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An NSGA-II Algorithm for the Green Vehicle Routing Problem

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Abstract. In this paper, we present and define the bi-objective Green Vehicle Routing Problem GVRP in the context of green logistics. The bi-objective GVRP 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. We review emission factors and techniques employed to estimate co_2 emissions and integrate them into the GVRP definition and model. We apply the NSGA-II evolutionary algorithm to solve GVRP benchmarks and perform statistical analysis to evaluate and validate the obtained results. The results show that the algorithm obtain good results and prove the explicit interest grant to emission minimization objective.

Keywords: Green vehicle routing, Multi-objective optimization, Evolutionary algorithms, NSGA-II.

1 Introduction

A supply chain is a network [1] of suppliers, manufacturers, warehouses and distribution channels organized to acquire materials, convert them into finished products and distribute them to clients. The Supply Chain Management (SCM) consists of finding best practices, policies and strategies to solve efficiently all encountered problems. That is by employing the available resources with respect to different constraints and while optimizing many different and generally conflicting objectives. One of the most important SCM phases is the logistics and transportation processes that allow the moving of different materials from and to different nodes in the supply chain network. Generally, the objective of the logistics process is to optimize transportation related costs like traveled distance, time, routes flexibility and reliability. Recently, the concept of greenness for sustainable development has emerged to represent a human concern for the undesirable effect of the industrial processes on the environment. This environmental awareness intend to show the effect of toxic emissions on the environment

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and to call governments and industrials to seriously consider this concern. Several industries started enhancing their procedures to show an explicit interest to minimize the volumes of their missions. In transportation, the aim is to construct low cost routes for vehicles, trucks, planes and ships to transport goods. However, while moving theses engines generate huge quantities of co_2 that affect directly the quality of breathed air particularly in large cities. The major concern, for transportation firms, is the materiel benefit without reviewing vehicle emissions and their effect on the environment. Recently, and for many reasons, transportation companies start taking explicitly into account the emissions reduction objective in definition of their working plans. This trend was encouraged by governmental regulations and customer preference to consume environment friendly products. Then, the generated working plans must minimize costs and co_2 emissions. These two objective are not necessarily positively correlated and for some cases they are completely conflicting.

The basic transportation model generally used to represent the problem of finding routes for vehicles to serve a set of customers is the Vehicle Routing Problem (VRP) [27]. In the basic VRP and also in many other variants the objective to optimize is unique and it is to minimize the overall transportation costs in term of distance, time, number of vehicles, etc. Here, the literature is really huge where several single objective VRP was studied and solved efficiently. However, like other optimization problems, the objectives may be multiple and conflicting. Then, the multi-objective VRP was defined to represent a class of multi-objective optimization problem.

In this paper, the scope is the study and the definition of the bi-objective Green Vehicle Routing Problem (GVRP). The bi-objective GVRP asks for designing vehicle routes to serve set of customers while minimizing the total traveled distance and the total co_2 emissions with respect to classical routing constraints mainly capacity constraints. consequently, we will implement the NSGA-II evolutionary algorithm to solve the bi-objective GVRP model via solving some well known benchmarks. The NSGA-II is a non-dominating sorting genetic algorithm that solves non-convex and non-smooth multi-objective optimization problems. The objective of the paper is to show the effectiveness of explicitly considering emissions minimization as separate objective to optimize and to prove that short routes are not necessarily less pollutant.

The paper is organized as follow. In the next section, we present the concept of green logistics, enumerate all emission factors and how co_2 emissions could be estimated and then integrated into quantitative models. Section 3 is devoted to define the vehicle routing problem with emissions, review the corresponding literature and propose a mathematical model for the bi-objective GVRP. In the section 4, we present the evolutionary solving approach based on the NSGA-II algorithm. Section 5 will report the NSGA-II implementation details and computational results. Statistical analysis will be performed to measure the effectiveness of the model and the obtained results. Finally, we present the conclusions of this project and state some perspectives for future work.

