MULTI-OBJECTIVE OPTIMIZATION USING GENETIC ALGORITHMS IN MOTSP (CO2 EMISSIONS)

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ABSTRACT

In recent years, consumers and legislation have been pushing companies to optimize their activities in such a way as to reduce negative environmental and social impacts more and more. In the other side, companies must keep their total supply chain costs as low as possible to remain competitive.

This work aims to develop a model to traveling salesman problem including environmental impacts and to identify, as far as possible, the contribution of genetic operator's tuning and setting in the success and efficiency of genetic algorithms for solving this problem with consideration of CO2 emission due to transport. This efficiency is calculated in terms of CPU time consumption and convergence of the solution. The best transportation policy is determined by finding a balance between financial and environmental criteria.

Empirically, we have demonstrated that the performance of the genetic algorithm undergo relevant improvements during some combinations of parameters and operators which we present in our results part.

KEYWORDS

Multi-objective optimization, Meta heuristic, Environnemental impact, CO2 emissions, traveling salesman problem, transport

Nomenclature

(S)TSP	=	(Symmetric) Traveling salesman problem;
GA	=	Genetic algorithm;
MOP	=	multi-objective problems;
LCA	=	life cycle analysis;

1. INTRODUCTION

In the context of a global supply chain in which the objectives may differ and the constraints may cross, genetic algorithms come as a simple and effective approach, to find approached acceptable solutions in NP-hard problems, but it requires a wise choice of parameters and operators (the generation of the initial population, the selection, the crossovers, the mutation, etc).

Solve NP-hard problems and more particularly the traveling salesman problem (TSP) thanks to genetic algorithms, was gradually used by the literature. However, the use of these methods

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involves a preliminary definition of a number of parameters, what can entail deep effects on the results, and what leads effectively to the success of the algorithm or its failure.

In the literature we find a vast range of methods: the use of the orthogonal crossover as method of resolution of the affectation problem [1], the combination of the genetic algorithms with a local search and production of hybrid and mimetic algorithms [2], the use of genetic algorithm (GA) to solve multi-objective problems in networks MPLS (Multiprotocol Label Switching) in [3].

In this work, we are interested in the multi-objective optimization in combinatorial problems.
Our work consists in applying GA as a method of resolution of NP-hard problems to identify the contribution of a good combination of genetic operators and parameters to end up with the best tuning in a multi-objective TSP context taking into account the green aspect by including the estimation of CO2 gas emissions in our calculations.

The present document is organized as follows. In the section 1, the basic concepts related to genetic algorithms and to the traveling salesman problem are presented. The mathematical Model, as well as the methods of estimations of greenhouse gas emissions and the details of the implementation of the adopted approach are presented in the section 2 and 3. Section 4 and 5 contains the results of the calculations and finally the conclusions are given in the section 6.

2. LITERATURE REVIEW

2.1. Multi-objective Problems

Traditionally, the multi-objective problems (MOP) were very often approached as mono-objective problems using the combination of all criteria on a simple scalar value.

During the last years, there was a rising of a number of multi-objective meta heuristics approaches from which the purpose is to obtain a set of solutions for multi-objective problems at once and without needing to convert the initial problem into a mono-objective problem. Most of these techniques realized a big success in optimization of the real multi-objective problems [4].
A problem of combinatorial optimization is defined by a finished set of discreet solutions and one objective function or more, associating a single value (generally a real value) with each solution of the set. It consists on the optimization of the criteria under various constraints and determining all the realizable solutions.

The combinatorial multi-objective optimization includes a wide class of problems having applications in numerous domains. The traveling salesman problem TSP [5] is one of the studied problems in this optimization category.

Heuristic methods became necessary to solve large-sized multi-objective problems.

Most of the heuristic approaches proposed in the literature are based on the transformation of a multi-objective problem into a mono-objective problem, generally with a weighting of the multiple criterias [6].

Among these methods are the methods based on aggregation, the e-constraints methods, and the methods of the goal programming.

The optimization of the mono-objective problem so reformulated guarantees the optimality of the found solution, but only finds the one and only solution. Generally, in the real situations, the decision-makers need several alternatives.

The genetic algorithms were used to solve several MOP transformed into mono-objective problems: sequencing [7] , generation of chemical structures [8] , conception of filters IIR [9] & [10] , transport [11, 12].

2.1.1. Aggregation Method

It is one of the first methods used for the generation of Pareto optimal solutions. It consists in transforming the MOP into a mono-objective problem which means that we combine the various cost functions fi of the problem into a single objective function F generally in a linear way [13] :

$$F(x) = \sum_{i=1}^{n} \gamma_i f_i(x) \qquad (1)$$

The strategies of choice of the weights lambda can vary from a determinist choice of simple constants to a completely random choice [14].

