Sustainable Decisions in a High-tech Electronic Product Supply Chain Considering Environmental Effort and Social Responsibility: A Hierarchical Bi-level Intelligent Approach

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***Abstract*—With the intensification of market competition, high-tech electronic products need to be constantly updated. The accelerated elimination of outdated products has led to a waste of resources and severe environmental pollution. High-tech electronic enterprises are facing more severe problems than other industries in terms of how to coordinate environmental protection and social responsibility while maintaining their profits, because of the high product elimination rate. However, little research on this aspect exists in previous literature. In this paper, we consider the sustainable development of a high-tech product supply chain from the perspectives of profits, environmental protection efforts and social responsibility costs. Considering the hierarchical structure of the supply chain, a bi-level programming model is constructed under the guidance of the manufacturer. The corresponding hierarchical intelligent algorithm is developed to solve and analyze the model. Based on a sensitivity analysis, key research findings with management significance are obtained, as follows: (1) Compared with a carbon emission penalty strategy, changing the carbon tax exerts a greater impact on the optimal decisions and the manufacturer's and retailer's profits. (2) Social welfare costs have significant impacts on product prices, green innovation expenditure and the leader's profit in a supply chain. (3) Higher retailer carbon abatement costs could help reduce the carbon emissions per unit product. (4) The wholesale price decline rate has a greater impact on product price and manufacturer's environmental protection efforts than the component purchase cost decline rate and selling price decline rate.**

***Keywords*—Sustainable supply chain; high-tech electronic industry; bi-level programming; intelligent algorithm**

I. INTRODUCTION

As a fast-growing industry, the rapid development of the high-tech electronic products market and the continuous development of technology have accelerated the speed at which products are upgraded. For example, since Apple launched its first mobile phone in 2007, the company has launched new iPhones almost every year. The corresponding high product elimination rate has caused high-tech electronic enterprises to face the problem of how to coordinate environmental protection with the development of the company. On the one hand, the rapid development of science and technology has shortened the life cycle and accelerated the update speed of a series of electronic high-tech electronic products, such as computers and mobile phones [1]. This has resulted in a high elimination rate of high-tech enterprises. On the other hand, due to increasing consumer awareness of environmental protection issues, as well as the new environmental laws and regulations, high-tech electronic enterprises need to meet consumers' green needs and create social benefits, while simultaneously reducing their own costs and increasing their profits. Therefore, with ever-increasing market competition and increasingly stringent environmental regulations, the importance of the sustainable development of high-tech enterprises is particularly prominent. High-tech electronic enterprises need to effectively integrate environmental protection and social responsibility into their daily operations, as well as their management of supply chain operations.

Nowadays, protecting the environment has increasingly become a key consideration, affecting and restricting social and economic development. With the rapid development of human society and the economy, the living environment of the global human population has become increasingly seriously impacted, causing many social problems and posing a threat to the survival and development of human beings. Enterprises have also begun to study their own supply chains, in order to make them sustainable [2]. The term sustainable supply chain refers to the concept of integrating sustainable development into the entire supply chain, in order to achieve the coordinated optimization of economic, social and environmental benefits and ultimately achieve the sustainable development of the supply chain [3]. In a high-tech product supply chain, managers should give their full attention to managing the trade-off between profits and environmental performance.

Based on the diminishing value of high-tech electronic products and consumers' environmental awareness on the demand side, this paper comprehensively considers the hierarchical structure characteristics of the supply chain. Under a bi-level programming framework, the environmental issues, social performance and supply chain operation problems caused by high-speed product updates

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and high elimination rates in a high-tech supply chain are studied. Further, the impact of three carbon regulations (carbon taxes, carbon penalties and a combination of carbon regulations) and the social responsibility of supply chain members with regard to product pricing, ordering, carbon reduction efforts, and supply chain member profits are also investigated. In addition, the impact of the decline rate of high-tech electronic products on the above variables and supply chain members' profits are also analyzed.

The remainder of this paper is organized as follows: A three-part literature review is presented in Section 2. Section 3 introduces the preliminaries of a manufacture-guided bi-level model. The solution process of the solving method and model evaluation, respectively, are given in Sections 4 and 5. Finally, Section 6 summarizes the findings of the previous section.

II. LITERATURE REVIEW

This section focuses on a three-part literature review. The first part is related to sustainable supply chain management research; the second part examines pricing and ordering strategies, which are directly related to a company's profit. This includes high-tech product pricing and ordering issues. The third part relates to the main method of modeling, a bi-level programming technology-related overview.

A. Sustainable Supply Chain Management

With increasingly serious environmental problems being faced throughout society, the study of sustainable supply chains has received more and more attention in academia. Khan et al. [4] focused on the social dimension of sustainability by introducing information sharing in a two-level sustainable supply chain model. Bendul et al. [5] linked sustainable supply chain management discourse with insights from the Base of the Pyramid studies. Acquaye et al. [6] presented a robust environmental sustainable performance measurement model, underpinned by industrial lifecycle thinking. Ding et al. [7] developed a model to investigate the opportunity to outsource a pollutant-reduction service. Raj et al. [8] studied the coordination issues of a sustainable supply chain that arise due to the simultaneous consideration of greening and corporate social responsibility initiatives. Sang [9] studied the impact of a manufacturer's social responsibility with regard to pricing and green level decision-making. The study points out that the manufacturer's social responsibility is directly proportional to the greening level of the product and inversely proportional to the retail price of the product. Employing a SEM analysis, Jadhav et al. [10] found that the orientation construct of supply chain collaboration and communication could directly affect both environmental and social sustainability performance.

B. Pricing and Replenishment Problems

As two of the most important topics of business and academic researches [11], many scholars have made many contributions to the study of pricing and replenishment problems. Li et al. [12] studied a joint pricing, replenishment and preservation technology investment problem for non-instantaneous deteriorating items. Özelkan et al. [13] investigated the reverse bullwhip effect in joint replenishment and pricing decisions by using a leader-follower game theoretical framework. Mohr [14] focused on finding optimal replenishment decisions without having complete price information available at the outset by using online algorithms. Considering that replenishment intervals are probabilistic, as well as partial backordering, Taleizadeh et al. [15] developed an inventory control model to determine the optimum amount of replenish-up-to level in special sales offers. Wang and Choi [16] considered the lot sizing optimization of carbon management in a manufacturing industry, so as to help enterprises achieve economic benefits and reduce the ecological deterioration caused by carbon emissions. Hezarkhani et al. [17] and Nouri et al. [18] also focused on pricing or replenishment problems under different perspectives by using different methods.

Compared with other products, high-tech products have the characteristics of high-tech content, high income and high risk. As such, these products are facing more intense market competition and pricing environments than other products in the trading process. Rapid technological innovation has led to significant declines in spare parts costs, sales prices and demand. Therefore, it is particularly important to formulate appropriate pricing and ordering strategies for high-tech enterprises. Thus far, few studies have been conducted that examine pricing and replenishment models of high-tech products. Yang et al. [1] established a collaborative pricing and replenishing model with a finite horizon when the vendor's purchase cost and the end-consumer's market price are reduced simultaneously. Then, Yang et al. [19] developed an economic order quantity model with a finite planning horizon for a buyer. Based on the model proposed in [1], Gao et al. [20] employed a bi-level programming technical model to analyze the pricing problems of hi-tech products.

However, most of the above literatures' efforts are purely focused on pricing or ordering issues; they are not linked to environmental and social performance in sustainable supply chains. Few have considered pricing and replenishment strategies for high-tech products, and the common modeling methods are integrated, while the hierarchical characteristics of the supply chain are ignored.