2 Green Logistics

Traditional logistics ensure the movement of materials between all actors in the supply chain starting from raw materials locations to final customers via firms factories. These transportation tasks should be completed efficiently to report more benefit to the company. The efficiency is usually measured in terms of money, time and reliability. Recently, the concept of green logistics for sustainable development has soared due to governmental regulations and customers preference for green products. Consequently, transportation companies are reviewing their processes to take into account such concern. The revision consider all the steps in the production process including the choice of raw materials, factoring, packaging, alternative fuels, etc. In some cases transforming the traditional logistics systems to be environmentally friendly will give a cutting down in costs and then it will meet classic logistics objectives. However, in many other situations such review may cost more and come into conflict with traditional logistics.

For transportation companies, green logistics mean transporting goods with lower effect on the environment. Basically, the effect of transporting materials on the environment comes from gazes emissions generated from moving engines like trucks, planes and ships. Then, greener transportation yields to low co_2 emission routes. But, those routes are generally determined using analytical model that consider only saving money as primer objective. Then, the aim of considering the environmental effect will be transformed into a revision of the analytical tools used to generates routing policies and strategies. That, could be completed by determining emission factors and quantifying trucks emissions to integrate them into logistics systems.

2.1 Emission Factors

There are a number of factors that could affect vehicle fuel economy in real world:

1. Vehicle weight:a vehicle carrying more weight requires more energy to run, thus directly affect in fuel economy [4].
2. Vehicle speed and acceleration:fuel consumption and the rate of co_2 per mile traveled decrease as vehicle operating speed increase up to approximately 55 to 65 mph and then begin to increase again[1]. Moreover, the co_2 emission double on a per mile basis when speed drops from 30 mph to 12.5 mph or when speed drops from 12.5 to 5 mph [3]. The relationships between these factors and fuel economy are not simple. For example, the implication of vehicle operating speeds on fuel consumption is not linear and depends on vehicle type and size. It also varies on the model year and age of the vehicle. For instance, studies of vehicle fuel economy taken during the 1990s show less of a drop off in vehicle fuel economy above 55 miles per hours than similar studies of vehicles during the 1970s and 1980s, due to vehicle design changes and engine operating efficiency [14].

3. Weather conditions: weather condition affect vehicle fuel economy. For instance, head-winds reduce vehicle fuel economy as the vehicle needs additional power from the engine to combat the wind drag. Hot weather induces the use of air conditioning, which places accessory load require on the engine.
4. Congestion level: It is commonly known that as traffic congestion increases, co_2 emission (and in parallel fuel consumption) also increase. In general, co_2 emission and fuel consumption are very sensitive to the type of driving that occurs. In fact, traveling at a steady-state velocity will give much lower emissions and fuel consumption compared to a stop-and-go movement. Thus, by decreasing stop-and-go driving, co_2 emissions can be reduced [4].

2.2 Emission Estimation Techniques

To examine the environmental impact of the Vehicle Routing, it is necessary to weigh the environmental impacts of co_2 emission. It is difficult to do an exact estimation because of the uncertain effects of climate change and the setting of a price tag on human health. The DEFRA estimated in 2007 the cost of emitting a tone of co_2 at 25.5. Furthermore, the IPCC [15] published estimates range between 5 and 25. Emissions are estimated using average grams of co_2 per kilometer. The study of Mc Kinnon [25] shows that the load carried is an important parameter to estimate emissions. Thus, we can estimates co_2 from the distance traveled by vehicles and the quantity of goods carried. There are other methods to estimate co_2 emission for vehicle. We can cite for example the fuel-based approach and the distance-based method.

