International Journal of Soft Computing 11 (6): 409-417, 2016
ISSN: 1816-9503

A Hybrid Metaheuristic to Minimize the Carbon Dioxide Emissions and the Total Distance for the Vehicle Routing Problem

[1]E.L. Bouzekri El Idrissi Adiba, [2]Messaoud Elhassania and [2]Elhilali Alaoui Ahemd
[1] Engineering Sciences Laboratory for Energy, National School of Applied Sciences, El Jadida, Morocco
[2]Modeling and Scientific Computing Laboratory, Faculty of Sciences and Technology, University Sidi Mohammed Ben Abdellah, Fez, Morocco

Abstract: A better synonym of "green transportation" is "sustainable transportation". The word 'sustainable' clearly means activities that support the long term livelihood of our society. Even, the transportation system is very important because it represents the physical connection between the companies in the supply chain, this system is a major contributor to greenhouse gas emissions, as well as increased costs. This study discusses problem of routing freight vehicles, according to the criteria of the CO_2 emissions and the costs, named Multi-objective Green Vehicle Routing Problem (MGVRP) in the context of green transportation. The MGVRP presents the problem of finding routes for vehicles to serve a set of customers while minimizing the total cost and the total CO_2 emissions which can be formulated as combinatorial optimization problems. In this research, we propose, to solve the MGVRP, a mathematical model and a simulated hybrid metaheuristic based on the ant colony system algorithm which shows good performance on both the traditional CVRP and the MGVRP in terms of the cost and the emissions.

Key words: Vehicle routing problem, multi-objective optimization, greenhouse emissions, ant colony system, freight transport

INTRODUCTION

The industrial revolution and increasing consumption of goods and progress in technology have had many negative impacts on our society, health and environment are mainly the result of increases in the abundance of atmospheric greenhouse gases in particular carbon dioxide (CO_2), methane (CH4), Nitrous Oxide (N2O) and halogenated compounds but the carbon dioxide is the primary greenhouse gas emitted through human activities. The Inventory of US Greenhouse Gas Emissions and Sinks indicates in 2013, CO_2 accounted for about 82% of all US greenhouse gas emissions from human activities (Fig. 1).

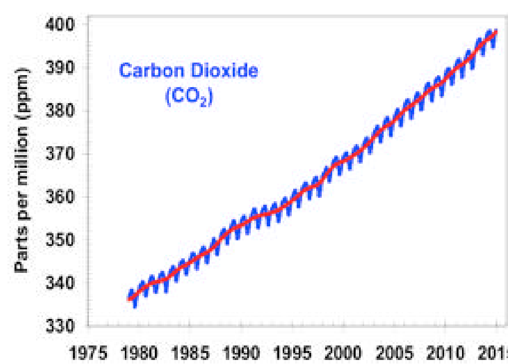

Fig. 1: Overview of greenhouse gases, inventory of US greenhouse gas emissions and sinks: 1990B2013 (April 2015)

The CO_2 growth rate has increased over this period, averaging about 1.4 ppm per year before 1995 and 2.0 ppm per year thereafter, according weekly data using to create a smoothed north-south latitude profile from which a global average is calculated (Fig. 2) (Dlugokencky *et al*., 1998, 2003).

This study shows that the growth rate of CO_2 has averaged about 1.74 ppm per year over the past 36 years and has increased over this period, averaging about 1.4 ppm per year before 1995 and 2.0 ppm per year thereafter.

The most contributor sectors of dioxide carbon emissions (resulting from the combustion of petroleum-based products, like gasoline in internal combustion

Corresponding Author: E.L. Bouzekri El Idrissi Adiba, Engineering Sciences Laboratory for Energy, National School of Applied Sciences, El Jadida, Morocco

Table 1: Strategies for reduce green house gas emissions

Type	How emissions are reduced	Examples
Fuel switching	Using fuels that emit less CO_2 than fuels currently being used. Alternative sources can include biofuels; hydrogen; electricity from renewable sources such as wind and solar or fossil fuels that are less CO_2-intensive than the fuels that they replace	Using electric or hybrid automobiles, provided that the energy is generated from lower-carbon or non-fossil fuels Using renewable fuels such as low-carbon biofuels
Improving Fuel Efficiency with Advanced design, Materials and technologies	Using advanced technologies, design and materials to develop more fuel-efficient vehicles	Developing advanced vehicle technologies such as hybrid vehicles and electric vehicles that can store energy from braking and use it for power later Reducing the weight of materials used to build vehicles
Improving operating Practices	Adopting practices that minimize fuel use' Improving driving practices and vehicle maintenance	Reducing the average taxi time for aircraft Driving sensibly (avoiding rapid acceleration and braking , observing the speed limit). Reducing engine-idling. Improved voyage planning for ships, such as through improved weather routing, to increase fuel efficiency.
Reducing travel demand	Employing urban planning to reduce the number of miles that people drive each day. Reducing the need for driving through travel efficiency measures such as commuter, biking and pedestrian programs	Building public transportation, sidewalks and bike paths to increase lower-emission transportation choices Zoning for mixed use areas, so that residences, schools, stores and businesses are close together, reducing the need for driving

