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EFFECT OF GREEN TECHNOLOGY FOR A PRODUCTION SYSTEM THROUGH A REVERSE LOGISTIC PROCESS

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Abstract. In modern times, customers are increasingly aware of the environmental risks posed by the premature expiration of smart products. To safeguard the environment, companies have embraced green technology when procuring products. As a result, it is challenging for business managers to capture the market by offering the best quality products at a reasonable price, regardless of the economic situation. This paper presents a production model incorporating reverse logistics to identify defective products. The model involves learning through production and utilizes green technologies. Additionally, a portion of the assembled products is remanufactured after being received from consumers. The remanufactured items are screened and distributed to markets. Both new and remanufactured products are sold to the market based on their quality in the first and second markets, respectively. To reduce product spoilage, manufacturers employ green technology like liquid cooling technology. The numerical results demonstrate that by investing in liquid cooling technology, the production store can reduce spoilage items by 8.50%, a positive environmental outcome regarding waste reduction, and due to the learning effect, the total cost can decrease by 1.44%. The paper includes numerical and sensitivity analyses accompanied by graphs.

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1. Introduction

Environmental problems are major concerns arising due to multiple factors. Companies are increasingly adopting new technologies to enhance their product offerings, which may simplify human life but can be harmful to the environment. The proliferation of smart devices is a significant problem as they flood the market with new technology that can be detrimental to both human health and the environment. Companies face numerous

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challenges, including continuously improving product quality, extending product lifecycles, and maintaining competitive prices. Companies are turning to innovative green technology (GT) to address these challenges to prevent their products from deteriorating rapidly. By utilizing GT, companies can mitigate the negative impact of smart products and extend their lifespan, reducing the spoilage rate. This approach benefits the environment and increases customer appeal, making green development a popular choice for many businesses. Overall, GT has a significant positive impact on both the product lifecycle and the environment. Manufacturing industries, such as automobile, smart TV, and mobile companies, are introducing new techniques to make their products more attractive. For example, GT is being widely used with constant technological improvements, resulting in improved quality of the products. With the rise in technological innovations, the standard of living is improving, and economic stability is achievable; however, many products are now rapidly flowing toward the end of the supply chain. Reverse logistics (RL) plays a crucial role in green supply chain management (GSCM); it ensures that our responsibility remains with the environment. Learning has become essential for many companies because they require a workforce with specialized skills to achieve maximum profit or minimize cost. This process will create a better environment for the industry and increase the ease of doing business. Over the past few years, a significant focus has been on logistics-based models incorporating GT.

Cohen *et al.* [10] investigated the impact of government incentives on the manufacturing industry's adoption of GT. They found that direct customer incentives influence suppliers' manufacturing and pricing decisions. Nouira *et al.* [48] presented two models, one in which a company sells a single product whose demand depends on its level of greenness and another in which the market is segmented into ordinary and green customers, each provided with a different selection of production items. The primary objective of Golpira's [18] research was to implement the green opportunistic supply chain concept (GrOSC). Datta [11] developed a green model that assumed the output rate is a decision variable and the demand rate is a selling price function that decreases linearly. To move towards greener manufacturing systems, manufacturers invest in new technologies, energy-efficient machinery, non-conventional energy, and other initiatives. The manufacturer's budget for GT modernization programs serves as a ceiling on the sum of the investment. Mardani *et al.* [40] explored the most promising opportunities for growth in green and sustainable supply chain management (SCM) and the primary industries and businesses contributing to this field. Mridha *et al.* [47] investigated the sustainable production model for a carbon tax and the controllable rate of carbon emissions cap for green products but without any GT. Mishra *et al.* [42] studied a sustainable inventory management in the context of a greenhouse farm's controllable carbon emissions. Investing in the preservation and GT activities is crucial in various backorder situations. Lu *et al.* [35] examined the potential competitive and cooperative issues associated with sustainable inventory models of goods and mutual investment in reducing carbon limits and adopting carbon caps and carbon offset policy technologies.

Jain *et al.* [28] investigated a sustainable inventory model with rework for faulty products, addressing the effects of random defects and combining economic and environmental variables on the economic order quantity with price and promotional effort-dependent demand. Sepehri *et al.* [63] demonstrated a production-inventory system capable of producing deteriorated products. During the manufacturing process, defective products were generated. They used preservation technology to reduce the deterioration rate. Singh and Saxena [67] established an RL model based on the idea of using a subordinate material for deteriorating items, referred to as flexible production/remanufacturing. Krishnamoorthi and Panayappan [33] developed inventory control policies in a manufacturing system for a single product during the product life cycle, a model involving the introduction, growth, and decline stages. Govindan *et al.* [19] established that RL attracted several manufacturers' attention, as RL activities were linked to the cover process of end-of-life items. Yadav *et al.* [77] developed a model that considers preservation technology to improve the shelf-life of deteriorated products; otherwise, waste of deteriorated products impacted the environment.

1.1. Research gaps and contributions of the research

According to the literature, insufficient effort is being made to achieve sustainability with a remanufacturing process for a spoiling product system. This gap inspires to create a remanufacturing model that incorporates expenses associated with liquid cooling technology and learning effects for faulty and spoilage products. In order to fill this research gap, a RL model under SCM is developed with GT for special key liquid cooling technology, inflation, and learning effect. This research examines the model with liquid cooling technology investment under a RL system. The model describes how to control waste to save the environment. It discusses two ways: first, the remanufacturing cycle and production cycle without learning effect, and second, the remanufacturing cycle and production cycle with learning effect. Still, the cost is effective with the learning effect. This study can be used in the electronic industry, smart products, and other fields in the real-world.

1.2. Structure of the paper

The following is a breakdown of the work: Section 2 explains the literature review. Section 3 describes the notation and assumptions used in this study. Section 4 shows the mathematical formulation of the proposed model and its solution. Section 5 presents numerical examples and sensitivity analysis. Finally, Sections 6 and 7 describe managerial insights and conclusions of the study, respectively.

2. Literature review

A detailed literature review is provided in this section.

2.1. Closed-loop supply chain

A mathematical model with two approaches to replenishment cycles about waste management was studied by Sexena *et al.* [62]. A closed-loop supply chain model was discussed, contrasting primary and secondary market principles and sequential production/remanufacturing policies. The vendor developed a policy of remanufacturing responsibility sharing by sharing the technical license with other supply chain partners. Sarkar *et al.* [59] proposed the environmental, social, and economic perspectives within sustainable SCM for green product management. Kar *et al.* [29] proposed an emissions-controlled production system without considering any closed-loop. Dey *et al.* [13] investigated a smart manufacturing system to avoid inspection errors from the production system. Saxena *et al.* [61] discussed a green supply chain where the vendor and buyer took part in remanufacturing. Maheshwari *et al.* [36] designed a resource-efficient rework and remanufacturing model. The three layers of the supply chain were believed to have a forward supply chain, closed-loop supply chain, and reverse supply chain for effective inventory control. A collection center connected the three layers. The collecting center stored returned items and categorized them as minor or severe defects. Minor defective items were submitted to the rework facility to be reworked and made as good as new.

2.2. Reverse logistics (RL) within a closed-loop supply chain

Mishra *et al.* [43] thoroughly reviewed many features of RL and closed-loop supply chains in implementing and achieving circular economy goals. Alamri [1] developed a model for integrating new objects and returned items. Singh and Saxena [66] investigated the optimal return policy using an RL inventory model with backorders. Selecting more functions in an RL is crucial to make the RL more robust. Govindan *et al.* [19] examined several scopes and attributed them to be used to assess and choose a third-party RL provider (3PRLP). Bazan *et al.* [6] studied RL models' usage based on the order or amount of production. Ullah and Sarkar [73] suggested a product tracking facility which could be used for product collection in RL. Rani *et al.* [52] developed a model based on GSCM and focused on deteriorating commodities by ensuring product recycling and RL. They assumed that remanufactured products would find high demand in the second-hand market. The demand for remanufactured products was considered quadratic, whereas that for new products was deemed to be linear. Guo *et al.* [23] noted that RL is the key to GSCM, as it helped achieve better presentation and might allow companies to use the growing rate of return of end-of-life goods. Ullah *et al.* [74] derived a closed-loop supply chain model for returnable products where the retailer sent back the containers to the manufacturer.

2.3. Reworking within the RL

Zarbakhshnia *et al.* [79] studied a multi-objective model for an RL network project. Soleimani *et al.* [70] established green logistics involving social issues, including environmental protection and socioeconomic norms. Bai and Sarkis [3] examined the selection of 3PRLPs and were instrumental in reverse supply chains' operation and implementation. Dutta *et al.* [14] established a multi-objective RL model in the Indian e-trade bazaar. Sarkar *et al.* [57] developed a closed-loop supply chain model under budget and storage constraints with a single-supplier, manufacturer, and retailer. The concept of smart production system for international SCM was introduced by Guchhait and Sarkar [21]. They used smart production system with automated inspection and thus, there was no reworking. Sanni *et al.* [55] investigated an RL model demonstrating when and how much to buy as the products flew back; they minimized total costs. Sarkar *et al.* [58] formulated an advertisement-dependent demand under uncertain conditions. Sarkar *et al.* [60] investigated a production system which produced an innovative product to reduce the environmental effect. Mahin *et al.* [37] discussed the use of RL within a multichannel RL model but without a reworking procedure. They found a direct relationship between all supply chain players and RL service providers that could improve the service.

