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Development of a Cournot-oligopoly model for competition of multi-product supply chains under government supervision

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Abstract. Globalization, increased governmental regulations, and customer demands regarding environmental issues have led the organizations to review the measures necessary for the implementation of the Green Supply Chain Management (GSCM) to improve the environmental and economical performances. The paper proposes a Cournot-oligopoly model for green supply chain management. It provides a novel approach to construct a model that maximizes government tariff and profits of the suppliers and manufacturers in all the GSCs. The bi-level model is converted to a single-level model by replacing the second level with its Karush Kuhn Tucker (KKT) conditions and linearization techniques. Then, a Genetic Algorithm (GA) is utilized to solve the single-level model using MATLAB software. Afterwards, the obtained results are compared with optimal solutions acquired by Enumerative Method (EM) to evaluate the validity and feasibility of the proposed GA. The sensitivity analysis of this model indicates that the fiscal policy of the government greatly affects the reduction of environmental pollution costs caused by industrial activities such as automobile production in a competitive market. Therefore, the amount of non-green products' taxes is directly related to the decrease of environmental pollution.

1. Introduction

The control of any pollution of environment in different highly polluted regions of cities is an important task for the modern society. Air pollution has been steadily increasing during the last decades, and the need to set up effective control strategies for the air pollution problem has become even more significant. Air pollution is also a serious environmental health problem, which influences developed and developing countries in the world. Increasing amounts of dangerous and harmful gases as well as particles caused by various reasons are being emitted into the atmosphere, which inevitably damage the human health and the environment.

The economic growth increases the level of energy and material consumption, which contributes to the environmental issues and resource-depletion problems. It has become increasingly significant for organizations facing competitive, regulatory, and community pressures to balance economic and environmental performances [1]. As a result, GSC, practices by forward-thinking organization, emerges as a new systematic environmental approach in supply chain management, enjoying wide-spread and increasing acceptance [2]. In

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recent years, this field has expanded with the interests of both academia and industry.

Effects of governmental supervision on multi-product GSC have been rarely studied by researchers in GSCM and the related areas. Furthermore, due to various reasons, such as globalization, increased governmental regulations, and the customer demands regarding environmental issues, we believe it is essential for organizations to review the measures necessary for the implementation of the Green Supply Chain Management (GSCM) to improve the environmental and economic performances. Accordingly, this work studies the interactions of GSCs under government's financial and environmental supervision. In this paper, we propose a bi-level Cournot-oligopoly model for green supply chains with different brands and various degrees of environmental consciousness. It provides a novel approach to construct a model that maximizes government payoff as well as the suppliers and manufacturers' profits in all the GSCs. This paper, also, utilizes a Cournot framework in which the firms compete using their product flows as strategic variables [3]. The generalized framework in this paper captures the competition among the companies and firms in different GSC activities of procurement and manufacturing. The government is assumed to not only seek to maximize its own income, but also to reduce the environmental pollution throughout its intervention in the competition. The bi-level model is converted to a single-level model by replacing the second level with its Karush Kuhn Tucker (KKT) conditions and linearization techniques; subsequently, a Genetic Algorithm (GA) is utilized to solve the single-level model. Afterwards, the obtained results are compared with optimal solutions acquired by Enumerative Method (EM) to evaluate the validity and feasibility of the proposed GA. Other research questions are as follows:

- Regarding the leadership role of the government, how can the interactions of several GSCs and government be modeled?
- What are the responses of GSCs to taxes and subsidies of the government?
- What is the best strategy of the government in the competitive market of several GSCs?

This paper is organized as follows. Section 2 briefly reviews the related literature. In Section 3, after introducing some notations and assumptions, we develop the bi-level GSC in oligopoly model. In Section 4, we present the solution methodology of this study in detail. Section 5 presents the practical implementation of the model; finally, Section 6 concludes the paper.

2. Literature review

This study is related to green supply chain management, bi-level programming models, genetic algorithm, and Cournot-oligopoly; thus, we review the subjects in the following subsections.

2.1. Survey on GSC studies

GSC involves a fundamental rethinking of supply chain management practices, and how they can be integrated with the company's environmental strategy [4].

Since the early periods of the industrial revolution, the survey and management of industrial pollution has been an important issue for the government and society. During these early days, industrial pollution and GSC topics were not a major and serious subject for management or economics researchers. Subsequently, the perspective has changed from GSC as a burden to GSC as a potential source of competitive advantage [5]. After that, some researchers began to consider environmental manager in a different role [6]. Some subjects, such as greener manufacturing and operations [7], relationship between environmental and economic performance of firms [8], study of the Environmental Management System (EMS) implementation operations [9], and overview of management problems and environmental consequences in reverse manufacturing [10] have been discussed by researchers in this field. In addition, Lee and Chan [11] proposed a GA to maximize the coverage of customers and minimize the total reverse logistics cost. Also, Lee and Lam [12] proposed a sustainable industrial marketing framework of the latest requirement of green and sustainable operation. Likewise, Zhang et al. [13] studied CVRP from an environmental perspective and introduced a new model, called Environmental Vehicle Routing Problem (EVRP), with the aim of reducing the adverse effect on the environment caused by the routing of vehicles. In this study, the environmental influence is measured through the amount of the carbon dioxide emission, which is a widely acknowledged criterion and accounts for the major influence on the environment.

In the recent literature, similar research studies have been done on this topic, as well. Chibeles-Martins et al. [14] studied the supply chain design and planning problem and proposed an optimization model to support the associated decisions. Their model was generated using Mixed Integer Linear Multi-Objective Programming, which was solved through a simulated annealing-based multi-objective meta-heuristics algorithm (MBSA). Prior to that, Tognetti et al. [15] investigated the interplay between the emissions and costs of the supply chain contingent upon the production volume allocation and the energy mix.

