A multi-objective evolutionary approach to improve the environmental performance of a supply chain

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***Abstract*—The problem of improving the environmental performance of a supply chain without entailing excessive cost is becoming a frequent problem as companies face an increasing pressure from governments and customers for reducing the environmental impact of their activities. As the environmental improvement of an operating supply chain implies not only technology upgrading decisions, but also decisions regarding the structure of the supply chain itself; deciding on what strategy to follow is a complex task. The aim of this work is to provide a bi-objective solution approach for finding such strategy so that both the environmental and financial goals are best met.**

***Keywords*—Sustainability, supply chain design, multi-objective optimization, evolutionary computation**

I. Introduction

A supply chain is considered to be sustainable if two conditions are met: first, it should continue to be profitable in the future; and second, it should be accountable for no harm to the environment and the society [1]. From the environmental perspective, most companies today face a steady growing pressure to alleviate the environmental impact directly related to their operation, not only from governments, but also from their customers, as they become more environmentally aware [2]. In this context, companies are concerned with the problem of assessing the environmental impacts of their supply chains so that action can be taken to mitigate them. In particular, the amount of CO_2 emissions resulting from their operations, also known as the carbon footprint, has emerged as the international standard to assess the environmental impact of a given company. According to the 2014 annual report of the Intergovernmental Panel on Climate Change [3], global industrial greenhouse gas emissions accounted for about 30% of the total greenhouse gas emissions in 2010, not including the sectors of power generation and transportation; and CO_2 accounted for approximately 85% of the total emissions in 2010 [3]. According to the United States Environmental Protection Agency (EPA), in 2010 the supply chain of a typical industrial organization was responsible for around two thirds of the total emissions of the company [4]. Finally, the authors in [3] conclude that the energy intensity of the industrial sector "could be reduced by approximately up to 25% compared to current level through the wide-scale deployment of best available technologies, particularly in countries where these are not in practice and for non-energy intensive industries". Which means that there is room for significant environmental improvement of many supply chains currently in operation.

We focus our attention on the cement industry given its high demand, large energy use and substantial emissions of CO_2. The reason for its high demand is that concrete is the second most consumed material worldwide, only surpassed by water [6]; and a typical concrete mix contains around 10% to 15% of cement. This, combined with the fact that its worldwide demand is expected to grow around 1.3% per year in the near term [7], explains the claim. Regarding energy use, the cement industry consumed around 8.5% of the total industrial energy consumed in 2012 [7]. Regarding the emissions of CO_2, in 2012 it was estimated that the production of one metric ton of cement releases to the environment between 650 and 950 Kg of CO_2. Approximately 50% of this total comes from the chemical reaction that takes place when the calcium carbonate ($CaCO_3$) is fed into a kiln to produce clinker, the main component of cement. The actual value of emissions depends mainly on the technology used in the production process, the sources of heat and electricity, and the raw materials mix [8, 9]. In summary, the cement industry is responsible for around 5% of the human-produced CO_2, and 34% of total industry CO_2 emissions [6]. These elements combined show the relevance of reducing the environmental impact of this industry.

Researchers in the field agree on the opportunity around reducing the environmental impact of current industrial processes by using cleaner fuels and more energy efficient processes. On the other hand, the need of a simultaneous evaluation of both environmental and financial aspects has been widely recognized from the point of view of the supply chain design. Several literature reviews have been recently published in the areas of sustainable supply chain management [10-12], green supply chain management [13, 14], and sustainable supply chain network design [15]. In this work we extend a previous study in which the authors propose a multi-objective mixed integer linear programming (MILP) formulation for solving the problem of finding the best supply chain configuration with the objective of balancing two conflicting objectives: emissions of CO_2 and total cost [16]. To achieve this goal, the model considers the current state of the supply chain, and allows for adopting cleaner technologies at various capacity levels and more efficient fuels within a cement supply chain that is currently in operation. Other similar research works related to the problem under study that we are aware of are those of references [17-19] as these works consider improving the environmental performance of a supply chain that is currently in operation. In [17] the authors addressed the problem of determining the configuration of a three-echelon supply chain with the objectives of maximizing the net present value and minimizing the environmental impact, whereas in [18] the authors expanded the scope by allowing uncertainty associated with the parameters representing the assessment of the different environmental impacts. A simulation approach is presented in [19] to select the best of three supply chain scenarios for the cement industry: make-to-stock, pack-to-order, and grind-to-order. To make the decision, the simulation integrates economic, environmental and social dimensions. A detailed analysis of the above mentioned references shows that among operations research techniques, multi-objective optimization is one of the most common solution approaches used to tackle these problems. However, to the best of our knowledge, the crucial subject of technology update decisions in the context of an operating supply chain, and the impact of these decisions on the environmental and financial performance of a firm, has not received due attention in the literature. Heuristic approaches cannot be compared to MILP approaches solving the problems optimally. However, they can provide promising solutions for both larger and nonlinear variants of the environmental optimization problems. The aim of this work is to extend the work in [16] by providing a heuristic solution approach for the problem of simultaneously selecting a technological upgrade strategy and designing a new network configuration for an operating supply chain, that takes into consideration the current state of the system, and that considers the environmental and financial implications of the recommended solutions.