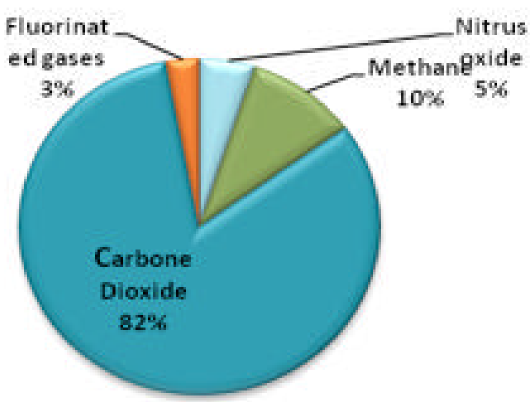

Fig. 2: Global average abundances of the major, well mixed, long-lived

engines) is the transportation sector, where the largest sources of transportation GHGs in 2006 were passenger cars (34%) and light duty trucks which include sport utility vehicles, pickup trucks and minivans (28%) (US Department of transportation).

To achieve the objectives of the sustainable transportation, there are a variety of strategies to reduce greenhouse gas emissions associated with transportation. Some examples are shown in Table 1.

In this study, we are interested in the organization of the transport process, more specifically on green transport within the framework of green logistics for satisfying some strategies indicated above for reducing the amount of dioxide of carbon and total cost. These two objectives are not necessarily positively correlated and for some cases they are completely conflicting.

The basic transportation model generally used to represent the problem of finding routes for vehicles to serve a set of customers is the Vehicle Routing Problem (VRP) (Toth and Vigo, 2001). In this study, the scope is the definition and the study of the Multi-objective Green Vehicle Routing Problem (MGVRP) where the multi-objective VRP was defined to represent a class of multi-objective optimization problem. The MGVRP asks for designing vehicle routes to serve set of customers while minimizing the total travelled distance and the total CO_2 emissions with respect to classical routing constraints mainly capacity constraints. Consequently, we will implement the ant colony system to solve the MGVRP model with an aggregation method that solves non-convex and non-smooth multi-objective optimization problems. In the next study, we present the Multi-objective Green Vehicle Routing Problem (MGVRP): the literature review and the difference between VRP, GVRP and MGVRP.

Literature review

The Multi-objective Green Vehicle Routing Problem (MGVRP): Optimizing the amount of emissions of the vehicle generally relies on solutions to the Vehicle Routing Problem (VRP). The VRP is an extension of the Traveling Salesman Problem (TSP), the goal is to find the shortest route for visiting a number of destinations before returning to the origin. The VRP extends the TSP to consider multiple routes over a fleet of vehicles and the green vehicle routing problem extends the VRP with the objective of reducing consumption level and consequently reducing the CO_2 emissions from road transportation. In general, this class of problems minimizes a particular amount of emissions for a fleet of vehicles picking-up or delivering goods.

Few researchers have developed tools to optimize the emissions for the VRP. Seemingly, the awareness with the contribution of VRP to green transportation was initiated with the studies by Sbihi and Eglese (2007) and Palmer (2007). Sbihi and Eglese (2007) considers the basic Vehicle Routing and Scheduling Problem (VRSP) models that relate to environmental issues including the time dependent, the transportation of hazardous materials and dynamic VRSP models.

Palmer suggests an integration of logistical and environmental aspects into one freight demand model with the aim of enhancing policy analysis. Bektas and Laporte (2011) develops the pollution routing problem as an extension of the classical VRP with a broader and more comprehensive objective function that accounts not only the travel distance but also the amount of greenhouse emissions, fuel, travel times and their costs. Bouzekri and Alaoui (2014), Bouzekri and Elhilali (2013) and regard emissions matrix as a load dependant function and add it to the classical CVRP to extend traditional studies on CVRP with the objective of minimizing the total emissions produced by the vehicle. Figliozzi has developed an Emissions Minimization Vehicle Routing Problem (EVRP) solution which explicitly includes emissions in the cost minimization of a traditional vehicle routing problem with time windows. In this model, emissions are directly related to travel speed.