2.2. GENETIC ALGORITHMS

2.2.1. overview

The genetic algorithm (GA) is a method of stochastic heuristic search in which the mechanisms are based on simplifications of the evolutionary processes observed in nature.

These methods of combinatorial optimization are based on the natural selection described by Charles Robert Darwin. The natural selection indicates that the most adapted generation stays whereas the least adapted disappear as time goes by. The genetic algorithms are evolutionary algorithms, which consider at first an initial population and evolve through the genetic operators like selection, cross over and mutation. A GA can be seen as a kind of random oriented search, developed by Holland [15], it is able to obtain a global optimal solution in a complex multidimensional search space. Goldberg [16] gave a complete description of the basic principles of the genetic algorithms in its book known as a reference in this domain.

2.2.2. Genetic algorithm Structure

Most of the genetic algorithms work on a population of solutions rather than on a unique solution. The genetic search begins with the initialization of a population of individuals. Solutions, or genomes, are chosen among the populations (selection) according to one or several criteria (evaluation = fitness), and mate to form new solutions. The process of the mating operate by combining (crossover) the genetic material of two parents to form the genetic material for one or two new solutions (offspring).a random mutation is periodically applied to insure the diversity in the population. If the new solutions are better than those already found, the worst individuals of the population are replaced.

This process is illustrated by the algorithm below:

BEGIN
+ Initialize the time (t = 0).
+ Generate and evaluate the individuals in the initial population (P0).
+ **WHILE** (stop criteria)
- Select among Pt
- Apply the genetic operators to reproduce the offspring.
- evaluate the offspring.
- Select the offspring to be inserted into the next population (P_{t+1}) and replace the worst individuals in P_t.
- Increment the current time (t = t + 1).
The END

Figure.1 GA STRUCTURE

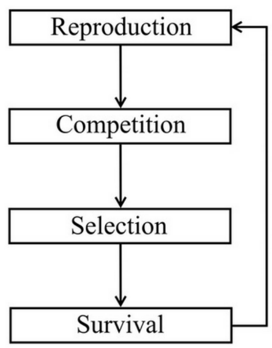

Figure.2 GA MACRO STRUCTURE

When we apply GA to problems in which the search space is very large and the ratio between the number of feasible solutions and unfeasible solutions is low, it is necessary to take good care to define the representation, the operators, and the objective function. Factors such as the crossover and mutation rates, the size of the populations and the techniques of elitisms must be well chosen when a genetic algorithm is intended for a given problem. The genetic operators have to balance effectively the exploration and the exploitation so that the genetic algorithm will be able to avoid the local minima and find small improvements by the local search [17].

2.3. TRAVELING SALESMAN PROBLEM (TSP)

2.3.1. Overview

The mathematician of the 19th century William Hamilton approaches the question of the existence of a circuit which visits every vertex in a graph, only once. This problem is called the traveling salesman problem (TSP).TSP implies that a person or a vehicle moving along the shortest road of a vertex of departure, visits every vertex of the network one by one, and then returns to its point of departure.

It is a part of a wide class of problems for which we know that it is not possible to develop guaranteed algorithms to find the absolute optimal solution in a reasonable delay. Instead, the researchers work on the development of heuristic algorithms (as GA) that look for approximated solutions of the optimal solutions. These algorithms have generally two phases. The first phase aims at finding a good initial solution. The second phase consists on minor modifications in the best solution found to find better and better adapted one.

2.3.2. Mathematic Formulation

The traveling salesman problem (**TSP**) is formulated [18] [19] as being a matrix of costs in **n dimensions** of the values $\mathbf{d_{ii}}$, where the purpose is to obtain a permutation of these values, such as the sum of the costs $\mathbf{d_{ij}}$, for every **i** and **j**, **i** being a vertex and **j** its following vertex in a sequence, is minimal. More formally, we have :

$$MINIMIZE \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} x_{ij} \qquad (1)$$

Under :

$$\sum_{j=1}^{n} x_{ij} = 1, \forall i, \qquad \sum_{i=1}^{n} x_{ij} = 1, \forall j, \qquad x_{ij} \in \{0,1\}, \forall i, j \qquad (2)$$

$$\sum_{i,j \in S}^{n} x_{ij} \langle |S|, \forall S \subset V, S \neq \phi \qquad (3)$$

X_{ij} is the decision matrix (connection).
S is a vertex Set from the global set V.
We consider $\mathbf{d_{ij} = d_{ji}, \forall\, i, j}$ to work on the symmetric TSP (**STSP**);

