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Optimizing Joint Sustainable Supply Chain Decision-Making under Emission Tax: A Stackelberg game model

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Abstract - **In practice, manufacturers and retailers jointly make decisions by capitalizing on decision interactions while respecting the carbon emission tax and subsidy determined by local governments. Though studies have been published to address the joint decision-making, they involve only a very few of the important supply chain decisions due to the problem complexities. In this study, we investigate a comprehensive joint decision-making of a manufacturer and his independent retailer with considering both carbon emission tax and subsidy. Per the decision interactions, we analyze the decision-making of the manufacturer and the retailer as a Stackelberg game. The game model developed, by nature, is a mixed 0-1, non-linear, and bilevel programming. In view of its complexity, we further develop a nested genetic algorithm (NGA) to solve the model. Numerical examples demonstrate the applicability of the game model in facilitating supply chain members to jointly make decisions and the robustness of the NGA. With Sensitivity analysis, we shed light on several important managerial implications.**

Keywords – **Joint decision-making, Stackelberg game, Bilevel programming, Sustainable supply chain decisions**

I. INTRODUCTION

In recent decades, more and more greenhouse gas emissions (e.g., carbon dioxide) have been emitted, and the increasing emissions have caused severe environmental changes. Because of the negative influences, the environmental issues have been receiving lasting attention from both academia and practice. In this situation, it is deemed important for manufacturers to decide if they should adopt environment-friendly production technologies (e.g., solar technology) that can lower the emissions but require increased production costs [1]. In the meanwhile, governments look for suitable regulation policies to reduce environmental damages by curbing emissions while improving social welfare. Among others, carbon emission tax has gained significant traction and is applied in many countries and local regions. In fact, economists regard a carbon tax as the most efficient way to reduce carbon emissions [2], and in some conditions, carbon emission tax is more effective than other regulations for economic growth and carbon reduction [3].

Under carbon emission tax, manufacturers are charged for each unit (i.e., metric ton) of their emissions at a fixed tax rate level. Because of the tax rate, manufacturers have to pay for an additional carbon emission cost, which, in turn, drives their total costs to increase. Regarding this, carbon emission tax, in fact, intervenes manufacturers' micro-behaviors (e,g., pricing decisions) and ultimately affects manufacturers' profits [4]. As noted in literature, carbon emissions are generated mainly from production processes where products are materialized. Consequently, manufacturers' decisions (e.g., technology selection, production quantity) affect significantly carbon emissions to be generated in the future production activities. In this regard, carbon emission tax plays an influential role in manufacturers' decision-making, the result of which determines emission abatement. Caused by the inherent interactions, it is of paramount importance that manufacturers need to make decisions by taking into account carbon emission tax [5].

In a supply chain (SC), the decisions and activities, be they within or beyond the boundaries of an individual member, are interrelated and affect one another. For examples, a retailer's order quantity influences the manufacturer's production quantity, which may alter his wholesale price; the manufacturer's wholesale price decision is an indispensable input for the retailer to determine his retail price, which affects the demand. In an effort to obtain maximum profits, chain members should make joint decisions while considering the above unavoidable interactions [6]. However, due to the complexities involved, joint SC decision-making involving many interactions is likely to be very difficult. This is especially true in the environments where carbon emission tax is implemented (because manufacturers' decisions are affected by carbon emission tax).

