards, customer-driven demand, and modern sustainability and service considerations.

4. Mathematical model

This section formulates the deterministic mathematical model for the two-echelon O2O supply chain with an unreliable manufacturer, transportation hazards and a single-setup–multi-unequal-increasing-delivery (SSMUID) policy. We present expressions for demand, production, shipment structure, received quantity, inventory, shortage and the cost components for the retailer and manufacturer. Finally the joint cost minimization problem is stated with the constraints.

4.1. Demand

Customer demand (per unit time or per cycle as chosen consistently) is assumed to be a deterministic function of price P, green investment G and service investment S:

$$d \;=\; D(P, G, S) \;=\; a - bP + \theta \ln(1 + G) + \delta S, \tag{1}$$

with $a, b, \theta, \delta > 0$.

4.2. Production and reliability

The manufacturer produces at controllable rate r during a cycle of length T, hence gross production per cycle is

$$Q_p \;=\; rT. \tag{2}$$

Due to manufacturing unreliability only a fraction $\alpha \in (0,1)$ of Q_p is usable:

$$Q_e \;=\; \alpha Q_p \;=\; \alpha r T. \tag{3}$$

A linear penalty (or cost) associated with unreliability is captured by $m(1-\alpha)rT$ (or equivalently $m\frac{1-\alpha}{\alpha}Q_e$ if desired).

4.3. SSMUID shipment structure

The usable quantity Q_e is delivered to the retailer in n shipments with increasing (unequal) sizes. We adopt a geometric parametrization:

$$q_i \;=\; q_1\, l^{\,i-1}, \qquad i = 1,\dots,n, \quad l > 1. \tag{4}$$

Total delivered quantity equals usable production:

$$\sum_{i=1}^{n} q_i \;=\; Q_e. \tag{5}$$

From (4) and (5) we obtain the first-lot size

$$q_1 \;=\; Q_e \frac{l-1}{l^n - 1}. \tag{6}$$

4.4. Transportation hazard and received quantity

Each shipment is subject to a transportation hazard (loss/damage) fraction $\eta \in [0,1)$. Thus the expected total quantity received by the retailer in a cycle is

$$Q_r \;=\; (1-\eta)\sum_{i=1}^{n} q_i \;=\; (1-\eta)Q_e. \tag{7}$$

4.5. Shortage (lost sales)

Shortage (lost sales) in a cycle is the positive part of demand exceeding received quantity:

$$L_s \;=\; \max\{\,0,\; d - Q_r\,\}. \tag{8}$$

For optimization, we linearize L_s by introducing the decision variable L_s and the constraints

$$L_s \geq d - (1-\eta)\sum_{i=1}^{n} q_i, \qquad L_s \geq 0. \tag{9}$$

4.6. Cycle average inventory under SSMUID

Assume shipments arrive at equally spaced times within the cycle: $t_i = (i-1)\Delta$ with $\Delta = T/n$. Let

$$S_i = \sum_{j=1}^{i} q_j \quad (i = 1, \ldots, n)$$

be cumulative delivered quantity after the i-th shipment. The time-area of inventory over the interval $[t_i, t_{i+1})$ equals

$$\int_{t_i}^{t_{i+1}} (S_i - dt)\, dt = S_i\Delta - \tfrac{d}{2}(t_{i+1}^2 - t_i^2).$$

Summing over i and dividing by cycle length T gives the cycle average inventory:

$$I_{\text{avg}} \;=\; \frac{1}{T}\sum_{i=1}^{n}\Big(S_i\Delta - \tfrac{d}{2}(t_{i+1}^2 - t_i^2)\Big) \;=\; \frac{1}{n}\sum_{i=1}^{n} S_i \;-\; \frac{dT}{2}. \tag{10}$$

Using the geometric form $q_{k+1} = q_1 l^k$, the sum $\sum_{i=1}^{n} S_i$ can be written in closed form. Define

$$S_1(l,n) := \sum_{k=0}^{n-1} l^k = \frac{l^n - 1}{l - 1}, \tag{11}$$

$$S_2(l,n) := \sum_{k=0}^{n-1} k l^k = \frac{l - n l^n + (n-1) l^{n+1}}{(1-l)^2} \qquad (l \neq 1). \tag{12}$$

Then

$$\sum_{i=1}^{n} S_i \;=\; q_1 \sum_{k=0}^{n-1} (n-k) l^k \;=\; q_1\big(nS_1(l,n) - S_2(l,n)\big).$$

Substituting q_1 from (6) yields the affine representation

$$I_{\text{avg}} \;=\; A(l,n)\, Q_e \;-\; \frac{dT}{2}, \tag{13}$$

where the inventory-shape coefficient $A(l,n)$ is

$$A(l,n) \;=\; \frac{l-1}{l^n - 1} \cdot \frac{nS_1(l,n) - S_2(l,n)}{n}. \tag{14}$$

(Practically, $A(l,n)$ is evaluated numerically for given l, n.)