C. Bi-level Programming

Bi-level programming is a system optimization problem with a hierarchical structure, which is motivated by game theory [21]. Bi-level programming techniques have been remarkably successful when applied to many fields, such as scheduling problems [22-24], traffic and location problems [25-27], finance [28] and energy [29]. Zhou et al. [30] established a new bi-level data envelopment analysis model with multiple followers. The model was solved by using the extended Kuhn-Tucker condition. Safay et al. [31] adopted a comprehensive optimization method and TOPSIS method to establish a robust bi-level optimization model for a supply distribution relief network. Xu and Li [32] re-formulated a two-layer nested structure bi-level programming as a single-level optimization problem by using conversion strategies. Wei et al. [33] proposed a bi-level scheduling model for virtual power plants, based on static and dynamic aggregation methods.

Considering the above researches in hi-tech pricing and replenishment policies in supply chains, this paper fills the following gaps in literature:

(i) This paper integrates a bi-level programming technique and the parameters of social and environmental sustainability to high-tech electronic product pricing and ordering modeling.

(ii) The significance of the environmental and social costs for high-tech electronic product pricing, carbon reduction efforts and supply chain members' profits are highlighted.

(iii) Different carbon emission reduction mechanisms for hi-tech electronic product pricing, carbon reduction efforts and supply chain members' profits are also highlighted.

III. MATHEMATICAL MODEL DESCRIPTION

This paper considers a two-echelon high-tech electronic product supply chain system, with a single manufacturer and single retailer. In this system, the decision and the manufacturing process are depicted as follows:

The manufacturer purchases parts from the supplier, and sells the final product to the retailer at the wholesale price after processing. The retailer sets the retail price to sell the product to the consumer, in order to maximize its own profits. In the whole process, the value of components and final products will decrease in time at a certain rate. Therefore, manufacturers and retailers should consider the impact of this decline rate on their own profits in the process of formulating strategies, so as to make pricing and ordering decisions that will maximize their respective profits. Besides considering the initial price and the order cycle, manufacturers also need to determine their respective environmental measures (such as recycling and remanufacturing) and develop low-carbon products, in order to assume environmental responsibility.

In this paper, the model is established based on the following assumptions. (1) The planning horizon is finite, and there is no shortage; the purchase lead-time is constant. (2) The replenishment rates of the manufacturer and the retailer are instantaneous, and the time interval for each order is the same. (3) The cost of component purchasing, the wholesale price and the retail price of the product continue to decline in unit time.

Tables 1 and 2 describe the notations used in the mathematical model.

In the following subsections, we illustrate in detail the decision problems and the constraints of the supply chain members.

A. *The Manufacturer's Total Profit*

The demand rate depends on the initial selling price and green innovation expenditure according to:

$$d\left(p_{r0},e\right)=r\cdot p_{r0}^{-m}\cdot e^{n} \tag{1}$$

Here, we assume that the demand function $d\left(p_{r0},e\right)$ is a joint non-linear function of the initial selling price (p_{r0}) and green innovation expenditure (e). For this hypothesis, please refer to [34].

Due to the manufacturer's purchase costs declining at a continuous rate of d_m, his/her unit purchase cost is $p_{s0}(1-d_m)^{iT/\beta}$ ($i=0,1,\Lambda,\beta-1$). The manufacturer-retailer-combined average inventory level is $\alpha Q/2$; the retailer's average inventory level is $Q/2$, and the manufacturer's average inventory level is $(\alpha-1)Q/2$. Therefore, the total hosting cost with the manufacturer in the planning horizon can be calculated as follows:

$$H_{cm}=\frac{c_{hm}T}{\beta}\sum_{i=0}^{\beta-1}p_{s0}(1-d_m)^{iT/\beta}\frac{(\alpha-1)Q}{2} \tag{2}$$

The unit product cost function of the manufacturer is

$$M_c=m_c+(1-\eta)\theta e^2 \tag{3}$$

where m_c indicates the conventional unit manufacturing cost, θ denotes the cost factor associated with emission reduction expenditures, and η represents the proportion of the emission reduction cost shared by the retailer, $0\le\eta<1$; similar cost functions can be found in [35]. Carbon emission costs incurred by the manufacturer during the production process can be calculated by the following formula:

$$E_{mc}=ETdC_{ec}+\sum_{i=1}^{n}Y_iC_{ep,i} \tag{4}$$

$$E=aR^2-bR+c \tag{5}$$

$$Y_i=\begin{cases}1 & if\ ETd>E_{li}\\ 0 & else\end{cases},\ where\ i=1,2,\Lambda,n \tag{6}$$

$$\rho Td\le R\le R_{\max} \tag{7}$$

where, $\rho\ge 1$, $R_{\max}\le 1.5Td$. For similar computational methods, please refer to [36].

As shown in [3], the manufacturer's social cost mainly includes four aspects: labor, health services, safety and philanthropy. This social cost can be derived from the following formula:

$$S_{cm}=\alpha\beta QS_m \tag{8}$$

Table 1. Decision variables

Manufacturer's decision variables	Retailer's decisions variables
β: Number of orders from the supplier to the manufacturer in the planning horizon	α: Number of orders from the manufacturer to the retailer per manufacturer's lot size
p_{m0}: The retailer's initial unit purchase price	p_{r0}: Initial selling price charged by the retailer
e: The manufacturer's environmental improvement	Q: Order quantity from the manufacturer to the retailer

Table 2. Notations

Parameter definitions
T : Monthly length of the planning horizon
d : Monthly demand rate
r : Scaling factor of demand function ($r>0$)
m : Price elasticity coefficient of demand function ($m>1$)
n : Elasticity coefficient of environmental improvement by the manufacturer ($0<n<1$, $n+1<m$)
d_m : Monthly decline rate of the manufacturer's purchase cost
d_r : Monthly decline rate of the retailer's purchase cost
d_p : Monthly decline rate of market price to the end consumer
p_{s0} : Manufacturer's initial unit purchase price
c_{hm} : Manufacturer's inventory holding cost per dollar per month
c_{hr} : Retailer's inventory holding cost per dollar per month
O_m : Manufacturer's ordering cost (\$/order)
O_r : Retailer's ordering cost (\$/order)
f_{sm} : Manufacturer's fixed ordering or setup cost (\$/year)
f_{sr} : Retailer's setup cost (\$/year)
E_m : Manufacturer's environmental cost parameter
E_r :Retailer's environmental cost parameter
S_m : Manufacturer's social cost parameter
S_r : Retailer's social cost parameter
m_c : Conventional unit production cost for manufacturer (\$/unit)
a : Emissions function parameter (ton·year2/unit3)
b : Emissions function parameter (ton·year/unit2)
c_{fp} : Transportation charge for a shipment of size Q (borne by the retailer)
l : Maximum truck load
t_c : Truck loading fee
R : Manufacturer's production rate (unit/year)
C_{ec} : Emissions tax (\$/ton)
$C_{ep,i}$: Emissions penalty for exceeding emissions limit i (\$/year)
E : Greenhouse gas (CO2) emissions (ton/unit)
E_{li} : Emissions limit i (ton/year)
π_M : Manufacturer's total profit
π_R : Retailer's total profit