Towards the end, in this study, we address the joint decision-making of a manufacturer and his independent retailer under carbon emission tax. More specifically, we focus on technology selection, production quantities, and wholesale price of the manufacturer and the retail price of the retailer while considering a fixed tax rate per unit carbon emission specified by the local government. Our literature review has shown that though the published articles deal with joint decision making of a manufacturer and its retailer, they did not comprehensively consider all the above decisions together. (Note: Considering the limited number of pages, we will be happy to provide the detailed literature review upon request.) As shown in literature, the Stackelberg game theory excels in modeling decision interactions of two players. We, thus, analyze the joint decision-making of the manufacturer and the retailer as a Stackelberg game. The game model developed consists of two submodels: an upper-level submodel and a lower-level one. The upper-level submodel sheds light on the decision-making process of the manufacturer, whilst the lower-level one details the retailer's decision-making. By nature, the game model is a mixed 0-1, nonlinear, bilevel programming, for which it is impossible to obtain analytical solutions. Nested genetic algorithm (NGA) excels in dealing with bilevel programming models by providing near-optimal solutions [7]. Thus, we further develop a specific NGA to solve the Stackelberg game model. Numerical examples demonstrate (i) the applicability of the Stackelberg game model and (ii) the robustness of the NGA. With sensitivity analysis, we arrive at several important managerial implications.

In the following section, the problem context is introduced. The Stackelberg game model and the NGA are presented in Sections 3 and 4, respectively. We describe numerical examples and sensitivity analysis in Section 5. The paper is ended in Section 6.

II. PROBLEM CONTEXT

In the SC in consideration, there are a manufacturer and an independent retailer. (Such SCs widely exist in practice, e.g., an automobile firm and his independent retailers in different regions.) In his planning horizon containing T periods, the manufacturer produces one type of products and sells them to the retailer at a wholesale price w. We assume that the wholesale price of the manufacturer is stable in the planning horizon. In practice, stable prices are preferred in business with sales volumes over a relatively long planning horizon, while dynamic pricing is important in finite selling seasons for cases, such as airlines and hotels [8]. There are two technologies: a green one and a dirty one with capacities of B_g *and* B_d, respectively. The manufacturer can select either the dirty or the green one to produce products in each planning period. The green technology generates less emissions than the dirty one from producing one unit of products. However, it incurs higher production costs. To abate emissions, the local government motivates the manufacturer to adopt the green technology by offering a subsidy of b per unit product produced by the green technology. Authors have demonstrated that with the subsidy, the local governments can better motivate manufacturers to adopt green technologies in production [9]. In each production run, the manufacturer pays a fixed setup cost s_d or s_g ($s_d < s_g$) for adopting the dirty or green technology. In general, green technologies are more complex and consist of more components than traditional dirty ones. Setting up green technologies, thus, requires longer time and/or more engineers/technicians, resulting in higher setup costs. Besides the fixed costs, the manufacturer pays a variable production cost per unit cost v_d or v_g ($v_d < v_g$) related to the use of the dirty/green technology. Assuming $v_d < v_g$ is rather intuitive. For instance, the (non-fuel related) variable cost of operating a hybrid car is certainly higher than that of a regular car as the hybrid car has many parts and devices that the regular car does not have. When producing one unit of products, the dirty and green technologies emit e_d or e_g ($e_d > e_g$) emissions, respectively. For each of the inventory k_i at the end of planning period i, the manufacturer needs to pay a cost of h; he also pays a cost of l for transporting one unit to the retailer. According to carbon emission tax mechanism, the local government charges a tax rate of τ for one-unit emission that the manufacturer emits from production. The manufacturer needs to select the dirty or green technology in planning period i, i.e., $x_i, y_i \in \{0,1\}$. In addition, he needs to determine production quantities q_{di} / q_{gi} related to the dirty/green technology to meet the retailer's demand in period i. The manufacturer also needs to determine w. The objective is to maximize his total profit $\Pr of_M$ in the planning horizon.

The retailer buys the products at w and sells them at a retail price of r. Similarly, in this study, we assume that the retail price is stable in the horizon. At the beginning of a planning period where the manufacturer adopts the green technology, the retailer carries out low-carbon advertising program to stimulate demand o_i. The amount of advertising investment is a. The retailer needs to determine the retail price r in order to maximize his total profit $\Pr of_R$ in the planning horizon.