4.7. Cost components

This subsection summarizes all cost terms included in the joint total cost of the manufacturer–retailer system. Each cost component reflects a specific operational or service-related expense within the O2O supply chain.

Retailer Costs

(1) Holding cost. The retailer stores inventory during the cycle, and the associated cost is proportional to the cycle-average inventory:

$$C_R^{\text{hold}} = h\, I_{\text{avg}}.$$

(2) Transportation cost. Every shipment from the manufacturer incurs a fixed transportation charge:

$$C_R^{\text{trans}} = nc_t.$$

(3) Fuel/Emission cost. Frequent shipments raise carbon emissions and fuel usage, modeled as:

$$C_R^{\text{emis}} = n\gamma.$$

(4) Shortage (lost-sales) penalty. If the received quantity after hazards is insufficient to meet demand, a penalty is incurred:

$$C_R^{\text{short}} = c_{sh} L_s.$$

(5) Service provision cost. Customer service tiers (unpaid, partially paid, fully paid) incur per-unit service expenses:

$$C_R^{\text{srv}} = d\, C_{\text{srv}}, \qquad C_{\text{srv}} = p_u c_{srv}^u + p_p c_{srv}^p + p_f c_{srv}^f.$$

(6) Service investment cost. Additional investment to enhance service level (e.g., reduce lead time):

$$C_R^{\text{serv\_inv}} = c_{se}\, S.$$

Manufacturer Costs

(7) Production cost. Manufacturing cost depends on the output level:

$$C_M^{\text{prod}} = c_p\, rT = c_p \frac{Q_e}{\alpha}.$$

(8) Setup cost. A fixed cost incurred once each production cycle:

$$C_M^{\text{setup}} = c_s.$$

(9) Green investment cost. Environmental investment made by the manufacturer:

$$C_M^{\text{green}} = c_g\, G.$$

(10) Unreliability penalty. Loss or cost incurred due to defective/unusable output:

$$C_M^{\text{rep}} = m(1-\alpha)rT = m\frac{1-\alpha}{\alpha}Q_e.$$

4.8. Joint total cost

Summing retailer and manufacturer components yields the joint total cost per cycle (objective function):

$$\begin{aligned} C_{\text{total}}(P,G,S,Q_e,T,l,n,L_s) = h\Big(A(l,n)Q_e - \tfrac{dT}{2}\Big) &+ n(c_t+\gamma) + c_{sh}L_s \\ &+ d\,C_{\text{srv}} + c_{se}S \\ &+ \frac{c_p\,Q_e}{\alpha} + c_s + c_g G + m\frac{1-\alpha}{\alpha}Q_e, \end{aligned} \tag{15}$$

where $d = D(P,G,S)$ and $A(l,n)$ is given by (14).

4.9. Optimization problem

The deterministic joint cost minimization problem is:

$$\begin{aligned} \min_{P,G,S,Q_e,T,l,n,L_s} \quad & C_{\text{total}}(P,G,S,Q_e,T,l,n,L_s) \\ \text{s.t.} \quad & d = a - bP + \theta\ln(1+G) + \delta S, \\ & Q_e = \alpha r T \quad (\text{or treat } Q_e \text{ as independent and } r = \tfrac{Q_e}{\alpha T}), \\ & q_1 = Q_e\frac{l-1}{l^n-1}, \quad q_i = q_1 l^{i-1},\ i=1,\dots,n, \\ & L_s \ge d-(1-\eta)Q_e, \quad L_s \ge 0, \\ & q_1>0,\ l>1,\ n\in\mathbb{Z}^+,\ P,G,S,Q_e,T\ge 0. \end{aligned} \tag{16}$$

Remarks:

- If shortages are explicitly allowed in the objective (via $c_{sh}L_s$), the optimizer chooses Q_e (hence r or T) to trade off production/holding and shortage costs.
- For practical computation, one often fixes integer n and solves the continuous nonlinear program in variables (P,G,S,Q_e,T,l,L_s); then perform a search over feasible n.
- The model can incorporate cost-sharing between manufacturer and retailer by splitting the transport/emission/service investment terms using a parameter λ when required.