Therefore, the manufacturer's total cost in the planning horizon is the sum of setup, purchase and production, ordering, emission and social costs and can be written as:

$$
\begin{aligned}
& TC_m(\beta, p_{m0}, e) \\
& = f_{sm} + \sum_{i=0}^{\mu-1} p_{s0}(1-d_m)^{iT/\beta} \lambda Q + m_c \alpha\beta Q + \frac{c_{hm} T(\alpha-1)Q}{2\mu} \sum_{i=0}^{\beta-1} p_{s0}(1-d_m)^{iT/\beta} \\
& \quad + \beta O_m + E_{mc} + \alpha\beta Q S_m
\end{aligned} \tag{9}
$$

The manufacturer's sales revenue in the planning horizon is expressed as:

$$
R_m = \sum_{i=0}^{\beta-1} \sum_{j=0}^{\alpha-1} p_{m0}(1-r_b)^{(i+j/\alpha)(T/\beta)} Q \tag{10}
$$

The manufacturer's total profit can be solved as the difference between total sales revenue and the above total cost as follows:

$$
\begin{aligned}
\pi_M(p_{m0}, \beta, e) = & \sum_{i=0}^{\beta-1} \sum_{j=0}^{\alpha-1} p_{m0}(1-r_b)^{(i+j/\alpha)(T/\beta)} Q - f_{sm} - \sum_{i=0}^{\beta-1} p_{s0}(1-d_m)^{iT/\beta} \alpha Q \\
& - m_c \alpha\beta Q - (1-\eta)\theta e^2 \alpha\beta Q - \frac{c_{hm} T(\alpha-1)Q}{2\beta} \sum_{i=0}^{\beta-1} p_{s0}(1-d_m)^{iT/\beta} \\
& - \beta O_m - E_{mc} - \alpha\beta Q S_m
\end{aligned} \tag{11}
$$

The constraints faced by the remanufacturer would include a production budget constraint B_m, price constraint and the positive integer constraint of order number; these are expressed as:

$$
\begin{cases}
M_c \cdot T \cdot d(p_{r0}, e) \le B_m \\
p_{s0} + M_c < p_{m0} < p_{r0} - \dfrac{c_{fp}(Q)}{Q} \\
\beta \in N^+
\end{cases} \tag{12}
$$

B. The retailer's Total Profit

Due to the retailer's purchase cost declining at a continuous rate of d_r, his/her unit purchase cost is: p_{m0}, $p_{m0}(1-d_r)^{T/\alpha\beta}$, $p_{m0}(1-d_r)^{2T/\alpha\beta}$, …, $p_{m0}(1-d_r)^{(\beta-1+((\alpha-1)/\alpha))T/\beta}$. The retailer's total hosting cost in the planning horizon is:

$$H_{c_r} = \frac{c_{hr}T}{\alpha\beta}\left(\left(\sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}\right)+\frac{c_{fp}(Q)}{Q}\right)\frac{Q}{2} \qquad (13)$$

The retailer's total cost is comprised of eight aspects: setup, purchase, holding, ordering, transportation, emission and social costs, and cost-sharing related to green innovation. The retailer's carbon emission cost mainly occurs in the transportation and storage of products, while the social cost is for their workers. Based on the above analysis, the retailer's total cost is calculated as follows:

$$\begin{aligned} &TC_r \\ &= f_{sr} + \sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}Q \\ &+ \frac{c_{hr}T}{\alpha\beta}\left(\left(\sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}\right)+\frac{c_{fp}(Q)}{Q}\right)\frac{Q}{2} \\ &+ \lambda\mu(O_r + c_{fp}(Q)) + \alpha\beta Q(E_r+S_r) + \eta\theta e^2\alpha\beta Q \end{aligned} \qquad (14)$$

Similarly, the retailer's total profit would be the difference between the revenue he/she receives from selling products to customers, and his/her total cost is:

$$\begin{aligned} \pi_R(p_{r0},\alpha) = &\int_0^T \left(p_{r0}(1-d_p)^t\right) d\,dt - f_{sr} - \sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}Q \\ &- \frac{c_{hr}T}{\alpha\beta}\left(\left(\sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}\right)+\frac{c_{fp}(Q)}{Q}\right)\frac{Q}{2} \\ &- \alpha\beta(O_r + c_{fp}(Q)) - \alpha\beta Q(E_r+S_r) - \eta\theta e^2\alpha\beta Q \end{aligned} \qquad (15)$$

The constraints faced by the retailer would include a marketing expenditure budget constraint B_r, a selling price constraint and the positive integer constraint of order number. These constraints are written as:

$$\begin{cases} \eta\theta e^2 \cdot T \cdot d(p_{r0},e) \le B_r \\ p_{r0} > p_{m0} + \dfrac{c_{fp}(Q)}{Q} \\ \alpha \in N^+ \end{cases} \qquad (16)$$

C. The Manufacturer-Guided Model

According to the characteristics of the hierarchical structure of a supply chain, a manufacturer-led two-level programming model will be constructed by using bi-level programming technology (the model and related concepts of bi-level programming problem can be seen in Appendix A). In this paper, we give priority to the interests of the manufacturer, so we regard the manufacturer as a leader and the retailer as a follower. In the bi-level model, the manufacturer determines p_{m0}, β and e at the upper level, subject to his/her own constraints. Then, the retailer reacts by choosing the optimal p_{r0} and α at the lower level. Based on the above equations displayed in Sections 3.1 and 3.2, the manufacturer-guided model can be presented as follows:

$$\begin{aligned} \max\ \pi_M(p_{m0},\beta,e) = &\sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-r_b)^{(i+j/\alpha)(T/\beta)}Q - f_{sm} - \sum_{i=0}^{\beta-1} p_{s0}(1-d_m)^{iT/\beta}\alpha Q \\ &- m_c\alpha\beta Q - (1-\eta)\theta e^2\alpha\beta Q - \frac{h_m T(\alpha-1)Q}{2\beta}\sum_{i=0}^{\beta-1} p_{s0}(1-d_m)^{iT/\beta} \\ &- \beta O_m - E_{mc} - \alpha\beta Q S_m \end{aligned}$$

$$\begin{aligned} &\textit{subject to} \\ &\quad M_c \cdot T \cdot d(p_{r0},e) \le B_m, \\ &\quad p_{s0} + M_c < p_{m0} < p_{r0} - e - \frac{c_{fp}(Q)}{Q}, \\ &\quad \beta \in N^+. \end{aligned}$$

where p_{r0} *and* λ *are solved by the following problem*

$$\begin{aligned} \max\ \pi_R(p_{r0},\alpha) = &\int_0^T \left(p_{r0}(1-d_p)^t\right) d\,dt - f_{sr} - \sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}Q \\ &- \frac{h_r T}{\alpha\beta}\left(\left(\sum_{i=0}^{\beta-1}\sum_{j=0}^{\alpha-1} p_{m0}(1-d_r)^{(i+j/\alpha)(T/\beta)}\right)+\frac{c_{fp}(Q)}{Q}\right)\frac{Q}{2} \\ &- \alpha\beta(O_r + c_{fp}(Q)) - \alpha\beta Q(E_r+S_r) - \eta\theta e^2\alpha\beta Q \end{aligned}$$

$$\begin{aligned} &\textit{subject to} \\ &\quad \eta\theta e^2 \cdot T \cdot d(p_{r0},e) \le B_r \\ &\quad p_{r0} > p_{m0} + e + \frac{c_{fp}(Q)}{Q}, \\ &\quad \alpha \in N^+. \end{aligned} \qquad (17)$$

In Equation (17), the relationship between the order quantity and order number is $Q = Td/\alpha\beta$, and $c_{fp}(Q)$ is calculated as $c_{fp}(Q) = \lceil Q/l \rceil t_c$ (a similar assumption can be found in [37]). The manufacturer-leader bi-level model presented above is an NP-hard problem and difficult to resolve using the classical method. Unlike the traditional optimization methods, an intelligent optimization algorithm is a kind of algorithm that has global optimization performance, strong universality and is suitable for parallel processing. This algorithm contains a differential evolution algorithm, ant colony optimization algorithm, particle swarm optimization algorithm, cuckoo search algorithm and so on. These algorithms have been successfully applied to various fields, because of their unique advantages [38, 39]. To tackle the proposed problem (17), an improved intelligent algorithm will be employed in Section IV to find the quasi-optimal solutions of the problem.