2.2. Survey on bi-level programming problems

Another field related to this study is Bi-Level Programming Problem (BLPP) that consists of two players at different levels, including the leader and the follower or followers.

In the context of BLPP, a number of subjects have been presented, including some effectual research studies [16,17], test problem generators [18], and some Evolutionary Algorithm (EA) studies [19-23]. Since then, a number of studies have been conducted on bi-level programming [24-26].

However, when BLPPs get complicated, other approaches, such as evolutionary techniques, will need to be used. Also, some of the evolutionary algorithms for BLPPs have been used as nested strategies that solve the lower level optimization problem for upper level decision problem [20,23,27-29]. Mathieu et al. [20], Yin [23], and Li and Wang [30] utilized the upper level optimization problem by using an evolutionary algorithm and the lower level using a classical approach.

Some researchers also replaced the lower level optimization problem with the KKT conditions to solve the single-level problem [26,30,31]. Also, Wang et al. [32] proposed an evolutionary algorithm based on a constraint handling scheme. Moreover, they solved a number of standard test problems. In this study, we will replace the lower level problem with the KKT conditions.

2.3. Survey on genetic algorithms

We utilize a Genetic Algorithm (GA) to solve the single-level optimization problem. GA was initially utilized by Liu [33] for solving Stackelberg-Nash equilibrium of nonlinear multi-level programming with multiple followers. After that, so many researchers used GA to solve similar problems; for instance, Hencheng and Yuping [34] proposed a genetic algorithm based on an exponential distribution for the aforementioned problems. Calvete et al. [35] developed a genetic algorithm for the linear bi-level problem in which both objective functions are linear, and the common constraint region is a polyhedron. Also, Wang et al. [36] constructed a genetic algorithm based on the simplex method to solve the Linear-Quadratic Bi-level Programming problem (LQBP). They transformed the LQBP into a single-level programming utilizing Kuhn–Tucker conditions of the lower level programming, which can be simplified to a linear programming by the chromosome according to the rule. Kuo and Han [37] applied bi-level linear programming to supply chain distribution problem and developed an efficient hybrid method based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Lin et al. [38] suggested a genetic algorithm to solve continuous and ingot casting scheduling problems; a genetic algorithm was proposed for solving the bi-level programming problem in steel-making production based on the characteristics of the problems involved.

2.4. Survey on Cournot-oligopoly models

Most of the studies in the field of decision-making procedures of GSC are chiefly based on the framework of game theory. Applications of game theory in SC problems have been discussed by different authors. However, game theory's applications to GSC are still under development. Acemoglu et al. [39] and Xiao et al. [40] investigated the efficiency of oligopoly equilibrium in a toll and capacity competition game. Sheu [41] studied the problem of negotiations between producers and Reverse-Logistics (RL) suppliers for cooperative agreements under government intervention. The author concluded that excessive intervention of the government may result in adverse effects on chain members' profits and social welfare. Masoumi et al. [42] constructed a generalized network oligopoly model with arc multipliers for SCs of pharmaceutical products using variation inequality theory. Their model captured the Cournot competition among the manufacturers who seek to determine their profit-maximizing product flows. Tsitsiklis and Xu [43] considered a Cournot oligopoly model in which multiple suppliers (oligopolists) compete by choosing quantities. The authors compared the social welfare achieved at a Cournot equilibrium to the maximum possible, for the case where the inverse market demand function is convex. Afterwards, Desgrangesa and Gauthier [44] studied rationalizability in a linear asymmetric Cournot oligopoly with a unique Nash equilibrium. Also, Goltsman and Pavlov [45] discussed the communication in a static Cournot duopoly model under the assumption that the firms have unverifiable private information about their costs. This paper states that if the firms can communicate through a third party, their communication can be informative, even when informative cheap talk is impossible.

2.5. Research gap

In this paper, we propose a Cournot-oligopoly bi-level model to analyze the competitions in multi-product GSCs under government supervision. effects of the governmental supervision on the multi-product GSCs have been rarely discussed in the earlier studies on GSCM and the related areas. Also, the multi-product bi-level GSC Cournot-oligopoly model in this study is a new formulation in perspective. We convert the bi-level model into a single-level model using KKT conditions and reformulate the NLP problem to a linear one in order to decrease the model's complexity. To the best of authors' knowledge, no study has considered these issues simultaneously. Also, we consider the trade-off between government revenue and environmental pollution cost in the first level of the problem. Furthermore, GA is utilized to solve the model; afterwards, the obtained results are compared with the results acquired by Enumerative Method (EM) to evaluate the validity and feasibility of the proposed GA.

3. Mathematical formulation

In this research, we formulate a competitive model in Multi-Product GSCs under government supervision to reduce the environmental pollution cost and also the related environmental pollution. In this section, we introduce mathematical model for the problem and its components.

Each SC consists of a raw material supplier and finished product manufacturer. In Figure 1, the overview of the problem is illustrated.

Government tries to reduce the environmental pollution cost by assigning tariff rate to raw materials (t_j) and also tariff rate to final products (T_k) for all GSCs. Positive tariff value of raw material j (i.e., t_j) means that the government assigns tax to the raw material; however, negative value of this variable means that the government assigns subsidy. Similarly, positive tariff value of final product, k (T_k), indicates that the government assigns tax to the final product, and negative final product tariff value represents that the government assigns subsidy to the final product. In the second level, each supplier in each GSC attains profit from raw materials' sale (q_{ij}) made to manufacturer. Also, each manufacturer, in each GSC, achieves profit from the final products' sale (Q_{ik}) in the competitive market. The price of each type of product is determined via the competition among different SCs.

