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A novel heuristic algorithm based on Clark and Wright Algorithm for Green Vehicle Routing Problem

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Abstract

A significant portion of Gross Domestic Production (GDP) in any country belongs to the transportation system. Transportation equipment, is supposed to be great consumer of oil products. In this paper a novel heuristic algorithm based on Clark and Wright Algorithm called Green Clark and Wright (GCW) for Green Vehicle Routing Problem is presented. The objective function is fuel consumption, drivers, and the usage of vehicles. Comparing obtained results by those of exact methods solutions for small-sized problems and Differential Evolution (DE) algorithm solutions for large-scaled problems, the results show efficient performance of the proposed GCW algorithm.

Keywords: Microscopic Emission Models; Green Vehicle Routing Problem (GVRP); Clark and Wright Algorithm; Differential Evolution (DE) Algorithm.

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1. Introduction

Using fossil fuels, transportation vehicle devices –dependent on how much fuel they need to consume- are supposed to be great producers of greenhouse gases (GHG) such as Carbon Dioxide (CO_2) (Kirby et al. 2000). Transportation is considered an important section of logistics – a fundamental non-changeable element of economic development – which consumes fossil fuels and emits the environment to a large extent (Zachariadis et al. 2009). The Vehicle Routing Problem (VRP) plays a key role in logistic and distribution management; a main part of logistic total costs belongs to the vehicles (Lin et al. 2014). The costs have been, for a long time, considered just as an economic problem, but nowadays, environmental factors are also added to the problem due to the environmental emission concerns; therefore, it is important to find a model to reduce the fuel consumption while considering both driver and vehicle costs (Barbarosoglu and Ozgur, 1999). This paper develops a heuristic solution for the green VRP, the performance of which is evaluated through exact solutions in small-sized problems and Differential Evolution (DE) solutions for large-scaled ones. The results show an appropriate performance of this algorithm.

2. Literature Review

Effective factors for fuel consumption are categorized into 5 clusters: vehicle, environmental factors, traffic, driver, and the external factors. Among most important effective factors on the consumption of fuel the following are of special note: speed, road steep, driver, crowd, maximum load, and the fleet combination or size (Demir et al. 2014). Xiao et al. (2012) formulated the consumption of fuel and suggested the fuel consumption rate of limited-capacity VRP. Both load and the distance passed by the vehicle were considered as variables which determine the fuel costs. It has been assumed that in their formula that fuel consumption is a linear function of load. Kuo (2010) added the vehicle velocity to the time-based VRP model besides the factors of passed distance and the carried load and solved the model through a Simulated Annealing (SA) algorithm. Ubeda et al. (2011) conducted a case study to minimize the distance passed and the emission produced by the vehicles; the results show it is important for controlling the GHGs to consider the load carried back. Faulin et al. (2012) combined the limited capacity VRP with environmental factors such as noise, crowdedness, and infrastructures frazzle. Rakha et al. (2003) reported that there were many aspects such as approach, structure, and the required data from which the models of GHG emission and available energy consumption are different. The fuel consumption models are divided into two main categories: in microscopic models the environmental factors and the motor features define how much fuel is consumed, while in the macroscopic models the amount of fuel consumed by the vehicles in diverse situations is calculated upon regression models. In the following section, an overview of the models is given.

Palmer (2007) combined the VRP model with CO_2 emission and the travel duration. He checked what effect reducing the rate of Carbone Dioxide emission had on fuel consumption in different traffic situations with time-windows constraints through a momentary fuel consumption model. The results showed it was possible to reduce Carbone Dioxide emission by 5% . Banderia et al. (2013) introduced a method for obtaining the information about the emissions on multiple routes among which a driver should randomly select one. He used Vehicle Specific Power (VSP). Bektas and Laporte (2011) presented the emission VRP with and without time-windows and formulated a to-be-minimized objective function of the costs of GHG emission, the operative cost of driver and the amount of consumed fuel through the Total Quality Emission Model. Demir et al. (2012) suggested Adaptive Large Neighborhood Search (ALNS) algorithm for emission VRP which had a high efficiency, especially in medium- and large-scaled instances. They also used the Total Quality Emission Model to solve a to-be-minimized two-objective-function problem of consumed fuel and the driving duration. Franceschetti et al. (2013) considered the consumed fuel, the amount of emitted Carbone Dioxide, and the driver costs in traffic-based situation and solved it by the Total Quality Emission Model. Koc et al. (2014) have studied the emission VRP under the heterogeneous fleet.

