

A HYBRID ANT COLONY SYSTEM FOR GREEN CAPACITATED VEHICLE ROUTING PROBLEM IN SUSTAINABLE TRANSPORT

¹EL BOUZEKRI EL IDRISSE ADIBA, ²MESSAOUD ELHASSANIA, ³EL HILALI ALAOU AHMED

^{1,2,3} Scientific Computing and Computer Sciences, Engineering Sciences
Modeling and Scientific Computing Laboratory

Faculty of Sciences and Technology

University Sidi Mohamed Ibn Abdelah, FES, MOROCCO

E-mail: ¹b.i.adibal@gmail.com, ²messaoud.dev@gmail.com, ³elhilali_fstf2002@yahoo.fr

ABSTRACT

The 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 these effects is depletion of ozone layer and climate change, that is the reason why we must be 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 (CO₂), states for the problem of finding routes for vehicles to serve a set of customers while minimizing the CO₂ emissions. We present in this paper the technique employed to estimate de CO₂ emissions, the emissions matrix and their integration into the CVRP model, then we propose a Hybrid Ant Colony System (HACS) to solve the CVRP with the objective of minimizing the CO₂. The effectiveness of our approach is tested on a well-known set of benchmarks. Note that our approach is the first adaptation for this problem by the ant colony system.

Keywords: *Environment, Green Transportation, Greenhouse Emissions, Capacitated Vehicle Routing Problem, Emission Matrix, Ant Colony System, Freight Transport.*

1. INTRODUCTION

Global warming and climate change have come to the fore as a key sustainable development issue. These phenomena 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 [1]. Warming of the climate system is unequivocal, and scientists are more than 90% certain that it is primarily caused by increasing concentrations of greenhouse gases (GHG) produced by human activities direct and indirect gases [2]. The GHG Protocol defines direct

emissions as emissions coming from sources that are owned or controlled by the reporting entity, for example, emissions from combustion, furnaces, and transportation of materials, products, and employees [3]. Amongst several environmental pollutants causing climate change, carbon dioxide (CO₂) is the predominant transportation GHG and is emitted in direct proportion to fuel consumption, with a variation by type of fuel [4]. The Carbon dioxide is held responsible for 58.8% of the GHG in a report of World Bank. The combustion of fossil fuels is the largest single contributor to CO₂ emissions and has grown the most rapidly over the period 1970 to the present. This means that global CO₂ emissions are growing faster than at any time since 1970. Nevertheless, car use, road freight and aviation are the principal contributors to greenhouse gas emissions from the transport sector. For example freight transport in the (UK) is responsible for 21% of the CO₂ emissions from the transport sector, amounting to 33.7 million tons, or

6% of the CO₂ emissions in the country, of which road transport accounts for a proportion of 92% [5]. In this context, our work 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 we resolve this problematic with Meta-heuristics. Our purpose is to introduce new objectives in the vehicle routing problem for minimizing the total traveled the CO₂ emissions for the green transportation, 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.

The present paper is organized as follows: in section 2, we provide the necessary background the concept of sustainable transportation; also we present in section 3 the method for estimate the emission factors and then integrated into quantitative models. In section 4, we analyze a literature review for the capacitated vehicle routing problem (CVRP) and CVRP with the ecological objective, then we propose the mathematical formulation of the problem. In section 5, we introduce an ant colony system to solve the CVRP with the matrix emission. Experimental results are presented in section 6. Finally, we end with conclusions in section 7.

2. SUSTAINABLE TRANSPORT

Transport systems have significant impacts on the environment, accounting for between 20% and 25% of world energy consumption and carbon dioxide emissions [6]. Greenhouse gas emissions from transport are increasing at a faster rate than any other energy using sector [7]. 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 [8]. 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 met safely and in a manner consistent with human and

ecosystem health, and promotes equity within and between successive generations."

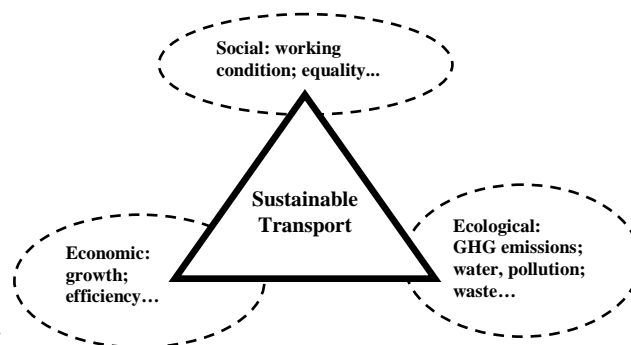


Figure 1: Concept Of Sustainable Transport

But in relation to the issue of sustainable transportation, especially if you want to integrate the concern about the greenhouse effect, it is necessary to study the air pollution including greenhouse gas emissions, particularly the CO₂. As we said before, this issue is closely related to energy consumption.