2.4. Production policies within a closed-loop supply chain

Some studies have investigated the economic production quantity (EPQ) model for incomplete quality, repair policy, and repair strategy. Khan *et al.* [30] examined a similar approach by suggesting an optimal production approach that manages imperfect procedures. Khan *et al.* [31] analyzed a model to determine an excellent seller by applying learning at the end of the seller's production process. They aimed at reducing the combined yearly cost suffered in SCM. Marchi *et al.* [39] investigated a vast model for a construction company; the model included direct and indirect relevant learning outcomes that affect its energy efficiency. Paul *et al.* [49] developed a default risk economic order quantity model. The major goal was to examine retailers' ideal replenishment time and credit duration for degrading items under selling price-dependent demand while maximizing profit per unit time. Sarkar and Guchhait [56] discussed a stochastic modelling for multiple emissions policies within a green supply chain model. Suryawanshi *et al.* [71] investigated the utility of resilience and sustainable solutions to reduce predicted economic costs and environmental impacts by effectively managing waste. Paul *et al.* [50] proposed a model where the demand rate was affected by both the selling price and the green concern level. Chan *et al.* [9] studied factors such as insufficient analysis of restaurant preferences and decisions, a superficial grasp of environmental performance, and a restricted assessment of multi-dimensional sustainability in third-party food delivery operations. Giri *et al.* [17] suggested a pricing policy within a closed-loop suppl chain model, but they did not consider any green policy from an environmental perspective. Zouadi *et al.* [80] examined a product recovery system with two types of products and solved the model using algorithms.

2.5. Environmental perspective within production and supply chain

Datta [11] analyzed a manufacturing model concerning GT investment under a carbon tax system. Saberi *et al.* [53] established a multi-period model with a freight carrier network. Mehdizadeh *et al.* [41] examined the learning effect on an aggregate production planning problem with labor and machine deterioration. Mohamed *et al.* [45] developed an algebraic model of a two-tier supply chain system for defective goods. Shah *et al.* [64] established an inventory model and presented a case where inventory declined at a constant rate, and the imperfect production process was improved by preservation technology. Hemapriya and Uthayakumar [26] presented an EPQ model that examines manufacturing and inspection faults under greenhouse gas production through learning. Dey *et al.* [12] investigated an work-process inventory management within a smart production system. Ali *et al.* [2] carried out a study to better understand the supply chain framework that deals with perishability challenges in production and distribution. The proposed methodology was intended for producers, warehouses, and retailers to manage delivery with lower deterioration losses.

Barman *et al.* [4] suggested a model with fluctuating demand throughout the current epidemic, with an emergency-level dependent demand rate considered. GT and preservation technology activities were utilized

Table 1. Some authors' recent research work.

Author (s)	Remanufacturing	Green technology	Screening	Learning effect	Production rate	Inflation
Habib *et al.* [24]	No	No	No	No	Constant	No
Rani *et al.* [52]	Yes	No	No	No	Linear	Yes
Hemapriya and Uthayakumar [26]	No	No	Yes	Yes	Constant	No
Saxena *et al.* [62]	Yes	No	No	No	Constant	No
Kumar *et al.* [58]	Yes	No	Yes	No	Linear	No
Weng *et al.* [75]	Yes	No	Yes	No	Constant	No
Barman *et al.* [4]	No	Yes	No	No	Constant	No
Pervin *et al.* [51]	No	No	Yes	No	Linear	No
Jain *et al.* [28]	No	No	Yes	No	Constant	No
Jain *et al.* [27]	Yes	No	Yes	No	Variable	No
Mridha *et al.* [46]	Yes	No	Yes	No	Variable	No
This study	Yes	Yes	Yes	Yes	Constant	Yes

to reduce greenhouse gas emissions and the pace of degradation. Pervin *et al.* [51] developed an inventory model with a composite demand function for non-instantaneous deteriorating items. Fan *et al.* [15] proposed an emissions reduction policy from the production system to save the environment, whereas Hajaji *et al.* [25] used additional investment policies for the sustainable development of the supply chain. Bhattacharyya and Sana [7] considered an eco-friendly production system that could emit restricted carbon into the environment. A flexible production system was used by Malik *et al.* [38] to improve the service level of products. They discussed coordination among supply chain players without consideration of environmental issues.

Saha *et al.* [54] discussed a replenishment policy for deteriorated products with preservation technology and solved the model by metaheruristic approach. Barman *et al.* [5] established a multi-objective SCM system considering deteriorating products as well as imperfect quality production in a neutrosophic environment. Preservation technology was used to decrease the rate of degradation. Singh *et al.* [68] used deteriorating waste animal fats as a raw material for other products instead of using them as waste. Some authors' recent research work is shown in Table 1.

3. Problem definition and assumptions

This section contains the specific definition of the research study, basic assumptions, and notation.

3.1. Problem definition

This supply chain model with reverse logistics is designed to reuse the defective product through remanufacturing and reduce the waste of the product to minimize the total cost. Using liquid cooling technology by manufacturing has made the cost somewhat expensive, but it maintains the product's greenness. Therefore, GT is used in RL, which benefits the environment. The manufacturer uses GT to reduce product flaws. This research study presents an RL model for determining damaged items and imperfect production. This study determines which items can be remanufactured, after which the items undergo the screening procedure and are then sent to the first or second markets based on their quality. Utilizing the learning effect, this model reduces the total cost and maintains the item quality. With the recent increase in cases registering mobiles bursting while playing mobile games or charging, this study focuses on smart products. The study's flow is depicted in Figure 1.

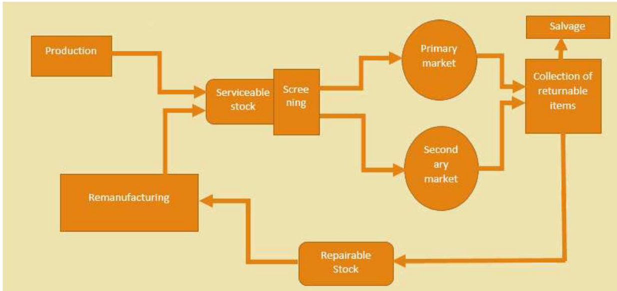

FIGURE 1. Involvement of the remanufacturing, production, and returned product management under RL.

3.2. Assumptions

The following assumptions are used to formulate the model.

(1) The manufacturer's investment in GT is used to reduce product breakdown.
(2) ρ_m and ρ_0 are the demolition rates of the production cycle with and without investment in GT, respectively, *i.e.*, $\rho_m = \rho_0 e^{-\pi\Delta}$, where π is the sense of investment in the demolition rate.
(3) ρ_r and ρ_1 are the demolition rates of the remanufacturing cycle with and without investment in GT, respectively, *i.e.*, $\rho_r = \rho_1 e^{-\pi\Delta}$.
(4) The rate of the items for the first and second markets as $\alpha_m D_m$ and $\alpha_r D_r$, respectively; after remanufacturing, the screening process starts.
(5) After the screening, the system stocks two different qualities and sends them to the first and second markets.
(6) The buyback items are assembled from the first and second markets, where the vendor with a favorable excellence level is chosen to remanufacture the goods, *i.e.*, $R = (\delta_m \alpha_m D_m + \delta_r \alpha_r D_r)$, otherwise, the remainder of the items are salvaged [67].

3.3. Notation

Notation of the study is provided in Appendix A.

4. Mathematical model formulation and solution methodology

The system consists of a remanufacturing cycle followed by a production cycle. The remanufacturing cycle takes place first, and after finishing the remanufacturing cycle, the production cycle starts. After completing the forward process of remanufacturing and production, the returned cycle takes place. In the returned cycle, used products are accumulated from the remanufacturing and the production cycle. After the screening process, the good quality products are sent to the first market, and the lesser good quality products are sent to the second market. The detailed explanation of the inventory position and associated times are described in the following sections. The model is divided into two cases. Case 1 describes the model without the learning effect, and Case 2 describes it with the learning effect. Production-related costs are only considered under the impact of inflation. Machine setup cost, ordering cost, holding cost, shortage cost, and investment is free from inflation.

4.1. Case 1. The remanufacturing cycle and production cycle without learning effect

In this model, it is considered that the remanufacturing and production cycles take place one by one. First, the cycle of the remanufacturing process is initiated. Besides, one must determine the market demand and any product damage, after which the stock level is maximized by time t_1. Then, the remanufacturing is stopped, after which the stock level starts decreasing and reaches zero over time t_2. Shortage then starts between $[t_2, T]$.