2.4. TRANSPORT ENVIRONMENTAL IMPACT:

2.4.1. Overview

The Transport has different impacts on the environment. These were mainly analyzed by means of the life cycle analysis (LCA). A deep inquiry of all kinds of repercussions on the environment was described in [20]. The following categories were determined :

1. Resources Consumption
2. Lands use
3. Greenhouse effects
4. The impoverishment of the ozone layer
5. Acidification
6. Eutrophization
7. Ecotoxicity (toxic effects on the ecosystems)
8. Toxicity for the man (toxic effects on the human beings)
9. Summer Smog
10. Noise pollution

The intermodal transport influence all the categories aforementioned, however the difficulty encircling the study of all these impacts in the green supply chain forced us to try to filter these impacts according to the importance of the impact compared with the global impact, the

availability of the data, and the methodological relevance for a quantitative comparison of the intermodal transport.
In this work we concentrate on the greenhouse gas and especially the CO2 which has most environmental effects.

2.4.2. CO2 Estimation

In the literature we find several methods for the estimation of greenhouse gases emissions. On what follows we cite some.

a. The method of simulation of **EcoTransIT [21]** which allows the calculation of the data of energy consumption and gas emissions of a transport chain all over the world.
b. The gas Emissions in broad terms (**G**) in transport depend on the level of activity (**A**) in passengers-kilometers (or tons-kilometers for the freight) in all modes; the modal structure(**S**); the intensity of the fuel for each mode (**I**), in liters by passenger-km; and the content of carbon in a fuel, what gives a emissions factor (**F**), in grams of carbon by liter of consumed fuel. The relation between these parameters is mathematically represented by the **ASIF** equation[22].
c. Reports and documents of the intergovernmental experts Group on the evolution of the climate **GIEC [23]** which is an intergovernmental body, propose several data and methods for the estimations of greenhouse gases.
d. The **ADEME [24]** also proposes a number of methods in the same purpose. One approach in transport context is presented more in detail in what follows for a later use in our simulation.

Transport is a source of greenhouse gas. Indeed, some carbon dioxide results from the combustion of fuels (oil, gas, etc.), Leakages linked to the air conditioning engender emissions of halocarbons, diverse local pollutants, which can be directly greenhouse gases (nitrogen oxides), or be precursors of the ozone, which is itself a greenhouse gas (the ozone of the low layers, still called tropospheric ozone, is responsible of about 15% of the human disturbance of the climatic system), etc.

The CO2 Emission relative to transport is thus a consequence of the use of fossil fuels. However the greenhouse gas emissions of transport equipment are strongly variable depending on its type. The estimation of the engendered emissions depends at the same time on the equipment characteristics (power of the engine and the used fuel, or filling ratio of a heavy vehicle as a truck or a bus), and others factors which are much more difficult to describe quantitatively (for example the type of driving for a road vehicle).

ADEME states that the numbers which convert observable data into greenhouse gas emissions, expressed as carbon equivalent, are called emission factors. The CEV *carbon equivalent* value is the "official" measure of greenhouse gas emissions, one kilogram of carbon dioxide (CO2) contains **0.27 kg** of carbon, and the emission of **1 kg of CO2** is therefore 0.27 kg carbon equivalent (Kgeq. C).

The unit of measurement of gas emissions is the gram Carbon equivalent, to convert grams Carbon equivalent into grams **CO2** equivalent, the multiplier is **3.67**. In practice, a road vehicle realizes some of its trips in charge, with some variable load, and another part empty weight.
Greenhouse gas emissions associated with fuel combustion of a vehicle (**EV**) can then be expressed in functions of the following five components:

1. The emission per km empty weight: **Evv**.
2. The emission per km fully loaded **Evpc**.

3. The tonnage for gross vehicle weight (that is to say the maximum payload **CU**).
4. The distance ratio as empty **Tdv** (ie, the fraction of the journey that is made empty).
5. The average load **Trm** on part of the journey that is made in charge.

The first three elements are characteristics of the vehicle, the last 2 are characteristic of the use of the vehicle. So we can say that there are only two variables for a given vehicle.

These informations therefore lead to know the emission factors applicable to the path considered when known:

- The distance ratio as empty, **Tdv**
- The average load ratio **Trm**.

If the company knows these two parameters, it can then use with the formula:

$$\mathbf{Ev = Evv + (Evpc - Evv) * (1 - Tdv) * Trm} \quad \mathbf{(7)}$$

At this point we can use national European averages as shown in Table 1:

TABLE 1
EMISSION FACTORS IN EMPTY WEIGHT AND FULLY LOADED OF GOODS TRANSPORTATION IN METROPOLIS

total permitted weight(PTCA)	combustion Emissions (g.equ/veh.km)		maximum payload (tonnes)
	empty weight	Fully loaded	
Road trucks	225	323	25.00

The functioning mode of road carriers and trucks used are very similar from one country to another, so that emissions for trips in empty weight and full load can be used in a Moroccan context.

