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MULTI-OBJECTIVE GENETIC ALGORITHMS FOR THE GREEN VEHICLE ROUTING PROBLEM: A COMPARATIVE STUDY

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ABSTRACT

The Green Vehicle Routing Problem (GVRP) is an extension of the standard VRP taking into account the awareness of companies and governments of the dangerous effect of gases emissions. The primary objective of the GVRP is to minimize the volume of emitted carbon dioxide (co_2) in adding to the optimization of the traveled distance and other functional objectives. In this paper, we model the GVRP as a bi-objective optimization problem for which many solving algorithms can be adapted and applied including deferent variants and extensions of Multi-Objective Genetic Algorithms (MOGAs). We select three elitist MOGAs: Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm - II (SPEA-II) and the Indicator-Based Evolutionary Algorithm (IBEA) to evaluate the quality of the returned Pareto fronts using deferent metrics: computation time, traveled distance, emissions volume, generational distance, spacing, entropy, and contribution. The comparison is performed on a set of standard benchmark problems. The experimental results show that IBEA outperforms other algorithms over many metrics.

Keywords: *Green Supply Chain, Green Multi-Objective VRP, Multi-Objective Genetic Algorithms*

1. INTRODUCTION

The green supply chain management concept has emerged following the increasing awareness of people, governments and Non-Governmental Organizations (NGO) about the threatening effect of co_2 emissions. By definition, a supply chain is a network of suppliers, manufacturers, warehouses and distribution channels organized to acquire raw materials, convert them into finished products and distribute them to clients. The concept of green supply has been launched by several logistics companies to reduce carbon dioxide emissions caused by transportation operations. The co_2 is a global pollutant, it represents a greater threat to the global environment since it affects the air in wide areas. co_2 is present in the atmosphere in significant quantities, representing 99.4 % of the six greenhouse gasses by tonnage [4]. Carbon dioxide is released from industrial processes, waste collection and transportation. Transportation companies have devoted significant efforts to upgrade and improve their transportation systems by developing strategies and policies to route their fleet of vehicles safely with minimized emissions. Emissions minimization in logistics operations passes through the integration of co_2 emission in optimization models [34]. The main transportation model is the VRP that consists of minimizing routing costs in terms of distance, time, number of vehicles, etc. In the context of green logistics, vehicles routing strategies consider minimizing the volume of emitted co_2 as a primary objective in adding to VRP classical objectives. The emitted co_2 volumes are estimated using two different types of models namely the macroscopic and the microscopic model depending on the considered variables like the speed, road gradient, traffic congestion, etc. [4]. Optimization models have integrated such emission estimation functions as objectives or constraints [29].

Vehicle routing optimization models integrating emissions minimization, in the literature, have different names like the GVRP [20], the VRP with emission [13] and also the Pollution-Routing Problem (PRP) [10]. Basically, the emission component in such models is a constraint or an objective to optimize. Particularly, in the GVRP, emission minimization represents the main objective to optimize in the presented model.

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Obviously, emissions minimization should be considered with other functional objectives like distance, time and number of vehicles minimization which will lead to a multi-objective optimization problem. The Multi-Objective Green VRP (M-GVRP) is then defined to represent a class of environment aware multi-objective optimization problems.

As a Multi-Objective Optimization Problems (MOOP), the solution of the bi-objective GVRP is a non-dominated solution from an optimal Pareto front [8]. Elitist multi-objective genetic algorithms represents a class of efficient solvers of MOOPs. They apply some sorting strategies to preserve best solutions and use them in future genetic combinations and future populations. In this paper, we present the results of an empirical study to evaluate the potential of multi-objective genetic algorithms for solving the bi-objective GVRP. We implemented three evolutionary algorithms namely NSGAII, SPEA-II and IBEA to solve the bi-objective GVRP. The selected algorithms were applied to solve 4 known benchmark problems and the generated Pareto fronts are then compared using different metrics. The initial comparisons are made on the computation time, the volume of emitted co_2 and the total traveled distance. Deep analysis on the quality of the returned Pareto fronts is then performed using specific metrics namely generational distance, spacing, entropy, and contribution. The objective of the paper is to show and prove the effectiveness of modeling the GVRP as a bi-objective optimization problem and to experimentally determine the most appropriate evolutionary algorithm for solving the bi-objective GVRP.