IV. SOLUTION FRAMEWORK OF THE PROPOSED MODEL

Differential evolution algorithm (DE) is a typical intelligent algorithm with many attractive characteristics [40]. A basic DE algorithm mainly contains the following steps: initialization, mutation, crossover and selection, and DEs have been successfully applied to many fields of science and engineering [41].

In this section, we employ a hierarchical DE-based algorithm with an exponential non-linear incremental crossover rate (HEDE) to find the solutions of the proposed model. In order to describe the HEDE process for solving Model (17) more intuitively, the pseudo codes of the algorithm are given in Table 3 and Table 4.

In Tables 3 and 4, the crossover rate *CR* plays an important role in the performance of the DE algorithm. Due to the fixed value *CR* easily leading to the algorithm falling into local extremum, we adopted an exponential non-linear incremental crossover rate *CR* to accelerate the convergence speed, maintain the diversity of population and avoid premature convergence.

$$CR = CR_{\min} + (CR_{\max} - CR_{\min}) * \exp\left(-u * (1 - t / T\max)^{v}\right) \quad (18)$$

where u and v are constants, and the values of u and v depend on the size of the problem itself. The crossover probability can balance the global search ability and the local search ability, and cause the algorithm to quickly converge to the best solution.

Table 3. The pseudo code of HEDE for solving Model (17)

Algorithm 1

Step 1. Initialization: population size N_U and N_L; the dimension of the decision variables of the upper and lower level problem D_U and D_L; maximum iterations $T_{\max U}$ and $T_{\max L}$; scaling factor F; upper and lower limits of crossover rate $CR_{\max}$ and $CR_{\min}$; penalty factor M; upper level decision variable's upper and lower bounds: x_{dupper} and x_{dlower}; lower level decision variable's upper and lower bounds: y_{dupper} and y_{dlower}.

Step 2. While ($t \le T_{\max U}$) do

Step 3. For $i = 1 : N_U$ do

Step 4. For $d = \{1, 2, \Lambda, D_U\}$, generate the ith initial position $x_{id}(t)$ of $x_i = \{p_{m0}, e, \beta\}_i$ by a random function as follows:

$$x_{id}(t) = x_{dlow} + rand * (x_{dupp} - x_{dlow})$$

Step 5. Set $x_{bestd}(t) = x_{1d}(t)$.

Step 6. For every given x_{igiven}, adopt algorithm DEL to solve the lower level problem. Then output the lower level problem's best-found solution $y^* = DE_L(x_{given}, y_i)$. (The pseudo of DE_L is given in Table 4).

Step 7. The i_{th} individual's fitness value is calculated as follows:

$$fitness_U(x_i(t), y^*) = F_U(x_i(t), y^*)$$
$$= -\pi_M(x_i(t), y^*) + M \cdot \sum_{k=1}^{p} \left(\max\{G_{Uk}(x_i(t), y^*), 0\}\right)^2$$

Step 8. Update x_{bestd} according to :

if $F_U(x_{best}(t), y^*) > F_U(x_i(t), y^*)$, then $x_{best}(t) = x_i(t)$

Step 9. Update the ith individual's position by the following equations:

Step 9.1. Mutation ("DE/current-to-best/2"):

$$v_{xid}(t) = x_{id}(t) + F \cdot (x_{bestd}(t) - x_{id}(t)) + F \cdot (x_{r_1 d}(t) - x_{r_2 d}(t)) + F \cdot (x_{r_3 d}(t) - x_{r_4 d}(t))$$

Step 9.2. Crossover:

$$u_{xid}(t) = \begin{cases} v_{xid}(t), & \text{if } \mathrm{rand}[0,1] \le CR \text{ or } d = d_{rand} \\ x_{id}(t), & \text{otherwise} \end{cases}$$

Step 9.3. Selection :

$$x_i(t+1) = \begin{cases} x_i(t), & \text{if } F_U(x_i(t), y^*) < F_U(u_{xi}(t), y^*) \\ u_{yi}(t), & \text{otherwise} \end{cases}$$

Step 10. $t = t + 1$

Step 11. End for

Step 12. Break

Step 13. Output the best-found solution $(x^*, y^*) = (p^*_{m0}, e^*, \beta^*, p^*_{r0}, \alpha^*)$

Table 4. The pseudo of DE_L for solving the lower level problem of Model (17)

DE_L

Step 1. While ($t \le T_{\max L}$) do

Step 2. For $i = 1 : N_L$ do

Step 3. For $d = \{1,2,\Lambda, D_L\}$, generate the i_{th} initial position $y_{id}(t)$ of $y_i = \{p_{r0}, \alpha\}_i$ by a random function as follows:

$$y_{id}(t) = y_{dlow} + rand * (y_{dupp} - y_{dlow})$$

Step 4. Set $y_{bestd}(t) = y_{1d}(t)$.

Step 5. For x_{given} proposed in Algorithm 1, the i_{th} individual's fitness value can be calculated as follows:

$$fitness_L(x_{given}, y_i(t)) = F_L(x_{given}, y_i(t))$$

$$= -\pi_R(x_{given}, y_i(t)) + M \cdot \sum_{k=1}^{q} (\max\{G_{Lk}(x_{given}, y_i(t)), 0\})^2$$

Step 6. Update y_{bestd} according to:

if $F_L(x_{given}, y_{best}(t)) > F_L(x_{given}, y_i(t))$, then $y_{best}(t) = y_i(t)$.

Step 7. Generate the next generation population $y_{i+1}(t+1)$ according to the lower level problem's related parameters ($T_{\max L}$, $y_{r_1}(t)$, $y_{r_2}(t)$, $y_{r_3}(t)$, $y_{r_4}(t)$) and Step 9 of Algorithm 1.

Step 8. $t = t + 1$.

Step 9. End for

Step 10. Break

Step 11. Output $y^* = y_{best}$.

Table 5. Input parameters for numerical example

p_{s0}	r	m	n	c_{hm}, c_{hr}	f_{sm}, f_{sr}	O_m	O_r	B_m	B_r
200	10^6	1.5	0.3	0.001	200	2000	100	500000	50000
T	t_c	l	m_c	θ	a	b	c	ρ	E_{li}
12	200	500	200	2.0	3×10^{-7}	0.0012	1.4	120%	220

Table 6. Parameters setting of HEDE

N	$T_{\max U}$	$T_{\max L}$	F	$CR_{\max}$	$CR_{\min}$	u	v	M
45	1000	1000	0.5	0.6	0.2	50	5	10^8

V. MODEL EVALUATION AND MANAGERIAL INSIGHTS

In the previous section, a mathematical bi-level model that considers carbon emissions as well as emissions penalties and emissions taxes, and an interactive hierarchical DE algorithm, were proposed in a manufacturer-guided supply chain system. In this section, we intend to answer the four research questions proposed in Section 1. Tables 5 and 6, respectively, give the parameter settings of the proposed model and HEDE.