To reduce CO₂ emissions from freight transport, a European report [9] has identified various areas of research and works that can be mobilized including some approaches:

- Regulation: policy measures aiming at encouraging public transport "decarbonized", 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.
- Electric drive vehicle: uses one or more electric motors or traction motors for propulsion, it is quite clear that electric vehicles do not emit CO₂, but this is still limited by some constraints such as the need for greater power generation and decarbonization, 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% to 40% km traveled and therefore CO₂ emissions.

In this research, we 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 the CO₂ emissions. To this end, it is necessary to model CO₂ emissions to obtain emission factors for trucks that comply with

the need for optimization models and evaluation of the environmental performance of transport.

3. THE ESTIMATING CO₂ 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 [10]. The estimation of fuel consumption and CO₂ emission for mobile sources requires complex calculations, which are only represent an approximation because of the difficulty of quantifying some variables as driving style, weather conditions, congestion, and the like [11], [12]. With regard to transportation of goods by road, the modeling of CO₂ emissions is based on the methodology and results of the projects COST Action 319 [13] (updated by COST Action 346 [14]) and the project MEET Deliverable 22 [10], which produce the basic results for the software COPERT. An outline of the methodology is given below, and that is followed by a detailed description of the choice of the vehicle and its characteristics.

3.1. Basic Principales For Estiming CO₂ The Emission

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 [10]:

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

Where:

- E is the total emission
- E_{hot} is the emission produced when the engine is hot
- E_{start} is the emission produced when the engine is cold

- $E_{evaporative}$ is the emission produced by evaporation (only for VOC : Volatile Organic Compound)

Each of these contributions to the total emission (E_{hot} , E_{start} , $E_{evaporative}$) depends on an emission factor and one or more parameters relate to the operation of the vehicle, so that in general:

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

Where:

- E_x is one of the contributions to total emissions with x is a type of emission : hot, start or evaporative
- e_x is a emission factor of type x
- a_x is the amount of traffic activity relevant to emission of type x

The parameters e_x and a_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 out 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 [10].

3.2. CO2 Emissions Matrix From The Transport Of Freight

We recall that, from the perspective of sustainable development, this paper aims to evaluate the effect of this GHG emissions, especially CO₂ emissions with the CO₂ is not affected by this term E evaporation [10]. First of all, the mode of road transport here refers to transport by Heavy Duty Vehicle (HDV) only (32–40 ton for general merchandise). According to the emissions function for the HDV truck given by Hickman [10] and Jancovici [15] some assumptions are made:

- the average speed is 80km/h
- 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, we 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, formula (1) can be simplified and detailed as this for CO₂ emissions:

$$E = E_{hot} \tag{3}$$

By the methodology and results of the projects COST Action 319 [13] (updated by COST Action 346 [14]) and the project MEET Deliverable 22 [10], a result, the final CO₂ emissions function with the variable of load is:

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

where: $E(q)$ is the CO₂ emissions from a vehicle in kg/km with the variable of load q in ton; e_{fl} is the CO₂ emissions of a fully loaded (by weight) vehicle, which is $e_{fl} = 1.096$ kg/km for HDV truck; e_{el} is the CO₂ emissions of an empty vehicle, which is $e_{el} = 0.772$ kg/km for HDV truck; Q is the volume capacity of a vehicle. Function of CO₂ 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 formula below:

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

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 routes that generate the lower levels of CO₂ emissions to atmosphere and, in order to achieve this goal, it is necessary to build a matrix of CO₂ emissions based on the estimation of CO₂ emitted between each link [11]. The linearization of flow and emissions for the arc ij can be displayed as the emissions matrix:

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

In this section, it is shown how to estimate CO₂ emissions from transport freight. Thereafter, we incorporate those concepts in to the methodology used to solve the vehicle routing problem.

4. THE CAPACITATED VEHICLE ROUTING PROBLEM WITH EMISSIONS MATRIX

4.1. 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 limits 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. We deal here with the capacitated vehicle routing problem (CVRP) that is we 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. We 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.

