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A Genetic Algorithm for Optimizing the Amount of Emissions of Greenhouse GAZ for Capacitated Vehicle Routing Problem in Green Transportation

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Abstract: In today's highly competitive environment, green transportation issues are gaining interest from theoretical, political and social perspectives. Freight road transport that is one important aspect of environmentally responsible logistics is discussed in depth. The activity of transport causes a high rate of negative effects on the environment as pollutants emission (greenhouse gas). The immediate consequence of this effect is depletion of ozone layer and climate change that is the reason why researchers must been reducing the emissions from the sector. Nevertheless, the classical Capacitated Vehicle Routing Problem (CVRP) with the objective of minimizing the greenhouse gas especially the carbon dioxide (CO_2), states for the problem of finding routes for vehicles to serve a set of customers while minimizing the total traveled distance and the CO_2 emissions. Researchers present in this study the technique employed to estimate de CO_2 emissions, the emissions matrix and integrate them into the CVRP Model and proposes a genetic algorithm to solve this problem. The effectiveness of this approach is tested on a well-known set of benchmarks and compared to other works from literature.

Key words: Environment, green transportation, greenhouse emissions, capacitated vehicle routing problem, emission matrix, genetic algorithm, freight transport

INTRODUCTION

Global warming and climate change have come to the fore as a key sustainable development issue. These phenomenons on the world economy have been assessed intensively by the researchers since, 1990s. The world wide organizations such as the United Nations have been attempting to reduce the adverse impacts of global warming through intergovernmental and binding agreements. The Kyoto protocol is such an agreement that was signed in 1997 after hefty discussions and this protocol identifies constraints to environmental pollutants and requires a timetable for realizations of the emission reductions for the developed countries (Halicioglu, 2008). Warming of the climate system is unequivocal and scientists are >90% certain that it is primarily caused by increasing concentrations of Greenhouse Gases (GHG) produced by human activities direct and indirect gases (IPCC, 2007). By the GHG protocol defines direct emissions are emissions from sources that are owned or controlled by the reporting entity (GHG Protocol, 2005). Amongst several environmental pollutants causing climate change, carbon dioxide (CO_2) is the predominant transportation GHG and is emitted in direct proportion to fuel consumption with a variation by type of fuel (ICF, 2006). The carbone dioxide is held responsible for 58.8% of the GHG in a report of World Bank. Nevertheless, car use, road freight and aviation are the principal contributors to greenhouse gas emissions from the transport sector.

In this context, the research is based on the new scheme development sustainable and green logistics by the introduction of the matrix emissions in the vehicle routing problem with capacity constraints and researchers resolves this problematic with meta-heuristics. The purpose is to introduce new objectives in the vehicle routing problem for minimizing the total traveled the CO_2

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emissions where the traditional objectives of the VRP include minimizing the total distance traveled by all vehicles or minimizing the overall travel cost, usually a linear function of distance.

SUSTAINABLE TRANSPORT

Transport systems have significant impacts on the environment, accounting for between 20 and 25% of world energy consumption and carbon dioxide emissions (World Energy Council, 2007). The environmental impacts of transport can be reduced by improving the concept of sustainable transportation. This concept refers to the broad subject of transport that is or approaches being sustainable and makes a positive contribution to the environmental, social and economic sustainability of the communities they serve (Schafer, 1998). The term sustainable transport came into use as a logical follow-on from sustainable development and is used to describe modes of transport and systems of transport planning which are consistent with wider concerns of sustainability. One such definition, from the European Union Council of Ministers of Transport, defines a sustainable transportation system as one that: Allows the basic access and development needs of individuals, companies and society to be safely and in a manner consistent with human and ecosystem health and promotes equity within and between successive generations. To reduce CO_2 emissions from freight transport, a European report has identified various areas of research and works that can be mobilized include some approaches (Fig. 1):

- Regulation; it is policy measures aimed at encouraging public transport decarburized, e.g., the carbon tax
- New engine; this axis table on technical developments related to propulsion, it is expected that the next generation engine will be cleaner