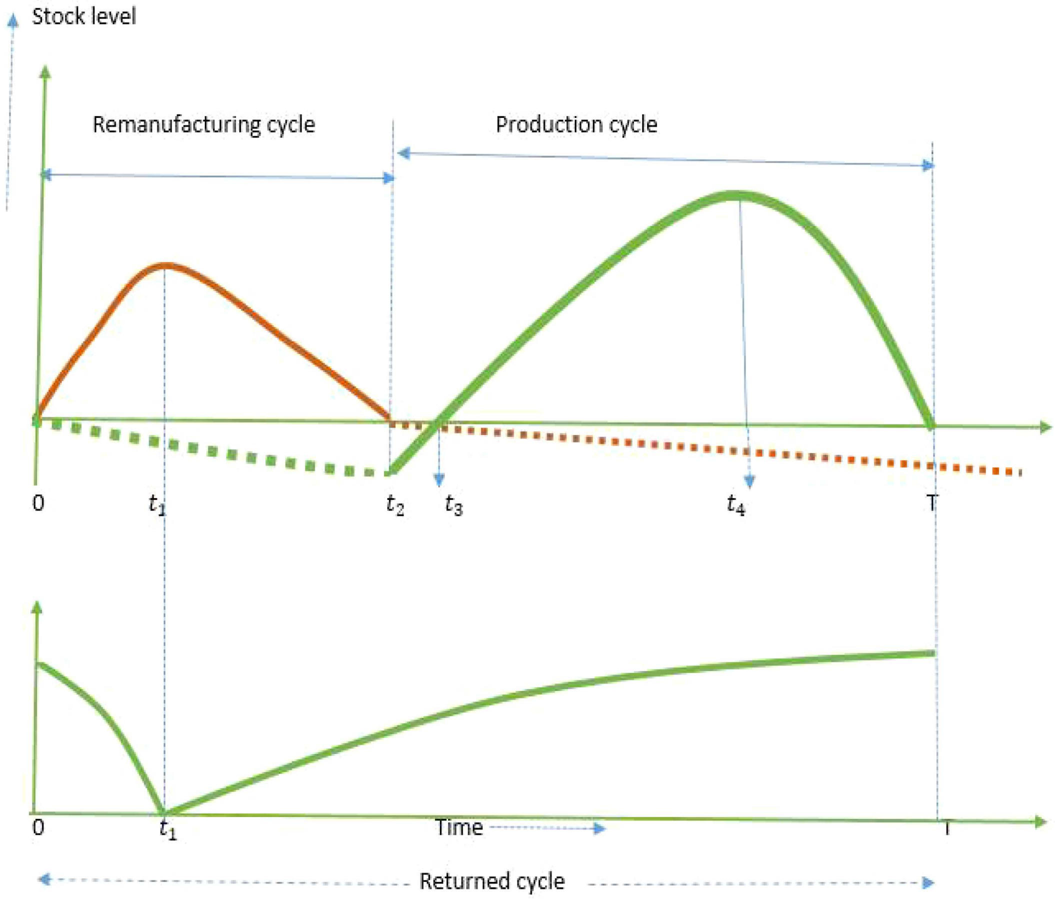

FIGURE 2. Behavior of RL inventory model.

After the production process starts, the shortage is overcome at the time t_3 and stock level reaches its maximum at the time t_4. Later, the production is stopped, and it reaches the zero level. Moreover, the stock level of the returned items in the cycle of $0-t_2$ is influenced by the remanufacturing and returned rates. For the initialization of the remanufacturing procedure, the inventory level starts decreasing and reaches zero at t_1, where the process stops. Therefore, the stock level increases at time T, as shown in Figure 2.

The differential equations at the inventory level for the remanufacturing cycle can be expressed as follows:

$$I_r'(t) + \rho_r I_r(t) = P_r - D_r \qquad 0 \le t \le t_1 \quad I_r(0) = 0 \tag{1}$$
$$I_r'(t) + \rho_r I_r(t) = -D_r \qquad t_1 \le t \le t_2 \quad I_r(t_2) = 0 \tag{2}$$
$$I_r'(t) = -D_r \qquad t_2 \le t \le T \quad I_r(t_2) = 0. \tag{3}$$

Differential equations for the production cycle are as follows:

$$I_m'(t) = -D_m \qquad 0 \le t \le t_2 \quad I_m(0) = 0 \tag{4}$$
$$I_m'(t) = P_m(t) - D_m \qquad t_2 \le t \le t_3 \quad I_m(t_3) = 0 \tag{5}$$
$$I_m'(t) + \rho_m I_m(t) = P_m - D_m \qquad t_3 \le t \le t_4 \quad I_m(t_3) = 0 \tag{6}$$
$$I_m'(t) + \rho_m I_m(t) = -D_m \qquad t_4 \le t \le T \quad I_m(T) = 0. \tag{7}$$

Inventory positions for the returned cycle are as follows:

$$I'_R(t) + \rho I_R(t) = R - P_r \qquad 0 \le t \le t_1 \quad I_R(t_1) = 0 \tag{8}$$
$$I'_R(t) + \rho I_R(t) = R \qquad t_1 \le t \le T \quad I_R(t_1) = 0. \tag{9}$$

The inventories can be obtained by solving equations (1)–(9) as follows. Remanufacturing inventories can be obtained as

$$I_r(t) = \frac{(P_r - D_r)(1 - e^{-t\rho_r})}{\rho_r}, \qquad 0 \le t \le t_1 \tag{10}$$
$$I_r(t) = \frac{-D_r\left(1 - e^{(t_2 - t)\rho_r}\right)}{\rho_r}, \qquad t_1 \le t \le t_2 \tag{11}$$
$$I_r(t) = D_r(t_2 - t), \qquad t_2 \le t \le T. \tag{12}$$

The manufactured inventories are obtained as

$$I_m(t) = -D_m t \qquad 0 \le t \le t_2 \tag{13}$$
$$I_m(t) = (P_m - D_m)(t - t_3) \qquad t_2 \le t \le t_3 \tag{14}$$
$$I_m(t) = \frac{(P_m - D_m)\left(1 - e^{\rho_m(t_3 - t)}\right)}{\rho_m} \qquad t_3 \le t \le t_4 \tag{15}$$
$$I_m(t) = \frac{-D_m}{\rho_m}\left(1 - e^{\rho_m(T - t)}\right) \qquad t_4 \le t \le T. \tag{16}$$

Finally, returned inventories can be obtained as

$$I_R(t) = \frac{(R - P_r)}{\rho}\left(1 - e^{\rho(t_1 - t)}\right) \qquad 0 \le t \le t_1 \tag{17}$$
$$I_R(t) = \frac{R}{\rho}\left(1 - e^{\rho(t_1 - t)}\right) \qquad t_1 \le t \le T. \tag{18}$$

4.1.1. Setup cost for the remanufacturing cycle, production cycle, and ordering cost for the returned cycle

The manufacturing systems must create products in the production and remanufacturing cycles. Therefore, the setup and ordering costs of the system are calculated as follows:

Setup cost is V_r for the remanufacturing cycle,
setup cost is V_m for the production cycle, and
ordering cost is V_R for the returned cycle.

Therefore, the total setup and ordering cost of the system is calculated as $Z_{MR} = V_r + V_m + V_R$. Inflation is not considered for these costs.

4.1.2. Production cost

The production cost reflects the business's overall expenditures and is essential for any production system. $P_m(t)$ is the production rate of the product at time t, and S_m is the unit production cost. The production process actives during t_2 to t_4. σ is the inflation rate. Then, the production cost is calculated as

$$\mathrm{PC}_v = S_m \int_{t_2}^{t_4} P_m(t) e^{-\sigma t}\,\mathrm{d}t = S_m\left(\frac{(e^{-\sigma t_2} - e^{-\sigma t_4})P_m}{\sigma}\right).$$

4.1.3. Remanufacturing cost

When used items are received from consumers, remanufacturing requires some expenditure. The remanufacturing takes place during the time 0 to t_1. S_r is the unit remanufacturing cost and $P_r(t)$ is the remanufacturing rate of the product at time t. The remanufacturing cost under the inflation is calculated as

$$\mathrm{RC}_v = S_r \int_0^{t_1} P_r(t) e^{-\sigma t}\,\mathrm{d}t = S_r\left(\frac{(1-e^{-\sigma t_1})P_r}{\sigma}\right).$$

4.1.4. Material cost for new and used products

The material and used product purchasing cost during the production and remanufacturing cycles, respectively, must be considered. B_m is the unit material cost (new products) for the production cycle, whereas B_R is the unit purchasing cost of the used product for the returned cycle. The returned cycle acts within 0 to T at the rate $R(t)$. Therefore, the total value of the material cost under the inflation rate σ is calculated as

$$\mathrm{IC}_v = B_m \int_{t_2}^{t_4} P_m(t) e^{-\sigma t}\,\mathrm{d}t + B_R \int_0^{T} R(t) e^{-\sigma t}\,\mathrm{d}t = \frac{(e^{-\sigma t_2} - e^{-\sigma t_4})B_m P_m}{\sigma} + \frac{\left(-e^{-T\sigma} + e^{-\sigma t_4}\right) R B_R P_m}{\sigma}.$$

4.1.5. Holding cost of manufactured, remanufactured, and returned products

The system must store newly manufactured, remanufactured, and returned products. Holding duration for remanufactured products is $[t_3, T]$, manufactured products is $[0, t_2]$, and returned products is $[0, T]$. Associative unit holding costs for remanufactured products, manufactured product, and returned product are H_r, H_m, and H_R, respectively. Inflation is not considered for holding products. Therefore, the holding cost of these products is calculated as

$$\begin{aligned}
\mathrm{HC}_v &= H_r\left[\int_0^{t_1} I_r(t)\,\mathrm{d}t + \int_{t_1}^{t_2} I_r(t)\,\mathrm{d}t\right] + H_m\left[\int_{t_3}^{t_4} I_m(t)\,\mathrm{d}t + \int_{t_4}^{T} I_m(t)\,\mathrm{d}t\right] + H_R\left[\int_0^{t_1} I_R(t)\,\mathrm{d}t + \int_{t_1}^{T} I_R(t)\,\mathrm{d}t\right] \\
&= H_R\left(\frac{R\left(-1 + e^{\rho(-T+t_1)} + T\rho - \rho t_1\right)}{\rho^2} + \frac{(R-P_r)(1 - e^{\rho t_1} + \rho t_1)}{\rho^2}\right) \\
&\quad + H_m\left(-\frac{D_m\left(1 - e^{(T-t_4)\rho_m} + (T-t_4)\rho_m\right)}{\rho_m^2} + \frac{(D_m - P_m)\left(1 - e^{(t_3+t_4)\rho_m} + t_3\rho_m - t_4\rho_m\right)}{\rho_m^2}\right) \\
&\quad + H_r\left(\frac{(-D_r + P_r)\left(t_1 + \frac{-1+e^{-t_1\rho_r}}{\rho_r}\right)}{\rho_r} + \frac{D_r\left(-1 + e^{(-t_1+t_2)\rho_r} + t_1\rho_r - t_2\rho_r\right)}{\rho_r^2}\right).
\end{aligned}$$