On the other hand and because of lack of data, the ratio of distance in empty weight and the average load will be estimated, otherwise the emissions vehicle-km may be incorrect from **10%** to **20%**.

Or use the table:

TABLE 2
CHARACTERISTICS OF GOODS TRANSPORTATION BY PTCA(TOTAL PERMITTED WEIGHT) CLASS

total permitted weight (PTCA)	Empty weigt distance rate T_{dv}[1]	maximum payload (tonnes)	average Tonnage per vehicle T_m[2]	Mean occupancy rate T_{rm}[3]
Road trucks	21.1%	25.00	14.31	57%

*1 Ministry of Transport, DAEI-SES; TRM Vehicle use, 2001 (transport for hire) Empty weigt distance rate are based on europeene data of 2001 **
2 using data from file "SITRAM-TRM 2000 "
3 This corresponds to the average tonnage per vehicle (Tm) divided by the maximum payload (CU).

We will consider a variability of **10%** in our simulations.

3. ADOPTED APPROACH

3.1. Representation and Coding

3.1.1. Genetic Representation

For TSP, a solution is typically represented by a chromosome whose length is equal to the number of nodes in the problem. Each gene on a chromosome has a label such that no node will appear twice in the same chromosome. We consider a representation which simply lists nodes label known as path representation [25]. a tour like $\{1 \rightarrow 2 \rightarrow 8 \rightarrow 4 \rightarrow 9 \rightarrow 6 \rightarrow 5 \rightarrow 3 \rightarrow 7\}$ can be represented as shown in figure 3.

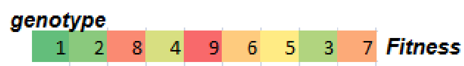

Figure.3 TSP- REPRESENTATION (7 CITES)

3.2. Operators (Initialization, selection, Cross over and mutation)

3.2.1. Initialization

Initializing a random initial population is adopted in the GA.

3.2.2. Cross Over

The crossover operator consists on recombining selected individuals for generating two new individuals. New Crossover points are randomly selected for each call to the operator as intermediate values of selected individuals I and J.

Several ways of making crossover are described in the literature: like the one-point crossover, the two-point crossover, the uniform crossover, the orthogonal crossover, Cut and splice crossover.

More specific ordered crossovers : edge recombination crossover (ERX) [26], Partially mapped crossover (PMX) [27] was among the first attempts in the application of GA to the TSP, cycle crossover (CX), order based crossover operator (OX), position-based crossover operator (POS), voting recombination crossover operator (VR), alternating-position crossover operator (AP) sequential constructive crossover operator (SCX).

Two cross were implemented in our work: partial match PMX crossover and edge recombination crossover ERX. But only the ERX is used in the simulation. PMX is quite poor in the ordered problems and especially the STSP [28].

3.2.3. Selection

We use the "**Roulette Wheel**" selection with **elitism**.

3.2.4. Mutation

The mutation operator randomly selects a position in the chromosome and change the corresponding allele, thus chromosome information is modified. For TSP, the classical mutation operator does not operate directly. For this work, we considered the 2-exchange mutation which randomly selects two nodes and exchange their locations Figure 4.

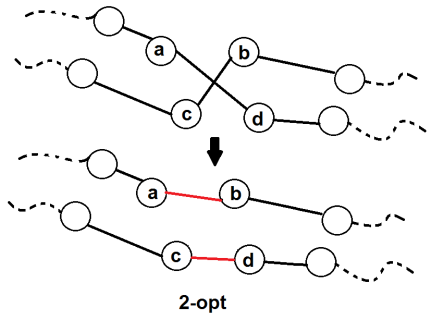

Figure.4 MUTATION 2-EXCHANGE

3.3. Fitness Function

3.3.1. Objective Function

For problems maximizing, the fitness function is generally the same as the objective function. **Fitness(x) = objective function(x).** For minimization problems, another way to define a fitness function is: **Fitness(x) = 1/objective function(x).**

In our case, we use the aggregation described above to specify two criterias :

1. **Euclidean Distance (F1)**
2. **CO2 emissions (F2)**

Such as:

$$\boxed{\textbf{Fitness}(x) = \gamma\, F1(x)+(1-\gamma)F2(x) \qquad (8)}$$

$\gamma = 0.6$

For the simulation part and As described in the previous sections we will use the formula (7) for the estimation of CO_2 emissions that come with a Tdv ratio not exceeding **30%,** a Mean occupancy rate equal **60%,** the emission per km at empty and emission per km at fully loaded corresponding to road transport by road tractors which gives us:

$$E_v = 225 + (323 - 225) * (1 - 30\%) * 60\%$$
$$= \underline{266.16} \text{ (g equ. C/vehicle.km)}$$

Equivalent to **976 (g equ. CO2/vehicle.km)**

3.4. Parameters setting

• **The population size:** It determines the number of chromosomes and therefore the amount of genetic material available for use in research.