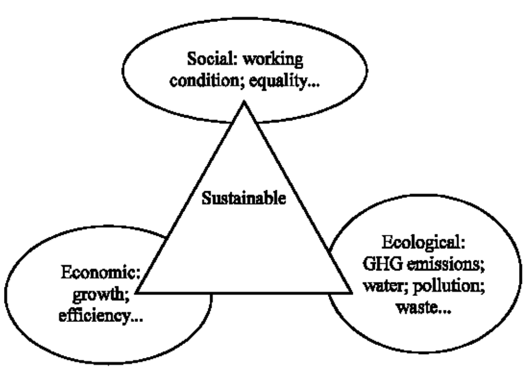

Fig. 1: Concept of sustainable transport

- Electric drive vehicle; uses one or more electric motors or traction motors for propulsion, it is quite clear that electric vehicles do not emit CO_2 but this is still limited by some constraints such as the need for greater power generation and decarburization, security, etc.
- Eco-driving; changing patterns of pipelines
- Modal: It consists in transferring flows from road to other less polluting modes such as rail
- New logistics patterns; by increasing the loading rate and reducing the number of empty trips could reduce from 10-40% km traveled and therefore CO_2 emissions

In this research, researchers included in the working axis new logistics patterns and more specifically in capacitated vehicle routing problem for finding routes for vehicles to serve a set of customers while minimizing the total of CO_2 emissions. To this end, it is necessary to model CO_2 emissions to obtain emission factors for trucks that comply with the need for optimization models and evaluation of the environmental performance of transport.

The estimating CO_2 emissions from freight transport: Road vehicle emissions have justifiably received the greatest attention of all transport modes because of their dominance as a means of transporting both passengers and goods. Not only does road transport have the biggest share of transport activity but its decentralized and ground borne nature bring it into close proximity with more people than the other modes. Because a large amount of information on road transport emissions is available, it has been possible to propose a relatively detailed methodology (Hickman *et al*., 1999). The estimation of fuel consumption and CO_2 emission for mobile sources requires complex calculations which can only represent an approximation because of the difficulty of quantifying some variables as driving style, weather conditions, congestion and the like (Palmer, 2007; Van Woensel *et al*., 2001). With regard to transport goods by road, the modeling of CO_2 emissions is based on the methodology and results of the projects COST Action 319 (Joumard, 1999) (updated by COST Action 346 (Sturm *et al*., 2005) and the project MEET Deliverable 22 (Hickman *et al*., 1999) which produces the basic results for the Software COPERT.

Basic principales: The main sources of emission from road vehicles are the exhaust gases and hydrocarbons produced by evaporation of the fuel. When an engine is started below its normal operating temperature, it uses fuel inefficiently and the amount of pollution produced is higher than when it is hot. These observations lead to the first basic relationship used in the calculation method (Hickman *et al*., 1999):

$$E = E_{hot} + E_{start} + E_{evaporative} \quad (1)$$

Where:
E = The total emission
E_{hot} = The emission produced when the engine is hot
E_{start} = The emission when the engine is cold
$E_{evaporative}$ = The emission by evaporation (only for VOC: Volatile Organic Compound)

Each of these contributions to the total emission depends on an emission factor and one or more parameters relating to the operation of the vehicle, so that in general:

$$E_x = e_x a_x \quad (2)$$

Where:
E_x = One of the contributions to total emissions
e_x = An activity related emission factor
α_x = The amount of traffic activity relevant to this type of emission

The parameters e_x and α_x are themselves functions of other variables. For hot emissions, the activity related emission factor, E_{hot} is expressed primarily as a function of the average speed of the vehicle. Modification factors (which may themselves be functions of other variables) allow corrections to be made for features such as the road gradient or the load carried by a vehicle. The activity is then the amount of operation (vehicle kilometers) carried at a particular average speed on roads with a certain gradient for vehicles with a certain load. Start emissions, because they only occur during the early part of a journey are expressed as an amount produced per trip and not over the total distance travelled. The emission factor E_{start} is calculated as a function of the average vehicle speed, the engine temperature, the length of the trip and the length of the cold part of the trip. The activity, a_x is the number of trips. This procedure is used only for light duty vehicles. Because data for other types is very limited such detail cannot be used and cold start emissions are proposed simply as constants (excess emissions per cold start). Evaporative emissions occur in a number of different ways. Fuel vapor is expelled from the tank each time it is refilled, the daily increase in temperature (compared with overnight temperatures) causes fuel vapor to expand and be released from the fuel tank and vapor is created wherever fuel may be released to the air, especially when the vehicle is hot during or after use.

