A GA for Solving a Type of Sustainable Supply Chain Design Problem

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***Abstract**. We propose a hybrid genetic algorithm (GA) for solving a sustainable supply chain design problem that arises in the public sector. There is little research being done in mathematical modeling and solutions methods for these problems. The paper describes a mixed-integer 0-1 model (MIP) for this sustainable problem in which we have to determine in a network of two layers the number of facilities to be located at sites chosen from among a given set of candidate sites. Sustainable issues are integrated into the model by reducing the greenhouse gas emissions produced by the transportation and the operation of the facilities. We report computational results for instances generated from a known OR test library.*

1. Introduction

In 1987 the United Nations World Commission on Environment and Development (UNWCED) published Our Common Future Report. In this report was defined sustainable development as “development that meets the needs of the present without compromising the ability of future generations to meet their own needs”. This report was a kick-off for a number of interdisciplinary studies in the field of sustainability.

By 2020 the economic impact of climate change in the world will reach 20% of the global GDP. Considering the magnitude of the impact on the global economy, the environment and the society, many agencies of the government and international institutions are taking actions to reduce and to control the emission of GHG. In this respect, this paper focuses on how governments can deploy supply chain networks for servicing people while minimizing the costs of installation, operation and transportation and, at the same time reducing the GHG emissions.

Governmental agencies and companies adopting a friendly sustainable management are facing a number of changes, from the strategy level till the operational point of view, affecting their people and impacting their business processes and their technology. In this regard, as Simchi-Levi et al. (2007) pointed out, “the strategic level deals with decisions that have a long-lasting effect on the firm. These include decisions regarding the number, location and capacities of warehouses and manufacturing plants, or the flow of material through the logistics network". They established a clear link between facility location models and strategic decisions of supply chain management (SCM). Also, governmental agencies and companies realized that to be committed with sustainable practices could imply changes in the criteria to design and to manage supply chain. That is to say, in addition to the costs of transport, operation and installation and considerations on the level of service, the sustainable models need to consider GHG emission costs.

Supply chain design based on economic consideration has been well covered in the literature. On the other hand, the field of sustainable supply chain design and management (SSCM) is quite new (Seuring and Muller, 2008). The greatest benefits of applying SCM are obtained by an extended analysis including organizations upstream -closer to the raw materials- and downstream -closer to the consumer- of the supply chain and then back again so that the unsold products are recycled. But, by extending the focus, what this really does implies more organizations, multiplying the relation between the organizations and getting a more complex supply chain (SC) to manage. Considering that, according to Choi and Wu (2009) the focus of the supply chain management literature has been on dyadic networks (supplier units-customer units).

This paper proposes a genetic algorithm for solving a supply chain network design problem that arises in the public sector considering sustainable constraints in the form of restrictions on the dioxide carbon equivalent emissions. The authors are not conscious of any article tackling the problem of sustainability that arises in the location of such public facilities as schools or hospitals. We present a mixed-integer 0-1 network design model who allows to analyze the impact of restrictions in the GHG emissions on the fixed and transportation costs and in the location of facilities in a network of two layers.

In this paper, in Section 2 is analyzed some literature in connection with the problem. In section 3 is presented the mixed-integer 0-1 programming model. In section 4, we discuss the genetic algorithm implementation for solving the problem. In section 5 we provide some numerical results. Finally in section 6 we give some conclusions of the work.

2. Literature Review

The UNWCED report published in 1987 defined sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs".

Above and beyond other aspects, there are principally two kinds of questions related to the sustainability. One of them is the emission of GHG. For the production of a big quantity of GHG to satisfy the present needs – for example, in the processes of manufacture and distribution - we affect the climate of a dangerous way that finally is going to compromise the capacity so that future generations could satisfy their own needs. In this paper we focus on reducing the GHG emissions caused by the operation of public facilities and the transportation activities to satisfy the demand. We model the problem considering a network of two layers. We locate facilities in these layers to satisfy a fixed demand, minimizing installation and operating costs and constraining the GHG emissions.

Supply chain management (SCM) is being used to address the problem of reducing the economic impact of climate change generated by GHG emissions. For the purpose of this paper, SCM is a multidisciplinary management approach to master a set of interacting organizations. These organizations share different resources, products, services and information, with the target to obtain competitive advantages and to improve the profitability, both in the individual form and in the collective form. (Simchi-Levi et al., 2007). Given the complexity of the network, according to Choi and Wu (2009), the focus of the literature of SC has been in networks of dyadic (supplier firms – customer firms).