1. The fuel-based approach: In the fuel-based approach [11], the fuel consumption is multiplied by the co_2 emission factor for each fuel. The emission factor is developed based on the fuels heat content, the fraction of carbon in the fuel that is oxidized and the carbon content coefficient. The fraction of gasoline oxidized depends on the transportation equipments used. Therefore, this variability is minimal. In the US inventory, this fraction is assumed to be 99 percent. In the case of road transportation, companies and other entities have the option to override these defaults if they have appropriate data of fuel used. In most case, default emission factors will be used based on generic fuel type categories(e.g., unleaded gasoline, diesel, etc) The fuel-based approach requires essentially two main steps:

   (a) Gather fuel consumption data by fuel type: Fuel use data can be obtained from several different sources. We can cite for example fuel receipts, financial records on fuel expenditures or direct measurements of fuel use. When the amount of fuel is not known, it can be calculated based on distance traveled and an efficiency factor of fuel-per-distance.The distance traveled basically come in three forms:

      – distance(e.g., Kilometers)
      – passenger-distance(e.g.,passenger-kilometers)
      – freight-distance (e.g., ton-miles)

The fuel economy factors depend on the type, age and operating practice of the vehicle in question. Thus, we obtain the following equation:

$$fuel\_consumption = distance * fuel\_economy\_factor$$

(b) Convert fuel estimate to co_2 emissions by multiplying results from step 1 by fuel-specific factors; The recommended approach is to first convert fuel use data into an energy value using the heating value of the fuel. The next step is to multiply by the emission factor of the fuel.

The fuel-based approach is the same for the different mode of transportation. The following equation outlines the recommended approach to calculating co_2 emissions based on fuel use. Thus, we obtain the following equation:

$$co_2\_emissions = fuel\_used * heating\_value * emission\_factor$$

2. The distance-based method :The distance-based method [11] is another method to estimate the carbon dioxide emissions can be calculated by using distance-based emission factor. This method can be used when vehicle activity data is in the form of distance traveled but fuel economy data is not available. It is obvious to formulate our problem using a distance-based method for calculating co_2 emissions. Calculating emissions requires two main steps:
   (a) Collect data on distance traveled by vehicle type and fuel type.
   (b) Convert distance estimate to co2 emissions by multiplying results from step 1 by distance based emission factors. Thus, we obtain:

$$co_2\_emissions = traveled\_distance * emission\_factor$$

   The estimation of emission factor is carried out following two main steps. The first one consists on estimate the fuel conversion factor ($2.61 kg.co_2/$ liter of diesel). The second step is to estimate the emission factor consists on finding a function taking into account data related to the average fuel consumption which depends on load factor.

3 The Vehicle Routing Problem with Emissions

3.1 Literature Review

In recent years, many research works about variants of the VRP in order to reduce the cost and the emission of co_2 was conducted. The Vehicle Routing and Scheduling Problem (VRSP) is an extension of the VRP. Its purpose is to determine the routes and schedules for a fleet of vehicle to satisfy the demand of a set of customers. Thus, it aims to minimize cost which is usually related to the number of vehicles and distance. The reduction in total distance will provide environmental benefits due to the reduction in fuel consumption.

The Time Dependent Vehicle Routing Problem (TDVRP) represents a method which should indirectly produce less pollution and achieve environmental benefits in congested area. The TDVRP is a variant of the VRP and has received less attention. It was originally formulated by Malandrakiand et al. Daskin [7] as mixed linear program. It consists of finding the solution that minimizes the number of tours by considering traffic conditions. The TDVRP provide environmental benefits, but in an indirect way. Consequently, less pollution is created when vehicle are traveling at the best speeds and for shorter time. The Time Dependent Vehicle Routing and Scheduling Problem (TDVRSP) consists of finding the solution that minimizes the number of tours and the total traveling time. It is motivated by the fact that traffic conditions cannot be ignored, because at peak time, traffic congestion on popular routes will causes delays. The TDVRSP provides also environmental benefits in indirect way. There is an extensive literature related to vehicle emission.Turkay et al. [20] and Soylu et al. [18] demonstrated a collaborative supply chain management for mended business and for decreasing environmentally harmful chemicals, while satisfying local regulation and Kyoto protocol for greenhouse gas emissions. The study of Halicioglu [12] tried to empirically treat the dynamic causal relationship between carbon emissions, energy consumption, income and foreign trade in the case of Turkay [20]. Recently, Van Woensel et al. [21] considered a vehicle routing problem with dynamic travel time due to the traffic congestion. The approach developed introduced the traffic congestion component based on queuing theory in order to determine travel speed. A tabu search method was used to solve the model. Results showed that the total travel time can be improved significantly when explicitly taking into account congestion during the optimization phase. The study of Figliozzi et al. [8] proposed a new methodology for integrating real-world network status and travel date to TDVRP. It developed efficient algorithms TDVRP solution methods to actual road networks using historical traffic data with a limited increase in computational time and memory. The results shows the dramatic impacts of congestion on carriers fleet sizes and distance traveled.