The paper is organized as follows. In the next section, we review the literature on green routing models, solving strategies and real life applications. In Section 3, we define formally the bi-objective GVRP and present a mathematical formulation. The following section is devoted to the candidate algorithms, we survey the main MOGAs and justify the choice of the three elitist algorithms and present their algorithmic schemas. Section 5 reports the results of the comparative study. We present initially, the comparison framework, followed by the experimentation environment and then the comparison results based on the defined metrics. Deeper statistical analysis is reported to strengthen the findings of this paper. Finally, we present the outcomes of this project with concluding remarks.

2. THE GREEN VEHICLE ROUTING PROBLRM: LITERATURE REVIEW

In green logistics, the main interest is grant to the process of carrying the transportation, warehousing, and manufacturing activities without affecting the environment. The transportation is one of the most pollutant activities due to the huge volumes of emitted co_2 by moving engines. Recent reviews on green routing problems [4, 6, 10, 22, 26, and 29] present the answers to the requirements of green and sustainable transportation. We present the GVRP literature over its three pillars:

1. Emission factors and fuel consumption estimation models,
2. Routing models including emission requirements and their solving approaches,
3. Real life applications.

2.1 Emission Factors And Fuel Consumption Estimation Models

Emission factors include the speed of moving vehicles, road gradient (landscape), traffic congestion, driver proficiency, fleet size and composition, payload, empty kilometers and the green freight corridors [4]. Such factors constitute the input of fuel consumption estimation models. The literature provides different models for estimating fuel consumption and emissions based on the considered factors. In [4] and [10], the authors presented two classes of fuel consumption models; the macroscopic and the microscopic type of models. In macroscopic models, the average speed of moving vehicles (the main factor) is integrated in different equations provided by different bodies like European Council, the Swedish organization NTM, the European Economic Area, etc. In microscopic models, the emissions are estimated instantly using different variables obtained on the spot from different vehicle sensors like speed, acceleration, cruise control, traffic status, etc. Later models provide more accurate estimation of emitted gases as they are using accurate and instantaneous inputs. A new score was proposed by Saharidis et al. [33] named Environment Externalities Score (EES) that aggregates different instantaneous emission factors in one score. In his review [6] Boulter et al. studied the road vehicle instantaneous emission factors and models. A Recent and exhaustive review of emission factors and different fuel consumption models and types can be found in [4].

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2.2 Green Routing Models And Solving Approaches

As mentioned in the introduction different problems were introduced to integrate emissions as constraints or objectives. The PRP was introduced by Bektas and Laporte [5] considering additional environmental objectives rather than distance like the amount of green emissions and the consumed fuel following the emission model. The authors study the effect of different parameters such as vehicle load and speed on the environmental objectives. Similarly, Huang et al. [18] studied the green VRP with simultaneous pickups and deliveries by including the fuel consumption and the carbon emission cost. In [11], the authors introduce the green VRP to help organizations to design routes with alternative fuel. In [42], the Fuel Consumption Rate (FCR) was studied and integrated within the classical Capacitated VRP. Figliozzi [14] studied the correlation between the co_2 emissions and the level of congestion using an archive of freeway sensors real data. The same author present in [13] some VRP models with emission minimization components. In [12], Faulin et al. integrated also environmental criteria into a capacitated VRP model and solved it.

The proposed GVRP models was solved by different algorithms and approaches ranging from exact methods to heuristics and metaheuristics. We enumerate below the main approaches applied for solving the GVRP per category:

- Exact methods including Branch and Bound algorithm, Dynamic Programming [29] and constraint programming [23].
- Heuristics like the Modified Clarke and Wright Savings heuristic (MCWS) and Density Based Clustering Algorithm (DBCA) of Erdogan and Miller-Hooks [11].
- Metaheuristics:
  - Simulated annealing [24, 42, 43]
  - Genetic algorithms [39],
  - Ant systems [1],
  - Tabu search [19],
  - Scatter search [31].

Routing problems with emission components were modeled also as multiobjective problems to integrate the emissions minimization objective along with other functional objectives [20, 27, 32, and 41]. The implemented algorithms are mainly based on genetic algorithms. For instance, the bi-objective pollution routing problem was studied by Demir et al. [10] considers the emissions and the driving time minimization and was solved by the Adaptive Large Neighborhood Search (ALNS) algorithm.