Jabali et al. (2012) studied the time-dependent VRP to analyze the influence of velocity limitation on the fuel consumption and the driving duration. They utilized the Methodology for calculating transportation emissions and energy consumption (MEET) which is assumed the macroscopic model [18]. Omidvar and Tavakkoli-moghaddam (2012) surveyed the VRP with alternative fuel by the help of the methodology for calculating the amounts of both emission and fuel consumption; their objective function minimized both of them. Maden et al. (2010) solved the time-dependent VRP in changing traffic status situations; the results showed a 7-percent decrease of Carbone Dioxide emission. Their model simultaneously minimized the driving duration and the GHG emissions based on the method of National Atmospheric Emissions Inventory (NAEI).

3. Problem description

Regarding the comparison of fuel consumption by Demir et. al., we found the Total Quality Emission Model had the nearest estimation to reality. The fuel consumption rate is calculated through the equation (1).

$$FR = \frac{\xi(kNV + P/\eta)}{\kappa} \tag{1}$$

Where ξ is the mass rate of fuel to air, k is the friction of vehicle motor, N and V are the motor's velocity and movement, respectively; η and κ are constants of diesel motor efficiency and fuel heat value, respectively; and P is momentary output power motor in terms of kilo Watt which is calculated through the equation (2).

$$P = \frac{P_{tract}}{\eta_{tf}} + P_{acc} \tag{2}$$

Where η_{tf} is the efficiency of moving axels of the vehicle, P_{acc} is the required power for the accessories of the vehicle such as cooler devices etc. which is assumed to be zero, here; P_{tract} is the required pulling force for the wheels in terms of kilo Watt which is calculated through the equation (3).

$$P_{tract} = \frac{(Ma + Mg\sin\theta + 0.5C_d\rho A v^2 + MgC_r\cos\theta)v}{1000} \tag{3}$$

Where M is the vehicle mass (including the load) in terms of kilo grams and a is the vehicle acceleration in terms of m/s^2; v, θ, and g are the vehicle velocity in terms of m/s, the road steep, and the gravity constant, respectively; C_d and C_r are the coefficients of air and rolling resistances, respectively; and ρ and A are the air density in terms of kg/m^2 and the vehicle frontal area in terms of m^2.

For the arc (i,j) with the length of$d$, and v is the velocity of a vehicle. If the factors remained constant except for velocity in the equation (1), the consumed fuel (in terms of liter) can be calculated by the equations (4) and (5).

$$F(v)= {}^{kNV\lambda d}\!/_{v} \tag{4}$$

$$+ {}^{P\lambda\gamma d}\!/_{v} \tag{5}$$

Where λ and γ can be obtained by the equations (6) and (7), respectively.

$$\lambda= {}^{\xi}\!/_{\kappa\psi} \tag{6}$$

$$\gamma= {}^{1}\!/_{1000\eta_{tf}\eta} \tag{7}$$

Where ψ is the convertor coefficient of fuel from g/s into lit/s.

M is divided into two factors of w and f which are the empty vehicle mass and the cargo mass, respectively. α and β are coefficients which can be calculated by the equations (8) and (9).

$$\alpha=a+gsin\theta+gC_r cos\theta \tag{8}$$

$$\beta=0.5C_d\rho A \tag{9}$$

The relative index of the arc (i,j) will be placed under the velocity, distance, load, α parameters of the arc. The equations (4) and (5) can be rewritten in the form of the equation (10) as follows (Demir, 2012):

$$F(v)= {}^{\lambda(kNV+w\gamma\alpha v+\gamma\alpha f v+\beta\gamma v^3)d}\!/_{v} \tag{10}$$

The parameters are initialized for a medium (5-ton) vehicle.

3.1. Mathematical Model

The parameters, indices, and the variables are introduced in Table 1 before the model introduction.