III. STACKELBERG GAME MODEL

A. Upper-Level Optimization for the Manufacturer

The upper level is to optimize the manufacturer's total profit, which is determined by his revenue and total cost in the planning horizon. The manufacturer obtains the revenue Π_M by (i) selling the products and (ii) receiving the subsidy for unit product from the local government if he adopts the green technology. The revenue Π_M can be expressed as Eq. (1). The second term indicates the total subsidy from the local government, which becomes a part of the manufacturer's total revenue.

$$\Pi_M = w\sum_{i=1}^{T} o_i + b\sum_{i=1}^{T} q_{gi} y_i \tag{1}$$

For the total costs, there are several cost factors, including a total production cost $P(q_{di}, q_{gi})$, a total inventory holding cost $TI(k_i)$, a total transportation cost $Tr(o_i)$, and a total carbon emission cost $J(q_{di}, q_{gi})$. The total production cost $P(q_{di}, q_{gi})$ can be computed using Eq. (2) below, while $TI(k_i)$, $Tr(o_i)$, and $J(q_{di}, q_{gi})$ are obtained based on Eqs. (3-5), respectively.

$$P\left(q_{di}, q_{gi}\right)=\sum_{i=1}^{T}\left(q_{di}v_d x_i+q_{gi}v_g y_i\right)+\sum_{i=1}^{T}\left(s_d x_i+s_g y_i\right) \quad (2)$$

$$TI\left(k_i\right)=h\sum_{i=1}^{T}k_i \quad (3)$$

$$Tr\left(o_i\right)=l\sum_{i=1}^{T}o_i \quad (4)$$

$$J\left(q_{di}, q_{gi}\right)=\tau\sum_{i=1}^{T}\left(q_{di}e_d x_i+q_{gi}e_g y_i\right) \quad (5)$$

In Eq. (2), the first term is the total variable production cost, and the second term is the total setup cost. Eq. (5) consists of two parts, the carbon emission related to green technology and the one to dirty technology. The total cost TC_M can be formulated as Eq. (6). ***Submodel M*** is developed based on Eqs. (1- 6).

$$TC_M=P\left(q_{di}, q_{gi}\right)+J\left(q_{di}, q_{gi}\right)+Tr\left(o_i\right)+TI\left(k_i\right) \quad (6)$$

Submodel M:

$$\max_{x_i y_i, q_{di}, q_{gi}, w} \Pr of_M=\Pi_M-TC_M \quad (7)$$

s.t. $$k_i+o_i=q_{di}x_i+q_{gi}y_i \quad (8)$$

$$q_{di}e_d x_i+q_{gi}e_g y_i \le q_{d(i-1)}e_d x_{i-1}+q_{g(i-1)}e_g y_{i-1} \quad (9)$$

$$q_{di}\le x_i\varphi,\ q_{gi}\le y_i\varphi \quad (10)$$

$$q_{di}\le B_d\ ,\ q_{gi}\le B_g \quad (11)$$

$$k_i\ge 0 \quad (12)$$

$$w>0\ ,\ q_{di}\ge 0,\ q_{gi}\ge 0 \quad (13)$$

$$x_i,\ y_i\in\{0,1\} \quad (14)$$

$$i=1,2,3,...,T,\ T\in N^+ \quad (15)$$

The objective function: Eq. (7) is to maximize the manufacturer's total profit. Constraint (8) ensures inventory and demand balance in each planning period. Constraint (9) reflects the essence of carbon emission regulation: carbon emissions generated in a later period must be no higher than those from the previous period. With φ being an arbitrary very large positive number, Constraint (10) ensures that production takes place only when technologies are adopted. Production capacities are respected in Constraint (11). Constraint (12) indicates that the inventory level is non-negative. The decision variables are non-negative in Constraint (13), and Constraint (14) imposes a binary restriction concerning the decision variables for selections of production technologies.

B. Lower-Level Optimization for the Retailer

The lower-level optimization is to maximize the retailer's profit. The retailer obtains his revenue from selling products. The costs incurred include the total cost for purchasing the products and the low-carbon advertising costs for spurring demand.