There are therefore a number of different emission factors, $E_{evaporative}$, depending on the type of evaporative emission. Generally, these factors are a function of the ambient temperature and the fuel volatility. Similarly, a number of activity data are also needed including total distance travelled and numbers of trips according to the temperature of the engine at the end of the trip. These principles apply with some exceptions to all pollutants and vehicle types but different classes of vehicle behave differently and relationships between emissions and operating characteristics vary for each pollutant. For that reason, an estimate of emissions from mixed traffic must be made as a summation of emissions from each homogeneous vehicle class in the traffic and where the area studied contains roads with different traffic behavior this must also be taken into account. And of course, this must be done separately for each pollutant (Hickman *et al*., 1999).

CO_2 emissions matrix from the transport of freight: Researchers recall that from the perspective of sustainable development, this study aims to evaluate the effect of this pooling on reducing GHG emissions, especially CO_2 emissions with the CO_2 is not affected by this term E evaporation (Hickman *et al*., 1999). First of all, the mode of road transport here refers to transport by Heavy Duty Vehicle (HDV) only (32-40 tons for general merchandise). According to the emissions function for the HDV truck given by Hickman *et al*. (1999) and Jancovici some assumptions are made:

- The average speed is 80 km h^{-1}
- The gradient of a road is not taken into account. In general the truck considered here is fully loaded with 25000 kg for weight

Particularly, for the care and grocery classes, it is assumed that the truck is fully loaded at the same time by weight and volume. Indeed, researchers assume that the underlying transport level supply networks are often over long distances which consist in neglecting emissions starting the vehicle which exist only when the engine is hot. Consequently, Eq. 1 can be simplified and detailed as this for CO_2 emissions:

$$E = E_{hot} \quad (3)$$

By the methodology and results of the projects COST Action 319 (updated by COST Action 346 (Sturm *et al*., 2005)) and the project MEET Deliverable 22 (Hickman *et al*., 1999), a result of the final CO_2 emissions function with the variable of load is:

$$E(q) = \left(\frac{e_{fl} - e_{el}}{Q}\right) q + e_{el} \quad (4)$$

Where:

$E(q)$ = The CO_2 emissions from a vehicle in kg/km with the variable of load q in ton

e_{fl} = The CO_2 emissions of a fully loaded (by weight) vehicle which is $e_{fl} = 1.096$ kg km^{-1} for HDV truck

e_{el} = The CO_2 emissions of an empty vehicle which is $e_{el} = 0.772$ kg km^{-1} for HDV truck

Q = The volume capacity of a vehicle

Function of CO_2 emissions (4) examines the case of a truck per km. Emissions to make a delivery with a distance and a given flow can be calculated by the generic equation:

$$E(q, d) = d \times \left[\left(\frac{e_{fl} - e_{el}}{Q}\right) q + e_{el}\right] \quad (5)$$

Typically, distance, time and cost are the parameters used to produce, respectively, a matrix of distance, time and cost between all delivery points and depot. Now, the objective is to design those routes that generate the lower levels of CO_2 emissions to atmosphere and in order to achieve this goal, it is necessary to build a matrix of CO_2 emissions based on the estimation of CO_2 emitted between each link (Palmer, 2007). The linearization of flow and emissions for the arc ij can be displayed as the emissions matrix:

$$E_{ij}(q, d) = d_{ij} \times \left[\left(\frac{e_{fl} - e_{el}}{Q}\right) q_{ij} + e_{el}\right] \quad (6)$$

In this study, it is shown how to estimate CO_2 emissions from transport freight. Thereafter, researchers incorporate those concepts in the methodology used to solve the vehicle routing problem.