With regard to the works that take into account several objectives; for example, we can cite the Jemai *et al.* (2012) which developed the bi-objective green vehicle routing problem while minimizing the total traveled distance and the $_{CO2}$ emissions. Also, Benedek and Rilett (1998) developed a traditional passenger assignment model by user equilibrium and system optimal cost functions to optimize the $_{CO2}$, finding minimal change in time or emissions between scenarios optimized for one or the other, their model did not consider routes with multiple stops, time windows or vehicle capacity and did not include the resulting costs for various routes. Wygonik and Goodchild modeled as an emissions minimization vehicle routing problem with time windows. The analyses of the different external policies and the internal operational changes provide insight into the impact of these changes in the cost, the service quality and the emissions. In the last, we cite the work by Bouzekri and Elhilali (2014) where the objective is to find routing and transportation policies that give the best compromise between the travelling costs and the CO_2 emissions, using the genetic algorithm. In this study, we propose a mathematic model and an ant colony system to simulate the multi-objective green vehicle routing problem.

Table 2: Data used in the example

Variables	ID	Coordinate	Demand
Depot	0	(1,1)	0
Customer 1	1	(2,3)	10000
Customer 2	2	(4,2)	7000
Customer 3	3	(5,5)	8000

Table 3: The details of the solution presented in Fig. 3a

Route in Fig. 3a

i, j	d_{ij}	Q_{ij}	E_{ij}
(0,1)	2.236	25000	2,450
(1,2)	2,236	15000	2,160
(2,3)	3.162	8000	2,768
(3,0)	5.657	0	4,367

D_{ij} = 13.291 Km, E_{ij} = 11,745 Kg CO_2

Table 4: The details of the solution presented in Fig. 3b

Route in Fig. 3b

i, j	d_{ij}	Q_{ij}	E_{ij}
(0,1)	2.236	25000	2,450
(1,3)	3.606	15000	3,484
(3,2)	3.162	7000	2,728
(2,0)	3.162	0	2,441

D_{ij}= 12.166 Km, E_{ij}=11,104 Kg CO_2

Table 5: The details of the solution presented in the Fig. 3(c)

Route in Fig. 3c

i, j	d_{ij}	Q_{ij}	E_{ij}
(0,2)	3.162	25000	3,465
(2,3)	3.162	17000	3,137
(3,1)	3.606	10000	3,251
(1,0)	2.236	0	1,726

D_{ij}= 12.166 Km, E_{ij} = 11,580 Kg $_{CO2}$

Difference between VRP, GVRP and MGVRP: In this study we present the difference in decisions made by CVRP and GVRP. We suppose there are three customers served by one vehicle departing and returning at the depot denoted by 0; e_{fl} is the CO_2 emissions of a fully loaded (by weight) vehicle which is e_{fl} = 1.096 kg/km for HDV truck; e_{el} is the CO_2 emissions of an empty vehicle which is e_{el}= 0.772 kg km^{-1} for HDV truck and Q = 25000 kg is the volume capacity of a vehicle. The demands and the locations of the customers/depots are shown in Table 2.

It is not difficult to find the shortest total distance (0-1-3-2-0) in Fig. 3a, b or (0-2-3-1-0) in Fig. 3c, these two routes as they have identical distances of 12.166 Km. However, these routes are different in terms of the emissions produced (b): E_{ij} = 11.104, (c): E_{ij} = 11.580). Moreover, we can find in Fig. 3a, the route (0-1-2-3-0) with a higher emissions produced (11.745) and a longer distance (13.291) (Table 3-5). The best solution is found with the route of Fig. 3b because the vehicle first serves the customers with the larger demands and the shortest distance, so that emissions produced can be lowered later in the route after the heavier goods have been unloaded. This example shows that it is necessary to develop a new optimization algorithm with lower emissions and shortest distance as objectives to optimize.