A. Sensitivity Analysis of Carbon Taxes and Emission Penalty

This section studies the influences of three carbon regulation strategies on pricing, ordering decisions, and manufacturers' carbon reduction efforts decisions, as well as the manufacturer's and retailer's profits.

Related parameters in this section are set as: $E_r = 200$, $S_m = S_r = 0.5$, $\eta = 0.4$, $d_p = d_r = d_m = 0.005$. Related results are shown in Tables 7-9, and corresponding figures are exhibited in Figures 1 and 2.

The three tables (Tables 7-9) and two figures (Figures 1 and 2) indicate that:

(i) When not considering the cost of a carbon emissions penalty, as the carbon tax C_{ec} increases, even though product prices and manufacturers' efforts to reduce emissions are rising, the profits of the supply chain members are decreasing.

(ii) As the carbon penalty cost C_{ep} increases, product prices and manufacturers' efforts to reduce emissions are decreasing, but the profits of supply chain members are increasing without considering the carbon tax.

(iii) When the costs of the carbon tax and carbon emissions penalty increase, the trends of product price, manufacturer's carbon emissions reduction efforts and members' profits are the same as Scenario 1 ($C_{ep} = 0$, and C_{ec} increases). This finding indicates that, compared with a carbon emissions penalty strategy, a change in carbon tax rates has a greater impact on the decision variables and member profits.

Table 7. Impact of a carbon tax system with no emissions penalty ($C_{ep} = 0$)

C_{ec}	p_{m0}	β	e	p_{r0}	α	π_M	π_R
18	1805.2	1	23.5	1887.8	1	5.1851e+005	6.5218e+005
28	1878.9	1	24.3	1952.4	1	5.1057e+005	6.4897e+005
38	2043.1	2	25.8	2121.2	1	5.0767e+005	6.3699e+005
48	2170.2	2	27	2251.8	1	5.0421e+005	6.2826e+005
58	2287.0	2	28	2371.8	1	5.0055e+005	6.2061e+005

Table 8. Impact of an emissions penalty with no carbon taxes ($C_{ec} = 0$)

C_{ep}	p_{m0}	β	e	p_{r0}	α	π_M	π_R
1000	2572.6	2	30.5	2664.8	2	5.0602e+005	6.0337e+005
2000	2190.0	1	27.2	2272.2	2	5.1656e+005	6.2694e+005
3000	1984.9	1	25.3	2061.4	2	5.1702e+005	6.4114e+005
4000	1941.9	1	24.9	2017.2	1	5.2631e+005	6.4427e+005
5000	1886.8	1	23.9	1943.2	1	5.2941e+005	6.4714e+005

Table 9. Impact of a combination of a carbon tax and emissions penalty

C_{ec} , C_{ep}	p_{m0}	β	e	p_{r0}	α	π_M	π_R
18, 1000	2244.2	1	27.6	2328.0	2	5.1157e+005	6.2335e+005
28, 2000	2300.3	1	28.1	2385.5	2	5.0689e+005	6.1950e+005
38, 3000	2336.2	1	28.5	2422.3	2	5.0287e+005	6.1750e+005
48, 4000	2622.5	1	30.9	2716.2	2	4.9538e+005	6.0035e+005
58, 5000	2732.7	1	31.8	2829.3	2	4.9033e+005	5.9442e+005

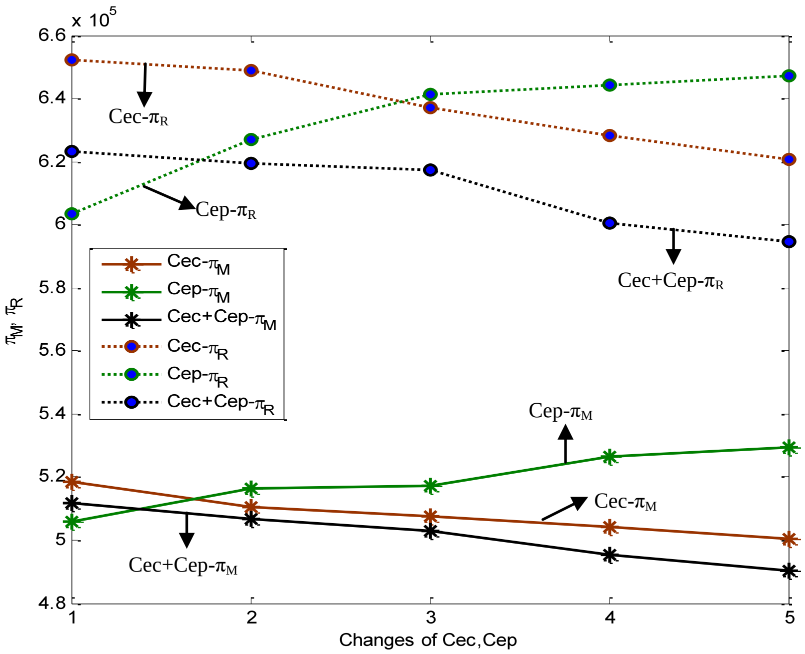

Figure 1. The impacts of three different carbon regulations on the profits of the manufacturer and the retailer

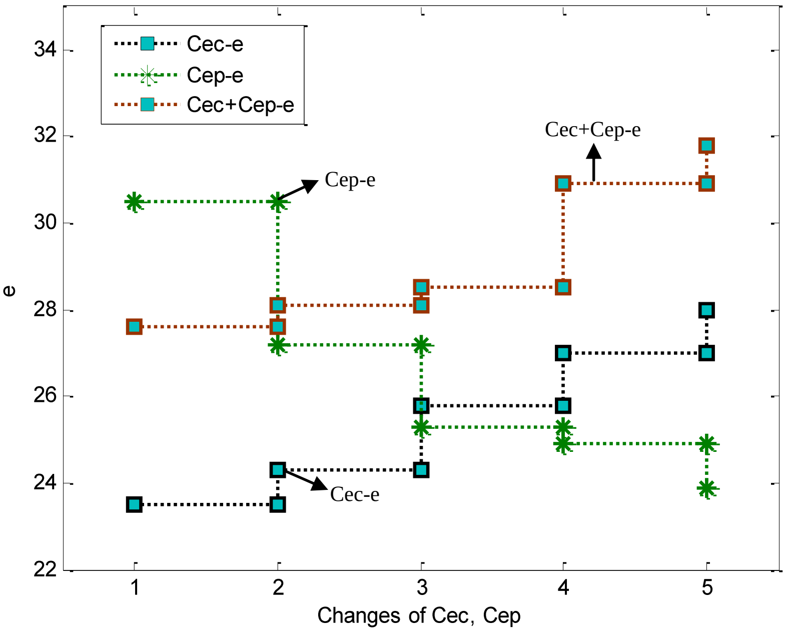

Figure 2. The impacts of three different carbon regulations on the environmental protection effort of the manufacturer

B. Sensitivity Analysis of Joint Emission Reduction Mechanism

In this section, we try to answer the following two questions: What percentage of the abatement costs that a retailer is responsible for is most beneficial to their respective profits? How does cooperation between a manufacturer and a retailer impact the generation of carbon emissions in a supply chain?