4.1.6. Shortage cost

Shortages are considered in the manufacturing and remanufacturing cycle for the first and second markets. A_r is the unit shortage cost of the remanufactured products, and A_m is the unit shortage cost of manufactured products. Shortage occurs during $[t_2, T]$ for remanufactured products and $[0, t_3]$ for manufactured products. Inflation is not considered for the shortage of products. The shortage cost is calculated as

$$\begin{aligned}
\mathrm{SC}_v &= -A_r \int_{t_2}^{T} I_r(t)\,\mathrm{d}t - A_m\left\{\int_0^{t_2} I_m(t)\,\mathrm{d}t + \int_{t_2}^{t_3} I_m(t)\,\mathrm{d}t\right\} \\
&= -A_r\left(-\frac{1}{2}T^2 D_r + T D_r t_2 - \frac{1}{2} D_r t_2^2\right) - A_m\left(-\frac{1}{2} D_m t_2^2 + (-D_m + p_m)(t_2 - t_3)(-t_2 + t_3)\right).
\end{aligned}$$

4.1.7. Screening cost

Returned items are inspected to classify them as products to be sent to the first market (for good quality products) or second market (for lesser good quality products). The unit screening cost is $\emptyset_{isp}$ for returned products. The screening process starts at time $t = 0$ and continues until t_s. At t_s, the screening process ends for returned products. The cost for conducting screening under inflation is expressed as

$$\mathrm{SP}_v = \emptyset_{isp} \int_0^{t_s} Re^{-\sigma t}\,\mathrm{d}t = \frac{(R - e^{-\sigma t_s} R)\phi_{isp}}{\sigma}.$$

t_s is the time when the screening process is completed, *i.e.*, $t_s = \frac{T}{n}$. $n(>1)$ is a scaler multiple of the cycle time.

4.1.8. Salvaging cost

The salvaging cost comprises the cost of resale of goods received from the first market of manufactured products and the second market of remanufactured products at the end of their lifetime. δ_m is the percentage of sold manufactured products, and δ_r is the percentage of sold remanufactured products. Thus, the salvaging cost of products under inflation is

$$\mathrm{SAC}_v = \frac{\{(1-\delta_m)\alpha_m D_m + (1-\delta_r)\alpha_r D_r\}\left(1 - e^{-T\sigma}\right)S_{vg}}{\sigma}.$$

4.1.9. GT cost

The GT is the cost spent by the manufacturer for the improvement of the existing liquid cooling technology. The cost can be expressed as

$$\mathrm{GC} = \Delta T.$$

The total cost of the system per cycle, $\mathrm{TC}_1(t_1, t_2, t_3, t_4, T)$, takes the following form

$$\mathrm{TC}_1 = \frac{1}{T}[Z_{MR} + \mathrm{PC}_v + \mathrm{RC}_v + \mathrm{IC}_v + \mathrm{HC}_v + \mathrm{SC}_v + \mathrm{SP}_v + \mathrm{SAC}_v + \mathrm{GC}]. \tag{19}$$

4.1.10. Solution methodology

This research aims to minimize the total cost function (see Appendix B or Eq. (B.1)). Given that t_1, t_2, t_3, t_4, and T correlates under the continuous condition,

$$0 \le t_1 \le t_2 \le t_3 \le t_4 \le T \tag{20}$$

$$\frac{(P_r - D_r)(1 - e^{-t_1\rho_r})}{\rho_r} = \frac{-D_r\left(1 - e^{(t_2 - t_1)\rho_r}\right)}{\rho_r} \tag{21}$$

$$\frac{(P_m - D_m)\left(1 - e^{\rho_m(t_3 - t_4)}\right)}{\rho_m} = \frac{-D_m}{\rho_m}\left(1 - e^{\rho_m(T - t_4)}\right) \tag{22}$$

$$-D_m t = (P_m - D_m)(t - t_3). \tag{23}$$

Equations (21)–(23) show that inventory levels $I_r(t)$ and $I_m(t)$ are identical at t_1, t_4, and t_2.

By using equations (21)–(23), the values of t_2, t_3, t_4 can be determined according to t_1 and T as follows:

$$t_2 = \frac{1}{\rho_r}\left[\log\left\{1 + \frac{(P_r - D_r)}{D_r}\left(1 - e^{-\rho_r t_1}\right)\right\} + \rho_r t_1\right], \tag{24}$$

$$t_3 = \frac{t_2 P_m}{(P_m - D_m)}, \tag{25}$$

$$t_4 = \frac{1}{\rho_r}\left[\log\left\{\frac{(P_m - D_m)e^{\rho_m t_3} + D_m e^{\rho_m T}}{D_m}\right\}\right]. \tag{26}$$

By substituting the values of t_2, t_3, and t_4 in equation (B.1), the total cost can be calculated as $\mathrm{TC}_1(T, t_1)$, where T and t_1 are decision variables. As TC_1 (see Appendix B) is difficult to solve theoretically, this study uses the numerical method and MATHEMATICA 11.0 to determine the values of decision variables T^* and t_1^*. Example 1 explains the current scenario. Then, the optimal value of the total cost function is $\mathrm{TC}_1(T^*, t_1^*)$. The following algorithm provides the optimum results numerically, and Figure 3 gives the flowchart of the solution methodology.

Algorithm

Step 1. First, substitute the first derivatives,

$$\frac{\partial \mathrm{TC}_1(T,t_1)}{\partial T}, \frac{\partial \mathrm{TC}_1(T,t_1)}{\partial t_1} = 0.$$

Then, compute the optimal values of T^* and t_1^*, and obtain $T^* = 80.961$ and $t_1^* = 8.02$.

Step 2. The sufficient condition of the total cost function is minimized if the Hessian matrix's following condition is satisfied.

$$J = \begin{bmatrix} \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T^2} & \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T \partial t_1} \\ \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T \partial t_1} & \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial t_1^2} \end{bmatrix}, \text{ where } \vartheta \to (T, t_1).$$

The values of $|J_{11}|$, $|J_{22}|$, and $|J|$ are all positive at the optimal values of T^* and t_1^*, *i.e.*,

$$|J_{11}| = \frac{\partial^2 \mathrm{TC}(\vartheta)}{\partial T^2} = 12.496 > 0,$$

$$|J_{22}| = \frac{\partial^2 \mathrm{TC}(\vartheta)}{\partial t_1^2} = 127.417 => 0,$$

$$|J| = \begin{vmatrix} \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T^2} & \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T \partial t_1} \\ \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial T \partial t_1} & \frac{\partial^2 \mathrm{TC}_1(\vartheta)}{\partial t_1^2} \end{vmatrix} = \begin{bmatrix} 12.496 & -13.834 \\ -13.834 & 127.417 \end{bmatrix} = 14\,026.85 > 0,$$

then the sufficient conditions for optimum solutions are satisfied.

Step 3. Substitute the value of t_1 and T in equations (24)–(26) and obtain $t_2^* = 41.167$, $t_3^* = 68.982$, and $t_4^* = 73.826$.

Step 4. Substitute these values in equation (B.1) and get the minimum value \$16 658.6. of the total cost function.

4.2. Case 2. The remanufacturing cycle and production cycle with the learning effect

Unit production and remanufacturing costs, including apparatus costs, such as machinery and labor, are expensive. Therefore, this research applies the learning effect in the production and remanufacturing processes.

4.2.1. Production cost under the learning effect

The production cost reflects the business's overall expenditure and is essential for any production system. The learning curve of the production cost is $S_{Lm}k^{-a}$, where k is the production count ($k > 1$), S_{Lm} is the production cost required to produce the first unit ($S_{Lm} > 0$), and a is the slope of the learning curve ($0 < a < 1$). Meanwhile, $S_{Lm}k^{-a}$ represents the required production cost to produce kth unit under the learning effect. Then, the unit production cost becomes $\mathrm{SL}(k) = (S_m + \frac{S_{Lm}}{k^a})$. Thus, the new production cost under the inflation and learning effect is

$$\mathrm{PC}_{Lv} = \left(S_m + \frac{S_{Lm}}{k^a}\right) \int_{t_2}^{t_4} P_m(t) e^{-\sigma t}\,\mathrm{d}t = \mathrm{SL}(k) \left(\frac{(e^{-\sigma t_2} - e^{-\sigma t_4}) P_m}{\sigma}\right).$$

4.2.2. Remanufacturing cost

The learning curve of the remanufacturing cost is $S_{Lr}k^{-b}$, where k is the remanufacturing count ($k > 1$), S_{Lr} is the remanufacturing cost required to remanufacture the first unit ($S_{Lr} > 0$), and b is the slope of the learning curve ($0 < b < 1$). Meanwhile, $S_{Lr}k^{-b}$ represents the required remanufacturing cost to remanufacture kth unit under the learning effect. Then, the unit remanufacturing cost becomes $Sr(k) = (S_r + \frac{S_{Lr}}{k^b})$. Thus, the new remanufacturing cost under the inflation and learning effect is

$$\mathrm{RC}_{Lv} = \left(S_r + \frac{S_{Lr}}{k^b}\right) \int_0^{t_1} P_r(t) e^{-\sigma t}\,\mathrm{d}t = Sr(k) \left(\frac{(1 - e^{-\sigma t_1}) P_r}{\sigma}\right).$$

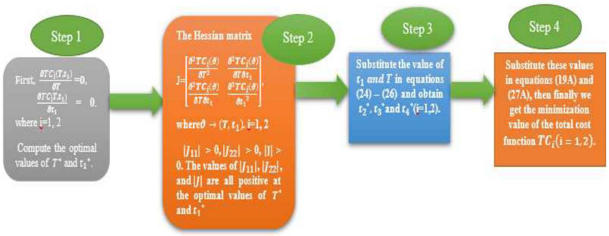

FIGURE 3. Flow chart of solution process.