Table 1. The introduction of the parameters

Parameter	Definition	Parameter	Definition
(i,j,m) n	The number of customers in a node	dem_i	The demand of customer i
(k) K	The number of vehicles	dp	The wage of an hour driving
cap_i	The customer i capacity	$capacity_k$	The capacity of vehicle k
c_{ij}	The distance between customers i and j	BM	A big number
$grade_{ij}$	The road steep between the customers i and j	vp	Constance cost of any vehicle

Parameter	Definition
X_{ij}^k	A zero-one parameter which is one when the vehicle k is moving between the customers i and j; and zero if otherwise.
f_{ij}^k	The load which vehicle k carries between customers i and j.
u_i^k	A variable which barriers a sub-tour construction.
I_k	A zero-one variable which is one when the vehicle k is being used; zero if otherwise.

The problem model is defined as following:

$$\begin{aligned} min z = & f_c kNV\lambda \sum_{i=0}^{n} \sum_{j=0, j\neq i}^{n} \sum_{k=1}^{K} c_{ij} / speed \\ & + \sum_{i=0}^{n} \sum_{j=0, i\neq j}^{n} \sum_{k=1}^{K} f_c.\lambda.\gamma.g(sin(grade_{ij}) + C_r.cos(grade_{ij}))c_{ij}.w.X_{ij}^k \\ & + \sum_{i=0}^{n} \sum_{j=0, i\neq j}^{n} \sum_{k=1}^{K} f_c.\lambda.\gamma.g(sin(grade_{ij}) + C_r.cos(grade_{ij}))c_{ij}.f_{ij}^k \\ & + \sum_{i=0}^{n} \sum_{j=0, j\neq i}^{n} \sum_{k=1}^{K} f_c \lambda\gamma c_{ij} (0.5 C_d A\rho)(speed)^2 \\ & + \sum_{i=1}^{n} \sum_{k=1}^{K} dp. c_{ij} / speed + \sum_{k=1}^{K} vp.l_k \end{aligned} \tag{11}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{K} X_{ij}^k = 1 \qquad \forall j = 1, ..., n, j \neq i \tag{12}$$

$$\sum_{j=1}^{n} X_{0j}^k \leq l_k \qquad \forall k = 1, ...K \tag{13}$$

$$\sum_{i=0}^{n}\sum_{j=0}^{n} X_{ij}^{k} \leq BM*l_k \qquad \forall k = 1,...,k \tag{14}$$

$$\sum_{i=0}^{n} X_{ij}^{k} - \sum_{m=0}^{n} X_{jm}^{k} = 0 \qquad \forall j = 0,...,n; k = 1,...,K \tag{15}$$

$$f_{ij}^{k} \geq \sum_{m=0}^{n} f_{mi}^{k} - dem_{i} - BM(1 - X_{ij}^{k}) \qquad \forall i, j = 0,...,n, j \neq 0; k = 1,...,K \tag{16}$$

$$f_{ij}^{k} \leq \sum_{m=0}^{n} f_{mi}^{k} - dem_{i} + BM(1 - X_{ij}^{k}) \qquad \forall i, j = 0,...,n, j \neq 0; k = 1,...,K \tag{17}$$

$$f_{0j}^{k} = \sum_{i=1}^{n} (dem_{i} * \sum_{m=0}^{n} X_{mi}^{k}) * X_{0j}^{k} \qquad \forall j = 1,...,n; k = 1,...,K \tag{18}$$

$$f_{0j}^{k} \leq capacity_{k} \qquad \forall j = 1,...,n; k = 1,...,K \tag{19}$$

$$u_{i}^{k} + 1 \leq u_{j}^{k} + BM(1 - X_{ij}^{k}) \quad u_{0}^{kt} = 0 \qquad \forall i, j = 0,...,n, j \neq 0; k = 1,...,K \tag{20}$$

$$X_{ij}^{k} \in \{0,1\} \qquad l_{k} \in \{0,1\} \qquad \forall i, j = 0,...n; k = 1,...,K \tag{21}$$

The equation (11) in the model is to-be-minimized objective function of six sections: the first section is the cost of consumed fuel, the second objective is the cost of fuel which would be consumed due to the vehicle weight, third one is the cost of fuel which would be consumed due to the load the vehicle carries, the fourth section is the cost of fuel which would be consumed due to the vehicle velocity, the fifth one calculates the driver costs [21], and the sixth section of the objective function includes the cost of using the vehicle. The constraint (12) to (15) assures visiting the customers through using the vehicles. The equations (16) to (19) shows the load carried between two customers and the load carried when the vehicle exits from the central stock. The 20th equation is the constraint which assures preventing from a sub-tour construction. The equation (21) defines the variables types.