The problem considered, in this study, consists of GSCs in which manufacturers of the finished product and suppliers of raw material compete to manufacture products under the supervision of the government. In this research, the issue of the environment policy for green products' production, using recycled raw materials and green energy, has been discussed.

In this study, the problem is formulated as a bi-level nonlinear programming model. In the first level, the government has considered tariff as decision variable that includes subsidies and taxes assigned to green and non-green raw materials and products, supplied and produced by different GSC members, respectively. This financial intervention by the government tries to reduce environmental pollution cost; therefore, in the first level, the government income will be maximized considering a constraint to control environmental pollution cost. At the second level, GSC members, such as raw material suppliers and finished product manufacturers, will maximize their profit.

3.1. Definition of sets and notations

Sets and Indices

$I = \{1, 2, \cdots, i, \cdots, N\}$	The set of SCs
$J = \{1, 2, \cdots, j, \cdots, m\}$	The set of product's raw materials
$K = \{1, 2, \cdots, k, \cdots, n\}$	The set of products

Parameters

α_{ijk}	The coefficient of component j in SC i in product k
ω_{ij}	The unit wholesale price of component j presented by supplier i
c_{ik}	The unit direct cost of final product k in SC i
ψ_{ik}	The environmental pollution cost caused by product k of SC i

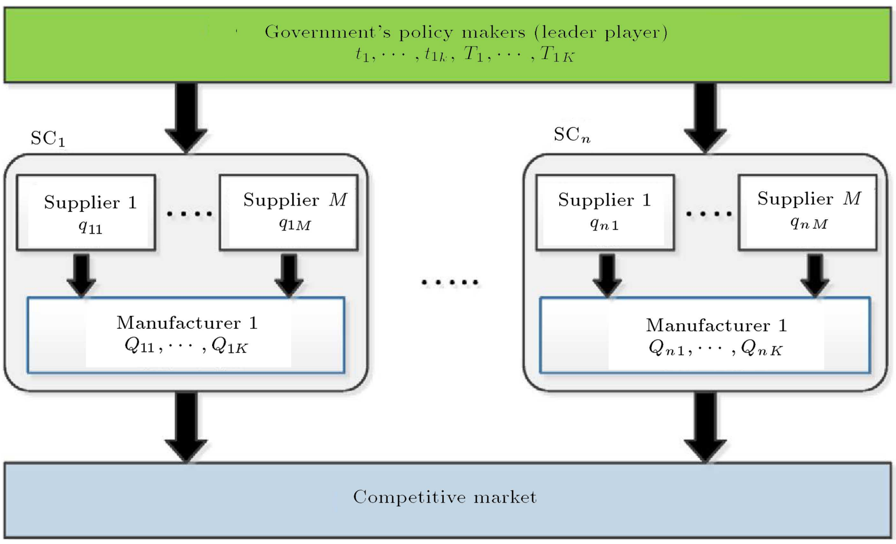

Figure 1. Overview of the competition of SCs.

ϕ_j The environmental pollution cost caused by production of component j

f_j The cost function coefficient of each supplier for raw material j

g_j The cost function coefficient of each supplier for raw material j

h_j The cost function coefficient of each supplier for raw material j

a_k The cost function coefficient of each manufacturer for product k

b_k The cost function coefficient of each manufacturer for product k

Decision's variables

q_{ij} The amount of component j supplied by supplier i

t_j The tariff on raw material j imposed by the government

T_k The tariff on product k imposed by the government

Q_{ik} The number of final product k produced by manufacturer i (in SC i)

3.2. Assumptions

In order to formulate the model, the following assumptions have been considered:

- The tariff set for the manufacturer and supplier will be considered for each unit of raw material and the final product. The tariff decision variables are free in sign, such that the positive values indicate tax allocation to raw material or final product. On the contrary, negative values represent subsidy allocation to raw material or final product by government;
- Each GSC manufactures and presents n types of product to the competitive market; hence, the SCs are assumed multi-product;
- Cournot games are used for the competition among manufacturers. Hence, the price of each product depends on production quantities of SCs. Oligopoly games are used for the competition among manufacturers. So, the sale price of any product is obtained by the total market demand.

3.3. Bi-level programming formulation

In this section, we propose the mathematical model for the problem. As mentioned before, the proposed model is a bi-level nonlinear model by which the upper level optimizes the government income and the lower level maximizes the supplier and manufacturer's profits in all GSCs.

The first level problem of government:

$$\max \quad \Pi_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} T_k Q_{ik} + \sum_{j=1}^{m} t_j q_{ij} \right], \tag{1}$$

s.t.:

$$\Gamma_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} Q_{ik}\psi_{ik} + \sum_{j=1}^{m} q_{ij}\phi_j \right] \leq \text{UB}, \tag{2}$$

$$\sum_{j=1}^{m} \omega_{ij} q_{ij} - (f_j q_{ij} + g_j q_{ij}^2 + h_j) - t_j q_{ij} \geq R_{s_i} \qquad \forall\, i, \tag{3}$$

$$\sum_{k=1}^{n} \left[\left(a_k - b_k \sum_{i=1}^{N} Q_{ik} \right) Q_{ik} - \sum_{j=1}^{m} \omega_{ij}\alpha_{ijk} q_{ij} - c_{ik} Q_{ik} - T_k Q_{ik} \right] \geq R_{m_i} \qquad \forall\, i. \tag{4}$$