Disciplines integrating environmental practices into the supply chain have been called in a number of different ways. Some of them are: Sustainable Supply Chain Management (SSCM) and, Green Supply Chain Management (GSCM). Srivastava (2007) did a careful review of the literature and he showed that a wide frame of reference for GSCM has not been sufficiently developed. He defined GSCM as an integrated environment, including product design, sourcing and selection of material, manufacturing processes, delivery of the final product to the consumers, and end-of-life management of the product after its useful life. In this paper, we do not make any distinction between sustainable and green supply chain.

Mathematical modeling for designing sustainable supply chain is attracting many researchers to this field. But, according to Seuring and Muller (2008), the field of sustainable supply chain design and management (SSCM) is quite new. In this work, the proposed model focuses on two sustainable issues: economic and environmental aspects of GHG emissions. On the other side, till now much research has been done in the field of private companies' location theory. The authors are not aware of any paper addressing the sustainable problem that arises in the location of such public facilities as schools or hospitals.

Hugo and Pistikopoulos (2004) develop a multi-objective mixed-integer 0-1 model for deciding location and capacity expansion of facilities (plants), and transportation issues in a given planning horizon. They maximize profit and minimize the environmental impact of the plant operations while satisfying the market demand for products. They presented numerical results for a small problem of 3 candidate plants, 3 customers, 2 products, 2 raw materials and 5 periods. In a later work, Hugo and Pistikopoulos (2005) extend the previous model and reformulate the problem as a stochastic programming model that can address the decision-making process under uncertainty. Ramudhin et al. (2008) propose a mixed-integer 0-1 programming model for the GSC design problem. Taking into account environmental aspects, they analyze the impact of transportation, subcontracting, and production activities on the design of a supply chain network. The model is tested considering the case of a steel product manufacturer with three freight transportation modes, a product with two semi finished products that are manufactured from four parts, and at least two suppliers are competing to supply each part. The model is first solved by CPLEX Interactive Optimizer V10.0. The authors also use Goal Programming to determine the best trade-offs between two conflicting objectives: the total logistics cost and carbon emissions. In Chaabane et al. (2010) is extended the previous model considering life cycle assessment (LCA) principles in addition to the traditional material balance constraints at each node in the supply chain. They propose a multi-objective mixed-integer 0-1 model to support sustainable supply chain design over a long-term period of time. The model distinguishes between solid and liquid wastes, as well as gaseous emissions due to various production processes and transportation modes. The model is used to evaluate the tradeoffs between economic and environmental objectives under various cost and operating strategies for an aluminum company. Finally, Diabat and Simchi-Levi (2010), use a mixed-integer 0-1 programming model including carbon emissions restrictions for designing green supply chains. The problem is to decide which plants and Distribution Centers (DCs) to open, how the DCs are allocated to the plants, and how the DCs distribute multiple types of products to satisfy retailers' demands. The objective is to minimize the total facility opening and products distribution costs subject to the total carbon emission is not more than a predetermined emission cap. They formulate the problem as a two-echelon multi-commodity facility location problem with a carbon emission constraint. They present numerical results for a 7 candidate plants, 18 candidate DCs, 63 retailers, and a single type of product. To solve the instances, the authors use ILOG CPLEX 11.0 MIP solver in the GAMS modeling language.

The problem of locating facilities and allocating customers is not new to the operations research community and covers the key aspects of supply chain design (Daskin et al., 2005). Simchi-Levi et al. (2007) establish a clear link between location models and strategic SCM. Altiparmak et al. (2006) pointed out that this problem is one of "the most comprehensive strategic decision problems that need to be optimized for long-term efficient operation of the whole supply chain". Notice that some small changes to classical facility location models are quite hard to solve (Farahani and Hekmatfar, 2009). For example, in Lai-Jun et al. (2009) a genetic algorithm was used to solve a kind of facility location problem on test networks with 10 potential facility sites and 30 demand points. In this paper we focus on the sustainable supply chain design problem that arises in governmental agencies, where you have to decide the location of schools, hospitals, police stations, fire stations, and so on, taking into account sustainable issues.