2.3 GVRP Real Life Applications

From the application side, many real life problems were modeled and solved as GVRP. The very first investigations were summarized in [30] where the authors reported a set of real automotive emissions from Fort McHenry and Tuscarora Mountain tunnels. In [40], Ubeda et al. modeled a real case at Eroski as a green routing problem with backhauls. Bauer et al. [3] studied the greenhouse gas emission minimization in the rail service design problem. Soysal et al. [36] modeled the international beef supply chain considering emissions minimization. Govindan et al. [16] proposed two-echelon multiple vehicle locations of sustainable supply chain network of perishable food. Kuo et al. [25] developed a carbon footprint inventory route planning and selection of hot spot supplier. Konur [23] developed a carbon constrained integrated inventory control and truckload transportation with heterogeneous freight trucks. Apaydin et al. [2] and Tavares et al. [38] studied the emission minimization in the waste collection problem. A real application in timbre transport solved with a three level algorithm by Obersheider et al. [27].

3 THE BI-OBJECTIVE GREEN VRP: FORMAL DEFINITION AND MATHEMATICAL MODEL

Formally, the bi-objective green vehicle routing problem is defined as the problem of designing a set of routes for serving geographically dispersed customers over a transportation network using a fleet of K vehicles. The set of customers is named V augmented with the central depot where vehicles are initially hosted.

The cardinality of the set V is then $(n + 1)$ where n is the number of customers and the depot is indexed to 0. Moreover, to each customer i is associated a demand q_i. The transportation network is noted $G(V;E)$ where E is the set of edges between customers defined by $E = \{(i; j): i,j \epsilon V; i \neq j\}$. Each two vertices in E are distanced by d_{ij}. Vehicles maximal load is set to Q. The classic routing objective is to minimize the overall distance. For the bi-objective GVRP, the co_2 emission volume is

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also to be minimized. To estimate co_2 emissions we use the distance based approach defined in [4] as microscopic model and used also in [18] and [42]. The emissions are calculated as follows:

$$e_{ij} = \mu d_{ij}(a * 10^{-3} * l_{ki} + b)$$

Where μ is the emission rate of the used fuel, a and b are the coefficients of vehicle fuel consumption and l_{ki} is the load of the vehicle k at point i. A route is then defined as the ordered sequence of customers to be visited by a vehicle k starting and ending at the depot. Each customer must be visited exactly once and the maximum vehicle capacity should be not exceeded. The routing plan should optimize two objectives; the overall traveled distance and the volume of emitted carbon dioxide. A bi-objective non-linear integer programming formulation is given as follows where x_{ij} is a binary decision variable set to 1 if the customer j is visited just after the customer i and to 0 if not. The positive integer variable l_{ki} represents the load of the vehicle k at the customer i. The mathematical model is reported below.

$$\text{Min} \quad \left[\sum_{i\in V, j\in V} x_{ij}e_{ij}\right], \quad \left[\sum_{i\in V, j\in V} x_{ij}d_{ij}\right] \tag{2}$$

S/ to

$$\sum_{i\in V} x_{ij} = 1, \qquad \forall j \in V\backslash\{0\} \tag{3}$$
$$\sum_{j\in V} x_{ij} = 1, \qquad \forall i \in V\backslash\{0\} \tag{4}$$
$$\sum_{i\in V} x_{i0} \leq K, \tag{5}$$
$$\sum_{j\in V} x_{0j} = \sum_{i\in V} x_{i0}, \tag{6}$$
$$l_{k0} = Q \qquad \forall k = 1..K \tag{7}$$
$$l_{kj} = x_{ij}(l_{ki} - q_i) \qquad \forall k = 1..K, \forall i, j \in V \tag{8}$$
$$x_{ij} + x_{ji} \leq 1, \qquad \forall i, j \in V\backslash\{0\} \tag{9}$$
$$x_{ij} \in \{0, 1\}, \qquad \forall i, j \in V \tag{10}$$
$$l_{ki} \geq 0, \qquad \forall i \in V, \forall k = 1..K \tag{11}$$

In the objective function (2), the first objective is the estimated volume of emitted carbon dioxide to be minimized and the second objective is the overall traveled distance. The constraint sets (3) and (4) ensure that each customer has to be visited exactly once. Constraint (5) set that the number of used vehicles is at most K and constraint (6) ensure that the number of vehicles leaving and going back to the depot are equal (flow conservation). The initial load (at the depot) of each vehicle is set to the maximum capacity Q (constraints 7) and the load l_{kj} of vehicle k is decreased by the demand q_i after leaving the customer i to visit customer j (constraints 8). Constraints 8 ensures also sub-tour breaking. In constraint (9), circular paths are avoided between the same two customers. Decision variables x_{ij} are defined to be binary in constraint (10) and l_{ki} should be positive integers in constraint (11).