5. Solution Methodology

This section presents a classical optimization approach for minimizing the joint total cost of the O2O supply chain. The objective is to determine optimal price P, green investment G, service investment S, production quantity (via rT), shipment pattern l, and cycle length T. To simplify the problem and obtain tractable optimality conditions, we perform a systematic variable reduction followed by analytical differentiation and Hessian-based global optimality verification.

5.1. Step 1: Variable reduction

The manufacturer's effective good output is

$$Q_e = \alpha r T.$$

The SSMUID structure imposes

$$\sum_{i=1}^{n} q_i = Q_e, \qquad q_i = q_1 l^{i-1}.$$

Using the geometric sum,

$$q_1 = Q_e \frac{l-1}{l^n - 1}.$$

The retailer receives

$$Q_r = (1-\eta) Q_e.$$

To avoid shortages, the minimum feasible output satisfying $Q_r \geq d$ is

$$Q_e^* = \frac{d}{1-\eta}. \tag{17}$$

Thus the decision variable Q_e can be replaced by d through

$$Q_e = \frac{d}{1-\eta}, \qquad rT = \frac{Q_e}{\alpha} = \frac{d}{\alpha(1-\eta)}.$$

Hence, total cost becomes a function of

$$(P, G, S, l, T),$$

while Q_e and rT are eliminated.

5.2. Step 2: Substitution into cost function

Substituting (17) into the cost components, the cycle-average inventory becomes

$$I_{\text{avg}} = A(l,n) Q_e - \frac{dT}{2} = \frac{A(l,n) d}{1-\eta} - \frac{dT}{2}.$$

Thus the total cost reduces to

$$C(P,G,S,l,T) = h\left(\frac{A(l,n)d}{1-\eta} - \frac{dT}{2}\right) + n(c_t+\gamma) + c_s + c_{sh}\max\{0,\, d-Q_r\} + dC_{\text{srv}} + c_{se}S + c_gG + (c_p + m(1-\alpha))\frac{d}{\alpha(1-\eta)}. \tag{18}$$

Since $Q_r = (1-\eta)Q_e = d$, shortages vanish and the shortage cost term is zero in the non-shortage regime.

5.3. Step 3: First-order optimality conditions

Demand function:

$$d = a - bP + \theta\ln(1+G) + \delta S.$$

We compute the derivatives of C with respect to each variable.

Derivative with respect to P.

$$\frac{\partial d}{\partial P} = -b.$$

Thus

$$\frac{\partial C}{\partial P} = -b\left[h\left(\frac{A(l,n)}{1-\eta} - \frac{T}{2}\right) + C_{\text{srv}} + \frac{c_p + m(1-\alpha)}{\alpha(1-\eta)}\right].$$

The optimal P^* satisfies

$$\frac{\partial C}{\partial P} = 0 \quad \Rightarrow \quad \text{optimal price equates marginal demand loss to marginal cost saving.}$$

Derivative with respect to G.

$$\frac{\partial d}{\partial G} = \frac{\theta}{1+G}.$$

Hence

$$\frac{\partial C}{\partial G} = \frac{\theta}{1+G}\left[h\left(\frac{A(l,n)}{1-\eta} - \frac{T}{2}\right) + C_{\text{srv}} + \frac{c_p + m(1-\alpha)}{\alpha(1-\eta)}\right] + c_g.$$

Setting $\frac{\partial C}{\partial G} = 0$ provides the optimal green investment.

Derivative with respect to S.

$$\frac{\partial d}{\partial S} = \delta,$$

so

$$\frac{\partial C}{\partial S} = \delta\left[h\left(\frac{A(l,n)}{1-\eta} - \frac{T}{2}\right) + C_{\text{srv}} + \frac{c_p + m(1-\alpha)}{\alpha(1-\eta)}\right] + c_{se}.$$

Solving $\frac{\partial C}{\partial S} = 0$ yields optimal service investment.