• **Crossover Probability or rate:** It specifies the probability of crossover occurring between two chromosomes.
• **Mutation Probability or rate:** It specifies the probability of a mutation.
• **Stop criteria:** It specifies when to end genetic research.

For Preliminary simulations, we chose to work with a pop size not very large as 10, 50 and 300 individuals, the ratio of crossover and mutation which vary from 0% to 100%, and a simple elitism. The tests were run for each possible combination in the algorithm; topologies in TSPLIB [29] were used. The results presented were obtained by testing 20 simulations for each combination.

4. RESULTS

The system was developed using the C + + language and the tests were performed on a personal computer Core2 Duo with a speed of 4 GHz and 4GB RAM running MS Windows 7.

The different operators of the genetic algorithm was written in C + + based on the Galib library. The initial population is generated randomly. The following common parameters are selected for the algorithm:

TABLE 3
SPECIFICATIONS ADOPTED FOR THE SIMULATED GA

population_size	**10, 50,300**
mutation_probability	**0,0.3,0.6,0.9,1**
crossover_probability	**0,0.2,0.4,0.6,0.8,1**
Crossover type	**Edge recombination cross over ERX**
Mutation type	**2-change**

Figure 5 and 6 describe the distributions (objectives, execution time) of each setting from a total of 90 data sets using a Box & Whiskers diagram and a colored graphic.

This diagram clearly shows that large populations achieve better goals but at the expense of execution times that increase significantly with large PopSizes (ie. From 0.3 second to 80 seconds).

It also shows that the gain is not as important as the resulting loss in execution performance. If the Pop size is too little, research has no chance of adequately cover the search space. If there is too much, GA is wasting too much time to evaluate the chromosomes. Thus, a moderate choice of Popsize (50 individuals in our case) is more convenient.

The diagram also shows that the mutation and crossover rates are very important for achieving the goals and exploration of the search space. Thus we will consider high crossover and mutation rates for the next experimental simulations.

Cross rates=80% and mutation rate=70% seems to be more convenient according to the results in figure 5.

We tested the algorithm with the chosen parameters set on 10 instances of STSP TSPLIB, classical TSP library described in[29], then on an example of 46 Moroccan cities (metropolises).

For the Moroccan context simulation, and because of lack of data, we use Latitude / Longitude coordinates as plan x/y coordinates and calculates the Euclidian distance as the crow flies to simplify the results.

In further work we will convert them to effective x/y coordinates and apply our GA on real Moroccan road map which is currently being finalized.

The experiments were carried out 30 times for each instance. The quality of the solution is measured by the percentage of the error above the optimum value of the solution in TSPLIB reported, as given by the formula:

$$\boxed{\textit{Error \%} = \frac{\textit{Solution} - \textit{Optimal solution}}{\textit{Optimal Solution}} * 100}$$

The results are shown in table 4.

We can see in figure 6 an example of GA evolving during 2000 iterations that shows the efficiency of the algorithm that combine the quickness and effectiveness.

In figure 9 we show a simulation of our algorithm with the settings chosen during our tuning on a real instance with real road datasets from Open Street maps which is a Volunteered Geographic Information. The concept of VGI has recently emerged from the new Web 2.0 technologies. The OpenStreetMap project is currently the most significant example of a system based on VGI [30] . It aims at producing free vector geographic databases using contributions from Internet users.

We cleaned up the data and arrange it for our use and transformed it into a road graph in QGIS [31].

We choose as a first step in a set of 128 cities among the most important and largest in terms of population and therefore the most requesting in term of commodity.

Then we run the dijkstra algorithm in order to find the shortest path between each of the selected cities, then we launched the GA with these input data to optimize the TSP.

5. TABLES AND FIGURES

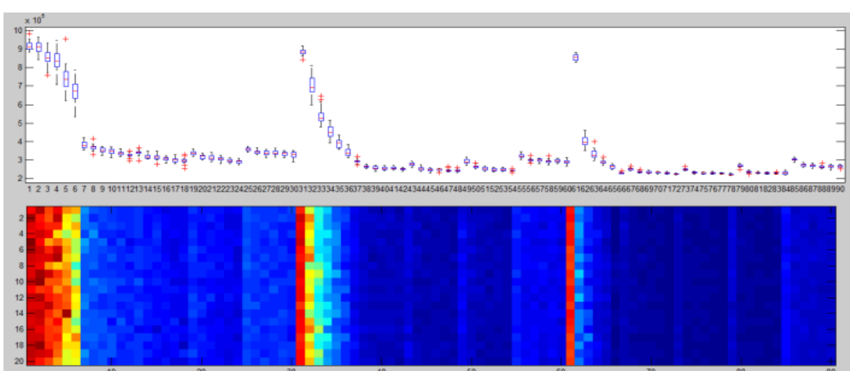

Figure.5. DISTRIBUTIONS (OBJECTIVES) OF 90 DATA SETS.