4 MULTIOBJECTIVE GENETIC ALGORITHMS

Genetic Algorithms (GAs) are stochastic and evolutionary optimization algorithms based on mechanisms of natural selection and genetics. The basic GA starts by generating a population of solutions and then apply iteratively as set of genetic operators (crossover, mutation, selection, etc.) until a stopping condition is met (finite number of iterations, no significant improvement of best solutions, etc.). Multi-objective GAs are adapted to the concept of Pareto dominance, which emphasizes on solutions satisfying all objectives. Multi-objective GAs are well suited for the search of Pareto front for their implicit parallelism to search over many good solutions at a time. The first multi-objective GA, called Vector Evaluated Genetic Algorithms (VEGA), was proposed by Schaffer et al. [35]. Afterward, several major multi-objective GA were developed such as Multi-Objective Genetic Algorithm (MOGA) [15], NSGA (Non-Dominated Sorting Genetic Algorithm) [37], NPGA (Niched Pareto Genetic Algorithm) [17], SPEA-II (Strength Pareto Evolutionary Algorithm) [44], PAES (Pareto Archived Evolution Strategy) [21], PESA (Pareto Envelope Based Selection Algorithm) [21], PESA-II [21], NSGA-II [9] and MICRO-GA (Micro-Genetic Algorithm) [7].

According to Coelho et al. [8], all methods cited above are easy to implement but have drawbacks. The disadvantages are their dependency on too many parameters, the absence of sorting or ranking technique, and sensitivity to additional constraints. The selected three algorithms (NSGA-II, IBEA, and SPEA-II) belong to the class of elitist GAs that implement a sorting mechanism to save best-found solutions and use them in future iterations. The NSGA-II tends to spread quickly and appropriately when a certain non- dominated region is found. The main advantage is that the strategy of preserving of diversity used in NSGA-II requires no parameters to fix. SPEA-II has three differences with respect to its predecessor (1) it incorporates an improved fitness assignment scheme, (2) it uses the nearest neighbor density estimation technique, which allows a more precise guidance of the search process; (3) it has an enhanced archive truncation method that guarantees the preservation of boundary solutions. IBEA is based on quality

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indicators where a function *I* assigns to each Pareto set a real value reflecting its quality that should be maximized [45]. The main advantage of the indicator concept is that no additional diversity preservation mechanisms are required. Since the principle is simple and the number of parameters is small, IBEA could be adapted to other types of problem approaches. It is for the above reasons that we selected the NSGA-II, IBEA, and SPEA-II for solving the bi-objective GVRP. Next subsections detail their algorithmic schemas.

4.1 Non-dominated Sorting Genetic Algorithm-II

This technique was proposed by Deb et al. [9]. In NSGAII, the child population *Q(t)* is first created from the parent population *P(t)* (randomly filled). They are then met into a set $R(t)=P(t)\cup Q(t)$ that is sorted according to the principle of dominance: All no dominated solutions of the population are assigned a fitness value *1* (first front), then they are removed from the population. All non-dominated solutions of the population are assigned a fitness value *2* (second front), then they are removed from the population. This process is iterated until all solutions are evaluated. To select subsets that will be placed in the population, a measure of the density of solutions in the space of criteria called crowding distance is used (Algorithm 2). The Pseudo Code of the NSGA-II is shown in algorithm 1.

Algorithm 1 NSGA-II Algorithm

1. create $Q(t)$ from $P(t)$ using the tournament and applying operators of genetic variation at the winner individual.
2. Meet populations of parents and child $R(t) = P(t) \cup Q(t)$. Sort the resulting set in subset F_i.
3. Initialize a new population $P(t+1) = \emptyset$ and initialize the counter of no dominated subsets $i = 1$.
4. While $\mid P(t+1) \mid + \mid F_i \mid < N$ Do:
   - $P(t+1) \leftarrow P(t+1) \cup F_i$.
   - $i \leftarrow i+1$
5. Order the set F_i according to "crowding distance" (the procedure of their calculation is presented below) and include $N- \mid P(t+1) \mid$ solutions that have the greatest value of distance in the population $P(t+1)$.

Algorithm 2 Calculation of the crowding distance

1. Initialize:
   - the number of individuals of $F : l =\mid F \mid$.
   - $d_i = 0$ for any solution i of F.
   - $m = 1$ (the counter of objective).
2. For objective m, reorder the set F of the way that values of f_m on the element decreases. Let $I^m = sort_{\mid f_m, > \mid}(F)$ the vector of indices, that is to say, I_i^m denotes the index of the solution i in the ordered list according to objective m.
3. For each solution i such as $2 \leq I_i^m \leq (l-1)$, update the value of d_i as follows: $d_i \leftarrow d_i + \frac{f_m^{I_{i+1}^m} - f_m^{I_{i-1}^m}}{f_m^{max} - f_m^{min}}$ and associate very large values of distance to the solutions on the ends of F that is to say if $I_i^m = 1$ or $I_i^m = l$, then $d_i = \infty$.
4. if $m = M$, the procedure is complete, otherwise increment the counter of the objectives $m \leftarrow (m+1)$ and return to step 2.