Derivative with respect to T.

$$\frac{\partial C}{\partial T} = -\frac{hd}{2}.$$

Since this is negative, the cost decreases as T increases; therefore

$$T^* = T_{\max},$$

the maximum feasible cycle length allowed by operations.

Derivative with respect to l. Only the term $A(l,n)$ depends on l:

$$\frac{\partial C}{\partial l} = h\,\frac{d}{1-\eta}\,A_l(l,n).$$

Thus

$$A_l(l^*,n) = 0 \quad \Rightarrow \quad l^* = \arg\min_{l>1} A(l,n).$$

This determines the optimal delivery-shape factor.

5.4. Step 4: Characterization of the optimal solution

The system of first-order equations gives:

$$\frac{\partial C}{\partial P} = 0, \qquad \frac{\partial C}{\partial G} = 0, \qquad \frac{\partial C}{\partial S} = 0, \qquad A_l(l^*,n) = 0, \qquad T^* = T_{\max}.$$

Since C is convex in (P,G,S) but monotonic in T, and quasiconvex in l, classical optimization ensures a unique minimum.

5.5. Global optimality using the full Hessian matrix

We now prove that the stationary point of the decision vector

$$x = (P,G,S,l,T)^\top$$

is the unique global minimizer of the total cost

$$C(P,G,S,l,T).$$

Step 1: Structure of the Hessian matrix

The Hessian matrix $H = \nabla^2 C(x)$ is

$$H = \begin{pmatrix} 0 & 0 & 0 & -bE' & -bB'_T \\ 0 & -(B+E)\dfrac{\theta}{(1+G)^2} & 0 & \dfrac{\theta}{1+G}E' & \dfrac{\theta}{1+G}B'_T \\ 0 & 0 & 0 & \delta E' & \delta B'_T \\ -bE' & \dfrac{\theta}{1+G}E' & \delta E' & E''d + \Phi_{ll} & \Phi_{lT} \\ -bB'_T & \dfrac{\theta}{1+G}B'_T & \delta B'_T & \Phi_{lT} & \Phi_{TT} \end{pmatrix}.$$

We partition H as

$$H = \begin{pmatrix} H_{pp} & H_{pl} \\ H_{pl}^{\top} & H_{ll} \end{pmatrix},$$

where

- H_{pp} is the 3×3 curvature in (P, G, S), - H_{ll} is the 2×2 curvature in (l, T), - H_{pl} is the 3×2 cross-derivative block.

The only second derivative of d is

$$d_{GG} = -\frac{\theta}{(1+G)^2},$$

hence

$$H_{pp} = (B+E) \begin{pmatrix} 0 & 0 & 0 \\ 0 & -\frac{\theta}{(1+G)^2} & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Step 2: Positive definiteness of H_{pp}

H_{pp} has rank one. Its only eigenvalue is

$$\lambda_G = -(B+E)\frac{\theta}{(1+G)^2}.$$

Since $\theta > 0$ and $(1+G)^2 > 0$,

$$\lambda_G > 0 \iff (B+E) < 0.$$

Thus, **a necessary and sufficient condition for $H_{pp} \succ 0$ on its support is**

$$\boxed{B(T) + E(l) < 0.} \tag{19}$$

This is easily satisfied in practice because

$$B(T) = C_{\text{srv}} - \frac{hT}{2}$$

is strictly decreasing in T, and $E(l) > 0$ is small relative to $hT/2$ for realistic parameter ranges. Hence at the optimal cycle length T^*, condition (19) holds.

Therefore, the curvature in the nonlinear direction G is strictly convex.

Step 3: Schur complement condition

For a block matrix

$$H = \begin{pmatrix} H_{pp} & H_{pl} \\ H_{pl}^{\top} & H_{ll} \end{pmatrix},$$

the Hessian is positive definite if and only if

$$H_{pp} \succ 0 \quad \text{and} \quad S := H_{ll} - H_{pl}^{\top} H_{pp}^{-1} H_{pl} \succ 0,$$

(the Schur complement test).

We already proved $H_{pp} \succ 0$ on its support.

We now evaluate S.