In literature, several important factors have been identified to formulate the product demand of a retailer, including the retail price, the advertising investment, and the carbon emissions of unit product. We follow the literature and assume the linearity between demand and retail price, advertising investment, and carbon emissions. With the linear assumption, the demand o_i of the retailer in planning period i is formulated in Eq. (16). The last term includes a square root to the retailer's total advertising cost. This reflects the diminishing returns to the advertising investment. The revenue Π_R and total cost TC_R in the planning horizon of the retailer are determined based on Eq. (17) and (18), respectively. The first term in Eq. (18) is the cost for promoting low-carbon products produced by green technology, and the second one is the purchasing cost.

$$o_i=M-e^r r+e^e y_i\left(e_d-e_g\right)+y_i e^a\sqrt{a} \quad (16)$$

$$\Pi_R=r\sum_{i=1}^{T}o_i \quad (17)$$

$$TC_R=\sum_{i=1}^{T}ay_i+w\sum_{i=1}^{T}o_i \quad (18)$$

Submodel R is developed below.

$$\max_{r}\Pr of_R=\Pi_R-TC_R \quad (19)$$

s.t. $$r>w \quad (20)$$

$$r>0 \quad (21)$$

$$i=1,2,3,...,T,\ T\in N^+ \quad (22)$$

The objective function in Eq. (19) is to maximize the retailer's total profit. Constraint (20) ensures that the wholesale price cannot be larger than the retail price.

C. Leader-follower joint optimization model

We model the decision-making processes of the manufacturer and his retailer as a Stackelberg game. The upper-level ***Submodel M*** is related to the manufacturer acting as a leader, while the lower-level ***Submodel R*** is for the retailer performing as a follower. Thus, the leader-follower optimization for this decision-making problem is formulated as the following bilevel program:

$$\max_{x_i y_i, q_{di}, q_{gi}, w}\Pr of_M=\Pi_M-TC_M \quad (23)$$

s.t. Constraint Eqs (8-15) (24)

where, for given x_i, y_i, q_{di}, q_{gi}, w , the variable r solves:

$$\max_{r}\Pr of_R=\Pi_R-TC_R \quad (25)$$

s.t. Constraint Eqs (20-22) (26)

In this leader-follower bilevel program, the decision-making sequence is as follows. With the carbon emission tax, the manufacturer first selects either the green or dirty technology or both for each planning period by decision variables x_i and y_i , and the quantity related to each technology by q_{di} and q_{gi} . Besides, the manufacturer needs to determine a wholesale price using decision variable w. In reaction, the retailer makes his decision of the retail price by decision variable r in response to the manufacturer's decision-making. The retail price would influence the market demand during each planning period; thus, the demand is the feedback to the manufacturer from the lower level.

IV. NGA-BASED SOLUTION METHOD

The bilevel game model developed is a non-linear program involving 0-1 variables and continuous variables and is NP-hard. Besides, the decision variable of ***Submodel R*** is involved in the objective function and Constraint (8) of ***Submodel M***. Considering the characteristics and complexities of the game model, we further develop a Nested GA (NGA) to obtain near-optimal solutions. The NGA has three phases, including i) constraint removing, ii) modified model solving, and iii) constraint evaluation. In Phase i), ***Submodel M***'s constraints involving r are removed; a modified game model is developed. In Phase ii), the modified model is solved. The values of all decision variables are obtained. In this phase, the solving of Submodel R is nested in that of the modified ***Submodel M***. In Phase iii), the constraints removed from ***Submodel M*** are evaluated using the decision variable values obtained in Phase ii). Based on the evaluation results, Phases ii) and iii) repeat till the final solution is obtained. See the algorithm details below.

Step 1 Removes Constraint (8) containing r from ***Submodel M***.
Step 2 Generates randomly an initial population of a pre-determined number of chromosomes corresponding to the solutions of ***Submodel M***.
Step 3 Evaluates the feasibility of chromosomes. If a chromosome is feasible, indicating the ***Submodel M***'s constraints are satisfied, goes to *Step* 4 to solve ***Submodel R***, else, goes to *Step* 6.
Step 4 Optimizes ***Submodel R*** based on the below *sub-steps 4-1* to *4-8*.