4.2 Strength Pareto Evolutionary Algorithm-II

SPEA-II [44] is an extension of the SPEA algorithm, where an affectation strategy of improved fitness values is proposed. SPEA-II manages intrinsically an internal archive of fixed size containing enough non dominated individuals, the archive is complemented by those dominated. The calculation of performance in SPEA-II considers the density of solutions. First, the value of Strength S_i is calculated for any solution *i*, preliminary performance R_i (row fitness) is defined as the sum of values of the strength of solutions that dominate *i*. Further, a preservation strategy of diversity based on a technique of k^{th} nearest neighbor is incorporated. The step of selection is elitist and consists of a binary tournament with a replacement which is applied only to the archive. Finally, given that the archive of SPEA-II has a capacity of storage of fixed size, mechanisms of the bounded archive, based on information of fitness and diversity is used when the size of the no dominated set is too high. Conversely, when the size of the archive is too small, dominated solutions are incorporated. The pseudo-code of the SPEA-II is shown in Algorithm 3.

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Algorithm 3 SPEA-II Algorithm

Input:

- N (population size)
- $\overline{N}$ (archive size)
- T (maximum number of generations)

Output:

- A (no dominated set)

1. **Initialization:** Generate an initial population P_0 and create the empty archive (external set) $\overline{P}_0 =$. Set $t = 0$.
2. **Fitness assignment:** Calculate fitness values of individuals in P_t and $\overline{P}_t$.
3. **Environmental selection:** Copy all no dominated individuals in P_t and $\overline{P}_t$ to $\overline{P}_{t+1}$. If size of $\overline{P}_{t+1}$ exceeds $\overline{N}$ then reduce $\overline{P}_{t+1}$ by means of the truncation operator, otherwise if size of $\overline{P}_{t+1}$ is less than $\overline{N}$ then fill $\overline{P}_{t+1}$ with dominated individuals in P_t and $\overline{P}_t$.
4. **Termination:** If $t \geq T$ or another stopping criterion is satisfied then set A to the set of decision vectors represented by the no dominated individuals in $\overline{P}_{t+1}$. Stop.
5. **Mating selection:** Perform binary tournament selection with replacement on $\overline{P}_{t+1}$ in order to fill the mating pool.
6. **Variation:** Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. Increment generation counter ($t = t + 1$) and go to Step 2.

4.3 Indicator Based Evolutionary Algorithm

It is a method based on a quality indicator I. The principle of IBEA [45] is to define initially the purpose of optimization, by establishing an operator of performance, and to use it directly in the selection process of the evolutionary algorithm. This one being chosen depending on the preference of the decision maker. Among the possible binary indicators, we can cite in particular the calculation of hyper-area (I_H) and I_ε. IBEA algorithm is shown in Algorithm 4.

Algorithm 4 IBEA Algorithm

1. **Initialization** : Start with an initial population P of size N given in parameter, or randomly generate.
2. **Assign a fitness value**: Calculate fitness values for each solution x of P:

$$F(x) \leftarrow \sum_{x' \in P \setminus \{x\}} -e^{-I(x',x)/k}$$

3. **Select for the replacement** : Repeat the following three steps while the size of the current population P exceeds N:
   - Choose a solution $x^* \in P$ with the smallest fitness value: $F(x^*) \leq F(x)$ for all $x \in P$.
   - Delete x^* of the population P.
   - Update the fitness values of the remaining solutions. For all $x \in P$: $$F(x) \leftarrow F(x) + e^{-I(x',x)/k}$$
4. **The stop condition**: If a stop condition is satisfied, return the no dominated solutions of P. Stop.
5. **Selection for reproduction** : Make a deterministic binary tournament selection with replacement on P and add the selected solutions in a temporary population P'.
6. **Variation**: Apply the operators of crossing and mutation to solutions of the temporary population P' and add the remaining solutions to the temporary population P. Go to the step 2.