Related parameters in this section are set as: $C_{ec}=18$, $C_{ep}=1000$, $E_r=200$, $S_m=S_r=0.5$, $d_p=d_r=d_m=0.005$. The results are given in Table 10, and corresponding figures are shown in Figures 3 and 4.

From Table 10 and Figure 3, we can see that, when the retailer's emission reduction sharing coefficient is less than or equal to 0.4 ($\eta \le 0.4$). That is, when the retailer bears a small part of the abatement cost, the joint emissions reduction can increase the profit of each member of the supply chain, based on the lower product price. This scenario is also conducive to reducing the cost of carbon abatement in the supply chain. When the manufacturer foists most of the carbon abatement costs on the retailer ($\eta > 0.4$), this will increase the cost of abatement and increase the price of the product, but the profits of all supply chain members will fall. In addition, Figure 4 indicates that the degree of the manufacturer's emissions reduction efforts has also shown a trend of decreasing first and then increasing in line with the increase of η, and the retailer's higher carbon abatement cost could help reduce the carbon emissions of each unit product.

Table 10. Impact of the retailer's carbon emissions reduction ratio

η	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0	2244.2	1	27.6	2328.0	2	5.1157e+005	6.2335e+005
0.2	2003.7	1	25.5	2080.7	2	5.1340e+005	6.3954e+005
0.4	1988.1	1	25.3	2064.7	2	5.1365e+005	6.4037e+005
0.5	2090.0	1	25.9	2163.5	2	5.1352e+005	6.3119e+005
0.6	2120.6	1	26.5	2200.9	2	5.1348e+005	6.3073e+005
0.8	2200.0	1	27.3	2282.4	2	5.1324e+005	6.2509e+005
1.0	2774.7	1	32.1	2872.0	2	5.0560e+005	5.9017e+005

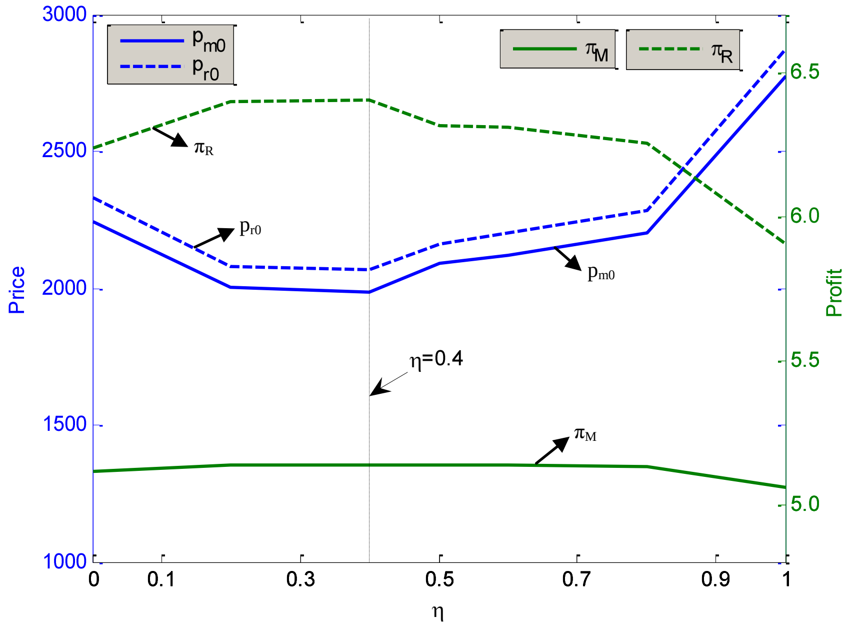

Figure 3. The impact of carbon emission reduction ratio on the initial product price and on the profits of the manufacturer and the retailer

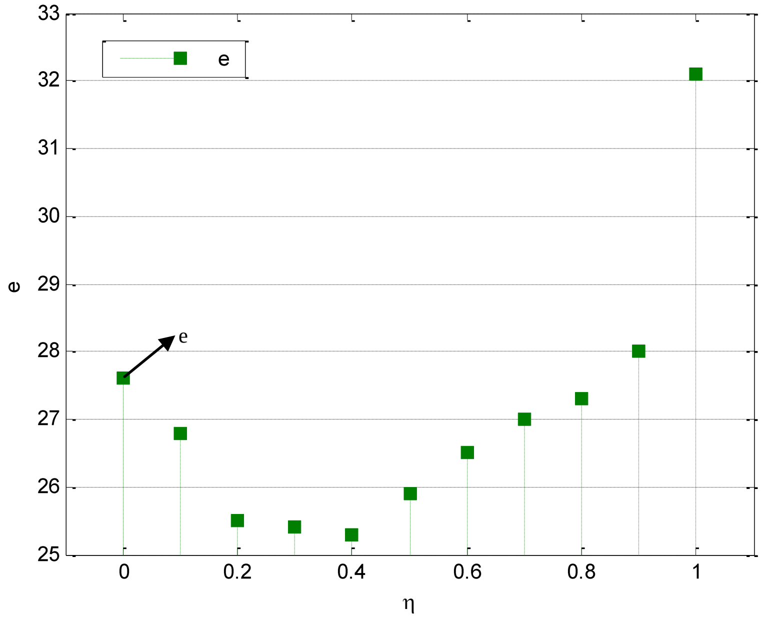

Figure 4. The impact of carbon emission reduction ratio on the environmental protection effort of the manufacturer

C. Sensitivity Analysis of Sustainable Factors

This section will discuss the impact of three sustainable factors (the retailer's environmental cost E_r, the manufacturer's social welfare cost S_m and the retailer's social welfare cost S_r) on decision variables and supply chain members' profits. Other related parameters in this section are set as: $C_{ec} = 18$, $C_{ep} = 1000$, $\eta = 0.4$, $d_p = d_r = d_m = 0.005$. The results are given in Tables 11-13, and corresponding figures are shown in Figures 5 and 6.

Table 11. Impact of retailer's environmental cost ($S_m = S_r = 0.5$)

E_r	p_{m0}	β	e	p_{r0}	α	π_M	π_R
200	1.9524	1	25	2.0280	2	5.1367e+005	6.0850e+005
400	1990.4	1	25.4	2068.0	2	5.1365e+005	5.3950e+005
600	1.9916	1	25.4	2.0682	2	5.1366e+005	4.7188e+005
800	1.9925	1	25.4	2.0692	2	5.1367e+005	4.1837e+005
1000	1998.6	1	25.6	2078.4	2	5.1365e+005	3.3907e+005

Table 12. Impact of retailer's social cost ($E_r = 200, S_m = 0.5$)

S_r	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0.2	2.6850	1	31.4	2.7801	2	5.0597e+005	5.0426e+005
0.4	2.3840	1	28.9	2.4714	2	5.1063e+005	5.0676e+005
0.6	2.1640	1	26.9	2.2454	2	5.1294e+005	5.0691e+005
0.8	2.1072	1	26.4	2.1871	2	5.1331e+005	5.0656e+005
1.0	2.0395	1	25.8	2.1175	2	5.1358e+005	5.0594e+005

Table 13. Impact of manufacturer's social cost ($E_r = 200, S_r = 0.5$)

S_m	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0.2	2.5975	1	30.7	2.6904	2	5.0751e+005	5.0513e+005
0.4	2.2805	1	28	2.3651	2	5.1190e+005	5.0706e+005
0.6	2.0308	1	25.7	2.1086	1	5.1275e+005	5.0601e+005
0.8	2.0189	1	25.6	2.0963	2	5.1353e+005	5.0587e+005
1.0	1.9960	1	25.4	2.0716	2	5.1397e+005	5.0567e+005