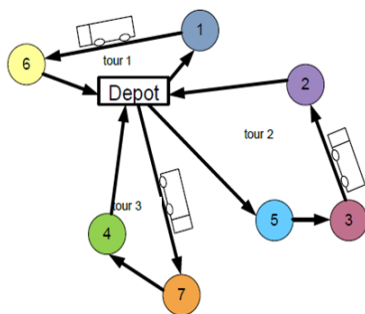


Figure 2: The Capacitated Vehicle Routing Problem Scheme

The capacitated vehicle routing problem (CVRP) has been described as the most common management problem in food, fuel and retail goods distributors. Our literature review revealed several different approaches to the CVRP. A good update of various heuristic methods appears in Van Breedam [16] paper. Other traditional papers about heuristic algorithms are Gaskell [17], Golden [18] and Bodin [19]. The most interesting reference in the VRP bibliography is Toth and Vigo [20], which provides a good list of excellent algorithms to solve the CVRP. Other reviews of the VRP are the following: Golden and Assad [21] and Cordeau [22]. Constructive methods have been shown to be applicable in the solution of real problems in the logistic activities of many companies [23]. These methods were thoroughly analyzed during the 1960s and 1970s, and found to give satisfactory results for small-scale problems. Nevertheless, sequential methods based on savings are quicker than other constructive algorithms, although the total distance of their routes is much greater. Similarly, 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 [25], which introduced the Tabu Route algorithm, and Laporte [26], which includes a thorough discussion of classical and modern heuristics. Nevertheless, the main source of current information about meta-heuristics is Toth and Vigo[20].

4.2. 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 CO₂ emissions from road transportation. The contribution of vehicle routing surveys is not limited to this implicit and unconscious contribution by minimizing travel distance 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 [28] and Palmer [11]. 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 [11], 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 we may start by mentioning the introduction of the "Pollution Routing Problem (PRP)" by Bektas [29]. 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 [30] 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. Other studies include [31; 32; 33]. Apparently, all these studies have been published recently, this shows that the topic is at its very beginning.

4.3. GVRP Formulation: Optimizing The Total Emission

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 $V = \{0, 1, \dots, n\}$ 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 $Z = \{0, 1, \dots, m\}$ of m vehicles.

For presenting the integer linear programming model for GVRP, 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 .

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

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

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

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). Our 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 (1) – (11).

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

subject to:

$$\sum_{i=1}^n x_{i0}^k \leq 1 \quad \forall k \in \{1, 2, \dots, m\} \quad (2)$$

$$\sum_{i=1}^n x_{0i}^k \leq 1 \quad \forall k \in \{1, 2, \dots, m\} \quad (3)$$

$$\sum_{i=1}^n y_i^k \leq M \cdot \sum_{j=1}^n x_{0j}^k \quad \forall k \in \{1, 2, \dots, m\} \quad (4)$$

$$\sum_{i=1}^n y_i^k \leq M \cdot \sum_{j=1}^n x_{j0}^k \quad \forall k \in \{1, 2, \dots, m\} \quad (5)$$

$$\sum_{k=1}^m y_i^k = 1 \quad \forall i \in \{1, 2, \dots, n\} \quad (6)$$

$$\sum_{i=1}^n x_{ij}^k = y_j^k \quad \forall j \in \{1, 2, \dots, n\} \quad i \neq j, \forall k \in \{1, 2, \dots, m\} \quad (7)$$

$$\sum_{j=1}^n x_{ij}^k = y_i^k \quad \forall i \in \{1, 2, \dots, n\} \quad i \neq j, \forall k \in \{1, 2, \dots, m\} \quad (8)$$

$$\sum_{i=1}^n q_i y_i^k \leq Q_k \quad \forall k \in \{1, 2, \dots, m\} \quad (9)$$

$$\sum_{i=0}^n \sum_{j=0}^n t_{ij} x_{ij}^k + \sum_{i=1}^n s_i y_i^k \leq T_k \quad i \neq j, \forall k \in \{1, 2, \dots, m\} \quad (10)$$

$$\sum_{i,j \in S} x_{ij}^k \leq |S| - 1 \quad i \neq j, \forall k \in \{1, 2, \dots, m\}, S \subset N, 2 \leq |S| \leq n-1 \quad (11)$$

Relation (1) is the objective function to be minimized including the total emission produced by the running vehicles. Constraints (2), (3), (4) and (5) ensure that all the vehicles begin and end their routes at the depot, while constraint (6) guarantees that each node, except the depot, is visited by a single vehicle. Furthermore, constraints (7) and (8) 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 (9) ensures that no vehicle can be over loaded, while constraint (10) does not permit that any vehicle exceed the maximum allowable driving time per day T_k . Finally, we introduce constraint (11) to avoid sub tours.

Since the purpose of our optimization project is to minimize the CO₂ emissions related to freight transport in two large supply chains, the emissions functions are adopted in the optimization model via an objective function. Nevertheless, we developed a Hybrid Ant Colony system (HACS) for the GVRP with emissions matrix.