Then, the total cost per cycle under the learning effect is

$$\mathrm{TC}_2 = \frac{1}{T}[Z_{MR} + \mathrm{PC}_{Lv} + \mathrm{RC}_{Lv} + \mathrm{IC}_v + \mathrm{HC}_v + \mathrm{SC}_v + \mathrm{SP}_v + \mathrm{SAC}_v + \mathrm{GC}]. \tag{27}$$

The total cost function (see Appendix C or Eq. (C.1)) is minimized with the help of Example 2.

5. Numerical analysis

This segment presents a numerical example to validate this model. The data is collected from the literature [62, 67] and modified according to the convergence of the objective function. Automobile products can be considered as an example to fit within the model.

Example 1. This study hypothesizes the following input parameter values: $D_r = 120$ units/day, $P_r = 620$ units/day, $P_m = 620$ units/day, $D_m = 250$ units/day, $V_m = \$24\,000$/setup, $V_r = \$16\,000$/setup, $V_R = \$14\,000$/setup, $S_m = \$94$/unit, $S_r = \$93$/unit, $B_m = \$10$/unit, $B_R = \$6$/unit, $\rho_0 = 0.02$, $\rho_1 = 0.01$, $\rho = 0.03$, $A_r = 0.1$, $A_m = 0.4$, $\pi = 0.04$, $\delta_r = 0.03$, $\delta_m = 0.04$, $\alpha_r = 0.45$, $\alpha_m = 0.5$, $H_m = \$7$/unit/day, $H_r = \$8$/unit/day, $H_R = \$9$/unit/day, $\emptyset_{isp} = \$3$/unit, $s_{vg} = \$1.2$/unit, $\sigma = 0.04$, $n = 6$, $\Delta = \$80$/cycle and $0 < t_1 \leq t_2 \leq t_3 \leq t_4 \leq T$. This study uses MATHEMATICA 11.0 software and develops the optimal solution and results. For minimization, the Hessian matrix condition must be satisfied, $J = \begin{bmatrix} 12.496 & -13.834 \\ -13.834 & 127.417 \end{bmatrix}$, where $|J_{11}| = 12.496 > 0$, $|J_{22}| = 127.417 > 0$, and $|J| = 1400 > 0$. Hence, the minimum total cost (TC_1) is obtained as \$16 658.6/cycle.

Example 2. Production and remanufacturing costs are effective with the learning effect. All input parameter values are same except some parameters $k = 3$, $a = 0.2$, $b = 0.4$, $S_m = \$84$/unit, $S_{Lm} = \$10$/first production batch, $S_r = \$83$/unit, $S_{Lr} = \$10$/first remanufacturing batch. The Hessian matrix condition must be satisfied, $J = \begin{bmatrix} 12.53 & -13.88 \\ -13.88 & 129.25 \end{bmatrix}$, where $|J_{11}| = 12.53 > 0$, $|J_{22}| = 129.25 > 0$ and $|J| = 14\,026.85 > 0$. Therefore, the minimum total cost (TC_2) is obtained as \$16 417.2/cycle. The optimal results on the base Examples 1 and 2 are represented in Table 2.

5.1. Discussions and comparisons

Learning is essential to reduce the cost of machinery and labor involved in the production and remanufacturing process. Special cases are discussed in Table 3 to compare the present study with some subcases.

(1) Deterioration items are examined in the production store. Deteriorated products from this study are 10 560.4 units/cycle, whereas deteriorated products become 11 541.56 units/cycle if no GT exists. A decrease of 8.50% in deterioration items due to the investment in liquid cooling technology is derived, which would reduce waste items. It is seen that a reduction of 1.44% in total cost in Case 2 of the learning effect compared to Case 1 without learning impact (Table 4).

TABLE 2. Optimal solution results (time unit defined as days).

	t_1^*	t_2^*	t_3^*	t_4^*	T^*	t_s^*	TC ($/cycle)
Example 1	8.02	41.167	68.982	73.826	80.961	13.49	16 658.6
Example 2	7.956	40.831	68.419	73.164	80.155	13.35	16 417.8

TABLE 3. Reduction in deterioration items without and with GT investment.

Special cases	Deterioration items in the production store
No liquid cooling technology investment	11 541.56 units
liquid cooling technology investment	10 560.40 units
Reduction in deterioration items (%)	8.50%

TABLE 4. Disparity in cost component between Cases I and II.

	Case 1	Case 2 (learning effect)	The disparity in cost (%)
Setup cost ($/setup)	666.98	673.69	−1.0
Production cost ($/unit)	2528.62	2521.93	+0.26
Remanufacturing cost ($/unit)	4887.25	4714.47	+3.53
Material cost ($/unit)	367.52	374.43	−1.88
Holding cost ($/unit/day)	12 501.1	12 398.2	+0.823
Shortage cost ($/unit)	4436.75 (−)	4409.38 (−)	+0.61
Screening cost ($/unit)	2.55	2.56	−0.39
Salvage cost ($/unit)	61.36	61.90	−0.88
Green technology cost ($)	80	80	0
Total cost ($/cycle)	16 658.6	16 417.8	+1.44

(2) In a similar environment, the total cost of the manufacturing system of Kumar *et al.* [29] is higher than the total cost of this study. This study is more beneficial and eco-friendly than the previous study.
(3) From the perspective of the deterioration, Paul *et al.* [49] discussed payment policy in their study without considering any environmental issues. But, this study focuses on environmental issues. Besides, Paul *et al.* [49] found the total profit of the system, whereas this study found the total cost of the system.
(4) In a similar perspective of deteriorative products, this study can be compared with Paul *et al.* [50] conceptually as Paul *et al.* [50] found the total profit of the system, and this study finds the total cost of the system. The present study uses GT for environmental issues, whereas Pervin *et al.* [51] used the concept of carbon emissions.
(5) Ali *et al.* [2] and Barman *et al.* [5] discussed perishable products in a fuzzy environment, whereas the present study discusses deteriorated products under environmental issues. These three studies are different such that any conceptual and methodological comparison is not possible.
(6) A conceptual comparison with Barman *et al.* [4] finds that both studies use deteriorated products and preservation technology to reduce waste. Both studies consider the environmental perspective, but Barman *et al.* [4] considered emissions reduction, whereas this study uses a GT to improve colling technology.
(7) Suryawanshi *et al.* [71] discussed the grocery service within an SCM without environmental issues, whereas the present model studies a production model applicable to the automobile industry with green investment.

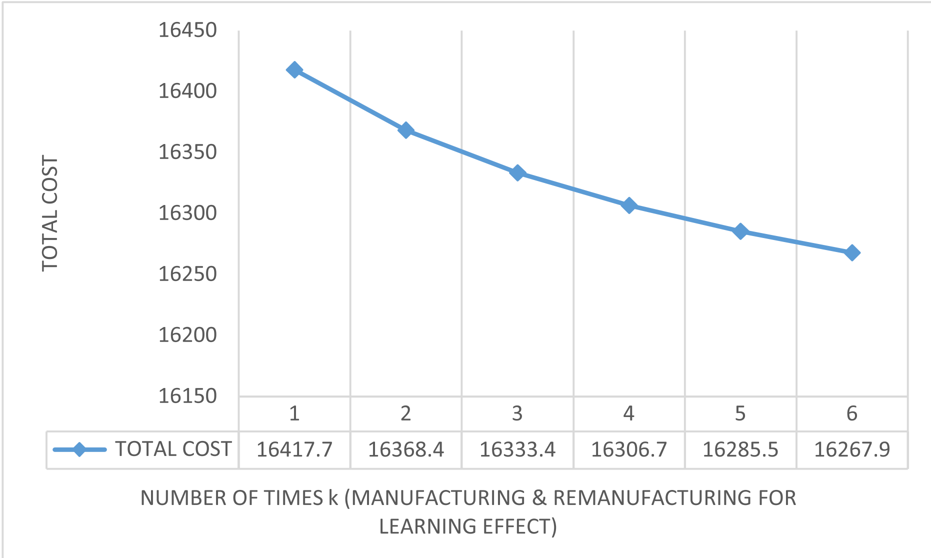

FIGURE 4. Learning effect of TC_1 for various values of k.

(8) Chan *et al.* [9] studied a review on third-party logistics (3PL) without consideration of any environmental factors, whereas this study considers RL with green investment for the environment. In a similar way, Mishra *et al.* [43] reviewed articles for RL and closed-loop supply chain.

(9) The learning effect of the total cost based on k is represented in Figure 4. When the number of times k for manufacturing/remanufacturing increases, the learning rate increases, owing to the total cost decreasing.

5.2. Sensitivity analysis

This research paper analyzes the minimum total cost to determine the changes in various parameters related to this model. It performs the analysis by fluctuating each parameter by -20%, -10%, 0%, $+10\%$, and $+20\%$ changes in the optimal cost. The sensitivity analysis results of the example mentioned above are presented in Table 5.