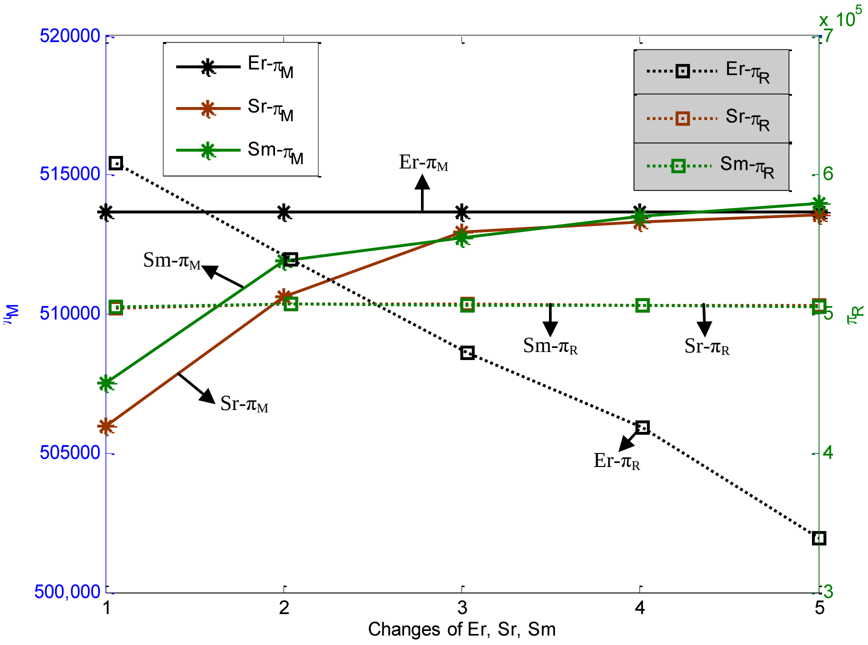

Figure 5. The impacts of E_r , S_r and S_m on the profits of the manufacturer and the retailer

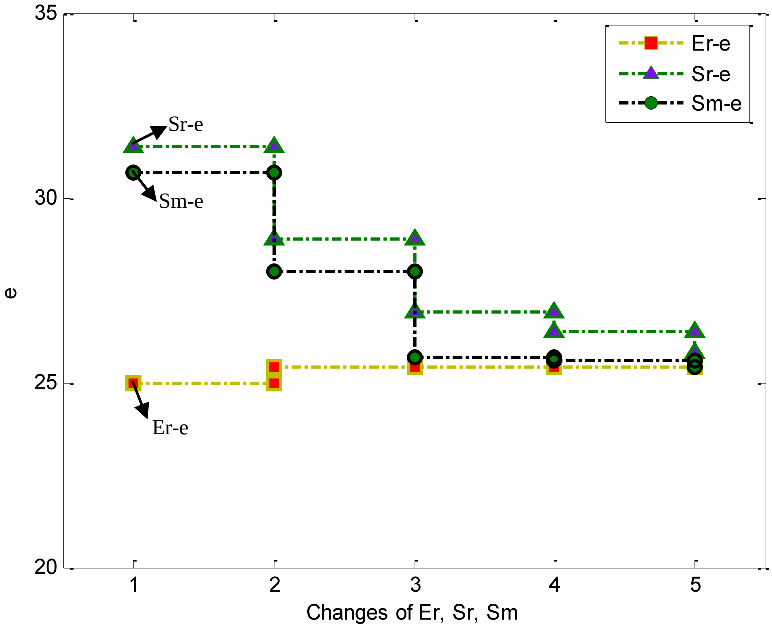

Figure 6. The impacts of E_r, S_r and S_m on the environmental protection effort of the manufacturer

Figures 5 and 6 show that, as the retailer's environmental cost (E_r) increases, the retailer's profit decreases. However, the product price, green innovation expenditure and manufacturer's profit remain almost unchanged, thereby indicating that E_r only affects the retailer's profit. As the retailer's social cost (S_r) and manufacturer's social cost (S_m) both increase, product prices (initial wholesale price and initial selling price) and green innovation expenditure all show a downward trend; the manufacturer's profit also shows a slight upward trend, while the retailer's profit is almost unchanged. This finding indicates that social costs will have a certain impact on product prices, green innovation expenditure and the leader's profit in a supply chain.

D. Sensitivity Analysis of Decreasing Attributes

This section aims to answer the following question: For the depreciation attribute of high-tech products, which factor (decreasing attributes of components purchase cost, product wholesale price and product retail price) has a greater impact on supply chain members' profits and carbon emission reduction efforts?

Related parameters settings are: $C_{ec} = 18$, $C_{ep} = 1000$, $E_r = 200$ $S_m = S_r = 0.5$, and $\eta = 0.4$. The results are given in Tables 14-16, and the corresponding figures are shown in Figures 7 and 8.

Table 14. Impact of monthly decline-rate of market price on the end-consumer ($d_r = d_m = 0.005$)

d_p	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0.2	1.9524	1	25	2.0280	2	5.1367e+005	6.0850e+005
0.4	1989.8	1	25.8	2073.9	2	5.1364e+005	5.8912e+005
0.6	2.0618	1	26	2.1400	2	5.1365e+005	5.6437e+005
0.8	2144.6	1	26.5	2219.6	2	5.1367e+005	5.4151e+005
1.0	2150.9	1	26.9	2231.7	2	5.1363e+005	5.2531e+005

Table 15. Impact of monthly decline-rate of the wholesale price ($d_p = d_m = 0.005$)

d_r	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0.2	1952.4	1	25	2028.0	2	5.1367e+005	6.0850e+005
0.4	2186.6	1	27.1	2268.7	2	5.0326e+005	5.9662e+005
0.6	2201.8	1	27.4	2300.9	2	4.8929e+005	5.9507e+005
0.8	2239.2	1	27.6	2322.7	2	4.8483e+005	5.9411e+005
1.0	2290.0	1	28.8	2379.6	2	4.7818e+005	5.9586e+005

Table 16. Impact of the monthly decline-rate of the component purchase costs($d_p = d_r = 0.005$)

d_m	p_{m0}	β	e	p_{r0}	α	π_M	π_R
0.2	1952.4	1	25	2028.0	2	5.1367e+005	6.0850e+005
0.4	1969.5	1	25.1	2045.6	2	5.1364e+005	6.0760e+005
0.6	2081.7	1	26.2	2160.9	2	5.1341e+005	6.0192e+005
0.8	2129.7	1	26.6	2210.2	2	5.1314e+005	5.9948e+005
1.0	2.1310	1	26.6	2.2117	2	5.1311e+005	5.9941e+005