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5 COMPARATIVE STUDY

The objective of this paper is to determine which algorithm among NSGA-II, SPEA-II and IBEA can provide better solutions for the bi-objective GVRP. The algorithms are implemented and applied to solve bi-objective GVRP benchmark problems and compared using the following criteria:

- Computation time required to return the final Pareto front for each algorithm per benchmark problem.
- The total volume of emitted co 2 (1^{st} objective).
- The total traveled distance (2^{nd} objective).
- Generational Distance (GD) which measures how far from the Pareto front is located a set of solutions.
- Spacing (S) metric to measure the distribution uniformity of points of the set of the solutions in the plan (1^{st} objective, 2^{nd} objective).
- Entropy (E) metric that uses the concept of a niche to evaluate the distribution of solutions on the front.
- Contribution *(C)* that compares two Pareto fronts *A* and *B*. If *C(A,B)=0* then *B* is better than *A*.

5.1 Implementation Environment and Benchmarks

The three algorithms were implemented under ParadisEO-MOEO framework. We use the statistical software ***R*** to perform the hypothesis testing. Computational runs were performed on an Intel(R) Core™ 2 Duo CPU T7250 (2×2.00 GHz) machine, with 2 Go of RAM. The performance of the metaheuristics has been tested on 4 different instances token from the VRPLIB [28]. These instances involve between 16 and 500 nodes. The number at the end of an instance' name represents the number of vehicles for the instance under consideration while the number at the first represents the number of customers. The stopping condition of all methods tested is a maximum number of generations. The results presented below are based on the following GA parameters: the population size is *100*, the maximum number of generations is *100*, the crossover probability is *0.25*, the mutation probability is *0.35*, and the IBEA scaling factor *kappa=0.05*.

5.2 Comparison Results

Below, we present the results of the comparative study.

1. Computation time:

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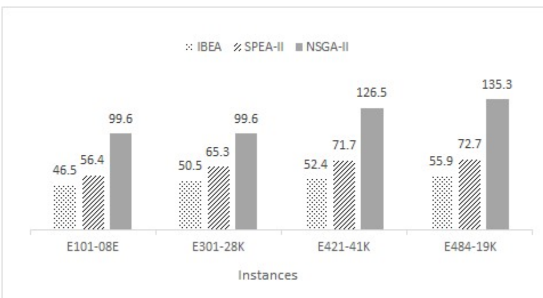
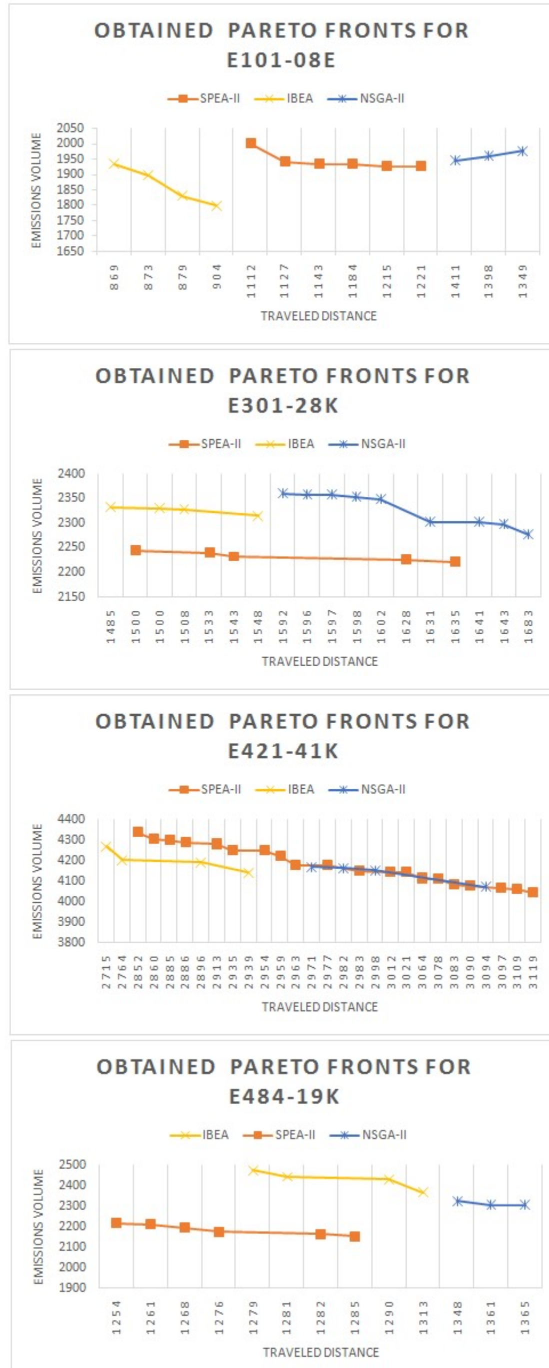
The time consumed by each algorithm is a function of its complexity and the size of the problem being solved. Ordered by complexity, the IBEA has a complexity on $O(N^2)$ where N is the population size. Second, the SPEA-II with a complexity on $O(M^2 logM)$ where M is the sum of the size of the main population and the archive population. Third, the NSGA-II with a complexity on $O(MN^2)$ with M is the number of objectives and N is the size of the population. It is obvious to see that the time required by IBEA is always around half of that needed by NSGA-II. Moreover, the computation time needed by SPEA-II is better than the time of NSGA-II but worse than IBEA due to the logarithmic multiplier. These observations are empirically confirmed by the computation times (in seconds) reported in Figure 1.