5.2.1. Observation I

The following are the conclusions drawn from the sensitivity analysis:

I. Figure 5 shows that the percentage of remanufacturing rate changes lead to growth in production and remanufacturing costs.
II. Figure 6 shows that the production rate's percentage changes result in a positive change in production and remanufacturing costs.
III. Figure 7 shows that the percentage changes in the remanufacturing rate slightly reduce the overall holding cost.
IV. Figure 8 shows that the percentage of production rate changes lead to increased holding costs.

5.2.2. Observation II

The following are the main conclusions drawn from the sensitivity analysis (Table 5).

I. Figure 9 clearly shows the percentage changes in production rate P_m, remanufacturing rate P_r, and the demand rate of the secondary-market demand parameter D_r. This combination results in a positive change in the total cost and a percentage change in the demand parameter D_m results in an adverse change in the total cost.

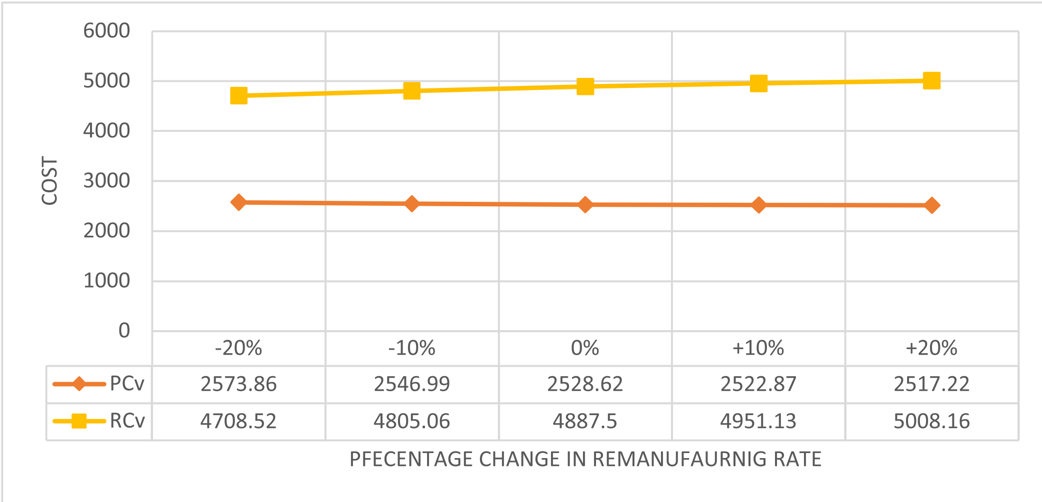

FIGURE 5. Effect on production cost and remanufacturing cost with the percentage change in the remanufacturing rate.

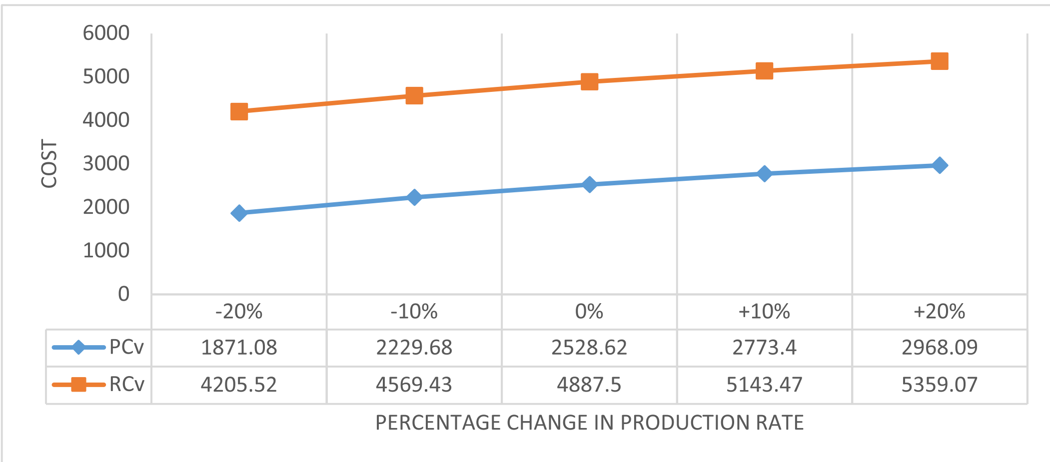

FIGURE 6. Effect on production cost and remanufacturing cost with the percentage change in production rate.

II. Figure 10 shows the percentage changes in production cost S_m, remanufacturing cost S_r, materials cost, and purchasing cost; these result in a positive change in the total cost.

III. Figure 11 shows that the percentage changes in production holding cost, remanufacturing holding cost, and returned products holding cost lead to some growth in the total cost.

IV. Figure 12 shows that the percentage changes in the manufacturing setup cost V_m, remanufacturing setup cost V_r, and ordering cost of the returned cycle V_R slightly increase the overall total cost.

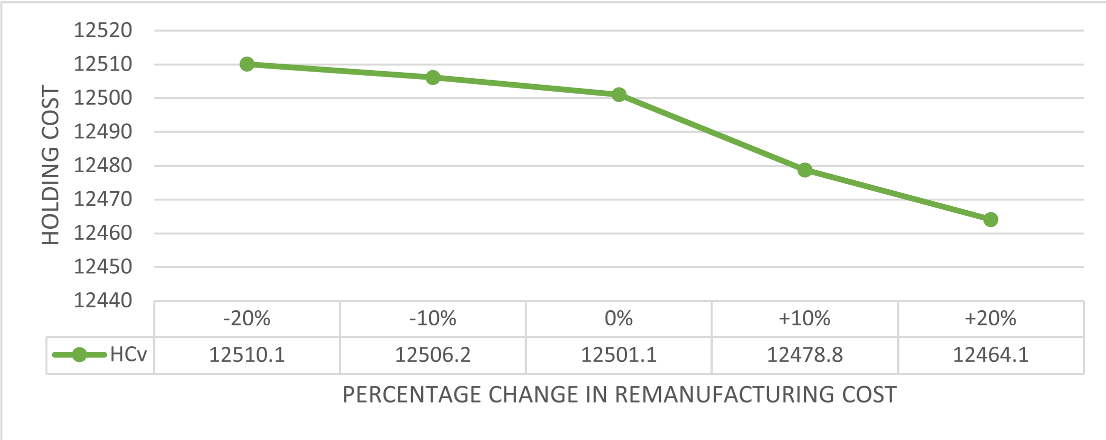

Figure 7. Effect on holding cost with the percentage change in the remanufacturing rate.

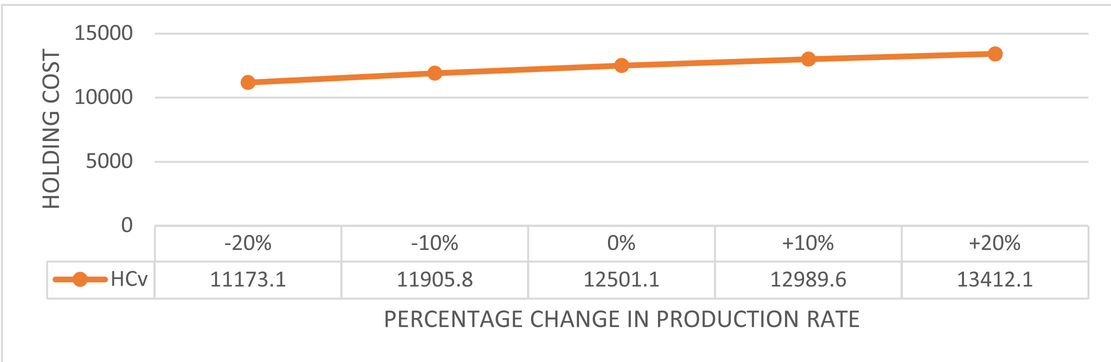

Figure 8. Effect on holding cost with the percentage change in production rate.

6. Managerial insights

Some important insights that will be helpful for consumers, manufacturers, and a sustainable environment are found in this investigation. Those insights are as follows:

- The production store's deterioration items are examined, and it is discovered that it decreases as a result of getting hold of liquid cooling technology. For this reason, a manufacturing company must keep the investment in liquid cooling technology to attract more buyers to purchase more products.
- It is essential for a company to address sustainability since balancing environmental, social, and economic factors protect customers' physical and mental well-being [44].
- At the end of the forward supply chain, substantial waste of wasted products is generated. In this study, products are classified as reusable. Therefore, collecting used products simultaneously serves two functions: reducing waste in the environment and reducing the manufacture of new products [54, 69].
- Remanufacturing improves the product's manufacturing cost. Therefore, the remanufacturing is advantageous to management in both economic and environmental terms [8].
- Learning is essential for lowering the cost of machinery and labor in the manufacturing and remanufacturing processes. It is important to minimize cost. Furthermore, it raises the total profit.

TABLE 5. Sensitivity analysis results.