THE CAPACITATED VEHICLE ROUTING PROBLEM WITH EMISSIONS MATRIX

Literature review for the CVRP: The Vehicle Routing Problem (VRP) requires the determination of an optimal set of routes for a set of vehicles to serve a set of customers. The problem as it appears on real life may have several classes of additional constraints as limit on the capacity of the vehicles, time windows for the customer to be served, limits on the time a driver can work, limits on the lengths of the routes, etc. Researchers deal here with the Capacitated Vehicle Routing Problem (CVRP) that is researchers have: a depot where vehicles start and end their routes, a set of clients and their demands, a set of vehicles with a maximum weight or volume that each one can load and costs or distances between clients and between clients and the depot. Researchers want to define routes for the vehicles starting and ending at the depot that satisfy the clients demand at a minimum total cost. As most VRP problems, CVRP is known to be NP-hard (Fig. 2).

The Capacitated Vehicle Routing Problem (CVRP) has been described as the most common management problem in food, fuel and retail goods distributors. The literature review revealed several different approaches to the CVRP. Other traditional papers about heuristic algorithms are Gaskell (1967), Golden *et al.* (1977) and Bodin and Berman (1979). The most interesting reference in the VRP bibliography is Toth and Vigo (2002) which provides a good list of excellent algorithms to solve the CVRP. Constructive methods have been shown to be applicable in the solution of real problems in the logistic activities of many companies (Clarke and Wright, 1964). Nevertheless, the use of meta-heuristics in VRP became popular during the nineties. Two of the most important papers on the use of heuristics and metaheuristics were Gendreau *et al.* (1994) which introduced the Tabu Route algorithm and Laporte *et al.* (2000) which include a thorough discussion of classical and modern heuristics. Nevertheless, the main source of current information about meta-heuristics is given by Toth and Vigo (2002).

Background of the Green Vehicle Routing Problem (GVRP): The while that CVRP aims at minimizing total travelling kilometers and total assigned vehicles, it is satisfying green transportation requirements by reducing consumption level and consequently reducing the CO_2 emissions from road transportation. The contribution of vehicle routing surveys is not limited to this implicit and unconscious contribution by minimizing travel distance

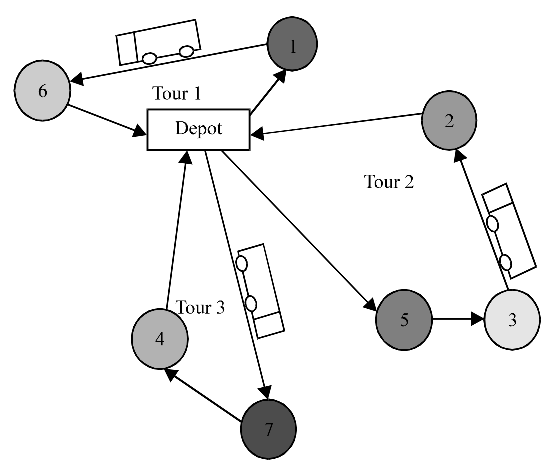

Fig. 2: The capacited vehicle routing problem scheme

and vehicle numbers, though and many more explicit factors related to green transportation issues could be considered in a CVRP Model. Seemingly, the awareness with the contribution of CVRP to green transportation was initiated with the studies of Sbihi and Eglese (2007) and Palmer (2007). However, regarding the existing literature they argue that reduction in total distance will in itself provide environmental benefits due to the reduction in fuel consumed and the consequent pollutants. Palmer (2007) on the other hand, suggests an integration of logistical and environmental aspects into one freight demand model with the aim of enhancing policy analysis. Citing the most relevant and explicit ones to the considerations of green transportation researchers may start by mentioning the introduction of the Pollution Routing Problem (PRP) by Bektas and Laporte (2011). They develop PRP 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. Xiao *et al*. (2011), regard Fuel Consumption Rate (FCR) as a load dependant function and add it to the classical CVRP to extend traditional studies on CVRP with the objective of minimizing fuel consumption.

Their proposal particularly aims at aiding organizations with alternative fuel powered vehicle fleets in overcoming difficulties that exist as a result of limited vehicle driving range in conjunction with limited refueling infrastructure. Apparently, all these studies have been published recently, this shows that the topic is at its very beginning.