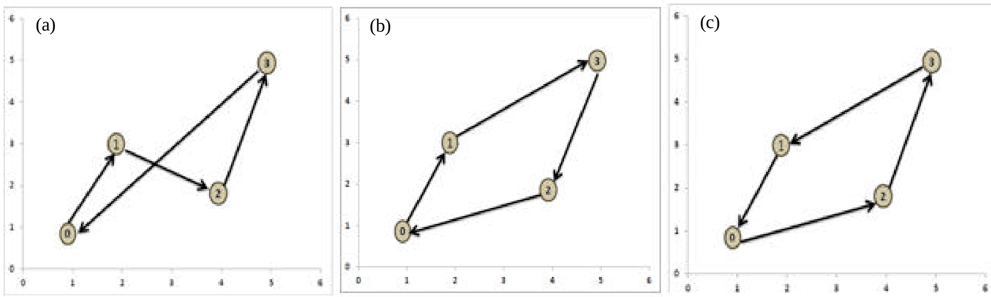

Fig. 3: Routes of the example with the shortest distance and the lowest emissions: a) D_{ij} = 13.291 Km, E_{ij}=11,745 Kg CO_2; b) D_{ij} = 12.166 Km, E_{ij} = 11,104 Kg CO_2 and c) D_{ij} = 12.166 Km E_{ij} = 11,580 Kg CO_2

MATERIALS AND METHODS

Mathematical formulation of MGVRP: Let G = (V, A) be a directed graph with V = {0, 1, 2, Y, n} as the set of vertices and the set of are A = {(i, j)/i, j∈V, i≠j}. A distance d_{ij} and driving time t_{ij} between the nodes i and j are associated with each are (i, j)∈A. Each customer i has a certain amount of demand and a service time S_i. A set of m identical vehicles of capacity Q and maximum allowable driving time T are available at depot 0 to visit the customers.

The MGVRP problem consists in finding the minimum total distance and the minimum volume of emitted CO_2 for the tours which start and end at the depot, such that each customer should be visited exactly once, where the sum of all the demands of any tour (route) does not exceed the capacity of the vehicle Q.

In order to model the GMVRP as an integer programming problem, we consider a very large number L and we define the variables q_{ij}^k, x_{ij}^k and as y_i^k follows:

- q_i^k: The quantity transported by the vehicle k between nodes i and j

$$x_{ij}^k = \begin{cases} 1 \text{ if vehicle k visits customer i after customer j} \\ 0 \text{ otherwise} \end{cases}$$

$$y_i^k = \begin{cases} 1 \text{ if vehicle k visits customer i} \\ 0 \text{ otherwise} \end{cases}$$

In our model, we consider two different objectives:

- The minimization of the total distance of transport:

$$f = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m} d_{ij} \,.\, x_{ij}^k \tag{1}$$

- The minimization of the total emissions for all vehicles:

$$g = \sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{k=1}^{m}(d_{ij} \times \left[\left(\frac{e_{fl} - e_{el}}{Q}\right) \times q_{ij}^k + (e_{el} \times x_{ij}^k)\right] \tag{2}$$

Our objective function is composed by two different objectives which aren't on the same scale. To optimize these objectives, we used the aggregation method which combines the various functions of the problem into a single function; so the problem is to minimize:

$$\text{Min}\left[\beta_1\left(\frac{f}{f^*}\right) + \beta_2\left(\frac{g}{g^*}\right)\right] \tag{3}$$

where, β_1 reflects the relative importance of the objectives, f* and g* are the optimal solutions associated with the only objective function f and g, respectively. Our objective is minimized under the following constraints:

$$\sum_{i=10}^{n} x_{i0}^k \le 1 \qquad \forall k \in \{1,\ldots,m\} \tag{4}$$

$$\sum_{i=10}^{n} x_{i0}^k = \sum_{i=10}^{n} x_{i0}^k \quad \forall k \in \{1,\ldots,m\} \tag{5}$$

$$\sum_{i=1}^{n} y_i^k \le L.\sum_{i=1}^{n} x_{j0}^k \quad \forall k \in \{1,\ldots,m\} \tag{6}$$

$$\sum_{k=1}^{m}\sum_{i=10}^{n} x_{ij}^k = 1 \quad \forall j \in \{1,\ldots,n\} \tag{7}$$

$$\sum_{j=0}^{n} x_{ji}^k = \sum_{j=0}^{n} x_{ij}^k \;\; \forall k \in \{1,\ldots,m\}; \forall i \in \{1,\ldots,n\} \tag{8}$$

$$\sum_{k=1}^{n} q_{ij}^k \le Q.\sum_{k=1}^{m} x_{ij}^k \quad \forall i,j \in \{0,\ldots,n\} \tag{9}$$

$$\sum_{k=1}^{m}\sum_{j=0}^{n} q_{ij}^{k} - \sum_{k=1}^{m}\sum_{j=0}^{n} q_{ij}^{k} = d_i \forall i \in \{1,...,n\} \tag{10}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} t_{ij} \times X_{ij}^{k} + \sum_{i=1}^{n} S_i y_i^k \leq T \quad \forall k \in \{1,...,m\} \tag{11}$$

$$X_{ij}^{k} \in \{0,1\} \; \forall k \in \{1,...,m\}; \forall i,j \in \{0,...,n\} \tag{12}$$

$$y_i^k \in \{0,1\} \; \forall k \in \{1,...,m\}; \forall j \in \{1,...,n\} \tag{13}$$

$$q_{ij}^{k} \geq 0 \; \forall k \in \{1,...,m\}; \forall i,j \in \{0,...,n\} \tag{14}$$