3. Problem Formulation

The sustainable supply chain network design problem consists in deciding the number and location of facilities, and the allocation of customers to these facilities, minimizing the installation and transportation costs integrated with GHG emissions constraints. We consider a public supply chain that provides products/services and it consists of two layers hierarchically related. In the general case, these supply chain consists of two layers (mid and high) of distinct types of facility. For example, health care systems may consist of local clinics and hospitals or medical centers; higher education systems may consist of technical schools and universities. For further details on related problems see the paper by Bastani and Narges Kazemzadeh (2009). Our problem is uncapacitated by nature, following most of the research on locating public facilities, i.e., we do not restrict the capacity of the facilities to service the demand. Our interest is to analyze how service costs of governmental agencies located in both layers will be affected by sustainable restrictions. We assume that GHG emissions come mainly from the operation of the facilities located in both layers and from the transportation activities involved to service a fixed demand. Notice that, the clients can be attended by only one facility of the mid layer and each mid layer facility must be allocated to one high layer facility. We suppose that GHG emissions are proportional to the demand, i.e. population to be attended, and the travel distance. Then each facility has a carbon footprint proportional to the demand attended. We model this using a parameter to be adjusted from the IPCC recommendations.

We introduce the following inputs and sets:

J = the set of demand nodes indexed by j

I = the set of candidate facility locations at the mid layer, indexed by i

K = the set of candidate facility locations at the high layer, indexed by k

h_j = demand at customer location $j \in J$

f_i = fixed cost of locating a mid layer facility at candidate site $i \in I$

g_k = fixed cost of locating a high layer facility at candidate site k $\in K$

c_{ij} = is the unit cost of supplying demand $j \in J$ from a mid layer facility located in $i \in I$

l_{ik} = is the unit cost of supplying demand $i \in I$ from a high layer facility located in $k \in K$

M = cardinality of J

α_i = GHG emissions factor of a facility located at candidate site $i \in IUK$, in tons of CO_2e per unit demand

β_{ij} = GHG emissions factor per unit distance and per unit demand between candidate facility site $i \in I$ and customer location $j \in J$, in tons of CO_2e per km and unit demand. We also use this factor for facilities located at a higher layer ($k \in K$) that are serving mid layer facilities ($i \in I$).

We consider the following decision variables:

$$y_i = \begin{cases} 1 \text{ if we locate a facility at candidate site } i \in I \\ 0 \text{ otherwise} \end{cases}$$

$$z_k = \begin{cases} 1 \text{ if we locate a high layer facility at candidate site } k \in K \\ 0 \text{ otherwise} \end{cases}$$

$$x_{ij} = \begin{cases} 1 \text{ if the demand of } j \in J \text{ is serviced by a facility located at } i \in I \\ 0 \text{ otherwise} \end{cases}$$

$$w_{ik} = \begin{cases} 1 \text{ if the demand of } i \in I \text{ is serviced by a facility located at } k \in K \\ 0 \text{ otherwise} \end{cases}$$

The general supply chain design problem with sustainable constraints (($GUSSCP$) is defined by:

$$v(GUSSCP) =$$

$$Minimize \sum_{i \in I} f_i y_i + \sum_{i \in I} \sum_{j \in J} h_j c_{ij} x_{ij} + \sum_{k \in K} g_k z_k + \sum_{k \in K} \sum_{i \in I} h_i l_{ik} w_{ik} \qquad (1)$$

$Subject\ to$:

$$\sum_{i \in I} x_{ij} = 1 \qquad \forall\, j \in J \qquad (2)$$

$$\sum_{j \in J} x_{ij} \le M y_i \qquad \forall\, i \in I \qquad (3)$$

$$\sum_{k \in K} w_{ik} \geq y_i \qquad \forall\, i \in I \qquad (4)$$

$$\sum_{i \in I} w_{ik} \leq z_k \qquad \forall\, k \in K \qquad (5)$$

$$\sum_{i \in I}\sum_{j \in J} \alpha_i\, h_j x_{ij} + \sum_{k \in K}\sum_{i \in I} \alpha_k\, h_i w_{ik} + \sum_{i \in I}\sum_{j \in J} \beta_{ij} h_j c_{ij} x_{ij} + \sum_{k \in K}\sum_{i \in I} \beta_{ik} h_i l_{ik} w_{ik} \leq GHG \qquad (6)$$

$$x_{ij}, w_{ik}, y_i, z_k \in \{0,1\} \qquad \forall\, i \in I, \forall\, j \in J, \forall\, k \in K \quad (7)$$