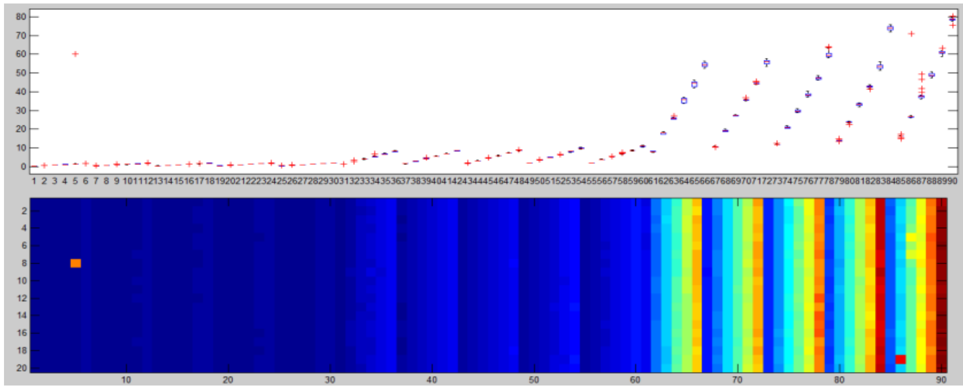

Figure.6. DISTRIBUTIONS (EXECUTION TIME) OF 90 DATA SETS.

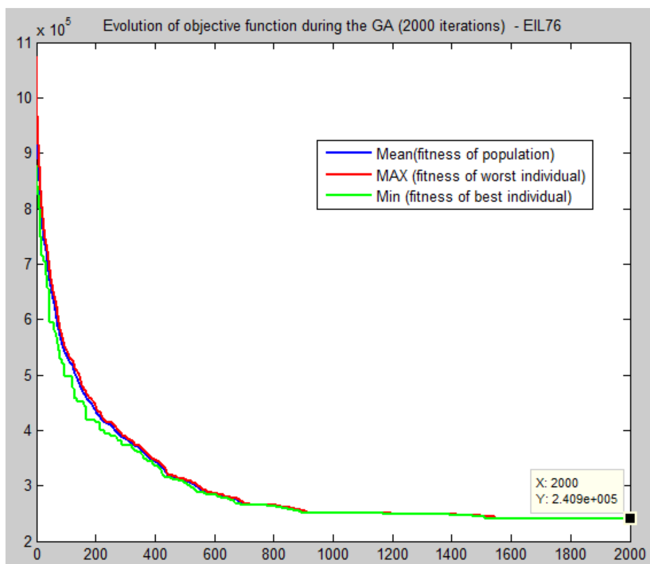

Figure.7. GA EVOLVING DURING 2000 ITERATIONS FOR EIL76 INSTANCE - FITNESS.

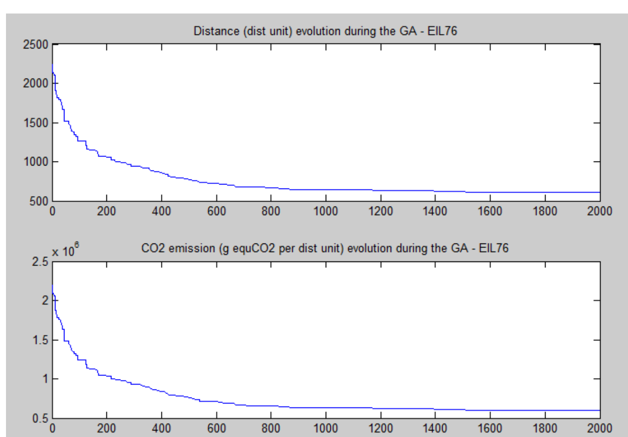

Figure.8. GA evolving during 2000 iterations for EIL76 instance – DIST and CO2 Emission.