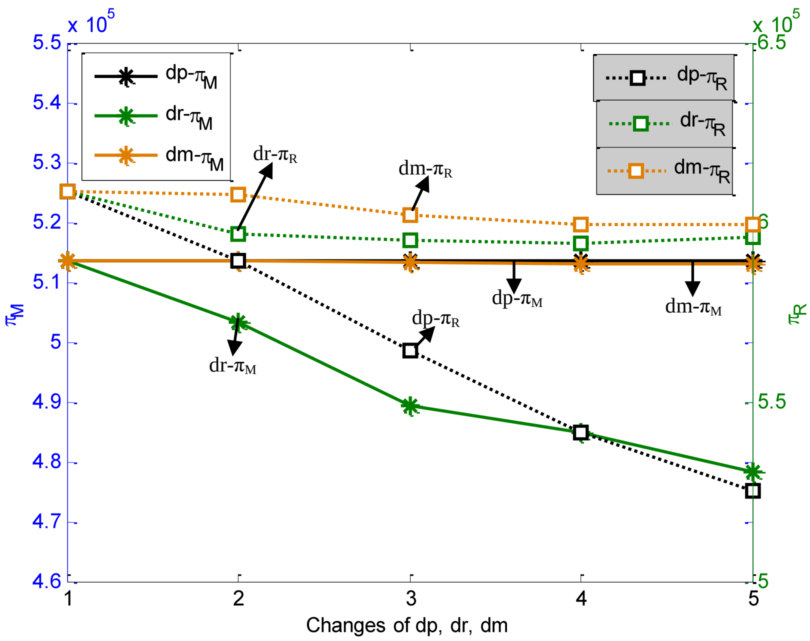

Figure 7. The impacts of d_p, d_r and d_m on the profits of the manufacturer and the retailer

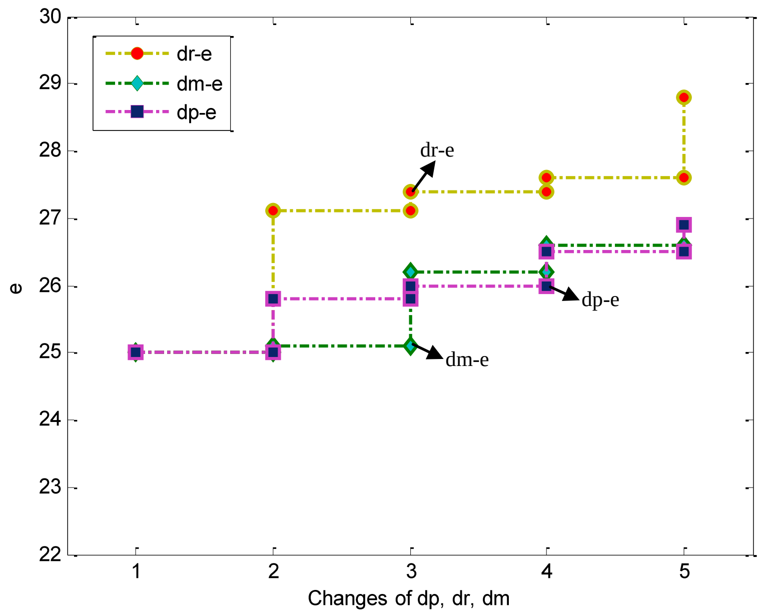

Figure 8. The impacts of d_p, d_r and d_m on the environmental protection effort of the manufacturer

Figure 7 indicates that, when d_p increases, the manufacturer's profit is almost unchanged, but the profit of the retailer is greatly reduced. This finding indicates that the increase in the finished product's selling price decline rate has a greater impact on the profit of the retailer. When d_r increases, the profit of the manufacturer is greatly reduced; meanwhile, the profit of the retailer remains almost unchanged. This indicates that an increase in the wholesale price decline rate of the product has a greater impact on the profit of the manufacturer. When d_m increases, the profits of both the manufacturer and retailer decrease slightly. This indicates that an increase in the rate of decline in parts purchase costs has a lesser impact on the profitability of supply chain members.

From the above three tables and Figure 8 we can see that, as d_p, d_r and d_m increase, the initial selling price of the product and the environmental protection effort of the manufacturer all show different degrees of increases. Also, when d_r changes, the increase is larger, which indicates that an increase in the wholesale price decline rate (d_r) has a greater impact on product price and manufacturer's environmental protection efforts than the other two parameters (d_p and d_m).

VI. CONCLUSION

This paper studies the sustainable development problem of a high-tech electronic product supply chain. Considering the hierarchical structure characteristics of the supply chain, we employ a bi-level programming technique to model the high-tech supply chain's operation problems. The paper's proposed DE-based hierarchical intelligent solution algorithms are also developed. Optimal pricing, ordering and green effort are derived. Then, we investigate the impacts of three different types of carbon regulations and the manufacturer's and retailer's social welfare costs on product pricing, ordering, carbon reduction efforts, and supply chain member profits. Finally, the impacts of price decline rates on the decision variables and supply chain members' profits are analyzed. Within our modelling framework, the computational analyses provide the following findings: Compared with a carbon emissions penalty strategy, the change in carbon taxes exhibits a greater impact on the decision variables and the profits of the supply chain members. Retailers shouldering a small part of the emission reduction costs will help increase the profits of supply chain members, while higher retailer carbon abatement costs could help reduce the carbon emissions of each unit product. The retailer's environmental cost only affects the retailer's profit, while both the retailer's and manufacturer's social costs clearly have important impacts on product price, carbon abatement costs, and the leader's profit in a supply chain. The wholesale price decline rate has a greater impact on product price and the manufacturer's environmental protection efforts than the component purchase cost decline rate and selling price decline rate.

This paper mainly investigates the high-tech sustainable supply chain operation problems with a single product under a deterministic environment. Further research can be extended to focus on the decision-making problems with multiple alternative products in a high-tech sustainable supply chain, by considering production uncertainty or demand uncertainty.

APPENDIX A

A bi-level programming model can be generally divided into upper and lower levels. The upper level is a compound optimization problem with lower level optimal decision variables (or optimal objective function values); the lower level is a parametric program with upper level decision variables as parameters.

Assuming $x \in R^{n_1}$, $y \in R^{n_2}$, $F_U, F_L : R^{n_1} \times R^{n_2} \to R$, $G_U, G_L : R^{n_1} \times R^{n_2} \to R$, we then have the general model of bi-level programming problem (BLPP)

$$\begin{aligned} &\min_{x\in X} \; F_U(x,y) \\ &\quad s.t. \;\; G_U(x,y) \le 0 \\ &\text{where, for given } x, \text{ the vector } y \text{ solves} \\ &\qquad \min_{y\in Y} F_L(x,y) \\ &\qquad\quad s.t. \;\; G_L(x,y) \le 0 \end{aligned} \tag{18}$$

where, x and y represent the upper and lower decision variables respectively. $F_U(x,y)$ and $F_L(x,y)$ denote the upper level objective function and the lower level objective function respectively, and $G_U(x,y) \le 0$ and $G_L(x,y) \le 0$ indicate corresponding upper and lower level constraints.

Note:

Constraint region $S = \{(x,y) \mid G_U(x,y) \le 0, G_L(x,y) \le 0\}$

For given $x \in R^{n_1}$, the feasible region of the lower level problem is $S(x) = \{y \mid G_L(x,y) \le 0\}$

The projection of constraint region S in the decision space of the upper problem is

$S(X) = \{x \mid \exists y, G_U(x,y), G_L(x,y) \le 0\}$

For $x \in S(X)$, the rational response set of the lower problem is

$P(x) = \{y \mid y \in \arg\min[F_L(x,y) \le 0 : y \in S(x)]\}$

The induction domain of the bi-level single objective programming problem is

$IR = \{(x,y) \mid (x,y) \in S, y \in P(x)\}$

The following definitions give the expression of the optimal solution of the bi-level programming problem.

Definition 1. If $(x,y) \in IR$, then (x,y) is called the feasible point of Problem (1).

Definition 2. For $\forall (x,y) \in IR$, if $(x^*, y^*) \in IR$, and $F_U(x^*, y^*) \le F_U(x,y)$, then (x^*, y^*) is called the optimal solution of Problem (18).

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