The objective function (1) minimizes the sum of the installation facility costs and the demand-weighted supplying costs. Constraints (2) warranty that all demand at area $j \in J$ is met by one mid layer facility. Constraints (3) warranty that a demand node $j \in J$ must be allocated to a mid layer facility $i \in I$ already opened. Constraints (4) ensure that each open mid layer facility must be allocated to one high layer facility. Constraints (5) warranty that the demand of a mid layer facility must be serviced by a high layer facility. Constraint (6) limits the total Greenhouse Gas (CO_2e) emissions to *GHG*. Constraints (7) are standard binary constraints. Regarding constraints (3), when they are replaced by constraints

$$x_{ij} \leq y_i \qquad \forall\, i \in I, \forall\, j \in J \quad (3a)$$

we got a stronger formulation for the problem, as it was also discussed in a related facility location problem (Cornuejols et al., 1977). This problem is NP-hard as generalization of well-known location problems, and therefore cannot be solved in polynomial time.

4. Genetic Algorithm Implementation

Genetic Algorithms (GAs) are a type of evolutionary algorithms (EVA) used to solve a number of combinatorial optimization problems. See for further details the papers by Goldberg (1989). According to Osman and Kelly (1996), an EVA is composed by five basic components: (a) a genetic representation of solutions to a problem; (b) a way to create an initial population of solutions; (c) an evaluation function; (d) genetic operators that alter the genetic composition of children during reproduction and (e) values for the parameters. In this section we briefly describe these components and the GA implementation for solving the *GUSSCP* problem. The basic scheme of our GA can be represented as follow:

1. Generate an initial population;
2. Compute the fitness of each individual in the population;
3. while not Finish do
    a. Compute the Fitness for all the individuals in the population;
    b. Apply selection process;
    c. Do a crossover of individuals;
    d. Generate individuals using the mutation operation;
    e. Apply the feasibility procedure
4. Endwhile;

4.1. Representation, Initial Population and Feasible Solutions

In our implementation, each solution (individual) to the problem is coded as a chromosome such that each gene corresponds to a facility location decision variable at both layers, taking value 1 if a facility is open either at the mid or high layer, and zero otherwise. We use a $(|I| + |K|)$ dimensional string to represent facilities located at both layers.

The initial population of 100 individuals is generated randomly. Then we recombine this initial population and generate randomly two sets of 100 individual each. Each gene of the chromosome is generated by a 0-1 uniform probability distribution. For each chromosome we apply a solution procedure. This procedure consists in getting a solution to *GUSSCP* disregarding sustainable constraints as follows: Given a chromosome, for every customer $j \in J$ we assigned its nearest opened mid layer facility. Then for each opened mid layer facility we assigned its nearest opened high layer facility. Regarding the GHG emissions, that mechanism of generating chromosome could generate unfeasible solutions for *GUSSCP*, but our strategy was to explore the behavior of the algorithm based on an initial population composed of a number of unfeasible solutions. For our test problems, the GA implemented in this way rapidly generated a large number of unfeasible solution and we obtained poorer solutions than the next approach we will discuss it. In the second approach, after the crossover and mutation operations, we introduce a greedy-random procedure to generate to every iteration of the GA at least 50% of feasible solutions. Then our new population in every iteration has at least 50% of feasible solutions. The procedure is as follow: we generate a random individual consisting of a number of facilities opened/closed. Then based on the transportation costs we apply the solution procedure, i.e., we allocate the nearest customer to each opened mid layer facility and then for each mid layer facility we find the nearest opened high layer facility. We repeat the procedure till we get 50% of feasible solutions for the new population. We replace unfeasible solutions for the new individuals obtained through this procedure. Finally the best 100 individuals will be part of the new initial population to start the main iteration of GA. As we can see later in this paper, computational results are very good.

The fitness of a chromosome is calculated using the objective function (1). To compute the first term (installation costs) of (1) is straight forward from the chromosome. To compute the second term (transportation costs) of (1), we use the solution procedure described above: for each customer we find its nearest opened facility (minimal transportation cost) and the we do the same for each opened mid layer facility. Then we sum up both parts (installation and transportation costs) to get the objective function value for each individual of the population.