Figliozzi [9] also created a new type of VRP which is denoted the Emission Vehicle Routing Problem(EVRP). The research presented a formulation and solutions approaches for the EVRP where the minimization of emission and fuel consumption is the primary objectives or is part of a generalized cost function. A heuristic is proposed to reduce the level of emission given a number of feasible routes for the TDVRP. Search results indicated that they may be significant emissions saving if commercial vehicles are routed taking emissions into consideration. Moreover, congestion impacts on emission levels are not uniform. Bauer et al. [2] identified and addressed some environmental consideration in the context of intermodal freight transportation and proposed ways to introduce environmental costs into planning model for transportation. They proposed a formulation for scheduled service network design problem with fleet management, it is an integer program in the form of a linear cost multi commodity and capacitated network design formulation that minimize the amount of green house gas emission for transportation activities. The formulation has been implemented on a real life intermodal rail network data.

3.2 The Bi-objective Green Vehicle Routing Problem

The green vehicle routing problem is an answer for the recent environmental awareness in the field of transportation and logistics. The objective is to find routing and transportation policies that give the best compromise between traveling costs and co_2 emissions. The literature on transportation problems especially vehicle routing problems had considered this environmental interest. Later studies show and implicit interest to handle the objective of gazes minimization But, without viewing it as a major distinct objective like distance and time. We can cite the TDVRP, VRSP and the emissions VRP. In this paper, we consider the the emissions minimization as a separate major objective in addition to the distance minimization objective. Therefor, we define a bi-objective combinatorial optimization problem named the bi-objective green vehicle routing problem.

The bi-objective GVRP [28] could be defined as follow: Giving a set of N customers located in a transportation network and a distance matrix D_{ij} representing the costs of moving between customers i and j and a set of M vehicles hosted in a central depot. A solution of the bi-objective GVRP is composed by a set of routes with minimum traveled distance and the minimum volume of emitted co_2 while visiting each customer once and with respect to vehicles capacity constraints. It is clear that the bi-objective GVRP is an NP-hard problem due to the fact that it is an extension of the standard VRP which is NP-hard.

4 NSGA-II Algorithms for the Bi-objective GVRP

Genetic Algorithms (GA) are stochastic and evolutionary optimization algorithms based on mechanisms of natural selection and genetics. GAs attempt to solve hard non-convex single and multiobjective optimization problems. Multiobjective GAs are based on the concept of Pareto dominance, which emphasizes a research satisfying all objectives. They are well suited for the search of Pareto front through their implicit parallelism to reach optimal solutions more efficiently than an exhaustive method. Many multiobjective genetic algorithms can be cited [6].

The NSGA-II is more efficient than its previous version NSGA [5]. This algorithm 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. For these reasons, we choose to resolve our problem using this approach. In NSGA-II, the child population $Q(t)$ is first created from the parent population $P(t)$(randomly filled). They are then met into a set $R(t) = P(t) \bigcup Q(t)$ that is sorted according to the principle of dominance: all non-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. And so on. This process is iterated until all solutions whose fitness value is upon to evaluate is empty [6]. 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.