II. Mathematical Model

Here we present the mixed integer linear formulation (MILP) originally proposed in [16] with a minor modification that allows for changing only the fuel in a given facility, without changing the technology nor the capacity level.

A. Sets

- F: facilities
- T_i: Available technologies for facility $i \in F$
- Q_{ij}: Available capacities for technology $j \in T_i$ at facility $i \in F$
- L_{ijk}: Fuels available for technology $j \in T_i$ at facility $i \in F$ with capacity q_{ijk}
- C: Customers

B. Parameters

- h_i: Annualized cost of taking facility $i \in F$ out of operation.
- q_i^0: Current capacity at facility $i \in F$
- f_i^0: Current annual fixed cost at facility $i \in F$
- v_i^0: Current variable unit cost at facility $i \in F$
- α_i^0: Current unitary thermal energy consumption at facility $i \in F$
- β_i^0: Current unitary electrical energy consumption at facility $i \in F$
- γ_i^0: Current unitary cost of thermal energy associated with the fuel used at facility $i \in F$
- e_i^0: Current unitary emissions of CO_2 due to thermal energy associated with the fuel used at facility $i \in F$
- q_{ijk}: The k-th capacity value in Q_{ij}
- s_{ijkr}: Annualized cost of installing technology $j \in T_i$ at facility $i \in F$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$
- f_{ijkr}: Annualized fixed cost associated with technology $j \in T_i$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$ at facility $i \in F$
- v_{ijkr}: Variable unit cost associated with technology $j \in T_i$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$ at facility $i \in F$
- α_{ijkr}: Unitary thermal energy consumption of technology $j \in T_i$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$ at facility $i \in F$
- β_{ijkr}: Unitary electrical energy consumption of technology $j \in T_i$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$ at facility $i \in F$
- γ_r: Unitary cost of the thermal energy when generated with fuel $r \in L_{ijk}$
- e_r: Unitary emissions of CO_2 per unit of thermal energy generated with fuel $r \in L_{ijk}$
- η: Unitary cost of the electrical energy
- θ: Cost of transporting one unit of product for one unit of distance
- μ: Emissions of CO_2 per unit of product due to the chemical reaction in the cement production process
- ψ: Emissions of CO_2 per unit of electrical energy used
- ρ: Emissions of CO_2 due to the transportation of one unit of product for one unit of distance
- d_{ic}: Distance from facility $i \in F$ to customer $c \in C$
- δ_c: Demand of customer $c \in C$

C. Decision Variables

- z_i: Binary variable such that z_i=1 if facility $i \in F$ is kept in operation; and z_i=0 if otherwise.
- u_i: Binary variable such that u_i=1 if it is decided to change the technology and/or the capacity and/or fuel at facility $i \in F$; and u_i=0 if otherwise
- y_{ijkr}: Binary variable such that y_{ijkr}=1 if technology $j \in T_i$ is installed at facility $i \in F$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$

- x_{ijkr}: Continuous variables representing the production quantity assigned to facility $i \in F$, produced with technology $j \in T_i$ with capacity q_{ijk} and operated with fuel $r \in L_{ijk}$
- π_i: Continuous variables representing the amount of product that facility $i \in F$ will continue to produce with its current technology and capacity
- w_{ic}: Continuous variables representing the amount of product shipped from facility $i \in F$ to customer $c \in C$

D. *Cost Expressions*

- Setup:

$$\sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} s_{ijkr} \cdot y_{ijkr} \tag{1}$$

- Fixed:

$$\sum_{i \in F} f_i^0 \cdot (z_i - u_i) + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} f_{ijkr} \cdot y_{ijkr} \tag{2}$$

- Closing:

$$\sum_{i \in F} h_i \cdot (1 - z_i) \tag{3}$$

- Production:

$$\sum_{i \in F} v_i^0 \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} v_{ijkr} \cdot x_{ijkr} \tag{4}$$

- Thermal energy:

$$\sum_{i \in F} \gamma_i^0 \cdot \alpha_i^0 \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} \gamma_r \cdot \alpha_{ijkr} \cdot x_{ijkr} \tag{5}$$