Figure 1: Computation time per problem (s)



2. Emissions and travelled distance:
The initial trivial observation from the returned Pareto fronts is their small cardinality. This fact can be explained by the correlation between the objectives. For instance, the emission objective is written as a function of the distance objective (Equation 1). From another side, we can see for the four instances, that obtaining solutions with minimal distance do not imply minimal emissions. For example, the minimum emission for the instance E101-08E is 1928 with a distance of 1221. However, the best distance for the same instance is obtained Pareto front is 1112 with 2001 emitted co_2. As plotted in Figure 2, it is important to see that the Pareto fronts of IBEA are located in the bottom left corner of the graph for instances E101-08E and E421-41K which means that IBEA solutions are better than those returned by SPEA-II and NSGA-II for such problems. However, for instances E301-28K and E484-19K, SPEA-II returns better Pareto fronts than those of IBEA and NSGA-II. It is important to mention also that the solutions returned by NSGA-II are always worse than those of IBEA and SPEA-II.

Figure 2: The generated Pareto fronts by each algorithm per problem



5.3 Statistical Analysis

To evaluate the algorithms rigorously and to estimate the confidence of the, an Analysis Of Variance (ANOVA) and a Wilcoxon test was performed on the indicators of performance GD, S, E and C. By applying a Shapiro-test on the

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distribution, we found that it's a normal distribution. Consequently, we used a two-factor analysis of variance (ANOVA) test which is based on the central assumption of normally data distribution to check whether a factor has a significant effect on the performance of the algorithm. In our case, the experiments and algorithm are taken as a factor and the metrics are taken as dependents variables. The hypothesis is:

H_0: $\mu_1=\mu_2=\mu_3=\mu_4$ ***Versus*** H_1: $\mu_i=\mu_j$
With *i,j € {1,2,3,4} and i≠j*

Table 2 shows the ANOVA results for metrics GD, S, E and C. The ANOVA for metric GD, S, E and C found significant differences (p-value < 0.05). In fact, the linear effect of the instance and algorithm are significant. Moreover, the intersection of the instance and algorithm are significant. Hence, the effect of the factors experiment and algorithm influence the variables of measures of performance and consequently, we conclude that there is a significant difference among the three algorithms.

Table 2: ANOVA Table for metrics GD, S, E and C.

Metrics		Sum of square	DF	Mean square	F-value	Prob>F
GD	A (Instance)	87.41	3	29.136	4.0422	0.009115 *
	B (Algorithm)	401.32	2	200.659	27.8381	1.777e-10 *
	A*B	161.65	6	26.941	3.7376	0.002038 *
	Residuals	778.47	108	7.208		
S	A (Instance)	315.01	3	105.00	18.2855	1.149e-09 *
	B (Algorithm)	2132.33	2	1066.17	185.6670	< 2.2e-16 *
	A*B	175.41	6	29.24	5.0912	0.0001226 *
	Residuals	620.17	108	5.74		
E	A (Instance)	0.21609	3	0.07203	9.9041	7.992e-06 *
	B (Algorithm)	1.49780	2	0.74890	102.9721	< 2.2e-16 *
	A*B	0.47615	6	0.07936	10.9116	1.795e-09 *
	Residuals	0.78547	108	0.00727		
C	A (Instance)	0.4215	3	0.14051	2.4429	0.0680686
	B (Algorithm)	1.0535	2	0.52675	9.1583	0.0002119 *
	A*B	3.0914	6	0.51523	8.9581	6.163e-08 *
	Residuals	6.2117	108	0.05752		

*give significant effect (0.05)

To meaningfully compare the algorithms, we performed the hypothesis test of Wilcoxon which is a nonparametric test that makes no assumptions about the distribution of variables. For the metrics GD, S, and E, we made a right-sided test. The test is as follows:

H_0: no difference between the algorithms ($\mu_1=\mu_2$)
H_1: The values of sample 1 are generally higher than that of sample 2 ($\mu_1>\mu_2$)

In Table 3, the T column indicates the result of the statistical test for a p-value less than 5 percent: For each instance whether the algorithm located on a column dominates significantly the algorithm on a given line (>) whether there is no difference (≡). According to the GD metric, the IBEA algorithm is significantly more efficient than NSGA-II and SPEA for all instances except for instance E421.41K. For the S metric, we found that there is no significant difference between IBEA and NSGA-II for the instance E101-08E. Similarly, there is no difference between SPEA-II and NSGA-II for instances E301-28K, E421-41K, and E484-19K. However, we note that the IBEA algorithm is more efficient for all instances except for E101-08E. For the metric E, the IBEA algorithm is more efficient than SPEA-II for the four instances. However, there is no significant difference between IBEA and NSGA-II. The contribution metric is used to compare two Pareto fronts A and B of 2 different algorithms. Indeed, if C(A, B) = 0 then B is better than A. We realized a Wilcoxon test to determine the best algorithm. The test is as follows:

H_0: no difference between 2 algorithms ($\mu_1=\mu_2=0$)
H_1: Algorithm 2 is better than Algorithm 1 ($\mu_1\neq\mu_2$)

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TABLE 3: COMPARISON OF THE THREE ALGORITHMS ACCORDING TO THE METRICS GD, S AND E USING A WILCOXON TEST

Instances	Alg.	GD				S				E			
		SPEA-II		IBEA		SPEA-II		IBEA		SPEA-II		IBEA	
		p-value	T	p-value	T	p-value	T	p-value	T	p-value	T	p-value	T
E101-08e	NSGA-II	1	≡	0.8237	≡	1.083e-05	>	0.1813	≡	1	≡	1	≡
	SPEA-II	-	-	0.02621	>	-	-	8.93e-05	>	-	-	1.083e-05	>
E301-28k	NSGA-II	1	≡	0.09516	≡	0.9955	≡	0.0001103	>	0.9986	≡	0.5733	≡
	SPEA-II	-	-	2.165e-05	>	-	-	8.106e-05	>	-	-	5.413e-06	>
E421-41k	NSGA-II	1	≡	0.9784	≡	0.9999	≡	0.0002900	>	1	≡	1	≡
	SPEA-II	-	-	*0.5147*	≡	-	-	*9.083e-05*	>	-	-	*0.05256*	≡
E484-19k	NSGA-II	*1*	≡	*0.01285*	>	*1*	≡	*7.599e-05*	>	*1*	≡	*0.8078*	≡
	SPEA-II	-	-	*0.004541*	>	-	-	*5.534e-05*	>	-	-	*0.0002187*	>

Table 4 shows that there is no difference between NSGA-II and IBEA. However, NSGA-II and IBEA are better than SPEA-II.

TABLE 4: COMPARISON OF THE THREE ALGORITHMS ACCORDING TO THE METRIC CONTRIBUTION USING A WILCOXON TEST.

Instances	Algorithms	SPEA-II		IBEA	
		p-value	T	p-value	T
E101-08e	NSGA-II	0.009152	>	1	≡
	SPEA-II	0.00714	>	-	>
E301-28k	NSGA-II	0.009152	>	0.005889	≡
	SPEA-II	0.001953	>	-	>
E421-41k	NSGA-II	0.001953	>	0.001953	≡
	SPEA-II	0.001953	>	-	≡
E484-19k	NSGA-II	0.01379	>	0.008551	>
	SPEA-II	0.02249	>	-	>

6 CONCLUSIONS AND PERPSECTIVES

The interest grant to green logistics is growing due to customers, governments and international organizations pressure on transportation companies to implement eco-friendly operations. Reducing co_2 emissions starts to be the key performance indicator of transportation policies. In this paper, we define the green bi-objective vehicle routing problem with the co_2 emission minimization as primary objective along with the overall traveled distance. We developed a synthesis of the GVRP literature and proposed a mathematical model capturing its features. We focused on the performance of multi-objective genetic algorithms to solve the green bi-objective GVRP and implemented three elitist MOGAs namely: NSGA-II, SPEA-II, and IBEA and applied them to solve bi-objective GVRP benchmark problems. The obtained results are evaluated using different specific metrics. The performed evaluations are strengthened by advanced statistical analysis and show that the IBEA algorithms outperform NSGA-II and SPEA-II.

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