4. Solution method

This section introduces the algorithms used for the proposed method.

4.1. Green Clark and Wright Algorithm

Clark and Wright (1964) presented an algorithm for VRP which was based on saving concept (Lysgaard, (1997)). The paper Takes accounts of fuel consumption reduction in VRP and propose a solution inspired by a heuristic algorithm, called GCW with the following steps:

Step 1: assign a vehicle to each node.

Step 2: Calculate the savings earned by the connection of every pairs of the nodes by the help of the equation (22) where this amount is noted as sum_{ij} for the arc (i,j).

$$(sum_{0i}+sum_{i0})+(sum_{0j}+sum_{j0})-(sum_{0i}+sum_{ij}+sum_{j0})=sum_{i0}+sum_{0j}-sum_{ij} \tag{22}$$

If one opens the equation (22), it gets as the equation (23):

$$\begin{aligned}
&c_f\, kNV\lambda\, (dis_{i0}+dis_{0j}-dis_{ij})\big/ speed \\
&+c_f\, \lambda\gamma W\, (\alpha_{i0}dis_{i0}+\alpha_{0j}dis_{0j}-\alpha_{ij}dis_{ij}) \\
&+c_f\, \lambda\gamma\, (\alpha_{0j}dis_{0j}dem_{j}-\alpha_{ij}dis_{ij}dem_{j}-\alpha_{0i}dis_{0i}dem_{j}) \\
&+c_f\, \lambda\gamma\beta\, (dis_{i0}+dis_{0j}-dis_{ij})speed^{2} \\
&+p(dis_{i0}+dis_{0j}-dis_{ij}\big/ speed)
\end{aligned} \tag{23}$$

The equation (23) shows the optimum velocity (causing minimum driver and fuel cost) by the variable $speed$ which is obtained by differentiating (in terms of velocity) from the equations holding velocity, driver costs and fuel costs. The equations (24) and (25) show the procedure.

$$\begin{aligned}
&\frac{\partial}{\partial(\mathrm{v})}=0 \rightarrow \\
&\frac{-f_c kNV\lambda c_{ij}}{v^{2}}+2f_c\beta\gamma\lambda c_{ij}v-dp\frac{c_{ij}}{v^{2}}=0
\end{aligned} \tag{24}$$

$$v^{*}=\left(\frac{KNV}{2\beta\gamma}+\frac{dp}{2\beta\lambda\gamma f_c}\right)^{\frac{1}{3}} \tag{25}$$

Step 3: sort the savings calculated in step 2 in descending order.

Step 4: start from the beginning of the list, one should connect two nodes if the sum of their demands is less than the vehicle capacity and otherwise, skip to the next one, until a tour (with more than one node) is constructed. If No tours is constructed in this step, The next step will be skipped.

Step 5: do the sub-steps 5-1 and 5-2 for all the nodes which do not belong to the tour:

5-1: assign the node to both beginning and end of the tour, separately, and calculate the saving earned by each one.

5-2: choose the node with the most saving. If all the earnings for the non-assigned nodes are negative, go to step 2.

Step 6: if all the nodes are assigned, go to step 7.

Step 7: the algorithm is stopped and the rout of each vehicle is reported.

To improve the solution gained by GCW, a 2-opt neighborhood developer is used (Agarwal et al. 2004). A two-opt neighborhood of the tour T includes all the tours $\hat{T}$ which can be obtained by eliminating the arcs $(i,i+1)$ and$(j-1,j)$, and adding the arcs $(i,j-1)$ and$(i+1,j)$.