- Electrical energy:

$$\sum_{i \in F} \eta \cdot \beta_i^0 \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} \eta \cdot \beta_{ijkr} \cdot x_{ijkr} \tag{6}$$

- Transportation:

$$\sum_{i \in F} \sum_{c \in C} \theta \cdot d_{ic} \cdot w_{ic} \tag{7}$$

E. *Emissions of CO_2 Expressions*

- Production:

$$\sum_{i \in F} \mu \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} \mu \cdot x_{ijkr} \tag{8}$$

- Thermal energy:

$$\sum_{i \in F} e_i^0 \cdot \alpha_i^0 \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} e_r \cdot \alpha_{ijkr} \cdot x_{ijkr} \tag{9}$$

- Electrical energy:

$$\sum_{i \in F} \psi \cdot \beta_i^0 \cdot \pi_i + \sum_{i \in F} \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} \psi \cdot \beta_{ijkr} \cdot x_{ijkr} \tag{10}$$

- Transportation:

$$\sum_{i \in F} \sum_{c \in C} \rho \cdot d_{ic} \cdot w_{ic} \tag{11}$$

Let *TC* be the total cost, computed as the sum of expressions (1) to (7); and let *TE* be the total emissions of CO_2, computed as the sum of expressions (8) to (11). A MILP formulation to the problem under study follows.

$$Min\{TC, TE\} \tag{12}$$

Subject to:

$$\sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} y_{ijkr} = u_i \ \forall i \in F \tag{13}$$

$$u_i \le z_i \ \forall i \in F \tag{14}$$

$$x_{ijkr} \le q_{ijk} y_{ijkr} \ \forall i \in F, j \in T_i, k \in Q_{ij} \mid k = 1, r \in L_{ijk} \tag{15}$$

$$q_{ijk-1} \cdot y_{ijkr} \le x_{ijkr} \le q_{ijk} \cdot y_{ijkr} \quad \forall i \in F, j \in T_i, k \in Q_{ij} \setminus \{1\}, r \in L_{ijk} \tag{16}$$

$$\pi_i \le q_i^0 \cdot (z_i - u_i) \ \forall i \in F \tag{17}$$

$$\sum_{c \in C} w_{ic} = \sum_{j \in T_i} \sum_{k \in Q_{ij}} \sum_{r \in L_{ijk}} x_{ijkr} + \pi_i \ \forall i \in F \tag{18}$$

$$\sum_{i \in F} w_{ic} = \delta_c \ \forall c \in C \tag{19}$$

The objective (12) is to minimize the total cost and the total emissions of CO_2. Constraints in (13) ensure that if it is decided to change the current technology at a given facility, one single option should be chosen. Constraints in (14) ensure that a technology upgrade can only be undertaken in a facility if the facility is kept in operation. Expressions (15) and (16) correspond to the capacity constraints in the case of a change in the current technology at a given facility. Constraints in (15) and (16) ensure that the production quantity assigned to a facility lies within the corresponding capacity interval in the case when it is decided to change the technology at a given facility. Similarly, expression (17) corresponds to capacity constraints for the case when it is decided not to change the technology at a given facility. Constraints in (18) and (19) are required to enforce flow balance, whereas the constraints that define the domains of the decision variables can be deduced from their definition.

III. METAHEURISTIC OPTIMIZATION MODELS

We modeled two heuristic optimization methods using Evolutionary Strategies (ES). ES is a population based metaheuristic optimization algorithm that uses biology inspired mechanisms such as mutation, crossover, and survival of the fittest in order to refine a set of solution candidates iteratively. The advantage of ES compared to other optimization methods is its “black box” character that makes only few assumptions about the underlying objective functions. Moreover, it is simple and applicable to any type of problems in continuous domain. ES uses primarily mutation and selection as search operators. The operators are applied in a loop and an iteration of the loop is called a generation. In our solution representation, we used real numbers between 0 and 1, therefore mutation is performed by adding a normally distributed random value to each element of the matrix. The mutated strategy parameter σ controls the mutation strength. We select a (μ+λ) strategy as our population strategy. The sigma value changes according to the 1/5 rule [20]. Therefore, the algorithm is self-adaptive in terms of generating new solutions. The structure of the ES algorithm is shown in Figure 1. In order to handle violated constraints, we used the near feasibility threshold (NFT) penalty method described in [21]. Since the search can benefit from searching areas outside the feasible region, the NFT penalty method gives some infeasible solutions a chance to be in the population by penalizing less at early generations, but it penalizes much more as generations evolve. The continuous search space contains a large number of infeasible solutions due to over and under capacitated facilities. Therefore, we selected a basic mutation-only ES, a continuous optimization method that explores both infeasible and feasible regions. However, it escapes from infeasible regions through the use of the NFT penalty method.

```
for all parents i in population of size μ do
Initialize x-vector randomly between its bounds
Calculate x-fitness value
end for
while maximum iterations not reached do
for all offspring j in children population do
Select a parent x randomly
Draw z-vector from the normal distribution N(0, σ²)
y-vector = x + z
if f (y) < f (x) then
increase success rate
else
decrease success rate
end if
end for
Join parent and children population and select μ fittest
for the next generation
if successrate > 0.2 then
σ = σ/0.85 //Increase sigma
else
σ = σ ∗ 0.85 //Decrease sigma
end if
end while
```