TABLE 4
SIMULATION OF 10 INSTANCES OF STSP

N	TSP NAME	BEST VALUE objective function	CPU time sec	Dist	CO2 gequCO2 per dist unit	TSP VALUE OPT	ERROR
1	**bier127**	57 216 500	16,664	**146328**	1,43E+08	**118 282**	**24%**
2	**ch130**	3 336 630	16,006	**8527,61**	8,33E+06	**6 110**	**40%**
3	**ch150**	3 936 750	21,904	**10060,6**	9,83E+06	**6 528**	**54%**
4	**eil76**	227 826	10,127	**578,99**	568696	**538**	**8%**
5	**eil101**	289 882	12,411	**736,246**	723600	**629**	**17%**
6	**kroA150**	16 265 800	20,19	**41593,2**	4,06E+07	**26 524**	**57%**
7	**kroA200**	24 455 000	32,127	**62534,8**	6,10E+07	**29 368**	**113%**
8	**kroB150**	16 539 500	20,402	**42292,7**	4,13E+07	**26 130**	**62%**
9	**kroB200**	24 674 900	33,326	**63097,3**	6,16E+07	**29 437**	**114%**
10	**kroC100**	9 593 810	12,504	**24532**	2,39E+07	**20 749**	**18%**

TABLE 5
SIMULATION IN A MOROCCAN CONTEXT

TSP NAME	best value objective function	CPU time sec	Dist	CO2 gequCO2 per dist unit
MAROC	**23169,1**	4,627	56,9832	57837,3

Figure. 9 SIMULATION ON 128 MOROCCAN CITIES (WITH THE SUCCESSFUL PARAMS SET).

6. CONCLUSION

We have presented and used a nature-inspired metaheuristic algorithm for the Traveling Salesman Problem TSP optimization. We considered the environmental impacts of transport by including gas emissions (CO2) into our objectives functions. We presented a comparative study for some benchmark TSPLIB instances. We have demonstrated that the performance of the genetic algorithm undergo relevant improvements during relatively high rates of mutation and cross over combinations and evolve correctly using moderate population size (50 in our case).

In the future we plan on conducting additional experiments aimed at improving overall performance of the GA algorithm. In particular we are going to investigate how GA could be combined with swarm-based approaches such as ACO[32], ABC [33] and BCO[34,35]. Special attention will be given to discovering better aggregation rules and specifying and classing criterions (using ELECTRE) and optimal ways of achieving diversity in the populations.

Finally we are very interested in developing others more efficient Genetic operators and applying them in green supply chain context and to other NP-Hard problems.

REFERENCES

[1] Q. Zhang and Y. W. Leung, "An orthogonal genetic algorithm for multimedia multicast routing," IEEE Transactions on Evolutionary Computation, vol. 3, pp. 53-62, 1999.
[2] L. S. Buriol, M. G. C. Resende, C. C. Ribeiro, and M. Thorup, "A hybrid genetic algorithm for the weight setting problem in OSPF/IS-IS routing," IEEE Networks, vol. 46, pp. 36-56, 2005.
[3] S. Huagang, C. Xiao, and W. Weinong, "A multiobjective optimization algorithm for LSP setup in diffserv and MPLS networks," 2007.
[4] L. Saadi, "Optimisation MultiObjectifs par Programmation Génétique " Magister en informatique, Faculté des sciences de l'ingénieur - Département d'informatique, université de BATNA, 2007.
[5] H. El Hassani, J. Benhra, and S. Benkachcha, "Utilisation des algorithmes génétiques (AG) dans l'Optimisation multi-objectif en logistique avec prise en compte de l'aspect environnemental (émissions du CO2)," in Colloque international LOGISTIQUA, RABAT, 2012.
[6] C. A. C. Coello, "An Updated Survey of GA-based Multiobjective Optimization Techniques," ACM Comput. Surv., vol. 32, pp. 109-143, 2000.
[7] G. Syswerda and J. Palmucci, "The application of genetic algorithms to resource scheduling," San Mateo, California, 1991, pp. 502-508.
[8] G. Jones, R. D. Brown, D. E. Clark, P. Willett, and R. C. Glen, "Searching Databases of Two-Dimensional and Three-Dimensional Chemical Structures Using Genetic Algorithms," San Francisco, CA, USA, 1993, pp. 597-602.
[9] W. Zhu, J.-a. Fang, Y. Tang, W. Zhang, and W. Du, "Digital IIR Filters Design Using Differential Evolution Algorithm with a Controllable Probabilistic Population Size," PLoS ONE, vol. 7, pp. e40549-e40549, 2012.
[10] K. S. Tang, K. F. Man, S. Kwong, and Z. F. Liu, "Design and optimization of IIR filter structure using hierarchical genetic algorithms," IEEE Transactions on Industrial Electronics, vol. 45, pp. 481-487, 1998.
[11] M. Gen, J. Choi, and K. Ida, "Improved genetic algorithm for generalized transportation problem," Artificial Life and Robotics, vol. 4, pp. 96-102, 2000.
[12] W. Ho and P. Ji, "A genetic algorithm for the generalised transportation problem," International Journal of Computer Applications in Technology, vol. 22, pp. 190-190, 2005.
[13] C.-L. Hwang and A. S. M. Masud, Multiple Objective Decision Making — Methods and Applications vol. 164. Berlin, Heidelberg: Springer Berlin Heidelberg, 1979.
[14] H. Ishibuchi and T. Murata, "A multi-objective genetic local search algorithm and its application to flowshop scheduling," IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews), vol. 28, pp. 392-403, 1998.
[15] J. H. Holland, "Adaption in Natural and Artificial Systems," The University of Michigan Press, 1975.