4-2- Differential Evolution Algorithm

Differential Evolution Algorithm is a metaheuristic method which uses NP members, each of which is a D-dim vector. The candidate solution can be written as $x_{i,G} = \{x_{i,G}^1, x_{i,G}^2, \dots, x_{i,G}^D\}$ $i = 1, \dots, NP$. The initial population should cover as much solution space as possible. For instance, jth parameter of ith member in the replication $G = 0$ is calculated by equation (26).

$$\left\{x_i \,\middle|\, x_i^l(j) \le x_i(j) \le x_i^u(j), i=1,\dots,N; j=1,\dots,D\right\} \tag{26}$$

$$x_i(j) = x_i^l(j) + rand(0,1).x_i^u(j) \tag{27}$$

The lower and upper bounds of jth parameter are noted by x_{min}^j and x_{max}^j, respectively. The initial population size is set as $2.5\sqrt{n}$.

Mutation: for every unique member $x_{i,G}$ of the population (a target vector) a mutation vector is constructed through the equation (28) where $x_{r,1}$, $x_{r,1}$, and $x_{r,1}$ are three randomly selected members which are different and are not the parents themselves.

$$v_{i,G+1} = x_{r1} + F\left(x_{r2} - x_{r3}\right), i \ne r1 \ne r2 \ne r3 \tag{28}$$

F is the scale constant in the interval $[0.5,1]$. The mutated vector is called the test vector. If the obtained number is within the interval $[0,0.5]$, the relative cell would be zero, and otherwise, one (Storn, 1997). The resulting number could be less than zero or greater than 1. If the number is greater than 1, a mirror procedure is applied on the number and it is subtracted from one. If it is less than zero, the absolute value is obtained. F in this paper is found best to be 0.7 by the help of try and error.

Crossover: once the mutation is done, the crossover operator makes the target and mutation vectors to reproduce the offspring vector. Uniform crossover combines the target vector x_i and the test vector v_i as follows:

$$u_i(j) = \begin{cases} v_i(j) \rightarrow if \begin{cases} (rand(0,1) \le CR) \\ \text{or}(j = j_{rand}) \end{cases} \\ x_i(j) \rightarrow otherwise \end{cases} \tag{29}$$

Where CR is the crossover constant which varies within the interval$[0,1]$. j_{rand} is a random index to insure at least a different element between the offspring vector and its parents. The best value of this parameter has been found to be 0.6 by try and error.

Selection: in minimizing problems the following function choose one between the offspring and parent vectors (Storn, 1997).

$$x_i^* = \begin{cases} u_i \text{ , } if \ \left(f\left(u_i\right) \le f\left(x_i\right)\right) \\ x_i \text{ , } otherwise \end{cases} \tag{30}$$

The triple conditions above-mentioned would be continued till the ending condition which is 50 times of replication.

5. Results

The numerical results are presented here, by explaining the small- and large-sized instance problems generating, solving and results comparing. Each problem is solved 5 times by the algorithm and the resulted mean values of time and the objective function are reported.

5.1. Instances

To generate the large size instances, Augerat test problems (set one) are used. The customers coordinates are the same as what in initial problem are. The maximum number of available vehicles are two times more than the optimum number of required vehicles of the initial test problem. The capacity of the vehicles are supposed to be 100 units which are multiplied by 50 in order to be converted into 5 tons; the same thing happens to the demands. To generate small size problems, some of the customers from a random large-scaled instance are selected.

5.2. Small Sized Problems

The results of solving small-sized instances are illustrated in table 2, in which the columns are problem definition (problem number – customers' quantity – maximum available number of vehicles), mean solution and the solving duration of the exact method, and the same values of each heuristic methods with the percentage of error respectively. For example, 1-3-2 means the first problem has 3 customers and can have at most 2 vehicles. To solve the problems exactly the Cplex method were utilized and the solutions of proposed methods are compared to exact solutions.