5 Implementation and Computational Results

In order to evaluate the effectiveness of the proposed model and to prove the effect of considering explicitly the emissions minimization objective, the NSGA-II algorithm was implemented to solve bi-objective GVRP instances. The proposed algorithm was implemented using the ParadisEO-MOEO library [26]. The performance of the metaheuristic has been tested on different instances taken from the VRPLIB [23]. These instances involve between 16 and 500 nodes. The number at the end of an instances name represents the number of vehicles while the number at the first is the number of customers. The stopping condition of all tests is based on the number of generation (100 generation). Computational runs were performed on an Intel Core 2 Duo CPU (2.00 GHz) machine with $2G\emptyset$ RAM. The results presented below are based on the following GA parameters:

- Chromosome encoding: a solution chromosome is represented by an integer string. A gene is a customer number, while a sequence of genes dictates a group of customers assigned to a vehicle. For instance, the chromosome (0,3,6,1,0,2,4,0,5,0) contains three routes (0 :: 3 :: 6 :: 1 :: 0), (0 :: 2 :: 4 :: 0) and (0 :: 5 :: 0). The population size is set to 100 chromosomes.
- Crossover: We utilized the standard crossover operator Partially-Mapped-Crossover (PMX). The first step is to Select a substring uniformly in two parents at random. The next step is to exchange these two substrings to produce proto-offspring. The third step is to determine the mapping relationship according to these two substrings. The last step is to legalize proto-offspring with the mapping relationship. The crossover probability is 0.25.
- Mutation: In the mutation stage, two customers are selected from different routes randomly. They are going to be swapped only if constraints are met after this operation. After swap, insertion is done in which we select randomly a customer from a route and try to insert rest of any one route if it satisfies all the constraints.The mutation probability is fixed to 0.35.

5.1 Computational Results

To demonstrate the efficiency of the metaheuristic implementation, measures related the computation time are computed and reported in Table.1. We can remark that the computation time of the implemented algorithm increases proportionally to the size of the instance due to algorithm complexity and especially the complexity of the computation of the crowding distance $O(MNlogN)$. It is important to observe that the cardinality of the pareto fronts is small. This fact can be explained by the correlation between our two objectives; for instance the emissions objectives was written as a function of the distance objective. From another side, we can see for four instances, that obtaining solutions with minimal distance does not imply minimal emissions.

5.2 Statistical Analysis

To evaluate the quality of the obtained solutions and measure the performance of the algorithm, metric measurements have been selected and calculated. We use three metrics: the first is the Generational Distance (GD) which measures how far from the Front Pareto is located a set of solutions, the second is the Spacing (S) metric which measures the distribution uniformity of points of the set of solution

Table 1. The obtained Pareto fronts and the needed computation time

Instance	Pareto front		CTime (s)
	Obj1(km)	Obj2(kg.co2)	
E101-08e			83.413
	1946	1411	
	1961	1398	
	1977	1349	
E301-28k			99.621
	2352	1598	
	2298	1643	
	2357	1597	
	2277	1683	
	2349	1602	
	2360	1592	
	2303	1631	
	2302	1641	
	2302	1596	
E421-41k			126.547
	4163	2982	
	4153	2998	
	4168	2971	
	4071	3094	
E484-19k			135.330
	2307	1365	
	2306	1361	
	2325	1348	

in the plan $(obj1, obj2)$, the third indicator of performance is the Entropy (E) metric that uses the concept of niche to evaluate the distribution of solutions on the front. The NSGA-II algorithm give different approximations for each execution. Thus, to empirically analyze the performance of our algorithms, we first run the same algorithm several times on the same instance of the problem. We get then a sample of approximation. We run the algorithm ten times for each instances. Table 2 presents averages of metrics GD, S and E over ten runs of the four instances.

Table 2. Averages of metrics GD, S and E for the algorithm NSGA-II

Instances	**GD**	**S**	**E**
E101-08e	3.931	4.632	0.227
E301-28k	4.063	6.878	0.422
E421-41k	3.009	6.515	0.095
E484-19k	5.396	2.570	0.371