[16] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning [Hardcover], 1 edition ed.: Addison-Wesley Longman Publishing Co USA, 1989.
[17] A. Jaszkiewicz, "Genetic local search for multi-objective combinatorial optimization," European Journal of Operational Research, vol. 137, pp. 50-71, 2002.
[18] M. Rocha, C. Vilela, and J. Nerves, "A study of order based genetic and evolutionary algorithms in combinatorial optimization problems," London,New Orleans, Louisiana, 2000.
[19] M. Dorigo and L. M. Gambardella, "Ant colony system: a cooperative learning approach to the traveling salesman problem," IEEE Transactions on Evolutionary Computation, vol. 1, pp. 53-66, 1997.
[20] J. Borken, A. Patyk, and G. Reinhardt, Basisdaten für ökologische Bilanzierungen - Einsatz von Nutzfahrzeugen in Gütertransport, Landwirtscahft und Bergbau, 1999.
[21] Ifeu Heidelberg Öko-Institut IVE / RMCON, "Ecological Transport Information Tool for Worldwide Transports Methodology and Data Update," IFEU Heidelberg Öko-Institut IVE / RMCON, Berlin – Hannover - HeidelbergJuly 31th 2011.
[22] L. Schipper, M. Cordeiro, and W.-S. Ng, "Measuring the carbon dioxide impacts of urban transport projects in developing countries," Proceedings of the Transportation Research Board Conference. Washington, DC. USA, 2007.
[23] M. Bhandari, "Intergovernmental Panel on Climate Change," The Wiley-Blackwell Encyclopedia of Globalization, 2012.
[24] Ademe Agence de l'Environnement et de la Maîtrise de l'Energie, "Guide des facteurs d'emissions calcul des facteurs d'émissions et sources bibliographiques utilisées," JANVIER 2007.
[25] P. Larrañaga, C. M. H. Kuijpers, R. H. Murga, I. Inza, and S. Dizdarevic, "Genetic Algorithms for the Travelling Salesman Problem: A Review of Representations and Operators," Artificial Intelligence Review, vol. 13, pp. 129-170, 1999/04/01 1999.
[26] J. Kęsy and Z. Domański, "Edge recombination with edge sensitivity in the tsp problem," Scientific Research of the Institute of Mathematics and Computer Science, pp. 55-60, 2003.
[27] D. E. Goldberg and R. Lingle, "Alleles, loci, and the traveling salesman problem," In Proceedings of the First International Conference on Genetic Algorithms and Their Applications, pp. pages 154-159., 1985.
[28] K. Puljic and R. Manger, "Comparison of eight evolutionary crossover operators for the vehicle routing problem," Mathematical Communications, vol. 18, pp. 359-375, 2013.
[29] G. Reinelt, "TSPLIB—A Traveling Salesman Problem Library," ORSA Journal of Computing, vol. 3, pp. 376-384, 1991.
[30] J.-F. Girres and G. Touya, "Quality Assessment of the French OpenStreetMap Dataset," Transactions in GIS, vol. 14, pp. 435-459, 2010.
[31] M.-H. Tsou and J. Smith, "Free and Open Source software for GIS education," San Diego, 2011.
[32] B. Chandra Mohan and R. Baskaran, "A survey: Ant Colony Optimization based recent research and implementation on several engineering domain," Expert Systems with Applications, vol. 39, pp. 4618–4627, 2012.
[33] D. Karaboga, B. Gorkemli, C. Ozturk, and N. Karaboga, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications," Artificial Intelligence Review, 2012.
[34] M. Nikolić and D. Teodorović, "Empirical study of the Bee Colony Optimization (BCO) algorithm," Expert Systems with Applications, vol. 40, pp. 4609–4620, 2013.
[35] M. Nikolić, D. Teodorović, and M. Šelmić, "Solving the Vehicle Routing Problem With Time Windows by Bee Colony Optimization Metaheuristic," in 1st Logistics International Conference, Belgrade, Serbia, 2013.

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