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A block recombination approach to solve green vehicle routing problem

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ABSTRACT

The vehicle routing problem (VRP) is one of the most important problem with many real world application in transportation and logistics area. Presently carbon dioxide emission is one of the major concerns for the researchers. Green vehicle routing problem (GVRP) is the extension of the vehicle routing problem. In GVRP we consider the minimum distance travelled by each vehicle from depot to distribution center as well as the total emitted carbon dioxide by the vehicle. In this paper, we consider the distance based approach to calculate the carbon dioxide emission. In addition, the truck load is considered as a factor for the carbon dioxide emission. We generate the different cluster for each city visited by different trucks and apply block recombination approach to solve the GVRP benchmark problem where each cluster represents as a block. To avoid the bias, we compare the experimental results with other well know evolutionary algorithms. Computational results show that the proposed methodology is very competitive and has the promising future.

1. Introduction

Climate change problem have become one of the major critical threats on earth. Toxic gases like carbon dioxide, carbon mono oxide and many greenhouse gases are one of the biggest contributors to the threats. Presently many firms are working for reducing this kind of gases from environment. From last few decades Green supply chain network distribution problem has been one of the major concerns for researchers. Green supply chain management (SCM) has recently received closed attention from the firms and government. A supply chain is a network of suppliers manufactures, warehouse and distribution centers organized in such a way that customers gets maximum benefits. The most important part of SCM is the transportation of material between the various centers, like between suppliers to manufacturers, manufactures to warehouses and warehouses to customers. Most of the researcher's objective is to minimize the total transportation cost, time and increased the reliability of network. Presently the environment awareness intends to show the effect of toxic emission on the environment, which gets sufficient attention from government as well as businessman. The concepts of Green supply chain have been launched by several logistic companies to reduce carbon dioxide emission caused by transportation. González-Torre et al. (2004) proposed an Environmental and reverse logistic policies in European bottling and packaging firms. Kunz et al. (2014) developed a new approach to disaster preparedness. Transport system has a major impact on environment in form of energy consumption as well as carbon dioxide, (2007) world energy council. Palmer (2007) developed an integrated routing and carbon dioxide emission model for goods vehicle. In transportation problem the main objective is to minimize the total distance travelled by truck, ships, planes and trains to transport the goods. This kind of transportation generates a lot of carbon dioxide in environment. Especially urban city is more polluted due to large carbon dioxide emission. The carbon dioxide emission from transportation sector has been given significant attention. According to the most recent review on green supply chain presented by Srivastava (2007), he proposed an integrated logistic operational model for green supply chain management. Paksoy et al. (2010) proposed a multi-objective model for optimization for green supply chain network. He proposed a new green supply chain to deal with the trade-offs between environmental and financial issues. Mirzapour Al-e-hashem and Rekik (2014) proposed a green approach for multi-product, multi-period inventory routing problem with a transshipment option As the global economy increased the transportation will increase proportionally. The necessity to find the way to reduce carbon dioxide in road

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freight transport is very important. Presently the transportation companies have providing sufficient efforts towards the reducing carbon dioxide and companies are upgrading and improving their system which will help to reduce carbon dioxide emission. The carbon dioxide emission depends upon numerous variables, distance travelled by the vehicle, load of the trucks, speed of vehicle, and kind of fuel used in vehicle. Weather condition also has impact on carbon dioxide emission. In bad weather like head-wind reduce vehicle speed, to increase the speed engines have to work more, which induce more carbon dioxide. The way of driving have some impact on carbon dioxide, a constant speed driving generate minimum carbon dioxide. Due to the material benefits most of the firms neglect the carbon dioxide emission and their effect on environment. Recently many companies and firm start taking carbon dioxide reduction as an objective using different kind of techniques. Distance is one the major factor to reduce the carbon dioxide. Carbon dioxide is proportional to the distance travelled by the vehicle. Vehicle routing problem is one of the major problems in the area of transportation and supply chain management. The vehicle routing problem (VRP) is a combinatorial optimization ad integer programming problem seeking to service a number of customers with a fleet of vehicles. The problem is that of delivering material located at central depot to customers who have placed orders for such material. The objective is to minimize the total travelling distance. In green vehicle routing problem second objective is to minimize the carbon dioxide. Soysal et al. (2014) proposed a modeling food logistic network with emission consideration, the case of an international beef supply chain. Joumard (1998) developed methods to estimate atmospheric emission from transport and Bauer et al. (2010) proposed an application to rail service design to minimizing greenhouse gas emission. Figliozzi (2010) developed a route improvement algorithm for the vehicle routing problem with time dependent travel times. Many researchers proposed many heuristic techniques to solve the vehicle routing problem. Wang and Lu (2009) proposed a hybrid genetic algorithm that optimizes capacitated vehicle routing problem. Malandraki and Daskin (1992) proposed heuristic to solve a Time-dependent vehicle routing problem. Two-echelon multiple vehicle location of sustainable supply chain network of perishable food was developed by Govindan et al. (2014). Past few years the green vehicle routing problem gains more attention. Green logistic at Eroski: A case study was proposed by Ubeda et al. (2011) and he proposed how logistics managers could lead the initiative in this area by incorporating environmental management principles into their daily decision-making process. A hybrid ant colony system for green capacitated vehicle routing problem in sustainable transport was proposed by Adiba et al. (2013) and he developed a technique which employed to estimate the carbon dioxide emissions, the emissions matrix and their integration into the CVRP model. Erdoğan and, Miller-Hooks (2012) conceptualizes and formulates a green vehicle routing problem. Vehicle routing problem with simultaneous pick-up and delivery service and delivery service was proposed by Montané and Galvão (2002). Figliozzi (2010) proposed a vehicle routing problem for emission minimization, in this paper they proposed a new formulation and solution methodology. Combinatorial optimization and green logistic has been proposed by Sbihi and Eglese (2007), author formulated the problem as combinatorial optimization problems and the paper particularly considers the topics of reverse logistics, waste management and vehicle routing and scheduling. There were many heuristic techniques proposed by researcher to solve the vehicle routing problem. Wang and Chen (2013) proposed a co-evolutionary algorithm for the flexible delivery and pickup problem with time windows and formulate the problem into a mixed binary integer programming model in order to minimize the number of vehicles and to minimize the total traveling distance. Baker and Ayechew (2003), Prins (2004) proposed evolutionary algorithms for the vehicle routing problem. Jaber et al. (2012) proposed a NSGA II algorithm for green vehicle routing problem, author formulated a bi-objective green vehicle routing problem in the context of Green logistic. Kuo et al. (2014) developed a carbon footprint inventory route planning and selection of hot spot suppliers. Konur (2014) developed carbon constrained integrated inventory control and truckload transportation with heterogeneous freight trucks. In this paper we present a block recombination approach to solve the green vehicle routing problem. In this paper our main objective is to minimize the total distance travelled by vehicle and reduce the emitted carbon di-oxide. Our first objective is to minimize the total distance travelled by vehicle. The second objective is to minimize the emitted carbon di-oxide and we used a formulation to calculate the emitted carbon di-oxide, which is proportional to the distance and weight of vehicle. Chang and Chen (2014) proposed a bi-variance estimation of distribution model to generate block. They divide the cities in different clusters; each cluster will represent one block. To generate the cluster, we use two different techniques; one is angel based and another is capacity based. Blocks are applied to generate the artificial chromosome and the block recombination techniques are used to get better artificial chromosomes. Rexeis et al. (2005) proposed that heavy vehicle have more carbon dioxide emission, author proposed an emission and fuel consumption from heavy duty vehicle. We consider vehicle load as a factor which has impact carbon dioxide emission. To avoid the bias in results we test our approach on different data sets and compare the result with other well-known optimization techniques.