In Eq. (1), the government's income is expressed by the total amount of tariff on raw materials and final products for all GSCs. Positive tariff value of raw material j (i.e., t_j) means that the government assigned tax to the raw material; negative value of this variable means that the government assigned subsidy to the raw material. Similarly, positive tariff value of final product k (T_k) indicates that the government assigned tax to the final product, and negative tariff value of final product represents that the government assigned subsidy to it. Hence, in the objective function, the government maximizes net income; we assume that pollution, even in green products, is unavoidable. Constraint (2) limits the pollution costs of agents to the Upper Bound (UB) which is maximum amount of pollution cost permitted by the government. The total pollution cost (Γ_G) is obtained from pollution costs caused by procurement of raw materials and production of final products in all GSCs.

Constraint (3) is Individual Rationality (IR) constraint under which GSCs agree to supply and manufacture in the market; otherwise, they refuse to conduct business and market demands will not be satisfied. The same explanation is true about Constraint (4). These two constraints express that a lower bound should be held for net profits of suppliers and manufactures in each GSC. On the other hand, these constraints preserve the supply chain structure and ensure the willingness of the GSCs to be present in the market and also their having long-term relationships with the government. This constraint has also been utilized by other researchers such as Xiao and Yang [46] and Hafezalkotob [47].

The problem of supplier i (the second level) is described as follows:

$$\max \ \pi_{s_i} = \sum_{j=1}^{m} \omega_{ij} q_{ij} - (f_j q_{ij} + g_j q_{ij}^2 + h_j) - t_j q_{ij}, \tag{5}$$

s.t.:

$$q_{ij} \leq cap_{s_{ij}} \qquad \forall\, j. \tag{6}$$

Objective function in Constraint (5) represents the profit of supplier in ith GSC obtained from selling raw materials to the manufacturer. To estimate the amount of procurement cost for each supplier, a quadratic function has been used to consider all direct and marginal costs. Constraint (6) shows the capacity of any raw materials.

Similarly, the problem of manufacturer i (second level) is described as follows:

$$\max\ \pi_{M_i} = \sum_{k=1}^{n} \left[\left(a_k - b_k \sum_{i=1}^{N} Q_{ik} \right) Q_{ik} - \sum_{j=1}^{m} \omega_{ij}\alpha_{ijk}q_{ij} - c_{ik}Q_{ik} - T_kQ_{ik} \right], \tag{7}$$

s.t.:

$$\sum_{k=1}^{n} \alpha_{ijk}Q_{ik} \leq q_{ij} \qquad \forall\, j, \tag{8}$$

$$Q_{ik} \leq cap_{m_{ik}} \qquad \forall\, k. \tag{9}$$

Objective function in Constraint (7) is the amount of manufacturer's profit in ith GSC which is acquired by selling finished products to the market. We consider oligopoly games among the manufacturers of all GSCs. Hence, the price of finished product is a function of demand for each output produced by product k. So, sale price of finished product is calculated as follows:

$$p_k = a_k - b_k \sum_{i=1}^{N} Q_{ik}.$$

On the other hand, the cost of purchasing raw materials and marginal cost will be deducted from manufacturers' income. The tax rate for non-green products or the amount of subsidy for green products will be added.

Constraint (8) declares that the amount of raw materials consumed in the process of final products' production could not be more than the available raw material purchased from supplier. Obviously, the amount of raw material consumption in final product's production should be equal to or less than the total amount of available raw material. Moreover, Constraint (9) states that quantity of final products should not exceed the capacity of production quantity of manufacturer i.

So, the single-level problem of the government can be rewritten as follows:

First level:

$$\max\ \Pi_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} T_kQ_{ik} + \sum_{j=1}^{m} t_jq_{ij} \right], \tag{10}$$

s.t.:

$$\Gamma_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} Q_{ik}\psi_{ik} + \sum_{j=1}^{m} q_{ij}\phi_j \right] \leq \text{UB}. \tag{11}$$

Second level:

$$\max\ \pi_{s_i} = \sum_{j=1}^{m} \omega_{ij}q_{ij} - (f_jq_{ij} + g_jq_{ij}^2 + h_j) \quad \forall\, i, \tag{12}$$

s.t.:

$$q_{ij} \leq cap_{s_{ij}} \qquad \forall\, j, \tag{13}$$

$$q_{ij} \geq 0 \qquad \forall\, j, \tag{14}$$

$$\max\ \pi_{M_i} = \sum_{k=1}^{n} \left[\left(a_k - b_k \sum_{i=1}^{N} Q_{ik} \right) Q_{ik} - \sum_{j=1}^{m} \omega_{ij}\alpha_{ijk}q_{ij} - c_{ik}Q_{ik} - T_kQ_{ik} \right] \quad \forall\, i, \tag{15}$$

s.t.:

$$\sum_{k=1}^{n} \alpha_{ijk}Q_{ik} \leq q_{ij} \qquad \forall\, j, \tag{16}$$

$$Q_{ik} \leq cap_{m_{ik}} \qquad \forall\, k, \tag{17}$$

$$Q_{ik} \geq 0 \qquad \forall\, k. \tag{18}$$

3.4. Reformulation as an NLP problem

Owing to the complexity of the multi-level programming problems and the lack of methods to solve them, we use KKT conditions to reformulate the problem as a single-level nonlinear programming model. Afterwards, we will explain the proposed method used in this study to solve the NLP problem. It should be noted that to establish KKT optimality conditions, we proved the lower-level problem's concavity.