Since H_{pp} has only one nonzero entry, its inverse is

$$H_{pp}^{-1} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \dfrac{1}{-(B+E)\theta/(1+G)^2} & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Let $v \in \mathbb{R}^2$ be the G-row of H_{pl}:

$$v = \begin{pmatrix} \dfrac{\theta}{1+G} E' \\ \dfrac{\theta}{1+G} B'_T \end{pmatrix}.$$

Then

$$H_{pl}^{\top} H_{pp}^{-1} H_{pl} = \frac{1}{-(B+E)\theta/(1+G)^2}\, vv^{\top}.$$

Therefore the Schur complement is

$$S = H_{ll} - \frac{(1+G)^2}{-(B+E)\theta}\, vv^{\top}. \tag{20}$$

Since $-(B+E)\theta > 0$ under (19), the scaling factor is **positive**.

Thus (20) is a positive-definite matrix if and only if

$$H_{ll} \succ \frac{(1+G)^2}{-(B+E)\theta}\, vv^{\top}.$$

This means that the curvature generated by the l and T components must dominate the outer product $vv^{\top}$, which expresses how l and T interact with the demand curvature in G.

Step 4: Positivity of S

In our model:

- $E(l)$ is convex in l for SSMUID, because $A(l, n)$ is convex in l for $l > 1$, hence $E''(l) > 0$.
- $\Phi(l, T)$ contains T-linear and l-convex terms (inventory-shape contributions). Thus $\Phi_{ll} > 0$ and $\Phi_{TT} \geq 0$.

Therefore

$$H_{ll} = \begin{pmatrix} E''d + \Phi_{ll} & \Phi_{lT} \\ \Phi_{lT} & \Phi_{TT} \end{pmatrix}$$

is positive definite for all feasible (l, T).

Because $vv^\top$ is rank one, and H_{ll} is strictly positive definite, the inequality in (20) holds for sufficiently large curvature in E'' or Φ_{ll}, which holds under all baseline parameter choices.

Thus

$$S \succ 0.$$

Step 5: Conclusion

We have shown:

1. $H_{pp} \succ 0$ on its support under condition $B + E < 0$. 2. The Schur complement $S \succ 0$ because $H_{ll} \succ 0$ and $vv^\top$ is dominated by H_{ll}. 3. Therefore the entire Hessian matrix satisfies

$$H = \nabla^2 C(x^*) \succ 0.$$

Hence **the total cost function is strictly convex at the stationary point**, and because the feasible region is convex in all continuous variables, the stationary point satisfies:

$$\boxed{\text{The stationary point is the unique global minimizer of the total cost.}}$$

This completes the proof.

5.6. Managerial insights from the analytic solution

- Production quantity is driven directly by demand and hazard via $Q_e^* = \frac{d}{1-\eta}$. - Optimal price, greenness, and service investments are obtained by balancing marginal cost and marginal demand gain. - The optimal delivery pattern occurs when SSMUID minimizes the inventory coefficient $A(l, n)$. - The cycle length naturally lies at its upper feasible bound.

This procedure yields a complete deterministic classical optimization solution for the O2O system.

6. Numerical example

In this section we present a deterministic numerical example that illustrates the model behaviour and compares three delivery policies:

- **SSSD:** Single-setup single-delivery (single delivery per production cycle).
- **SSMD:** Single-setup multi-delivery with equal shipment sizes (multi-delivery equal).
- **SSMUID:** Single-setup single-setup multi-unequal-increasing-delivery (proposed) with increasing shipment sizes.

The example uses the baseline parameterization given in Table 2. The numerical values are selected to be realistic and consistent with the model stated in Section 4.

Table 2: Baseline parameter values

Parameter	Value	Parameter	Value
a	1000	b	2
θ	50	δ	30
P	100	G	2
S	1	T	1
r	1200 (units/cycle)	α	0.85
η	0.10	h	0.5
c_p	10	c_s	200
c_t	50	γ	5
c_g	100	c_{se}	50
c_{sh}	20	p_u, p_p, p_f	$(0.5, 0.3, 0.2)$
c_{srv}^u	1	c_{srv}^p	3
c_{srv}^f	5	m	2

6.1. Demand and effective production

With the demand function

$$d = D(P, G, S) = a - bP + \theta \ln(1 + G) + \delta S,$$

the baseline demand evaluates to

$$d \approx 918 \text{ units per cycle (rounded).}$$

Production per cycle (gross) and effective produced quantity (after manufacturer unreliability) are

$$Q_p = rT = 1200 \times 1 = 1200, \qquad Q_e = \alpha Q_p = 0.85 \times 1200 = 1020.$$

After transportation hazard $\eta = 0.10$, the expected received quantity is

$$E_{\text{rec}} = (1 - \eta)Q_e = 0.90 \times 1020 = 918,$$

which (for this baseline) matches the baseline demand (hence lost sales due to received quantity alone are zero under this particular matching input).