5. THE HYBRID ANT COLONY SYSTEM FOR GVRP

Ant colony optimization is a part of the larger field of swarm intelligence in which scientists study the



behavior patterns of bees, termites, ants and other social insects in order to simulate processes. The ability of insect swarms to thrive in nature and solve complex survival tasks appeals to scientists developing computer algorithms needed to solve similarly complex problems. The use of ant colonies was first applied to the traveling salesman problem and the quadratic assignment problem [34] and has since been applied to other problems such as the space planning problem [35], the machine tool tardiness problem [36] and the multiple objective JIT sequencing problem [37]. The aim of this section is to propose an Hybrid Ant Colony System (HACS) to solve the GVRP formulated in the previous section, which has three phases.

5.1. Phase Of Route Construction

To solve the GVRP, the artificial ants construct vehicle routes by successively choosing customers to visit, until each customer has 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 on customer i will select the next customer j using the following probabilistic formula:

$$j = \begin{cases} \arg \max_{u \in N_i^k} [\tau_{iu}^\alpha(t) \cdot (\eta_{iu})^\beta] & \text{if } q \leq q_0 \\ J & \text{otherwise} \end{cases} \quad (7)$$

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 by $\tau_0 = \frac{1}{n \times E}$, where n is the number of customers, and E is the total emission produced by the execution of one ACS iteration without the pheromone component, it can make good initial pheromone trails on the arcs,
- η_{iu} is a heuristic information: $\eta_{iu} = \frac{1}{e_{iu}}$,
- N_i^k is a set of customers unvisited,
- β establishes the importance of emission in comparison to pheromone quantity,
- α is a parameter which determine 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 set of selected randomly according to the following probability, which favors short paths with high levels of pheromone.

$$P_{i,j}^k = \frac{\tau_{i,j}^\alpha \cdot \eta_{i,j}^\beta}{\sum_{h \in N_i^k} \tau_{i,h} \cdot \eta_{i,h}^\beta} \quad (8)$$

If the vehicle capacity constraint is met, 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.

5.2. 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 (9), and insists on the best solution by maximizing the pheromone trail value in global updating (10):

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \rho \cdot \tau_0 \quad (9)$$

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \rho \cdot \Delta \tau_{ij} \quad (10)$$

Where:

- ρ is a parameter that controls the evaporation of the pheromone trail,
- $\Delta \tau_{ij}$ is the inverse of the total emission produced by the best solution.

```

Procedure ACS
/* m is the number of ants and iteration_number is the
number of iterations*/
BestCost ← ∞
iter ← 1
For each arc (i, j)
    τij = τ0
EndFor
While (iter < iteration_number)
    For k:=1 to m
        While (Ant k has not completed its solution)
            Select the next customer j, according to (7) and
(8)
            Update the trail level τij, according to (9)
        EndWhile
        If (Cost of the current solution < CostBest)
            BestCost ← Cost of the current solution
            BestSolution ← current solution
    
```



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EndIf
EndFor
For each move (i, j) in solution BestSolution
Update the trace level  $\tau_{ij}$  according to (10)
EndFor
iter ← iter + 1
EndWhile
    