The constraints (4-6) ensure that each vehicle tour begins and ends at the depot while the constraint (7) guarantees that each node, except the depot, is visited by a single vehicle. Furthermore, the constraint (8) assures that each node, except the depot, is linked only with a pair of nodes, one preceding it and the other following it. The constraint (9) ensures that each vehicle cannot exceed its capacity and that the values of are null if there is n't any tour which visits j just after i. The constraint (10) ensures that the difference between the quantity transported before and after visiting a client i is exactly the demand of this customer. The maximum route duration is limited by the constraint (11). The constraints (12) and (13) guarantee the binary of the decision variables. Finally, the constraint (14) ensures that the load of each vehicle is always positive.

The hybrid ant colony system for MGVRP: The aim of this section is to propose a hybrid Ant Colony System (ACS) to solve the MGVRP formulated in the previous section through two phases.

Phase of route construction: To solve our problem, an individual ant constructs a solution by incrementally selecting customers until all customers have been visited. Whenever the choice of another customer would lead to an infeasible solution for reasons of vehicle capacity or total route length, the depot is chosen and a new tour is started.

At each step, every ant k computes a set of feasible expansions to its current partial solution and selects one of these probabilistically where an ant k positioned on customer i chooses the customer j to move, by applying the rule given by the equation (Taguchi *et al*., 1987).

$$j = \begin{cases} \operatorname{argmax}_{u \in N_i^k} \left[t_{iu}^{a}(t) \times (?_{iu})^{\beta} \right] \text{if } q \pounds q_0 \\ J \text{ otherwise} \end{cases} \tag{15}$$

where, τ_{iu} is equal to the amount of pheromone on the path between the current location i and possible locations u which is initialized:

$$\tau_0 = \frac{1}{n \times Obj}$$

where, n is the number of customers and objectif is the value of the objective produced by the execution of one ACS iteration without the pheromone component, it can make good initial pheromone trails on the are:

- η_{iu} = Is a heuristic information:

$$\eta_{iu} = \frac{1}{\beta_1 \times e_{iu} + \beta_2 \times d_{iu}}$$

- N_i^k is a set of customers unvisited
- α is the importance of our objective in comparison to pheromone quantity
- Determines the relative influence of heuristic information
- q is a random uniform variable [0, 1]
- q_0 is a parameter of the algorithm
- J is a random variable selected according to the probability distribution given in Eq. 16

$$P_{i,J}^{k} = \frac{\tau_{iJ}^{\alpha} \times \eta_{iJ}^{\beta}}{\sum_{h \in N_i^k} \tau_{ih}^{\alpha} \times \eta_{ih}^{\beta}} \tag{16}$$

If the constraints of capacity and duration are achieved, the ant will return to the depot before selecting the next customer. This selection process continues until each customer is visited and the tour is complete.

Phase of pheromone updating: An adaptive learning technique in ACS is to update the pheromone to cause improvement of new solutions. The colonies exchange information through pheromone updating. This process in ACS is conducted by reducing the amount of pheromone on all edges, in order to simulate the natural evaporation of the pheromone and to guarantee that no path becomes too dominant in local updating (Eq. 17). After every iteration, this phase insists on the best solution by maximizing the pheromone trail value in global updating (Eq. 18):