Percentage change in parameters	−20%	−10%	0%	+10%	+20%
			Variation		
P_m	13 603.6	15 298.8	16 658.6	17 777.0	18 717.2
P_r	16 587.7	16 623.0	16 658.6	16 692.0	16 723.3
D_m	18 617.4	17 758.8	16 658.6	15 349.2	13 855.8
D_r	13 286.6	15 045.6	16 658.6	18 151.7	19 544.3
S_m	16 110.2	16 395.5	16 658.6	16 902.1	17 101.2
S_r	15 674.9	16 168.2	16 658.6	17 145.2	17 630.0
B_m	16 604.1	16 631.4	16 658.6	16 685.2	16 711.7
B_r	16 638.5	16 648.5	16 658.6	16 668.2	16 677.9
H_m	16 433.4	16 556.8	16 658.6	16 743.4	16 815.6
H_r	14 896.2	15 813.1	16 658.6	17 442.5	18 173.7
H_R	15 953.8	16 310.1	16 658.6	16 999.1	17 332.7
V_m	16 599.0	16 628.7	16 658.6	16 688.0	16 717.6
V_r	16 618.0	16 638.6	16 658.6	16 678.9	16 697.9
V_R	16 623.8	16 641.1	16 658.6	16 675.7	16 692.9

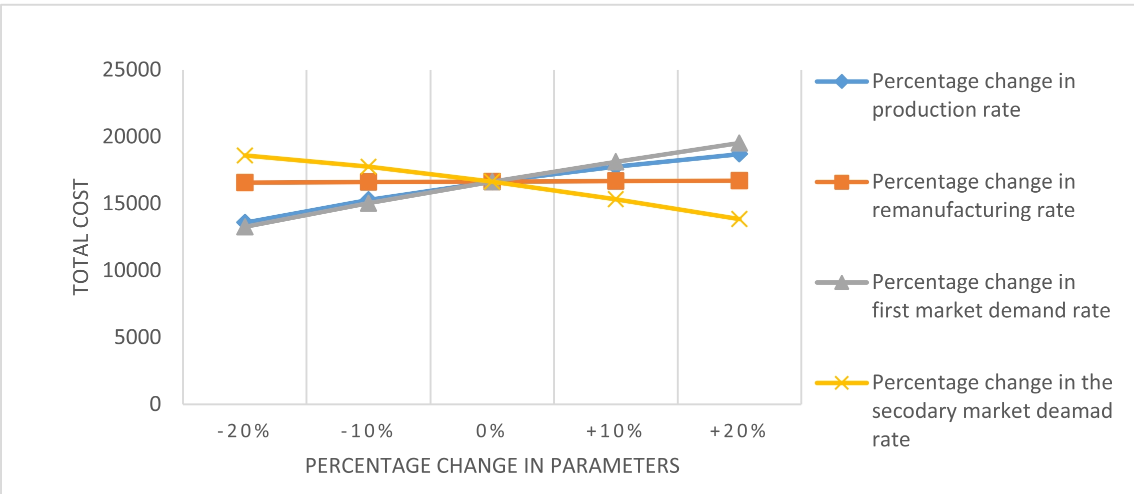

FIGURE 9. Effect of production, remanufacturing, and secondary market demand with respect to the total cost.

7. CONCLUSIONS

This research aimed to propose an RL system model for smart products, including a procedure for remanufacturing damaged items while minimizing the total cost. Unlike other studies, this model emphasized using GT, specifically liquid cooling technology, to prevent product spoilage. This research contributed to the literature by highlighting the importance of investing in GT in RL to reduce the number of remanufactured smart products and ultimately prevent waste. Liquid cooling technology led to a decrease in spoilage items and a positive environmental impact. Results indicated that the remanufacturing process did not need to be prolonged, and the company was able to reduce complaints about smart products. There was an examination in the production store, which observed an 8.50% decline in spoiling products due to the investment in liquid cooling technology

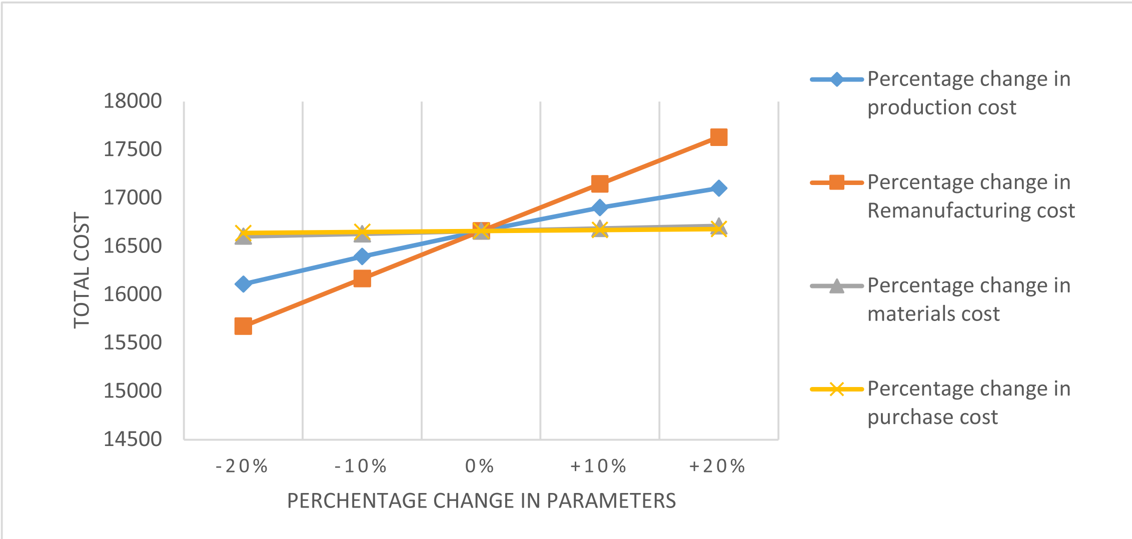

Figure 10. Effect of production, remanufacturing, material and purchasing cost with respect to the total cost.

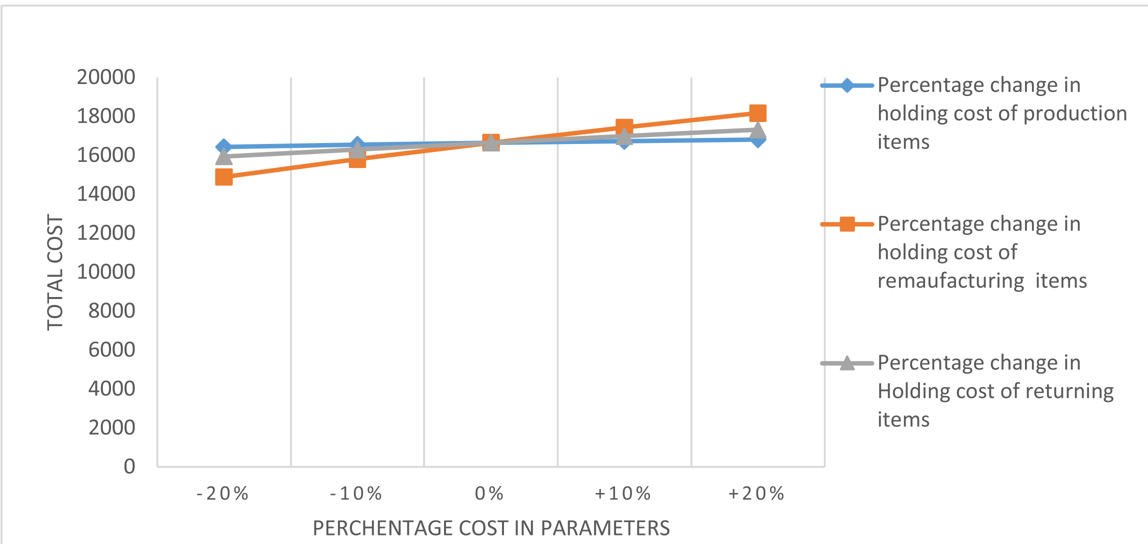

Figure 11. Effect of production, remanufacturing, and holding cost with respect to the total cost.

(Tab. 3), which would lead to reduced waste products, which proved to be very beneficial for the environment. The cost of unit production and remanufacturing was included in this study as a learning factor. The learning effect contributed to the decrease in the total cost, which was demonstrated in Table 4 and Figure 4. Sensitivity analysis of the total cost was represented in Figures 9–12. This model could be used in real-life mobile companies, smart TVs, automotive industries, and other electronics industries. Liquid cooling technology had a tremendous positive impact on industries by delivering consumer satisfaction. That was employed in the proposed sustainable model to reduce spoilage rates.

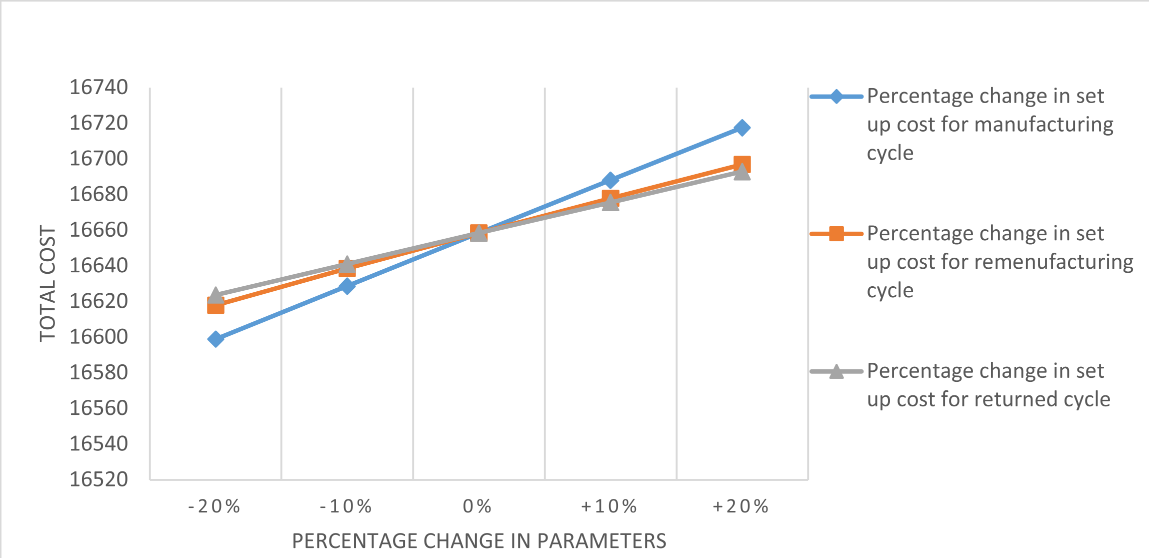

Figure 12. Effect of production, remanufacturing, and setup cost with respect to the total cost.