Sub-step 4-1 Substitutes ***Submodel M***'s decision variable values into ***Submodel R***.

Sub-step 4-2 Generates randomly an initial population of a predetermined number of chromosomes corresponding to the solutions of ***Submodel R***.

Sub-step 4-3 Evaluates the feasibility of chromosomes based on ***Submodel R***'s constraints. If the result is positive, goes to *Sub-step* 4-4, else, goes to *Sub-step* 4-6.

Sub-step 4-4 Obtains the value of r and further calculates the value of $\Pr of_R$ using Eq. (19).

Sub-step 4-5 Sets the fitness value of the infeasible chromosomes as 0 and removes them from the population.

Sub-step 4-6 Compares the current number of iterations with a predetermined one. If the current number is less, goes to *Sub-step* 4-7, else, goes to *Sub-step* 4-8.

Sub-step 4-7 Generates new chromosomes using three operators: selection, crossover, and mutation, then moves back to *Sub-step* 4-3.

Sub-step 4-8 Jumps out of the nesting, records the values of r and $\Pr of_R$, and moves to *Step* 5.

Step 5 Computes the value of $x_i, y_i, q_{di}, q_{gi}, and\ w$ with the input from *Sub-step 4-8*, further calculates the fitness value using Eq. (7), and obtains the value of $\Pr of_M$.
Step 6 Sets the fitness value for the infeasible chromosomes as 0 and removes them from the population if the chromosome is not feasible in *Step* 3.
Step 7 Checks the current number of iterations. If it is larger than the predetermined one, moves to *Step* 8, else, goes to *Step* 10.
Step 8 Evaluates Constraint (8) using current decision variable values.
Step 9 Checks if the constraints are satisfied. This is the termination condition of the algorithm. If they are satisfied, goes to *Step 11*, else, moves to *Step* 10.
Step 10 Generates new chromosomes corresponding to the solutions of ***Submodel M*** using the same three operators as above, and goes back to *Step* 3 to check the feasibility of chromosomes.
Step 11 Outputs the final values for all decision variables and the values of $\Pr of_M$ and $\Pr of_R$ as the final solution.

V. NUMERICAL EXAMPLES

In the base example, the manufacturer produces a type of air conditioners and sells them to an independent retailer. The planning horizon of the manufacturer is one year with two periods. The data was collected based on the industrial practice in China. More specifically, parameters describing the manufacturer and the retailer are as follows: $T = 2$, $b = 20$, $h = 4.5$, $l = 14$, $B_d = 10000$, $B_g = 8000$, $e_d = 600$, $e_g = 500$, $s_d = 7300$, $s_g = 8500$, $v_d = 240$, $v_g = 360$, $a = 51000$, $M = 11500$, $e^r = 0.79$, $e^a = 0.55$, *and* $e^e = 0.63$

In the numerical examples, we set the population size as 20 in solving the two submodels and set the number of iterations both within and out-side the nesting as 100. We use a selection probability of 0.02, crossover rate of 0.9, and mutation rate of 0.01. Such GA settings are commonly used in the literature [10]. The NGA is coded in MATLAB 2016b on a Core i5 CPU 2.7 GHz and an 8GB RAM.

D. Results and Analysis

In calculations, the NGA is converged at 30 iterations where the fitness values of the two submodels are optimal and remain unchanged in the following iterations, as shown in Fig. 1.

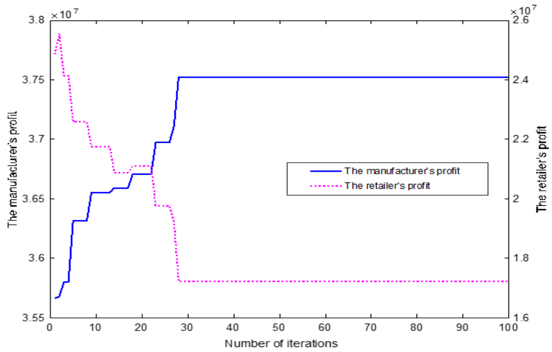

Fig. 1. NGA convergence.