Gvrp formulation (optimizing environmental with emissions matrix): The solution for the GVRP determines a set of delivery routes that satisfies the requirements of distribution points and obtains the minimum total emission for all vehicles. This problem exhibits the following characteristics:

- Known fleet size
- Homogeneous fleet (trucks loading 25000 kg)
- Single depot
- Deterministic demand
- Oriented network
- Goal: minimizing emissions

Denote by V = {0, 1, …, n} a set of n nodes, each representing a vehicle destination. The nodes are numbered 0 to n, node 0 being the depot and nodes 1 to n the delivery points. The transportation process will be carried by a set Z = {0, 1, …, m} of m vehicles. For presenting the integer linear programming model for VRP, the variables below are introduced:

- q_i: Demand of the node i
- s_i: Service time of the node i
- Q_k: Capacity of vehicle k
- e_{ij}: Emission between the nodes i and j
- t_{ij}: Driving time between the nodes i and j
- T_k: Maximum allowable driving time for vehicle k

Researchers define binary decision variables x_{ij}^k $(i \neq j)$ and y_i^k as follows:

$$x_{ij}^k = \begin{cases} 1 & \text{if vehicle k drives from customer i to customer j} \\ 0 & \text{otherwise} \end{cases}$$

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

Likewise, let us assume symmetrical distances, i.e., $d_{ij} = d_{ji}$ $(1 \leq i,\ j \leq n)$ and symmetrical driving times between nodes, i.e., $t_{ij} = t_{ji}$ $(1 \leq i,\ j \leq n)$ both verifying triangular inequality. The delivery process must satisfy fleet capacity constraints (Q_k) and maximum allowable driving time (T_k). The goal will be to construct several routes, one for each active (non-idle) vehicle, minimizing the sum of the total emissions. Then, the resulting model is given by Eq. 7-17:

$$\text{Min} \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{m} e_{ij} x_{ij}^k \quad i \neq j \tag{7}$$

Subject to:

$$\sum_{i=1}^{n} x_{i0}^k \leq 1 \quad \forall k \in \{1, 2, ..., m\} \tag{8}$$

$$\sum_{i=1}^{n} x_{0i}^k \leq 1 \quad \forall k \in \{1, 2, ..., m\} \tag{9}$$

$$\sum_{i=1}^{n} y_i^k \leq M \sum_{j=1}^{n} x_{0j}^k \quad \forall k \in \{1, 2, ..., m\} \tag{10}$$

$$\sum_{i=1}^{n} y_i^k \leq M \sum_{j=1}^{n} x_{j0}^k \quad \forall k \in \{1, 2, ..., m\} \tag{11}$$

$$\sum_{k=1}^{m} y_i^k = 1 \quad \forall i \in \{1, 2, ..., n\} \tag{12}$$

$$\sum_{i=1}^{n} x_{ij}^{k} = y_{j}^{k} \quad \forall j \in \{1, 2, ..., n\}\ i \neq j,\ \forall k \in \{1, 2, ..., m\} \tag{13}$$

$$\sum_{j=1}^{n} x_{ij}^{k} = y_{i}^{k} \quad \forall i \in \{1, 2, ..., n\}\ i \neq j,\ \forall k \in \{1, 2, ..., m\} \tag{14}$$

$$\sum_{i=1}^{n} q_i y_i^k \leq Q_k \quad \forall k \in \{1, 2, ..., m\} \tag{15}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} t_{ij}\, x_{ij}^{k} + \sum_{i=1}^{n} s_i y_i^k \leq T_k \quad i \neq j, \forall k \in \{1, 2, ..., m\} \tag{16}$$

$$\sum_{i,j \in S} x_{ij}^{k} \leq |S|\text{-}1 \quad i \neq j, \forall k \in \{1, 2, ..., m\}, S \subset N, 2 \leq |S| \leq n\text{-}1 \tag{17}$$

Relation (7) is the objective function to be minimized including the total emission produced by the running vehicles. Constraints (8-11) ensure that all the vehicles begin and end their routes at the depot while constraint (12) guarantee that each node except the depot is visited by a single vehicle. Furthermore, constraints (13) and (14) assure that each node except the depot is linked only with a pair of nodes, one preceding it and the other following it. Moreover, constraint (15) ensures that no vehicle can be over loaded while constraint (16) does not permit that any vehicle exceed the maximum allowable driving time per day T_k. Finally, researchers introduce constraint (17) to avoid sub tours. Since, the purpose of our optimization project is to minimize the CO_2 emissions related to freight transport in two large supply chains, the emissions functions are adopted in the optimization model via an objective function. Therefore, researchers developed a genetic Algorithm (AG) for the GVRP.