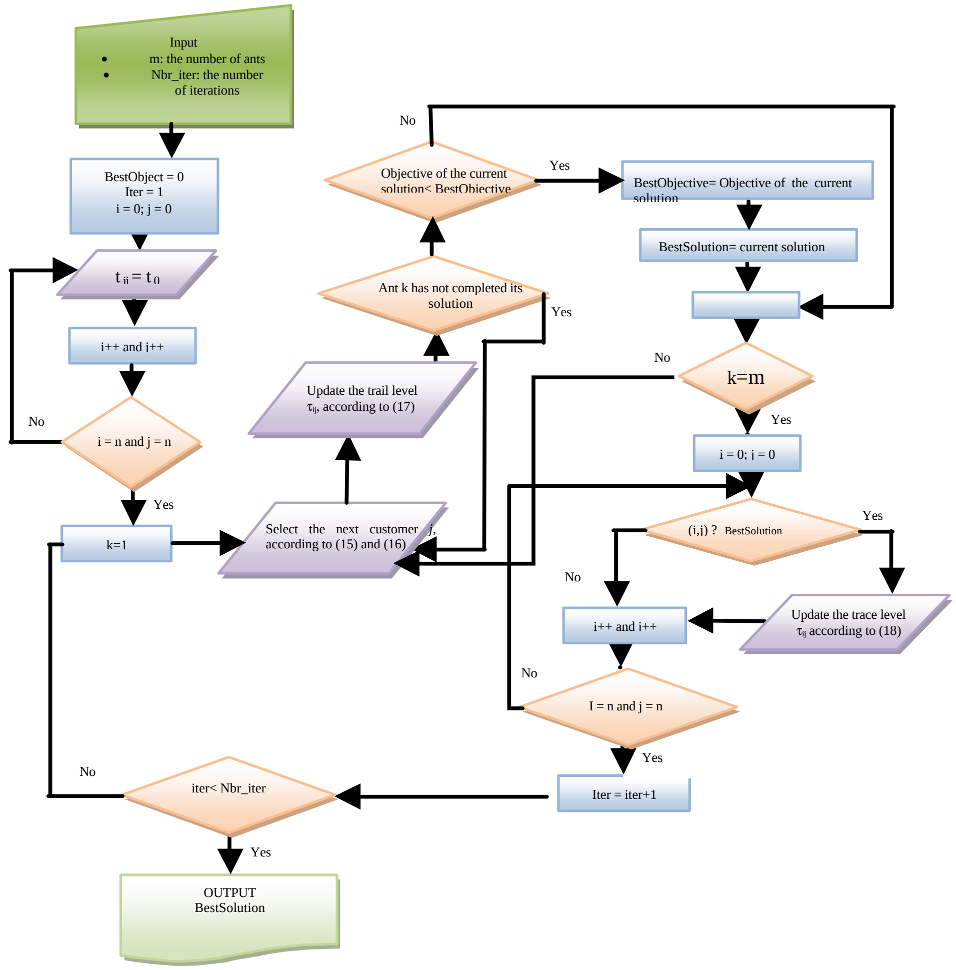

Fig. 4: Algorithm 1: ACS for the MGVRP

$$\tau_{ij}(t+1) = (1-\rho)\times\tau_{ij}(t)+\rho\times\tau_0 \tag{17}$$

$$\tau_{ij}(t+1) = (1-\rho)\times\tau_{ij}(t)+\rho\times\Delta\tau_{ij}(t) \tag{18}$$

where, ρ is a parameter that controls the evaporation of the pheromone trail. In addition, our approach implements a Large Neighborhood Search Algorithm to improve the quality of the feasible solutions. This algorithm uses implicitly a destroy and a repair method. A destroy method destructs part of the current solution by removing R customers. while a repair method rebuilds the destroyed solution by inserting removed customers in the best positions shown in Fig. 4.

RESULTS AND DISCUSSION

Computational results: To show the effectiveness of the proposed approach, this later is tested on the set of instances proposed by Elbouzekri *et al*. (2013). In these instances, there is a depot point which coordinate is (0, 0), a set of customer points which coordinates randomly belong to the region (0, 100 Km) and an unlimited homogenous fleet of vehicles, where the capacity of each vehicle is 25000 kg. The load volumes of customers randomly belongs to the region (500, 2500 Kg) and the service time of customers is fixed at 15 min. Suppose that service period of a vehicle belongs to the region (08, 18 h) and the average speed of vehicles is fixed at 80 km h^{-1}. Our algorithm was coded in C++ and executed on a MacBook Pro-Core i5/2.4 GHz- MacOS X 10.7 Lion.

The choice of parameters is so important for the success of the Ant Colony System Algorithm. To optimize the choice of these parameters, we apply the Taguchi method which is an experimental design that analyzes the effects of several variables (parameters) on the response variable (objective function) (Taguchi *et al*., 1987). The results obtained by the execution of the problem are