Table 2. Comparison of small-sized solutions by two algorithms

Problem Definition	Exact		DE			GCW		
	Optimum Solution	time (s)	Obj. Func.	time (s)	Error (%)	Obj. Func.	time (s)	Error (%)
1-3-2	40.56	1	40.56	0.67	0	40.56	0.11	0
2-5-2	59.42	2	59.42	0.85	0	59.42	0.14	0
3-6-2	92.84	28	92.84	1.27	0	92.84	0.14	0
4-6-3	87.87	50	87.87	1.5	0	87.87	0.2	0
5-7-2	93.89	55	94.22	1.83	0.35	93.89	0.35	0
6-7-3	113.28	397	113.28	2.3	0	113.48	0.28	0.17
7-8-2	117.64	430	117.64	1.61	0	117.64	0.16	0
8-9-2	115.60	527	115.60	1.81	0	115.60	0.25	0
9-10-2	104.27	598	104.27	1.23	0	104.27	0.29	0
10-8-3	143.48	4565	143.48	2.71	0	143.48	0.23	0
Mean		665.3		1.57	0.035		0.215	0.017

As shown in fig. 1, GCW algorithm and Differential Evolution algorithm cannot solve problems 6 and 5 optimally (with error means of 0.017 and 0.035), respectively. Fig. 1 illustrates the solution time of the algorithms.

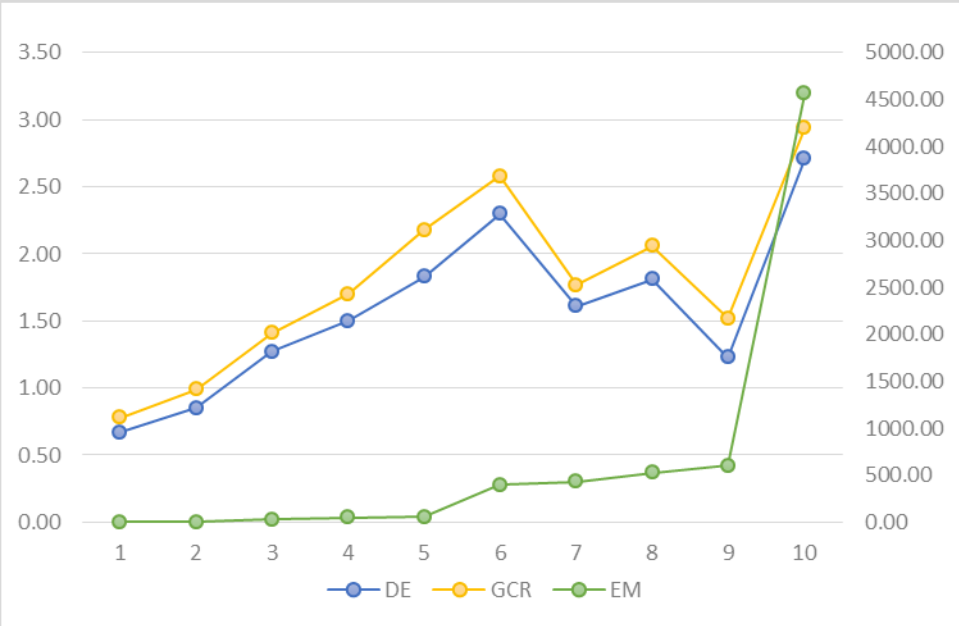

Figure 1. Solving duration for small-sized instances

The right vertical axis in fig. 1 belongs to exact method solution time and the left one show the metaheuristic ones. Regardless of time-consuming solutions of exact method, the duration increases exponentially by size increasing, while the similar relation for the metaheuristic methods is linear.

5.3. Large size problems

The results of 27 lage size test problems are illustrated in table 3.

As shown in table 3, GCW algorithm solves the test problems better than DE algorithm; their error means are 1.78% and 2.27%, respectively. The convergent status of DE is obtained later than GCW. Furthermore, GCW has better solutions than DE in 15 problems among 25 ones. Fig. 2 illustrates the error means of the problems solved by two algorithms.