THE GENETIC ALGORITHMS FOR THE GVRP

Backgound: The theory of natural selection was proposed by the British naturalist Charles Darwin. The theory states that individuals with certain favorable characteristics are more likely to survive and reproduce and consequently pass their characteristics on to their offspring. Individuals with less favorable characteristics will gradually disappear from the population. In nature, the genetic inheritance is stored in chromosomes, made of genes. The characteristic of every organism is controlled by the genes which are passed on to the offspring when the organisms mate. Once in a while a mutation causes a change in the chromosomes. Due to natural selection, the population will gradually improve on the average as the number of individuals having the favorable characteristics increases. The idea behind GA is to model the natural evolution by using genetic inheritance together with Darwin's theory. In GA, the population consists of a set of solutions or individuals instead of chromosomes. A crossover operator plays the role of reproduction and a mutation operator is assigned to make random changes in the solutions. A selection procedure, simulating the natural selection, selects a certain number of parent solutions which the crossover uses to generate new solutions also called offspring (Abounacer *et al*., 2009). At the end of each iteration the offspring together with the solutions from the earlier generation form a new generation, after undergoing a selection process to keep a constant population size. The solutions are evaluated in terms of their fitness values identical to the fitness of individuals.

The algorithm for GVRP: Some superior meta-heuristic methods have recently been developed and GA has been shown to be capable to solve CVRP (Baker and Ayechew, 2003). GA is a powerful algorithm for solving optimization problem including CVRP (Zheng and Liu, 2006). Others research also utilized GA to solve CVRP (Filipec *et al*., 1998; Chen *et al*., 2006; Skrlec *et al*., 1997). Therefore, in this study, researchers use GA for solving CVRP with emission matrix (GVRP) to analyze performance of GA in terms of solving GVRP. But all GA must have the following basic items that need to be carefully considered for the algorithm to research as effective as possible (Michalewicz and Schoenauer, 1996):

- A good genetic representation of a solution in a form of a chromosome
- An initial population constructor
- An evaluation function to determine the fitness value for each solution
- Genetic operators, simulating reproduction and mutation
- Values for parameters; population size, probability of using operators, etc.

The generalized procedure of the GA approach in this study is shown in Fig. 3.

Genetic representation and encoding: For solving GVRP with GA, it is usual to represent each individual by chromosomes which is a chain of integers, each of them representing a customer. In this representation each vehicle identifier (gene with index 0) represents in the chromosome a separator between two different routes and