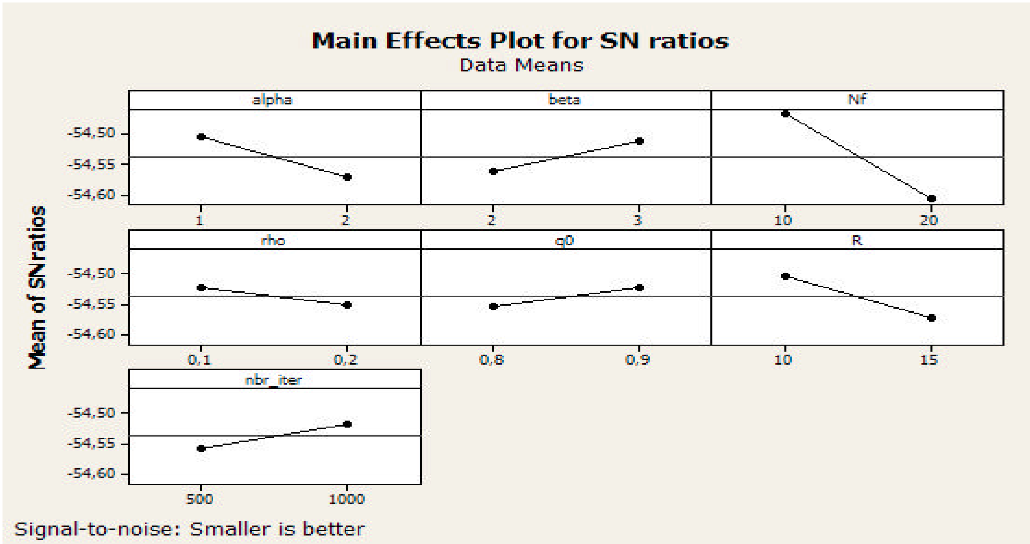

Fig. 5: Graphic of main effects

evaluated by transforming the value of the objective function (signal/noise). The S/N rate is calculated using the formula of "minimum value" expressed as follows:

$$S/N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$$

Where:

n = The number of executions

Y_i = Objective function value of the solution found during the execution I

Among the different experimental designs that exist, we choose to use the Taguchi design at two levels which consists to define two levels for each factor. The goal is to define the effects of each factor on the response (y).

We apply Taguchi design for an instance, we use Minitab software tool Minitab (2003) to fix different parameters of our approach. The influential factors results in our study are α, β, m, q_0, ρ N_f, R.

We define in the Table 6 a 2-level for the values of parameters Fig. 5. Figure 5 shows that the best results are obtained using the following values of different parameters presented in Table 7.

To evaluate the proposed approach, we will present firstly the numerical results by considering only the classic objective which minimizes the total traveled distance. Table 8 presents the results of our algorithm which correspond to the best value and the average of 3 runs. Each run is guaranteed to be independent of others

Table 6: Levels of the proposed approach's parameters

Levels	α	β	Nf	q_0	ρ	R	Nbr_iter
1	1	2	10	0.8	0.1	10	500
2	2	3	20	0.9	0.2	15	1000

Table 7: The values of the proposed approach's parameters

α	β	Nf	q_0	ρ	R	Nbr_iter
1	3	10	0.9	0.1	10	1000

Table 8: Numerical results of VRP for our approach compared to Bouzekri and Elhilali (2014)

	Bouzekri and Elhilali (2014)	Our approach	
Instance	Best	Best	Average
I1	358.53	352.07	352.07
I2	593.75	582.57	602.11
I3	1080.73	879.39	891.22
I4	1332.19	1202.13	1224,5
I5	1693.37	1463.23	1472.44
I6	1865.03	1764.34	1807.8
I7	_	2180.30	2199.65
I8	_	2682.14	2776.25
I9	_	3529.60	3580.92
I10	_	4175.72	4184.37

by starting with different random seeds. Table 8 shows the comparison of our approach with the results found by genetic algorithm proposed by Bouzekri and Elhilali (2014) (Table 8). Numerical results of VRP for our approach compared to Bouzekri and Elhilali (2014). As we can see our approach is very competitive. It outperforms El Bouzekri's genetic algorithm on all benchmark instances and it finds a feasible solution, unlike the genetic algorithm which is not tested or feasible solutions cannot be obtained for the instance I7, I8, I9 and I10. These results allow us to say that our approach is effective and

Table 9: Numerical results of MGVRP for our approach compared to Bouzekri and Elhilali (2014)

	Bouzekri and Elhilali, 2014		Our approach	
Instance	Distance	CO_2 emissions	Distance	CO_2 emissions
I1	317.73	350.64	352.07	324.96
I2	629.74	617.15	598.09	511.11
I3	940.5	1037.28	988.75	800.25
I4	1244.37	1753.16	1303.79	1053.23
I5	1615.6	2031.62	1573.61	1250.32
I6	2600.65	2331.28	1909.18	1515.11
I7	_	_	2318.37	1828.51
I8	_	_	2823.03	2221.47
I9	_	_	3500.92	2745.05
I10			4119.16	3220.88

shows the viability to generate very high quality solutions for the VRP. Now, to evaluate our approach to solve the MGVRP problem which minimize the total distance and the total CO_2 emissions related to freight transport, Table 9 shows our experimental results for this problem compared to Bouzekri and Elhilali (2014) where the weight of the emissions function (β = 60%) is higher than the distance function (β_2 = 40%).