The final solution in terms of the values of decision variables and profits is provided in Table 1. As shown, the manufacturer selects both the green and dirty technologies in each of the two planning periods. Though the set-up cost of the green technology is higher than that of the dirty technology, the subsidy from the local government motivates the manufacturer to adopt the green technology in production. In addition, the lower emission released from producing a unit of air conditioner contributes to lower total emission costs, which, in turn, justifies the selection of the green technology. Interestingly, the production quantity from the dirty technology in each period is higher than that from the green technology in spite of i) the subsidy, ii) the lower emission released from producing one unit, and iii) the fixed set-up cost of the green technology that is irrelevant to production quantities. There are two potential reasons. First, the production capacity of the green technology is limited. Second, the unit variable production cost of the green technology is higher than that of the dirty technology. Thus, producing more air conditioners using the green technology results in higher total variable production costs. To conclude, making suitable decisions on technology selection and corresponding production quantities is very important. Our model is expected to help manufacturers make such decisions.

Table 1: FINAL SOLUTION

Decision variable		Value
The dirty technology is or not selected	x_1	1
	x_2	1
The dirty technology is or not selected	y_1	1
	y_2	1
Production quantities of the dirty technology	q_{d1}	6126
	q_{d2}	5920
Production quantities of the green technology	q_{g1}	4870
	q_{g2}	1053
Wholesale price	w	2471
Retail price	r	3436
Objective		**Value**
The manufacturer's profit	$Prof_M$	$3.7524*10^7$
The retailer's profit	$Prof_R$	$1.7215*10^7$

D. Performance Evaluation of NGA

To evaluate the robustness of the NGA, we test 10 times the base example. In each test, we generate randomly 20 chromosomes in the initial population and use the same input data. The results in terms of the manufacturer's and the retailer's profits are obtained. Among these 10 tests, in six tests including Test 1, 4, 5, 7, 8, and 10, the manufacturer's profits are identical. This is the same for the retailer. For the manufacturer, the average, largest, and smallest profits are $3.7519*10^7$, $3.772*10^7$, and $3.7321*10^7$, respectively. The increase (decrease) percentage between the average and the largest (smallest) profits is 0.5% (0.5%). The retailer's average, largest and smallest profits are $1.7205*10^7$, $1.7484*10^7$, and $1.7013*10^7$, respectively. Similarly, the increase (decrease) percentage between the average and the largest (smallest) profits is 1.6% (1.1%). These insignificant change percentages indicate that the NGA is robust.

E. Sensitivity Analysis

We equally carry out sensitivity analysis to examine the impact of some parameters on the profits of the manufacturer and the retailer as well as on the decision variable value changes. These parameters include the emission released from producing one unit of product using the dirty technology (e_d), and the emission released from producing one unit of product using the green technology (e_g), the government tax per unit emission (τ), the subsidy offered by the local government (b), the advertising investment (a). For each parameter, we obtain some interesting results. However, due to the page limitation, we present below the results and analysis pertaining to e_d. The results and analysis for other parameters are available upon request.

Emission released from producing a unit of product using the dirty technology (e_d): In studying the impact of e_d, we change its values from 600 to 700 in steps of 10 and obtain the results. (The results before 600 and after 700 remain stable. Thus, we present the results pertaining to the range of (600, 700).) As shown in Fig. 3(a), in general, there is a decreasing trend in the manufacturer's profit changes. This is explainable. Increased e_d potentially increases the total emission costs, which reduce the manufacturer's profit. By examining closely, we can see that the manufacturer's profit changes can be classified into several stages, including i) the increasing stage till e_d is 630, ii) the decreasing stage till e_d reaches 660, iii) the increase stage till e_d is 680, and iv) the decreasing stage. Such specific profit changes might be caused by production quantity changes, as shown in Fig. 3(b). Responding to the increase of e_d, the manufacturer has to reduce the production quantity from the dirty technology and, in the meanwhile, increase the production quantity from the green technology. Regarding the retailer's profit, it steadily increases along with the increase of e_d, as shown in Fig. 3(a). This is reasonable. As mentioned above, the increase of e_d increases the production quantity from the green technology and reduces the production quantity from the dirty technology. With the help of advertising, this, in turn, stimulates more demand, confirming Eq. (16). The demand increase contributes to the steady increase in the retailer's profit.