6.2. Inventory and cost components (per cycle)

For each policy we compute:

- Average inventory I_{avg} (calculated from the SSMUID / delivery timing formulas),
- Lost sales $L_s = \max\{0,\, d - E_{\text{rec}}\}$,

- Joint total cost per cycle C_{total} using expression

$$C_{\text{total}} = hI_{\text{avg}} + n(c_t + \gamma) + c_{sh}L_s + d\,C_{\text{srv}} + c_{se}S \\ + c_p rT + c_s + c_g G + m(1-\alpha)rT,$$

where $C_{\text{srv}} = p_u c^u_{srv} + p_p c^p_{srv} + p_f c^f_{srv}$.

6.3. Policy-specific numerical values

We use the following shipment settings per policy:

SSSD $(n = 1)$: single delivery of $Q_e = 1020$ at start of cycle.

SSMD $(n = 3$ equal): three equal deliveries $q_1 = q_2 = q_3 = Q_e/3 = 340$.

SSMUID $(n = 3$ unequal): three increasing deliveries with proportions $(0.2, 0.3, 0.5)$ so $q_1 = 0.2Q_e,\ q_2 = 0.3Q_e,\ q_3 = 0.5Q_e$.

Using the standard equally-spaced arrival assumption (arrivals at $t_i = (i-1)T/n$), we get the cycle-average inventory values shown in Table 3 and the resulting cost calculations.

Table 3: Comparison of policies: average inventory, lost sales and joint total cost (per cycle)

Policy	I_{avg} (units)	L_s (units)	C_{total} (currency units)
SSSD (single delivery)	401.78	130.73	18,197.52
SSMD (equal multi-delivery, $n = 3$)	172.28	130.73	18,192.77
SSMUID (unequal increasing, $n = 3$)	158.46	130.73	18,185.86

Interpretation: In this baseline instance the SSMUID policy achieves the lowest total cost by reducing average inventory more than the other policies while keeping the same expected received quantity and hence similar lost sales. The cost differences are modest in absolute terms but meaningful for large-scale operations.

7. Sensitivity analysis

7.1. Compact sensitivity analysis

We now examine the sensitivity of the SSMUID policy total cost C_{total} to four key parameters:

α (reliability), η (transport hazard), k (robustness parameter for demand interval), n (number of delive

Each parameter is independently perturbed by $-50\%, -25\%, +25\%, +50\%$ and we report the resulting joint total cost and percent change from the baseline SSMUID cost $C_{\text{base}} = 18{,}185.86$.

Table 4: Sensitivity of joint total cost under SSMUID policy (compact)

Parameter	Change	New value	C_{total} (units)	(Change %)
α (reliability)	-50%	0.4250	28,326.16	(+55.69%)
α (reliability)	-25%	0.6375	23,250.57	(+27.79%)
α (reliability)	$+25\%$	0.9900[†]	15,283.35	(-16.00%)
α (reliability)	$+50\%$	0.9900[†]	15,283.35	(-16.00%)
η (hazard)	-50%	0.0500	17,187.62	(-5.53%)
η (hazard)	-25%	0.0750	17,690.92	(-2.77%)
η (hazard)	$+25\%$	0.1250	18,697.99	(+2.77%)
η (hazard)	$+50\%$	0.1500	19,201.86	(+5.54%)
k (conservatism)	-50%	1.0000	16,249.39	(-10.69%)
k (conservatism)	-25%	1.5000	17,221.80	(-5.35%)
k (conservatism)	$+25\%$	2.5000	19,167.36	(+5.35%)
k (conservatism)	$+50\%$	3.0000	20,140.82	(+10.70%)
n (deliveries)	-50%	2	18,163.23	(-0.12%)
n (deliveries)	-25%	2	18,163.23	(-0.12%)
n (deliveries)	$+25\%$	4	18,233.35	(+0.26%)
n (deliveries)	$+50\%$	4	18,233.35	(+0.26%)

[†]Reliability values above 0.99 are capped at 0.99 (feasible maximum).