Table 3. Comparison of large-scaled solutions by two algorithms

P	DE			GCW		
	Obj.	time (s)	E (%)	Obj.	time (s)	E (%)
1-31-5	404.7	63.86	0	433.08	9.44	7.01
2-32-5	355.78	69.01	2.94	345.61	8.8	0
3-32-6	382.24	41.38	0	403.71	9.3	5.61
4-33-5	372.5	49.56	5.15	354.25	9.28	0
5-35-5	403.78	83.35	0	426.6	9.17	5.56
6-36-5	363.55	90.97	0	381.44	9.21	4.29
7-36-6	480.77	13.48	0	485.01	9.09	0.88
8-37-5	397.64	16.04	8.51	366.43	8.69	0
9-38-5	432.29	25.19	0	444.19	9.17	2.75
10-38-6	447.01	71.12	0	462.75	9.04	3.25
11-43-7	496.39	142.99	0	530.91	9.29	6.95
12-44-7	539.69	139.37	2.27	527.71	9.11	0
13-44-7	563.31	117.91	0	582.12	9.3	3.33
14-45-7	512.63	157.23	3.8	493.85	9.43	0
15-47-7	574.17	170.19	0	591.55	12.04	3.02
16-52-7	609.49	28.38	8.16	563.48	9.38	0
17-53-7	632.57	20.96	3.38	611.88	9.48	0
18-54-9	608.7	39.62	5.63	576.22	9.22	0
19-59-9	557.96	245.76	0	566.15	9.31	1.46
20-60-9	707.33	420.63	6.12	666.53	9.71	0
21-61-8	729.61	106.05	2.23	713.67	9.21	0
22-62-9	711.84	215.13	1.79	699.29	9.75	0
23-62-10	863.69	358.66	1.07	854.54	9.92	0
24-63-9	690.76	57.26	2.38	674.64	9.55	0
25-64-9	737.07	44.37	3.99	708.77	11.29	0
26-68-9	656.49	99.95	0	676.94	9.8	3.11
27-79-10	993.58	116.76	4.1	954.39	10.03	0
Mean		107.63	2.27		9.51	1.78

As shown in fig. 2, the error in DE increases by size increasing. The efficiency of GCW is evaluated better than DE (maximum error of GCW is 7.01% which occurs for problem 1, while the maximum error of DE is 8.51% which occurs for problem 8).

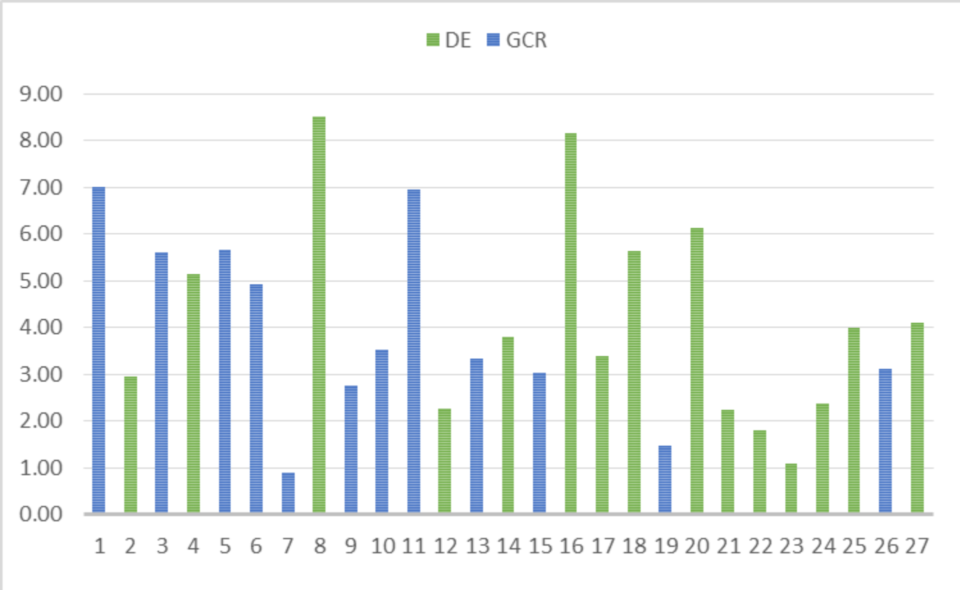

Figure 2. Error in large size problems

6. Conclusion

The paper introduces a heuristic method for GVRP. The objective function includes the reduction of fuels costs, driver costs, and the costs of vehicle usages. To evaluate the performance of proposed algorithm in small-size and large-size problems, the results are compared with those obtained by exact method and DE algorithm, respectively. GCW and Differential Evolution (DE) algorithms showed 0.017% and 0.035% error, respectively in small size problems. Solving 27 large size problems, GCW algorithm showed a better performance than DE in preciseness (1.78% against 2.27%) and CPU time. The solving duration of GCW algorithm is averagely 10 times better than DE algorithm which shows generally an acceptable performance.

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