Proposition. Π_{S_i} and Π_{M_i} are concave if and only if their Hessian matrix is Negative Semi-Definite (NSD), that is, we have $d^tH_{\Pi_{S_i}}d \leq 0$ and $d^tH_{\Pi_{M_i}}d \leq 0$ for all $d \in \mathbb{R}^n$, $d \neq 0$ [48]. The related proof has been brought as below:

The following proof shows the concavity of any

Π_{S_i} and Π_{M_i}. For any suppliers in GSCs, we have:

$$d^T H_{S_i} d$$

$$= \begin{pmatrix} d_1 & \cdots & d_m \end{pmatrix} \begin{pmatrix} -2g_1 & 0 \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots 0 & -2g_m \end{pmatrix} \begin{pmatrix} d_1 \\ \vdots \\ d_m \end{pmatrix}$$

$$= -2(g_1 d_1^2 + \cdots + g_m d_m^2) \leq 0.$$

Obviously, according to the values of g_j, matrix H_{S_i} is negative semi-definite; therefore, (Π_{S_i}) function will be concave.

Similarly, for manufacturer's objective function, we have:

$$d^T H_{M_i} d$$

$$= \begin{pmatrix} d_1 & \cdots & d_n \end{pmatrix} \begin{pmatrix} -2b_1 & 0 \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots 0 & -2b_n \end{pmatrix} \begin{pmatrix} d_1 \\ \vdots \\ d_n \end{pmatrix}$$

$$= -2(b_1 d_1^2 + \cdots + b_n d_n^2) \leq 0.$$

Obviously, according to the values of b_k, matrix H_{M_i} is negative semi-definite; therefore, (Π_{M_i}) function will be concave.□

$$\max\ \Pi_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} T_k Q_{ik} + \sum_{j=1}^{m} t_j q_{ij} \right], \tag{19}$$

s.t.:

$$\Gamma_G = \sum_{i=1}^{N} \left[\sum_{k=1}^{n} Q_{ik}\psi_{ik} + \sum_{j=1}^{m} q_{ij}\phi_j \right] \leq \text{UB}, \tag{20}$$

$$\sum_{j=1}^{m} \omega_{ij} q_{ij} - (f_j q_{ij} + g_j q_{ij}^2 + h_j) - t_j q_{ij} \geq R_{s_i} \quad \forall\, i, \tag{21}$$

$$\sum_{k=1}^{n} \left[\left(a_k - b_k \sum_{i=1}^{N} Q_{ik} \right) Q_{ik} - \sum_{j=1}^{m} \omega_{ij}\alpha_{ijk} q_{ij} - c_{ik}Q_{ik} - T_k Q_{ik} \right] \geq R_{m_i} \qquad \forall\, i \tag{22}$$

$$\left(a_k - b_k \sum_{i=1}^{N} Q_{ik} - b_k Q_{ik} - c_{ik} - T_k \right) - \sum_{j=1}^{m} u_{ij}\alpha_{ijk} - \sum_{k=1}^{n} v_{ik} = 0 \qquad \forall\, i,k, \tag{23}$$

$$\omega_{ij} - f_j - 2g_j q_{ij} - t_j - \sum_{j=1}^{m} \lambda_{ij} = 0 \qquad \forall\, i,j, \tag{24}$$

$$q_{ij} \leq cap_{s_{ij}} \qquad \forall\, j, \tag{25}$$

$$\sum_{k=1}^{n} \alpha_{ijk} Q_{ik} \leq q_{ij} \qquad \forall\, j, \tag{26}$$

$$Q_{ik} \leq cap_{m_{ik}} \qquad \forall\, k, \tag{27}$$

$$\lambda_{ij}(cap_{s_{ij}} - q_{ij}) = 0 \qquad \forall\, j, \tag{28}$$

$$u_{ij} \left(q_{ij} - \sum_{k=1}^{n} \alpha_{ijk} Q_{ik} \right) = 0 \qquad \forall\, j, \tag{29}$$

$$v_{ik}(cap_{m_{ik}} - Q_{ik}) = 0 \qquad \forall\, i,k, \tag{30}$$

$$Q_{ik} \geq 0 \qquad v_{ik} \geq 0 \qquad \forall\, i,k, \tag{31}$$

$$u_{ij}, \lambda_{ij} \geq 0 \qquad \forall \text{ı}, j, \tag{32}$$

$$q_{ij} \geq 0 \qquad \forall\, i,j, \tag{33}$$

$$T_k, t_j \quad \text{Free in sign} \qquad \forall\, j,k. \tag{34}$$

Eqs. (19)-(22) represent the objective function and constraints corresponding to the first level of the model. Eqs. (23) and (24) are the Lagrangian derivatives acquired from the second-level with λ_{ij}, u_{ij}, and v_{ik} as slack variables. Other constraints are the same in bi-level model and should be repeated in one-level model formulations. Constraints (28)-(30) are implemented to establish KKT conditions. Defining binary variables, we transform nonlinear Constraints (28)-(30) into linear ones; hence, the flowing constraint should be substituted for these equations:

$$q_{ij} - cap_{s_{ij}} \leq \eta_j M \qquad \forall\, j, \tag{35}$$

$$\lambda_{ij} \leq (1 - \eta_j)M \qquad \forall\, j, \tag{36}$$

$$\sum_{k=1}^{n} \alpha_{ijk} Q_{ik} - q_{ij} \leq \mu_j M \qquad \forall\, j, \tag{37}$$