The values obtained by the GD metric are small and vary between 0.6282 and 6.250 so are not large enough. We can then conclude that the set of solutions are near of the Pareto front. For the S metric, the results obtained for variants E101-08e and E421-41k and E484-19k are close to 0, so the points are well distributed in the set Parto front. For the instance E301-28k, the mean value is equal to 6.878, therefore the worse. By exploiting the solutions obtained by the Entropy metric, we note that the value found in the instance E421-41k is the closer to 1, thus the distribution of solutions for this instance on the front is better than the three other instances. To evaluate the metaheuristic rigorously and to estimate the confidence of the results to be scientifically valid, statistical tests are performed on the indicators of performance. Experiments are performed on the four instances E101-08e, E301-28k, E421-41k and E484-19k. The three algorithms are executed ten times for each instance and calculations of metrics GD, S and E are made. In order to determine whether the mean of the experiments are different or not at a statically significant level, an analysis of variance is done. By applying a Shapiro-test on the distribution, we found that this one follow a normal low. Consequently, we used a one 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 are taken as factor and the metrics are taken as dependents variables. The hypothesis is:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4$ Versus $H_1 : \mu_i \neq \mu_j$
with $i, j = 1, 2, 3, 4$ and $i \neq j$

Table.3 shows the ANOVA for metrics GD, S and E. The first ANOVA for metric GD don't found significant differences for the different experiments. Hence, the effect of the factor experiment does not influence the variables of measures of performance. The second ANOVA for metric S found significant differences. Consequently, there is an effect of the factor on the variable of measures of performance. The third ANOVA for metric E found also significant differences.

Table 3. ANOVA table for metrics GD, S and E

	Sum sq	DF	Mean sq	F-value	Prob > F
GD					
Factor	7.352	3	2.4508	0.7742	0.517
Residual	3.1728	36			
S					
Factor	137.09	3	45.696	10.977	2.9 $\exp^{-5}$
Residual	149.86	36	4.163		
E					
Factor	0.3981	3	0.1327	10.759	3.428 $\exp^{-5}$
Residual	0.4441	36	0.0123		

6 Conclusions

The green vehicle routing problem consists of designing a set of routes for a set of vehicles to serve customers over a transportation network. We model the GVRP as bi-objective optimization problem where the first objective is to minimize the overall traveled distance and the second objective is to minimize the volume of emitted co_2. Many solving approaches and algorithms are envisaged. In this paper, we choose evolutionary algorithms to find better pareto fronts for the GVRP. This choice is explained by the performance of evolutionary algorithms especially elitist algorithm like NSGA-II, SPEA-II and the IBEA algorithms for solving multi-objective combinatorial optimization problems. Hence, we implement the NSGA-II algorithm for solving GVRP benchmarks. The obtained results show and prove the effectiveness of considering the emissions minimization as a separate objective. Performed statistical tests confirm the quality of the generated pareto fronts and then the performance of the NSGA-II algorithm.

References

1. Aronsson, H., Brodin, M.H.: The environmental impact of changing logistics structures. Int. J. Logist. Manag. 17(3), 394–415 (2006)
2. Bauer, J., Bektas, T., Crainic, T.G.: Minimizing greenhouse gas emissions in intermodal freight transport: an application to rail service design. Journal of the Operational Research Society 61, 530–542 (2010), doi:10.1057/jors.2009.102
3. Bickel, P., Friedrich, R., Link, H., Stewart, L., Nash, C.: Introducing environmental externalities into transport pricing: Measurement and implications. Transp. Rev. 26(4), 389–415 (2006)
4. Boriboonsomsin, K., Vu, A., Barth, M.: CoEco-Driving: Pilot Evaluation of Driving Behavior Changes among U.S. Drivers. University of California, Riverside (August 2010)
5. Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 6(2), 181–197 (2002)
6. Coello, C.A., Lamont, G.B., Van Veldhuizen, D.A.: Evolutionary Algorithms for Solving Multi-Objective Problems, 2nd edn. Springer, New York (2007) ISBN 978-0-387-33254-3
7. Malandraki, C., Daskin, M.S.: Time-Dependent Vehicle-Routing Problems - Formulations, Properties And Heuristic Algorithms. Transportation Science 26(3), 185–200 (1992)
8. Figliozzi, M.A.: A Route Improvement Algorithm for the Vehicle Routing Problem with Time Dependent Travel Times. In: Proceeding of the 88th Transportation Research Board Annual Meeting CD rom (2009)
9. Figliozzi, M.A.: Vehicle Routing Problem for Emissions Minimization. Transportation Research Record 2197, 1–7 (2010)
10. Fonseca, C.M., Fleming, P.J.: Genetic Algorithms for Multiobjective Optimization: Formulation, Discussion and Generalization. In: Forrest, S. (ed.) Proceedings of the Fifth International Conference on Genetic Algorithms, San Mateo, California, pp. 416–423. University of Illinois at Urbana- Champaign, Morgan Kaufmann Publishers (1993)