The above results and analysis reveal that i) certain ranges of e_d values, in fact, contribute to manufacturer's profit increase and ii) some ranges lead to manufacturer's profit decrease. Manufacturers, therefore, need to identify an "optimal" range, which can help them obtain higher profits. Our model is expected to facilitate the identification of such an "optimal" range of e_d. On shop floors, manufacturers should control well the production processes where dirty technologies are used so that the emissions released from producing a unit of product will fall in the "optimal" ranges. Because retailers' profits always increase when e_d increases, they might establish certain contracts to encourage manufacturers to engage more/less the green/dirty technology in production.

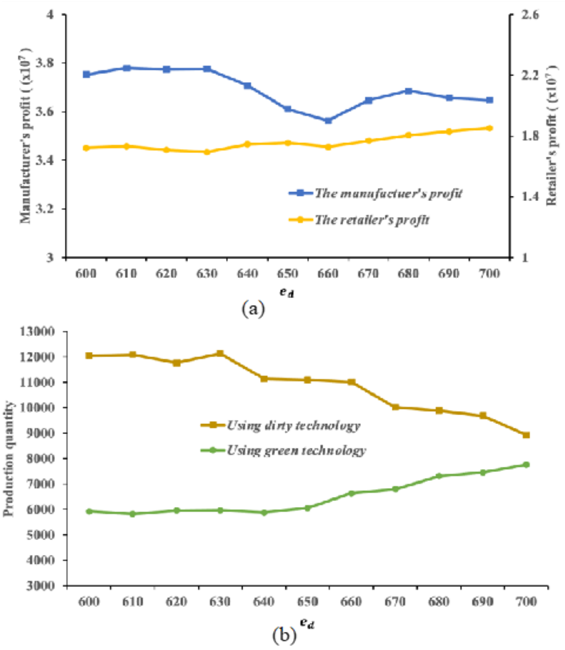

Fig. 3. Profit and quantity changes caused by the change of e_d .

VI. CONCLUSIONS

Given the inherent interactions between carbon emission tax and supply chain decisions and these among supply chain decisions and the resulting decision-making complexities, in this study, we investigated the joint decision-making of a manufacturer and his independent retailer under carbon emission tax. A Stackelberg game model including two submodels was developed to help i) the manufacturer optimally select technologies, determine production quantities and wholesale price and ii) the retailer optimally determine the retail price. We further developed an NGA to solve the game model for obtaining near-optimal solutions. Numerical examples demonstrated the applicability of the game model and the robustness of the algorithm.

Based on the sensitivity analysis, we highlighted several important managerial implications. For example, manufacturers' profits do not decrease when the emission tax rate increases (Note: this is from the result analysis of τ). Therefore, local governments need to be very careful when determining the tax rate such that manufacturers can obtain higher profits without releasing increased emissions to the environments. Along this line, there are several avenues for potential future research. As initial efforts, we studied the joint decision-making of a manufacturer who produces one product and his independent retailer. Future research efforts might be made to develop models and solution algorithms for the situations where there are multiple substitute products and/or multiple competing retailers under carbon emission tax. It is interesting to see how the manufacturer and retailer make their optimal decisions in these situations. As carbon tax rates significantly affect emission abatement and social welfare, how a local government can determine an optimal tax rate together with manufacturers' and retailers' joint decision-making might deserve future investigation.

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