There are some limits to this proposed study. It is limited to the electronics industries: mobile firms and automobile industries. The model can be extended for different industries and products with specific characteristics of those products. Besides, an RL sector requires a specific transportation system, which was not considered in this study. The treatment for unused products from the system was not taken into consideration, and a proper discard process for unused products was missing too from this study [78]. From an environmental perspective, only investment was considered in the study. Other emissions reduction policies [72] from a production system can be used further. The model can be extended in several dimensions, along with the removal of the present limitations. This future model can be developed to consider permissible delay-in-payments and reliability. This model can be further modified under a fuzzy environment [16, 46]. The present study can be examined to time-dependent production and demand scenarios. In the future, this model can be developed with different GTs which are more compatible with liquid cooling technologies. Except for the theoretical development, new methodologies can be applied to find better solutions than this study [22, 34]. The model can be solved in a competitive perspective [76] with the presence of multiple players.

Appendix A.

Parameters

$P_m(t)$	Production rate of items (units/time unit)
$P_r(t)$	Remanufacturing rate of returned items (units/time unit)
D_m	Demand rate of the manufactured products from the first market (units/time unit)
D_r	Demand rate of remanufactured products from the second market (units/time unit)
V_r	Setup cost (\$/setup) per remanufacturing cycle
V_m	Setup cost (\$/setup) per production cycle
V_R	Setup cost (\$/setup) for the return cycle
ρ_m	Deterioration rate for the production cycle
ρ_0	Deterioration rate without investment for the production cycle
ρ_1	Deterioration rate without investment for the remanufacturing cycle

ρ_r	Deterioration rate for remanufacturing cycle
ρ	Deterioration rate for the production cycle
π	Shape parameter of green investment
σ	Inflation rate
H_r	Holding cost for remanufacturing items (\$/unit/unit time)
H_m	Holding cost for production items (\$/unit/unit time)
H_R	Holding cost for collected returned items (\$/unit/unit time)
A_m	Shortage cost for production (\$/unit)
A_r	Shortage cost for remanufacturing (\$/unit)
δ_m	Scaling parameter, determination of salvaged goods from the first market
δ_r	Scaling parameter, determination of salvaged goods from the second market
S_m	Unit production cost (\$/unit)
S_r	Unit remanufacturing cost (\$/unit)
$\mathrm{SL}(k)$	Unit production cost under learning effect (\$/unit)
$Sr(k)$	Unit remanufacturing cost under learning effect (\$/unit)
S_{Lm}	Unit production cost required for the first production batch under the learning effect (\$/unit)
S_{Lr}	Unit remanufacturing cost required for the first remanufacturing batch under the learning effect (\$/unit)
B_m	Unit cost of material for the production cycle (\$/unit)
B_R	Unit purchasing cost of the product for the returned cycle (\$/unit)
α_m, α_r	Scaling parameter for return rate formulation (from first and second markets, respectively)
$\emptyset_{isp}$	Screening cost per unit (\$/unit)
R	Annual return rate of used items (unit/cycle)
Δ	GT (liquid cooling technology) cost (\$/cycle)
n	Scaling of the cycle time for screening time
S_{vg}	Unit salvage cost (\$/unit)
a, b	Slope of the learning curve for the production and remanufacturing scenarios, respectively
k	Production/remanufacturing count for the learning process ($k > 1$)
$I_r(t)$	Inventory level at time t for remanufacturing cycle
$I'_r(t)$	Differentiation of inventory level at time t for remanufacturing cycle
$I_m(t)$	Inventory level at time t for the production cycle
$I'_m(t)$	Differentiation of inventory level at time t for production cycle
$I_R(t)$	Inventory level at time t for return cycle
$I'_R(t)$	Differentiation of inventory level at time t for returned cycle
TC_1	Total cost without learning effect (\$/cycle)
TC_2	Total cost with learning effect (\$/cycle)

Dependent variables

t_2	Time at which the remanufacturing-stock level is zero (time units)
t_3	Time at which the shortage is overcome (time units)
t_4	Time at which the manufacturing-stock level is maximum (time units)
t_s	The time when the screening process is complete (time unit)

Decision variables

T	Cycle length (time unit)
t_1	Time at which the remanufacturing-stock level is maximum (time unit)

Appendix B.

$$
\begin{aligned}
\mathrm{TC}_1 = \frac{1}{T}\Bigg[& V_r + V_m + V_R + S_m\left(\frac{(e^{-\sigma t_2} - e^{-\sigma t_4})P_m}{\sigma}\right) + S_r\left(\frac{(1-e^{-\sigma t_1})P_r}{\sigma}\right) \\
& + \frac{(e^{-\sigma t_2} - e^{-\sigma t_4})B_m p_m}{\sigma} + \frac{\left(-e^{-T\sigma} + e^{-\sigma t_4}\right)RB_R p_m}{\sigma} \\
& + H_R\left(\frac{R\left(-1 + e^{\rho(-T+t_1)} + T\rho - \rho t_1\right)}{\rho^2} + \frac{(R-P_r)(1-e^{\rho t_1} + \rho t_1)}{\rho^2}\right) \\
& + H_m\left(-\frac{D_m\left(1 - e^{(T-t_4)\rho_m} + (T-t_4)\rho_m\right)}{\rho_m^2} + \frac{(D_m - P_m)\left(1 - e^{(t_3+t_4)\rho_m} + t_3\rho_m - t_4\rho_m\right)}{\rho_m^2}\right) \\
& + H_r\left(\frac{(-D_r + P_r)\left(t_1 + \frac{-1+e^{-t_1\rho_r}}{\rho_r}\right)}{\rho_r} + \frac{D_r\left(-1 + e^{(-t_1+t_2)\rho_r} + t_1\rho_r - t_2\rho_r\right)}{\rho_r^2}\right) \\
& - A_r\left(-\frac{1}{2}T^2 D_r + TD_r t_2 - \frac{1}{2}D_r t_2^2\right) - A_m\left(-\frac{1}{2}D_m t_2^2 + (-D_m + p_m)(t_2 - t_3)(-t_2 + t_3)\right) \\
& + \frac{(R - e^{-\sigma t_s}R)\phi_{isp}}{\sigma} + \frac{\{(1-\delta_m)\alpha_m D_m + (1-\delta_r)\alpha_r D_r\}\left(1 - e^{-T\sigma}\right)S_{vg}}{\sigma} + \Delta T\Bigg]. \qquad \text{(B.1)}
\end{aligned}
$$

By substituting the values of t_2, t_3, t_4, and t_s in the cost function, which is a non-linear function.

Appendix C.

$$
\begin{aligned}
\mathrm{TC}_2 = \frac{1}{T}\Bigg[& V_r + V_m + V_R + \left(S_m + \frac{S_{Lm}}{k^a}\right)\left(\frac{(e^{-\sigma t_2} - e^{-\sigma t_4})P_m}{\sigma}\right) \\
& + \left(S_r + \frac{S_{Lr}}{k^b}\right)\left(\frac{(1-e^{-\sigma t_1})P_r}{\sigma}\right) + \frac{(e^{-\sigma t_2} - e^{-\sigma t_4})B_m p_m}{\sigma} + \frac{\left(-e^{-T\sigma} + e^{-\sigma t_4}\right)RB_R p_m}{\sigma} \\
& + H_R\left(\frac{R\left(-1 + e^{\rho(-T+t_1)} + T\rho - \rho t_1\right)}{\rho^2} + \frac{(R-P_r)(1-e^{\rho t_1} + \rho t_1)}{\rho^2}\right) \\
& + H_m\left(-\frac{D_m\left(1 - e^{(T-t_4)\rho_m} + (T-t_4)\rho_m\right)}{\rho_m^2} + \frac{(D_m - P_m)\left(1 - e^{(t_3+t_4)\rho_m} + t_3\rho_m - t_4\rho_m\right)}{\rho_m^2}\right) \\
& + H_r\left(\frac{(-D_r + P_r)\left(t_1 + \frac{-1+e^{-t_1\rho_r}}{\rho_r}\right)}{\rho_r} + \frac{D_r\left(-1 + e^{(-t_1+t_2)\rho_r} + t_1\rho_r - t_2\rho_r\right)}{\rho_r^2}\right) \\
& - A_r\left(-\frac{1}{2}T^2 D_r + TD_r t_2 - \frac{1}{2}D_r t_2^2\right) - A_m\left(-\frac{1}{2}D_m t_2^2 + (-D_m + p_m)(t_2 - t_3)(-t_2 + t_3)\right) \\
& + \frac{(R - e^{-\sigma t_s}R)\phi_{isp}}{\sigma} + \frac{\{(1-\delta_m)\alpha_m D_m + (1-\delta_r)\alpha_r D_r\}\left(1 - e^{-T\sigma}\right)S_{vg}}{\sigma} + \Delta T\Bigg]. \qquad \text{(C.1)}
\end{aligned}
$$

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