$$u_{ij} \leq (1 - \mu_j)M \qquad \forall\, j, \tag{38}$$

$$Q_{ik} - cap_{m_{ik}} \leq \theta_k M \qquad \forall\, k, \tag{39}$$

$$v_{ik} \leq (1 - \theta_k)M \qquad \forall\, k, \tag{40}$$

$$\eta_j = 0 \quad \text{or} \quad 1, \tag{41}$$

$$\mu_j = 0 \quad \text{or} \quad 1, \tag{42}$$

$$\theta_k = 0 \quad \text{or} \quad 1, \tag{43}$$

where M is considered as a very large number; η_j, μ_j, and θ_k are binary auxiliary variables. Constraints (35) and (36) indicate Constraint (28) as a linear one using η_j as a binary variable that is defined in Eq. (41). Accordingly, Constraints (37) and (38) present Constraint (29) as a linear one using μ_j as a binary variable that is defined in Eq. (42). At last, Constraints (39) and (40) present Constraint (30) as a linear one using θ_k as a binary variable that is defined correspondingly in Eq. (43). Therefore, we reformulated the problem to a single-level MINLP that can be solved by GA implemented in MATLAB 7.11. For validation of the proposed GA, we compare the results of GA method with those of EM that produces optimal solution by counting all feasible space.

4. Solution methodology

Complexity of the problem depends on the size of the problem; therefore, solution time of the proposed algorithms is used as a criterion for evaluating the algorithms. To solve this problem, usually, metaheuristic methods can be utilized for these problems. Due to the non-linearity and mixed integer properties of our problem, the problem belongs to NP-hard class of problems; thus, EM requires a long to time to find the optimal solution and that is why we opt for GA.

GA is one of the evolutionary algorithms that combines the effect of the genetic code and data transfer as well as compatibility with the existing natural selection procedure based on environmental modeling. Better generation often arises from composition of better chromosomes. Sometimes, mutations in chromosomes may improve the next generation, and GA utilizes this idea to solve real problems. The proposed GA procedure for Problems (19)-(43) is described in Figure 2.

Representation chromosome is one of the most important factors of GA with significant impact on the GA performance. In this study, each chromosome is a one-dimensional array consisting of decision and auxiliary variables as the genes of each chromosome:

$$\begin{aligned} V = [&t_1, \cdots, t_m, T_1, \cdots, T_n, q_{11}, \cdots, q_{Nm}, \\ &Q_{11}, \cdots, Q_{Nn}, r_{11}, \cdots, r_{Nm}, \\ &u_{11}, \cdots, u_{Nm}, v_{11}, \cdots, v_{Nn}]. \end{aligned} \tag{44}$$

In Eq. (44), vector V, we employ government decision variables (t_j, T_k), supplier decision variables in each SC (q_{ij}), manufacturer decision variable in each SC (Q_{ik}), and the KKT variables, respectively, to represent the solution chromosome.

Now, we describe the main steps of the proposed GA:

- *Initialization:* In this study, p chromosomes are randomly generated to form the initial population. Each row of population matrix represents a chromosome. Therefore, a fixed number of the chromosomes are determined by a range of genes so that the initial random population can be formed;
- *Fitness function:* After generating the initial population, the fitness function should be calculated for each chromosome. Each chromosome represents a solution; thus, the fitness of the chromosome can be evaluated by computing objective function (government revenue) for the corresponding solution;
- *Selection strategy:* In the related literature, there are various selection methods such as the roulette wheel, tournament selection, and ranking selection. In this study, we use a ranking method as a selection strategy. Therefore, the current generation is sorted from the best to worst in order of their fitness value; hence, the chromosome with a high rank has more chance to be selected for a new generation;
- *Heuristic operator:* In this research, the proposed algorithm uses a heuristic function to create a new offspring. This function performs as follows: amount of each chromosome in a column will be replaced with mean value of the chromosomes in the higher rank of the population;
- *Crossover:* The action of combining two chromosomes (parents) and obtaining two new chromosomes (children) is called Crossover. Genes that need to be selected from each parent will be chosen in many ways, such as one-point or two-point crossover. In this study, firstly, a gene is randomly selected from each column. Secondly, the genes are written in reverse from the next point to the last gene in that column. Afterwards, we check the feasibility of the new offspring. If a new child is feasible, it will be considered as the new generation;

```
Select parameters;
Select initialize population;
While (the stop condition does not occur) do
Evaluate fitness function (Π_G in Eq. (19));
{
Check feasibility (Eqs. (20)-(43))
}
Select parents;
Heuristic function;
Crossover;
Mutation;
Sort population;
Select the best population as the final solution;
```

Figure 2. Pseudocode of the proposed GA.

Table 1. Supply and pollution costs as well as sale price of stochastic raw material in numerical example.

	GSC 1		GSC 2		Pollution cost in GSCs		Sale price in GSCs	
	1	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Raw materials	150	200	120	250	10	20	400	300
Final products	355	256	350	260	100	300	1000	1200

- *Mutation:* Besides crossover, mutation operation is also utilized to improve the solutions. This operation is performed in order to escape from being trapped in local optimum. In this study, a mutation operation is performed so that for each column of the population, two genes are selected, and then replaced with each other. Similarly, if a new child is feasible, it will be considered as the new generation;
- *Termination criterion:* The process is repeated several times to produce the next generation. In this research, after n number of iterations, the algorithm stops and reports the best obtained solution.

5. Results and discussion

A numerical example is first introduced, and then, a comparison between the results of EM and GA is presented for evaluating the validity of the methods.