Figure 1 - Pseudo-code for the ES

Our problem includes a linear transportation problem which is a well-known problem in supply chain management. There exist exact methods such as the stepping stone method [22] and heuristic approaches such as an initialization procedure with genetic algorithms [23] that solve the linear transportation problem effectively. Therefore, we incorporated these methods into our search algorithms. The first method utilizes a local search procedure for the transportation part of the problem using the stepping stone method [22]. The idea is that the entire transportation table is assumed to be a pond and cells that are occupied are the stones. These stones move in a certain way within the pond to cross it. The second method incorporates problem specific knowledge discussed in [23] which is called the initialization procedure. It satisfies all balance constraints by generating a matrix of at most $F + C - 1$ nonzero elements. The authors noted that there are several sequences of numbers where the initialization procedure would produce the optimal solution. The modified version of the initialization procedure in [23] is given in Figure 2 as follows:

```
input: arrays customer[k], facility[n], inpmat[k, n]
output: a matrix trp[k, n] that satisfies all constraints for
balanced transportation problem
for i = 0; i < n; i = i + 1
supply[i] = facility[i]
for j = 0; j < k; j = j + 1
if i == 0 then
demand[j] = customer[k]
end if
sortedList.add(i, j, inpmat [i, j ])
end for
end for
sortedList.Sort()//Sort solution values
for m = 0; m < sortedList.Size; m = m + 1
i = sortedList[m].i //assign row number
j = sortedList[m].j //assign column number
val = Min(supply[i], demand[j])
trp[i, j] = val
supply[i] = supply[i] – val
demand[j] = demand[j] - val
end for
```

Figure 2 – Initialization Procedure [23]

We now explain our solution representation with the example below.

Table 1 - Example Problem Parameters

# Customers	2
# Facilities	3
Average Techs	6
Average Caps	4
Average Fuels	3
Demand 1	200
Demand 2	800
Current Tech Index	1, 4, 3
Current Capacity Index	2, 1, 3
Current Fuel Index	2, 1, 2

Table 2 - Solution Representation

	Facility 1	Facility 2	Facility 3
Z	0.3	0.7	0.9
Weight	0.6	0.4	0.6
Technology	0.4	0.1	0.9
Capacity Level	0.3	0.7	0.5
Fuel	0.1	0.4	0.6
Customer 1	0.5	0.1	0.9
Customer 2	0.4	0.7	0.2

Table 3 - Problem Representation

	Facility 1	Facility 2	Facility 3
Z	0	1	1
Capacity	0	400	600
Technology	3	4	6
Capacity Level	1	3	2
Fuel	1	2	3
Customer 1	0	0	200
Customer 2	0	400	400

Our solution representation is unique in a way that we used real numbers between 0 and 1 in our solution representation (genotype). Each number can be decoded into a problem representation by using the problem parameters (phenotype). We used the random key [24] idea to handle specific dynamic lower bound situations for technology and capacity levels. It transforms the random numbers from [0, 1) space that are generated by ES into a discrete solution space. First, we calculate the lower and upper bounds of each variable shown in Tables 2 and 3 in a certain order (top to bottom) for each facility; we set the lower and upper bounds for all Z variables to 0 and 1, respectively; we discretize Z values for each facility. Second, we calculate the weight to total weight ratio for each open facility and distribute the total demand among those facilities (see Equations 20 and 21). If there is a rounding error in the total capacity of the facilities, we add the error to the last open facility. In this way, we make the problem balanced which is a characteristic of the optimal solution.