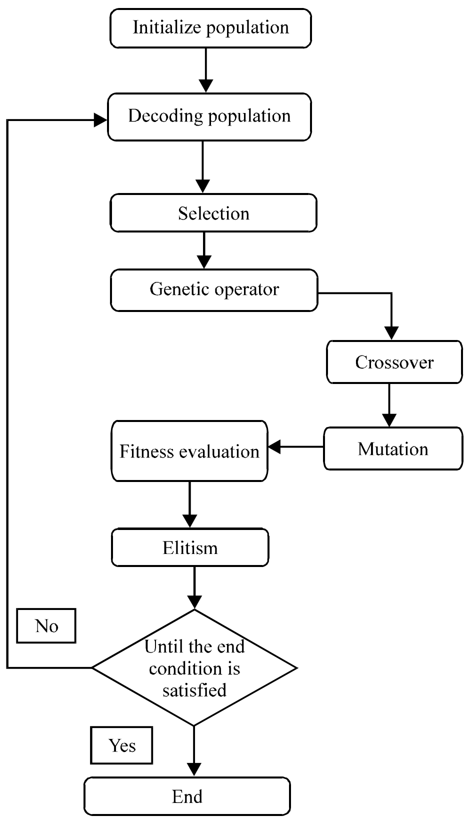

Fig. 3: Procedure of the proposed methodology

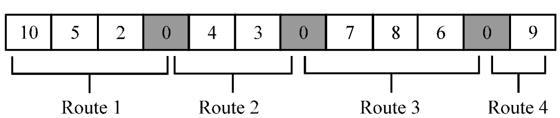

Fig. 4: Genetic representation of chromosome for 12 nodes

a string of customer identifiers represents the sequence of deliveries that must cover a vehicle during its route. Figure 4 shows a representation of a possible solution with 9 customers and 4 vehicles, each route begins and ends at the depot.

Initial population construction: An initial population is built such that each individual must at least be a feasible candidate solution, i.e., every route in the initial population must be feasible.

Selection: The selection process consists in choosing two individuals (parent solutions) within the population for mating purposes. The selection procedure is stochastic and biased toward the best solutions using a roulette-wheel scheme (Goldberg, 1989). In this scheme, the probability to select an individual is proportional to its fitness value. In the roulette wheel method, the probability of choosing an individual is directly proportional to its fitness value. For the GVRP; the objective function is to minimize total emission traveled.

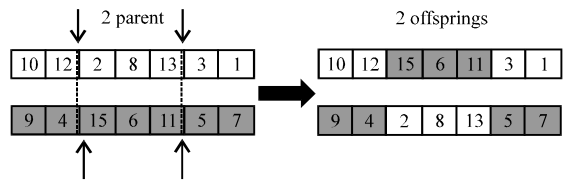

Fig. 5: Example of 2-point crossover

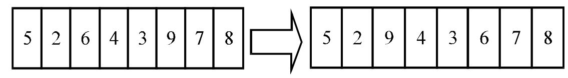

Fig. 6: Example of mutation

Genetic operators

Crossover: The main genetic operator is crossover which simulates a reproduction between two parents. It works on a pair of solutions and recombines them in a certain way generating one or more offsprings. The offsprings share some of the characteristics of the parents and by this way the characteristic are passed onto the future generations (Fig. 5).

Mutation: The other genetic operator is mutation which is applied to a single solution with a certain probability. Mutation operator makes small random changes in the solution. These random changes will gradually add some new characteristics to the population which could not be supplied by the crossover. In the study, Partial-Mapped Crossover (PMX) and swap mutation (Gendreau *et al*., 1994) are used for genetic operations of permutation based chromosomes (Fig. 6).

Elitism: The elitism strategy keeps a small number of good individuals and replaces the worst individuals in the next generation without going through the usual genetic operations.

EXPERIMENTAL RESULTS

The algorithm is implemented in C++ Language using DEV-C++ 4.9.9.2 on a PC with Intel (R) Pentium (R) Dual CPU T3400 @ 2.16 GHz Processor to 4 GB RAM. The computational experiments were performed on a set of benchmark problems which are publicly available at the VRPWeb at: http://neo.lcc.uma.es/radi-aeb/WebVRP/.

The GA has been tested with problem instances from the benchmarks of Christofides and Elion (1969) and

Table 1: Experimental results for different heuristics and GA on VRP

Instances	City	Capacity	Christofides and Elion (1969) and Fisher and Jaikumar (1981) (best value knoning)	HGA 2007	The GA
E-n22-k4	22	6000	375	375	374,609
E-n23-k3	23	4500	569	568	569.084
E-n30-k3	30	4500	534	517	534,479
E-n33-k4	33	8000	835	838	834,857
F-n45-k4	45	2010	724	722	724
E-n51-k5	51	160	521	-	544,218
E-n101-k8	101	200	815	-	851,57

Table 2: Results obtained for 10 different instances of 10-130 requests

Instances	n	TE (kg CO_2)	TD (km)	NV
I1	10	46.22	564.61	1
I2	30	55.76	1022.20	3
I3	50	72.06	1364.59	4
I4	70	91.82	1945.20	5
I5	100	112.03	2570.19	7
I6	130	138.75	3436.85	9

Jeon *et al.* (2007). As GA is a probabilistic algorithm results can vary from a run to another. Here, results of the algorithm correspond to the best value of five runs. Each run is guaranteed to be independent of others by starting with different random seeds. Table 1 shows the comparison of the GA with published results.