5.1. Numerical example

In this section, we will explain the problem in detail for the automotive industry that has been previously described. This problem is considered between two GSCs, such that each one contains a raw material supplier and a manufacturer that produces different vehicles with green and non-green qualities. Both raw materials have been utilized to produce green and non-green automobiles. Obviously, the consumption rate of each raw material to produce products is different. In this example, the maximum environmental pollution cost is considered 7000. Moreover, the amount of capacity required to produce both kinds of the final products is assumed 80. Other data utilized to solve the numerical example are shown in Tables 1 and 2.

Table 2. Coefficient of components and the cost function coefficient of each manufacturer.

	GSC 1		GSC 2		Cost coefficient in GSCs	
	1	**2**	**1**	**2**	**1**	**2**
Raw materials	0.2	0.1	0.1	0.1	0.8	0.9
Final products	0.1	0.2	0.1	0.1		

The proposed GA for solving Problems (10)-(43) is implemented by MATLAB 7. The values of the decision variables of suppliers, manufacturers of GSC, and the government for the best solution are shown in Table 3. Moreover, the values of the best solution for revenues of the government, suppliers, and manufacturers and environmental pollution cost are shown in Table 4. In addition, the values procured for binary variables and variables related to the KKT linear constraints are shown in Tables 5 and 6, respectively.

5.2. Computational results

As a numerical example, an oligopolistic competition between two GSCs is considered.

Due to the increasing environmental legislation, demands and requests of customers, the car manufacturers have tried to boost their green management. The vehicles' environmental compatibility is relevant to suppliers' environmental performance. As a result, the environmental requirements of the automobile manufacturers will meet the cooperation with suppliers. In this study, two approaches have been utilized in production process. In the first production method, we consider green materials and also green energy. In other words, in this method, recyclable raw material and green energy, such as solar energy or energies with less environmental impact, are considered to produce final green products. The second method regards non-green products and renewable raw materials. The production method selected for each manufacturer in SCs depended on the government's fiscal and environmental policies and available tariff rates.

According to Cournot game, the price of finished product is a function of product demand; also, with considering oligopoly competition, price of the final product is a function of the total demand in the market. For this problem, firstly, we introduce problem sizes regarding the number of suppliers and manufacturers shown in Table 7. Afterwards, we represent the results obtained by EM and GA. As mentioned before, we use EM to prove the validation of the proposed GA. Subsequently, the results are compared with those of the GA to validate the approach. These results are shown in Table 8.

Table 3. Decision variables values obtained by the proposed genetic algorithm.

q_{11}	q_{21}	q_{12}	q_{22}	Q_{11}	Q_{21}	Q_{12}	Q_{22}	t_1	t_2	T_1	T_2
69	77	80	66	80	75	70	80	44	39	-13	46

Table 4. Best solutions values obtained by the proposed genetic algorithm.

Government income	Supplier income 1	Supplier income 2	Manufacturer income 1	Manufacturer income 2	Environmental pollution cost
17398	9588	5629	121690	122670	6120

Table 5. Optimum values of the KKT variables in the proposed genetic algorithm.

v_{11}	v_{21}	v_{12}	v_{22}	u_{11}	u_{21}	u_{12}	u_{22}	r_{11}	r_{21}	r_{12}	r_{22}
0	$0 \geq$	$0 \geq$	0	0	0	0	$0 \geq$	0	$0 \geq$	0	0

Table 6. Optimum values of the binary variables in the proposed genetic algorithm.

η_1	η_2	μ_1	μ_2	θ_1	θ_2
1	0	0	1	0	0

Table 7. Test problem sizes.

Code	Number of suppliers	Number of manufacturers
2-2	2	2
3-3	3	3
4-4	4	4

In Table 8, results acquired by GA are presented in six columns. The first four columns represent the population size, number of iterations, objective function value, and the problem's solving time. The next two columns indicate the average value of the objective functions and the solving time of all problems, respectively. Moreover, results obtained by EM have two columns that show the optimal solutions of the problem and the solving time, respectively. Results presented in Table 8 express that the proposed GA on a greedy search is an efficient algorithm to produce good results.

By comparing the results, we can conclude that the difference between the solutions obtained by GA and the optimal solutions acquired by EM is one of the factors indicating the quality of the proposed method. With increasing the problem size, EM can no longer reach an optimal solution. Hence, large-sized problem should be solved by the proposed GA. Figure 3 clearly displays the difference between the results obtained from GA to the global optimum solutions of the problem obtained from EM.

Now, we analyze the sensitivity of government revenue with respect to the upper bound of environmental pollution cost (UB). Five values have been chosen for UB: UB1 = 7000, UB2 = 6000, UB3 = 5000, UB4 = 4000, and UB5 = 3000. Objective functions for these values are reported in Figure 4.

Table 8. Computational results for GA.

Code	Genetic algorithm						Enumerative method		%Error[1]
					Average				
	Pop	Iteration	Answer	Time (sec)	Answer	Time (sec)	Answer	Time (h)	
2-2	10	20	16945	597	17173.5	734	17398	85	% 1.3
	10	40	17124	675					
	10	60	17257	710					
	10	80	17368	954					
3-3	10	20	34951	758	35946.75	1020.25	36901	120	% 2.58
	10	40	35864	946					
	10	60	36102	1072					
	10	80	36870	1305					
4-4	20	20	56874	1486	58463.5	1784	N	N	—
	20	40	58421	1675					
	20	60	58705	1861					
	20	80	59854	2116					

[1] $\% \text{ Error} = \frac{\text{EM solution} - \text{GA solution}}{\text{EM solution}} \times 100$

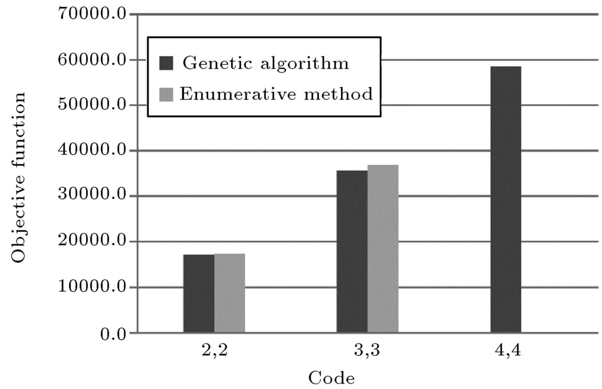

Figure 3. Comparison of the values of objective function obtained by GA and EM in different sizes.