Total weight = $\sum_{i \in F} z_i \cdot solution_{i2}$ (20)
Capacity i = $Round(z_i \cdot solution_{i2} \cdot Total\ Demand)$(21)

Third, we calculate the technology values using the current technology index for each facility as a lower bound and available technologies as an upper bound. Fourth, if the technology value is same as the current technology index, then we use the current capacity index as a lower bound and the available capacity levels as an upper bound; if the technology value is higher than the current technology index, then we use 1 as a lower bound and the available capacity levels as an upper bound. Fifth, we calculate fuel values using 1 as a lower bound and number of available fuels as an upper bound. These first five rows are problem independent and the remaining rows are based on the number of customers. Next, we solve the transportation problem using either stepping stone method or procedure initialization. In the first case, we disregard the transportation problem part of the solution representation, find the optimal assignments from open facilities to customers, and use them in problem representation. In the second case, we sort the numbers in the solution representation matrix regarding the transportation problem in ascending order, start with the cell that represents the smallest number and assign the minimum of the supply and demand values (see Figure 2). There are several sequences that will lead to the optimal solution for the transportation problem. Details of the algorithm are given in [23]. In our solution representation, we calculate u_i values based on the technology, capacity, and fuel levels. Therefore, they are not independent variables in our metaheuristic methods, but they are used in objective function calculations. If a facility has a technology, capacity, and fuel level same as current level, u_i becomes 0, otherwise it becomes 1. Since capacities of the open facilities are calculated based on the weights, there might be some facilities over or under capacitated for their technology and capacity levels. We calculate total under/over capacities for a given solution and use it as a violation in NFT. As the number of iterations increases, penalty of violating the capacity constraints increases. In this way, we do not omit the solutions which are not feasible at the beginning of the search since the optimal solution may lie at these boundaries.

IV. Computational Experiments

To approximate the set of non-dominated solutions, the formulation presented in Section 2 was solved as a single objective heuristic optimization by linearly combining the two objectives into a single one and adding a penalty function NFT to handle violated constraints.

$$Minimize\ \lambda \cdot TC + (1 - \lambda) \cdot TE + NFT \quad (22)$$

The methods were implemented in C#.NET 4.5 and the model was solved on a laptop computer running the 64-bit version of Windows 10 with an Intel Core i7 8-core processor running at 2.5 GHz with 16 GB of RAM. We used the problem instance described in [16]. The test instance built includes 30 customers, 10 facilities, 6 available technologies with 3 capacity levels per technology, and considers 4 types of fuels. The value of λ was varied from 0 to 1 in increments of 0.01, for a total of 101 values. For each λ value, we did 5 independent replications and picked the best solution among 5 replications. Both heuristic methods were able to find near optimal feasible solutions for every value of λ. We found 101 near optimal solutions in 25 minutes and 0.52 minutes on overall average by using the stepping stone method and the initialization procedure, respectively. Thirteen solutions are non-dominated for the stepping stone method and eleven solutions are non-dominated for the initialization procedure as depicted in Figure 1. As expected, we can observe that there is a clear trade-off between the environmental and financial goals. Also the stepping stone method outperforms the initialization procedure for every level of λ with an increased computational time requirement and they were very close to optimal solution for most values of λ.

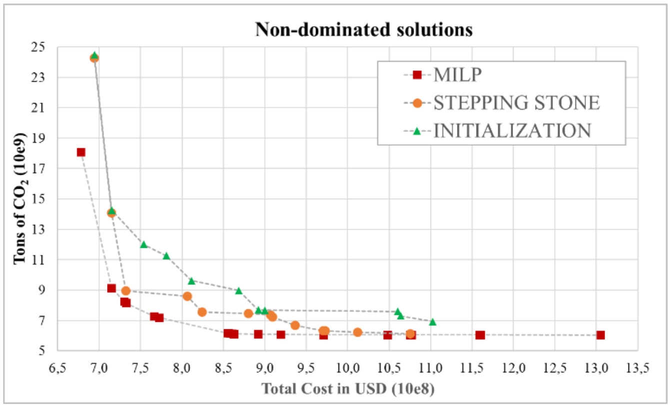

Figure 2 - Set of Non-dominated Solutions

V. Conclusions

In this paper we addressed the problem of improving the current environmental performance of an operating supply chain at the lowest possible cost using heuristic optimization methods. A corrected version of the mixed integer linear programming formulation proposed by [16] was presented. We showed how to model and solve the problem using evolutionary strategies with a (μ+λ) strategy and a 1/5 success rule, near feasibility threshold, stepping stone, and procedure initialization. A test instance described in [16] was used and the proposed approach was shown to be effective in finding a set of non-dominated solutions within a short amount of computational time.

Both approaches based on the ES algorithm are very slow when compared to the MILP because the MILP solves the problem in a few number of iterations, whereas the ES methods deal with establishing a set of potential solutions to the problem at each generation. However, it provides promising solutions for both larger and nonlinear variants of the environmental optimization problems.

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