The first column describes the various instances whereas the column 2 number of customer (city), 3 the capacity, 4 and 5 specify well-known published best results obtained using meta-heuristic algorithm. Finally, the column 6 refers to the best result of the method for these instances. The proposed algorithm has shown to be competitive with the best existing methods in terms of solution quality where the approach is better than hybrid AG except for instances E-n22-k4 and E-n33-k4 also in order to check the efficiency of the improved the GA, this study analyzed the results of the existing examples by using the Christofides and Elion (1969) and Fisher and Jaikumar (1981). One problem, F-n45-k4 gave the same distance and the other problems give produced better solutions. Finally, the approach of GA is effective and shows the viability to generate very quality solutions for the VRP.

Now, to evaluate the approach to solve GVRP problem which minimize the CO_2 emissions related to freight transport, researchers tested its performance on a set of instances generated randomly of 10-100 requests. 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 a vehicles is 25000 kg. The load volumes of customers randomly belong to the region [500, 2500 kg] and the service time of customers is fixed at 15 min. Suppose that service period of a vehicle belong to the region [8, 18 h] and the average speed of vehicles fixed at 80 km h^{-1}.

Table 2 shows the best results found for 6 different instances of 10-130 requests where n is the number of customers; the columns TE, TD and NV are the total emission, the total distance and the number of vehicles, respectively for the best solution found. To show the influence of the minimization of emissions on the quality of solution in term of total traveled distance, researchers tested the approach by considering the classic objective which minimize the total traveled distance on the 6 different instances generated randomly.

Table 3: Comparison of the experimental results between VRP and GVRP (km)

Instances	TD	TD*
I1	564.61	358.53
I2	1022.20	593.75
I3	1364.59	1080.73
I4	1945.20	133219.00
I5	2570.19	1693.37
I6	3436.85	1865.03

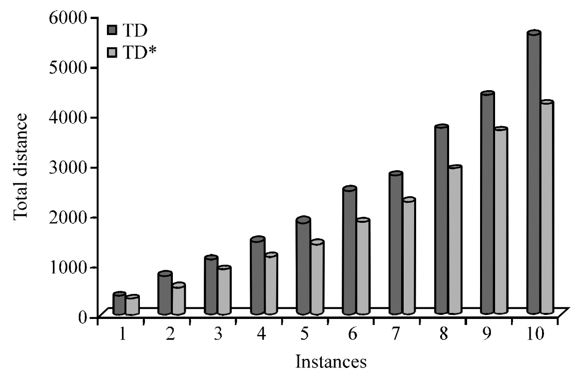

Fig. 7: TD compared with TD*

Table 3 gives a comparison between the total distance TD found for GVRP and the minimum total distance TD* found for VRP. Figure 7 shows that the total distance increases when researchers minimize the total emission which allows us to say that the minimization of the total traveled distance and the minimization of the total emission are conflicting objectives. Note also that the time is not important in this case in relation to the quality of results because the problem is of a strategic nature.

CONCLUSION

Transportation sector is the irreplaceable infrastructure upon which economic and social development is possible. Million tons of freight and numbers of passengers are carried by the sector each day. However, at the same time of its importance to the global life it is a danger to it, since it is one of the hugest consumers of petroleum products and hence a prime creator of the existing harmful particles including greenhouse gases and CO_2 as the most prevalent of them in the air.

It is a while that an urgency to reduce these emissions has been realized and global communities have been activated under the umbrella of the green transportation or the sustainable transport paradigm. Nevertheless, the minimization of distances and pollutant emissions associated to the introduction of changes in transport planning shows the importance of optimizing operations. Researchers present in this study that the research may also lead to the finding of cleaner routes, through the development of the performance of genetic algorithm with the environmental matrices (e_{ij}). The GA has been demonstrated that GAs are an effective approach to solving the basic VRP and also the GVRP. These methodologies may lead us to calculate the emissions more accurately and to facilitate the search for cleaner routes.

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