4.2. Genetic operators

We use the standard genetic operators. The crossover generates two new individual (chromosome) exchanging the genetic material of two (parental) individuals expecting that "good" solutions can generate "better" ones. We selected these individuals randomly from a two sets of individuals, each set composed of 100 individuals as described earlier. We do not limit the number of new chromosomes generated by crossover. In this work crossover probability (*cross_p*) is set to 0.7 (70%) and we perform one-point crossover. In the crossover procedure we generate a random value, if the *cross_p* value is greater than the random value then we pick one individual from each set. We generate another random value between one and the number of potential facility sites for each layer, i.e, a cut point dividing each individual (parent) into two segments. The first child is created by combining the first segment from the first parent and the second segment from the second parent. The second child is created from the first segment of the second parent and the second segment of the first parent. The mutation operator changes the value of a chromosome with some small probability. In our case, we get this probability to 0.1 (10%) and remain constant through generations of the GA. The gene in the chromosome is selected randomly and we switch its value (0-1). We do not limit the number of new chromosomes generated by mutation. After the crossover and mutation procedures, we got a number of unfeasible solutions in the population. In the next step we correct this;

4.3. Additional GA aspects

The selection operator is based on elitist selection, favoring individuals of better fitness value to reproduce more often than the worse ones when generating the new population. In every iteration the whole population (200 individuals) is ranked in a non-decreasing order of the objective function value. As we described earlier, feasibility of constraints (6) is verified. In case there is lesser than 50% of feasible solutions in the population, a greedy-random procedure was implemented to generate new (feasible) individuals. The best (100) solutions passed to the next iteration

In our case the total size of population is 200 individuals, and 100 of new individuals are generated each iteration. We set the total number of iteration to six.

5. Computational Results

The GA solution method for this problem was coded and implemented by Scilab software. According the sustainable supply chain literature discussed in previous sections, for testing our GA implementation we generated 11 size instances of *GUSSCP*. These instances correspond to test networks up to 26 potential sites and up to 50 demand nodes taken from the ORLIB (Beasley, 1996). For every instance we use one layer. As we do not know in advance how well is going to perform the GA, in order to validate our GA solutions we used GAMS on integer linear programming model described in section 3. Every test problem was running 5 times and we present an average value in Table 1. The optimal objective values were obtained by GAMS. As we can see in Table 1, besides the few number of iteration (6) used in our GA, the GAP obtained is quite small. Both methods (GA and GAMS) quickly converge on mentioned *GUSCPS* instances and their running times are not reported. The alpha (α) and beta (β) parameters were set to one and two respectively. This was done to analyze the behavior of the algorithm and also to check how the solution change when you penalty the transportation GHG emissions. Total GHG emissions were limited to values between 3,200.00 and 10,000.00 thousands.

We notice that, when you reduce the total amount of GHG emissions permitted, and the number of facilities remain free, the number of facilities to open increase, also increasing the cost of the solution but reducing the amount of GHG emitted by the transportation component.

6. Conclusions

In this paper, we introduced a novel kind of sustainable supply chain network design problem with a GHG emission constraint. The problem addressed the design of supply network arising mainly in the public sector, where we need to satisfy the demand for services like education and health care locating a number of facilities in two layers. We limit the GHG emissions generated by the facilities located in the mid and high layer and also the transportation involved in servicing the customers. The problem was formulated as a mixed integer 0-1 linear programming problem (MIP) and solved using a genetic algorithm coded in Scilab. We conducted an experimental study on instances taken from the ORLIB. In order to validate our GA solutions we used GAMS to obtain optimal objective values on the MIP. The genetic algorithm performs very good considering we set a few number of iterations. We observed that when you reduce the total amount of GHG emissions permitted, and the number of facilities remain free, the number of facilities to open increase, also increasing the cost of the solution but reducing the amount of GHG emitted by the transportation component.

Table 1. Computational Results. First column indicates number of problem instance; Fixed Costs in thousands; z* is the optimal solution; z(GA) is the solution value provided by GA.

# Probl	Fixed Costs	Total GHG	z*	z(GA)	GAP (%)
1	25,000	10,000	1,746,347	1,775,425	1.7
2	17,500	10,000	1,727,848	1,731,842	0.2
3	12,500	10,000	1,700,236	1,700,841	<0.1
4	25,000	5,000	1,746,348	1,775,425	1.7
5	25,000	3,200	1,953,224	1,953,224	0.0
6	17,500	3,200	1,840,724	1,840,724	0.0
7	12,500	3,200	1,765,724	1,765,724	0.0
8	7,500	3,200	1,690,724	1,690,724	0.0
9	7,500	3,300	1,663,018	1,684,578	1.3
10	12,500	3,300	1,700,236	1,765,723	3.9
11	17,500	3,300	1,730,236	1,773,011	2.5

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