The results found present the best solution generated by the proposed approach of 3 runs where we found that the proposed algorithm is more powerful than the genetic algorithm and this is evident in Table 9 where we can see that the quality of the result given by Bouzekri and Elhilali (2014) is bad compared to what we found in terms of two objectives except for the instances I1, I3 and I4. In addition, our approach was able to find feasible solutions for the instances I7, I8, I9 and I10, where the genetic algorithm which is not tested or feasible solutions cannot be obtained for these instances. In general, the routing cost is steadily decreased when the both objectives are minimized which indicate the conflicting behaviour between these objectives.

The experiments performed can show that our algorithm gives satisfactory results for multi-objective green vehicle routing problem.

CONCLUSION

In this study, a mathematical model and an ant colony system algorithm was proposed to solve the MGVRP. This algorithm seeks to construct the vehicle routes by successively choosing customers to visit, until each customer has been visited, minimizing the total distance traveled and the total emissions of the vehicles. The traffic in general and particularly goods transport has a very complex effect on the environment, giving a range of negative consequences which can be seen in air pollution, water pollution, noise, energy consumption, reduced safety, vibration and others.

Numerical experiments showed that this metaheuristic perform well compared to genetic algorithm and that it can be used to solve large problem instances. The correlation problems of distance minimization with emissions minimization allows to develop a wide range of tools to improve living conditions in urban areas.

In this respect, the estimation and modeling of CO_2 can be a powerful tool for air quality managers and environmentalists in order to examine the impact of different transport plans.

REFERENCES

Bektas, T. and G. Laporte, 2011. The pollution routing problem. Transp. Res. Part B. Methodol., 45: 1232-1250.

Benedek, C.M. and L.R. Rilett, 1998. Equitable traffic assignment with environmental cost functions. J. Transp. Eng., 124: 16-22.

Bouzekri, E.A. and A.E. Alaoui, 2014. Evolutionary algorithm for the bi-objective green vehicle routing problem. Int. J. Sci. Eng. Res., 5: 70-77.

Bouzekri, E.A.A. and A.Y.B. Elhilali, 2013. A genetic algorithm for optimizing the amount of emissions of greenhouse gaz for capacitated vehicle routing problem in green transportation. Int. J. Soft Comput., 8: 406-415.

Dlugokencky, E.J., K.A. Masarie, P.M. Lang and P.P. Tans, 1998. Continuing decline in the growth rate of the atmospheric methane burden. Nat., 393: 447-450.

Dlugokencky, E.J., S. Houweling, L. Bruhwiler, K.A. Masarie and P.M. Lang, 2003. Atmospheric methane levels off: Temporary pause or a new steady state?. Geophys. Res. Lett., Vol. 30, 10.1029/2003GL018126

Elbouzekri, A., M.E.S.S.A.O.U.D. Elhassania and A.E.H. Alaoui, 2013. A hybrid ant colony system for green capacitated vehicle routing problem in sustainbale transport. J. Theor. Appl. Inf. Technol., 53: 198-208.

Jemai, J., M. Zekri and K. Mellouli, 2012. An NSGA-II Algorithm for the Green Vehicle Routing Problem. In: Evolutionary Computation in Combinatorial Optimization, Hao, J.K. and M. Middendorf (Eds.). Springer, New York, USA., ISBN: 9783642291241, pp: 37-48.

Palmer, A., 2007. The development of an integrated routing and carbon dioxide emissions model for goods vehicles. Ph.D. Thesis, School of Management, Cranfield University, Cranfield, UK

Sbihi, A. and R.W. Eglese, 2007. The Relationship Between Vehicle Routing and Scheduling and Green Logistics a Literature Survey. Lancaster University, Lancester, England,.

Taguchi, G., S. Konishi and S. Konishi, 1987. Taguchi Methods Orthogonal Arrays and Linear Graphs: Tools for Quality Engineering. American Supplier Institute, Nasr City, Cairo, Egypt, ISBN-13: 9780941243018, pp: 8-35.

Toth, P. and D. Vigo, 2001. The Vehicle Routing Problem. SIAM, Philadelphia, Pennsylvania,.

Wygonik, E. and A. Goodchild, 2011. Evaluating CO_2 emissions, cost and service quality trade-offs in an urban delivery system case study. Iatss Res., 35: 7-15.