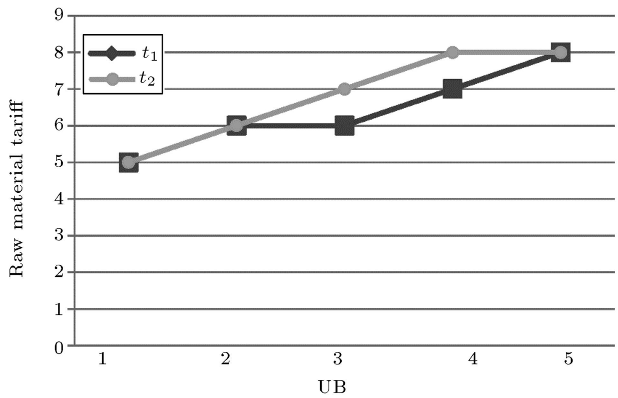

Figure 4. The sensitivity of objective value to different threshold of environmental standard.

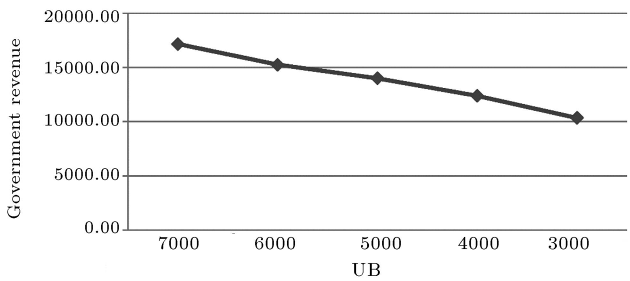

Figure 5. The sensitivity of raw materials' tariff to different threshold of environmental standard.

According to this figure, it is quite clear that the government income is decreased by reducing UB, that is, decreasing the threshold of environmental pollution standard would lead to producing more non-green products.

Figures 5 and 6 also indicate that the tariffs assigned to raw materials and the final products by the government are sensitive to changes of UB. In Figure 5, t_j (t_1 and t_2) refers to the tariffs on raw material j imposed by the government ($j = 1, \cdots, 2$). Also, in Figure 6, T_k (T_1 and T_2) refers to the tariffs on product k imposed by the government ($k = 1, \cdots, 2$). According to these figures, we can conclude that by

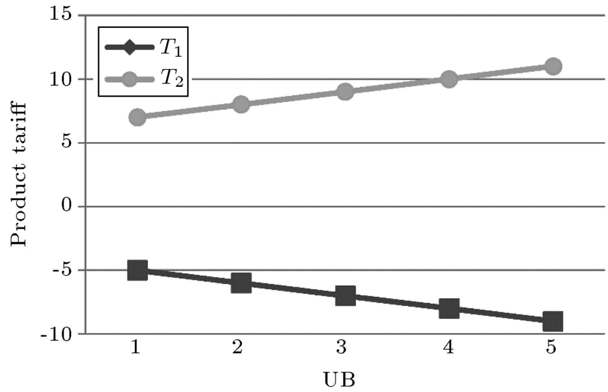

Figure 6. The sensitivity of products' tariffs with regard to threshold of environmental standard.

reducing UB, positive values of tariff rate (tax) assigned to non-green materials and finished products by the government will be increased. Similarly, the negative values of tariff rate (subsidy) allocated to raw materials and finished products are also raised by the government to convince GSC members to improve the quality of their products. This means that suppliers and manufacturers will reduce their production of non-green products; as a result, the environmental pollution cost decreases.

6. Conclusions and further study

In this research, a competitive market based on oligopoly and cournot games was considered between multi-product green supply chains with a focus on the automotive industry. Each supply consisted of a manufacturer and a set of suppliers. We investigated the role of government as a leader on the competition via finance intervention. In this regard, a nonlinear bi-level model is proposed, and in the first level, priorities of the government policy were to maximize its net income, control the environmental pollution, and increase social welfare. In the second level, the objective was to maximize the profit of each GSC member.

Subsequently, the bi-level model was converted to a single-level model by replacing the second level with its Kuhn Tucker conditions and using linearization techniques. The proposed approach was implemented and evaluated using MATLAB 7. Then, the results obtained from the GA were compared to the exact ones of EM in small-sized problems in order to validate the GA. The results showed that the GA was close to global optimum in smaller size problems. The sensitivity analysis of this model indicates that the fiscal policy of the government is greatly effective in reducing environmental pollution costs caused by industrial activities, such as automobile production, in a competitive market. We found that this effect was resulted from appropriate the tax and subsidy of the government. Many other aspects could be researched in future studies. Since the model was considered with certain values of price and demand, in future, uncertain values may be considered. Moreover, in the present model, only supplier and manufacturer were considered as GSC members. Other possible members, such as retailer and distributer, can be added to the model in the future study.

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