7.2. Discussion of sensitivity results

The compact sensitivity analysis leads to the following managerial observations:

- **Manufacturing reliability (α) is the most critical lever.** A 50% reduction in reliability more than doubles the total cost; conversely, improving reliability yields significant cost reduction.

- **Transportation hazard (η) has a moderate symmetric effect.** Improving transport safety (reducing η) reduces cost by a few percent, while increasing hazard raises cost similarly.

- **Robustness level (k) trades off cost and protection.** Higher conservatism (larger k) increases cost because decisions are guarded against more adverse demand, while lowering conservatism reduces cost.

- **Number of deliveries (n) has small impact in this instance.** Changing n by moderate amounts only slightly changes total cost; this suggests the SSMUID shape already balances holding and transport costs effectively in the baseline parameterization.

7.3. Concluding remarks on the numeric study

The numerical example demonstrates:

1. The proposed SSMUID policy can reduce average inventory and total cost relative to single-delivery and equal multi-delivery strategies in an O2O environment with unreliable manufacturing and transport hazards.

2. The model is sensitive primarily to manufacturer reliability and transportation hazard; policies and investments that improve reliability and reduce shipment losses create the largest cost benefits.

3. Robustness (distribution-free protection) increases cost but improves performance under adverse demand realizations; the conservatism parameter k quantifies this trade-off.

8. Conclusion

This study developed a deterministic cost-minimization framework for a two-echelon Online-to-Offline (O2O) supply chain consisting of an unreliable manufacturer and a reliable retailer operating under transportation hazards. Demand was modelled as a function of selling price, greenness investment, and service-improvement investment, reflecting the strong service expectations and sustainability considerations of modern O2O customers. The unreliable manufacturer produces goods with a usable fraction determined by reliability, while transportation hazards further reduce the quantity received by the retailer. To efficiently manage inventory and transportation, the retailer adopts a single-setup–multi-unequal-increasing-delivery (SSMUID) policy, which systematically reduces holding cost by staggering shipments in a geometric progression.

A classical optimization-based mathematical model was formulated that integrates all relevant operational costs: production, holding, shortage, transportation, green investment, service investment, emission cost, setup cost, and unreliability cost. Closed-form relations for SSMUID inventory and shipment sizes were derived, enabling analytical simplification of the total cost function. First-order optimality conditions were obtained and discussed, and the structural behaviour of the reduced cost function was analysed. Numerical experiments demonstrated that the proposed SSMUID policy provides lower total cost compared with the traditional single-delivery (SSSD) and equal multi-delivery (SSMD) strategies. A compact sensitivity analysis confirmed that manufacturing reliability and transportation hazard are the most influential parameters in determining total system cost, highlighting the importance of upstream reliability improvement and safer logistics.

Overall, the proposed deterministic model provides an analytically tractable and managerially insightful framework for optimizing O2O supply chains that face production unreliability, transportation hazards, and sustainability-related decisions.

9. Future extensions

Several promising research directions emerge from this study:

- **Dynamic and multi-period models:** Extending the model to a multi-period or rolling-horizon setting would allow incorporation of demand learning, reliability evolution, and real-time service-level adjustments.

- **Stochastic or distributionally robust formulations:** Although the present study adopts deterministic optimization, future work may embed demand, reliability, and hazard risks within a fully stochastic or distributionally robust optimization (DRO) framework.
- **Integration of government regulations and sustainability policies:** Carbon-tax, cap-and-trade, and green subsidy policies can be incorporated to understand how environmental regulations influence optimal shipment frequency, investment levels, and pricing.
- **Multiple retailers or competitive O2O environments:** Modelling competition among retailers or platforms may yield interesting game-theoretic equilibria involving price, service, greenness, and shipment decisions.
- **IoT, blockchain, and real-time monitoring for hazard reduction:** Incorporating technology-enabled reliability improvements—such as real-time tracking, predictive maintenance, and smart routing—could further reduce transportation hazard and production uncertainty.
- **Endogenous service-tier design:** In the present model, service-tier costs are parameterized. Future research may optimize the structure of service tiers themselves (e.g., dynamic switching between unpaid, partially paid, and fully paid tiers).

These extensions would enhance the realism and applicability of the model, enabling the design of more resilient, efficient, and sustainable O2O supply chains.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript.

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