11. The Greenhouse Gas Protocol Initiative: Calculating CO2 emissions from mobile sources. Guidance to calculation worksheets (2005), `http://www.ghgprotocol.org/standard/mobile.doc`
12. Halicioglu, F.: An econometric study of CO2 emissions, energy consumption, income and foreign trade in Turkey. Energy Policy 37, 1156–1164 (2009)
13. Horn, J., Nafpliotis, N., Goldberg, D.E.: A Niched Pareto Genetic Algorithm for Multiobjective Optimization. In: Proceedings of the First IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence, Piscataway, New Jersey, vol. 1, pp. 82–87. IEEE Service Center (June 1994)
14. ICF Consulting: Assessment of Greenhouse Gas Analysis Techniques for Transportation Projects. 9300 Lee Highway, Fairfax, Virginia 22031 (May 2006)
15. `http://www.ipcc.ch`
16. Knowles, J.D., Corne, D.W.: Approximating the Nondominated Front Using the Pareto Archived Evolution Strategy. Evolutionary Computation 8(2), 149–172 (2000)
17. David Scheffer, J., Grefenstette, J.J.: Multiobjective Learning via Genetic Algorithms. In: Proceedings of the 9th International joint Conference on Articial Intelligence(IJCAI 1985), Los Angeles, California, pp. 593–595. AAAI (1985)
18. Soylu, A., Oruc, C., Turkay, M., Fujita, K., Asakura, T.: Synergy Analysis of Collabo- rative Supply Chain Management in Energy Systems Using Multi-Period MILP. Eur. J. Oper. Res. 174(1), 387–403 (2006)
19. Srinivas, N., Deb, K.: Multiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. Evolutionary Computation 2(3), 221–248 (1994)
20. Turkay, M., Oruc, C., Fujita, K., Asakura, T.: Multi-Company Collaborative Supply Chain Management with Economical and Environmental Considerations. Comput. Chem. Eng. 28(6-7), 985–992 (2004)
21. Van Woensel, T., Kerbache, L., Peremans, H., Vandaele, N.: Vehicle routing with dynamic travel times: a queueing approach. European Journal of Operational Research 186, 990–1007 (2008)
22. Zitzler, E., Laumanns, M., Thiele, L.: SPEA2: Improving the Strength Pareto Evolutionary Algorithm. In: Giannakoglou, K., Tsahalis, D., Periaux, J., Papailou, P., Fogarty, T. (eds.) Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems, EUROGEN 2001, Athens, Greece, pp. 95–100 (2001)
23. `http://www.or.deis.unibo.it/research_pages/ORinstances/VRPLIB/VRPLIB.html`
24. De Jong, K.A.: An analysis of the behavior of a class of genetic adaptive systems. Ph.D. dissertation, University of Michigan, USA (1975)
25. Mckinnon, A., Cullinan, S., Browne, M.: Green logistics: Improving the environmental sustainability of logistics. Kogan Page, limited (2010)
26. Liefooghe, A., Jourdan, L., Talbi, E.: A software framework based on a conceptual unified model for evolutionary multiobjective optimization: ParadisEO-MOEO. European Journal of Operational Research 209(2), 104–112 (2011)
27. Toth, P., Vigo, D.: The Vehicle Routing Problem. SIAM, Philadelphia (2001) ISBN 0898715792
28. Jozefowiez, N., Semet, F., Talbi, E.: Multi-objective vehicle routing problems. European Journal of Operational Research 189(2), 293–309 (2008)