```

Algorithm 1: ACS for the GVRP

5.3. Phase Of Hybridization

To improve the quality of solution found, we will apply The Large Neighborhood Search (LNS) metaheuristic which is proposed by Shaw [38]. In this metaheuristic the neighborhood is defined implicitly by a destroy and a repair method. A destroy method destructs part of the current solution while a repair method rebuilds the destroyed solution by inserting removed customers. The LNS starts with an initial solution found by the ACS, next, in each iteration, p transportation requests are removed from their tours in the current solution, then a new solution is generated by inserting unscheduled transportation requests, using a greedy heuristic. Such a heuristic could simply scan all free customers; insert the one whose insertion emission is the lowest and repeat inserting until all customers have been inserted. The new solution is accepted as the next current solution if the total emission produced by the new solution is decreased. If no termination criterion is fulfilled, the algorithm continues with the next iteration.

6. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness of the proposed approach and to prove the effect of considering explicitly the emissions minimization objective, the HACS algorithm must be tested with GVRP instances, which do not exist in the literature. Therefore, to show the effectiveness of our approach, we will present firstly their numerical results by considering the classic objective which minimize the total traveled distance, to compare it with other heuristics on the literature, in a different set of problems, which are, Savings Algorithm and Savings Algorithm with 3-opt by Clarke and Wright [39], ACO by Mazzeo [40], sweep algorithm+ ant colony system by yousefikhoshbakht [41], and HACS is the algorithm we developed. The HACS was coded in C++ and executed on a MacBook Pro-Core i5/ 2.4 GHz - MacOS X 10.7 Lion, with the following parameter settings which give a good compromise between

the computation time and the solution quality for the proposed HACS :

- $\rho = 0.1$
- $m = 10$
- $q_0 = 0.9$
- $\alpha = 1$
- $\beta = 2$

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/>. As HACS is a probabilistic algorithm results can vary from a run to another. Here are some results of our algorithm which correspond to the best value of five runs.

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

Instance	saving algorithm m (1964)	saving algorithm m+ 3-opt (1964)	ACO (2004)	SW+ ACS (2012)	HACS
E-n51-k5	584.64	578.56	521	521	524.61
E-n76-k10	900.26	888.04	877	838	843.54
E-n101-k8	886.83	878.70	845	839.2	835.28
M-n101-k10	833.51	824.42	838	823.74	819.56
M-n121-k7	1071.07	1049.43	1189	1050	1090.01
M-n151-k12	1133.43	1128.24	1105	1030.46	1054.92
M-n200-k17	1395.74	1386.84	1606	1325.62	1377.71

Each run is guaranteed to be independent of others by starting with different random seeds. Table 1 shows the comparison of our HACS with published results. The first column describes the various instances, whereas the columns 2, 3, 4 and 5 specify well-known published best results obtained using metaheuristic algorithms. Finally, the column 6 refers to the best result of our method for these instances. The proposed algorithm has shown to be competitive with the best existing methods in terms of solution quality, where our approach is better than saving algorithm and saving algorithm with 3-Opt, except for instances M-n121-k7. It even shows a slightly better performance on E-n101-k8 and M-n101-k10 for sweep algorithm+ ant colony system, and we remark also that HACS is better than ACO except for an instance E-n51-k5. Finally our approach shows a better than all these methods for E-n101-k8 and M-n101-k10. All these results allow us to say that our approach is effective and shows

the viability to generate very high quality solutions for the VRP. Now, to evaluate our approach to solve GVRP problem, which minimize the CO2 emissions related to freight transport, we tested its performance on a set of instances generated randomly of 10 to 300 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 Km, 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 Kg, 2500 Kg], and the service time of customers is fixed at 15 min. Suppose that service period of a vehicle belong to the region [08 h, 18 h], and the average speed of vehicles is fixed at 80 km/h.

Table 2: Results obtained for 10 different instances of 10 to 300 requests

Instance	n	TE	TD	NV
I1	10	55.22	396.89	1
I2	30	56.00	820.26	3
I3	50	72.30	1112.03	4
I4	70	92.81	1510.73	5
I5	100	110.55	1910.30	7
I6	130	137.50	2520.75	9
I7	160	160.62	2811.93	10
I8	200	194.57	3768.76	13
I9	250	235.00	4432.88	16
I10	300	276.71	5636.64	19

The table 2 shows the best results found for 10 different instances of 10 to 300 requests, where n is the number of customers the columns TE, TD and NV are respectively 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, we tested our approach, by considering the classic objective which minimizes the total traveled distance, on the 10 different instances generated randomly. The table (3) gives a comparison between the total distance TD found for GVRP and the total distance TD* found for VRP. The figure (1) shows that the total distance increases when we 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.

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

Instance	TD	TD*
I1	396.89	352.07
I2	820.26	591.41
I3	1112.03	926.11
I4	1510.73	1207.56
I5	1910.30	1449.01
I6	2520.75	1865.03
I7	2811.93	2296.69
I8	3768.76	2959.90
I9	4432.88	3691.38
I10	5636.64	4237.85

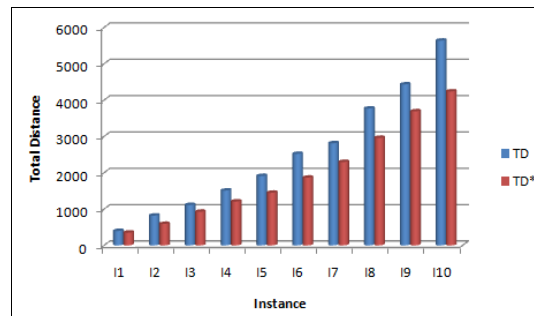


Figure3: TD Compared With TD*

7. 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 CO₂ as the most prevalent of them, in the air.

It has been a while since the 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. On the one



hand, the minimization of distances and pollutant emissions associated to the introduction of changes in transport planning shows the importance of optimizing operations. We present in this paper that our research may also lead to the finding of cleaner routes, through the development the performance of ACS method with the environmental matrices (e_{ij}). These methodologies may lead us to calculate the emissions more accurately and to facilitate the search for cleaner routes.

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