The rest of paper is arranged in this manner that Section 2 describes the problem description and notation Section 3 describes the proposed block recombination optimization technique. Section 4 explains the result and discussion Section 5 gives the conclusion of the research.

2. Green vehicle routing problem

The green vehicle routing problem is one of the standard vehicle routing problem. This problem has two objectives; one is to find the minimum distance and the second objective is to find the minimum carbon dioxide Emission. The solution of the GVRP determines a set of delivery routes which satisfy the distribution center requirement and obtain the minimum cost of transportation travel from depot to the set of distribution center. In general, the total minimum cost is equal to the total distance travelled by the entire vehicle. All vehicles have a minimum and maximum capacity and they deliver the goods from a single depot to distribution points and return back to the depot area. The number of vehicle is not constraint; only one vehicle allows traveling all the distribution area. The mathematical model of the GVRP can be expressed as follows:

$$\text{Minimize} \sum_{i=1}^{n}\sum_{j=1}^{n} D_{ij}x_{ij} \tag{1}$$

$$\sum_{i=1}^{n} q_i y_{ik} \le Q \quad k = 1, \dots, m \tag{2}$$

$$\sum_{i,j \in S} x_{ij} \le |S| - 1 \quad S \subseteq \{2, \dots, n\} \tag{3}$$

$$\sum_{i=1}^{m} y_{ik} = \begin{cases} m, & i = 1 \\ 1, & i = 2, \dots, n \end{cases} \tag{4}$$

$$\sum_{i=1}^{n} x_{ij} = \sum_{i=1}^{n} x_{ji} = \begin{cases} m & j=1 \\ 1, & j=2,\ldots,n \end{cases} \tag{5}$$

$$x_{ij} \in \{0,1\}, \quad i=1,\ldots,n; \quad j=1,\ldots,n \tag{6}$$

$$y_{ik} \in \{0,1\}, \quad i=1,\ldots,n; \quad k=1,\ldots,n \tag{7}$$

$$CO_2\text{emission} = V \times A_d \times E_f \tag{8}$$

2.1. Variable and parameter

D_{ij}	distance from ith distribution center to jth distribution point.
x_{ij}	assignment condition of distance from ith distribution center to jth distribution point.
Y_{ik}	represents the condition of the ith distribution point serviced by the kth truck
i,j	represents the distribution centers
k	number of truck used to distribute the goods
V	represents the vehicle load
A_d	represents the average distance travelled by vehicle
E_f	average carbon di-oxide emission factor.
Y_{ik}	represents the condition of the ith distribution point serviced by the kth truck
q_i	is the requirement of the ith distribution point
Q	is the maximum capacity of the vehicles

Our first objective is to calculate the minimum distance travelled by vehicle. Where D_{ij} represents the distance from the ith distribution center point to the jth distribution point: x_{ij} represents the assignment condition of distance from ith distribution center to jth distribution point: $x_{ij}=1$ is the assignments, and $x_{ij}=0$ is not assignments; Y_{ik} represents the condition of the ith distribution point serviced by the kth truck: $Y_{ik}=1$ indicates that the ith distribution point serviced by the kth truck; $Y_{ik}=1$: $Y_{ik}=0$ indicates that the ith distribution point is not serviced by the kth truck; q_i is the requirement of the ith distribution point; Q is the maximum capacity of the vehicles.

In this paper we use the distance based approach to calculate the carbon dioxide emission. We consider load as a factor which have a large impact on generated carbon dioxide. Eq. (8) represents the formula to calculate the carbon dioxide, where CO_2 emission represents the minimum carbon dioxide emission factor. V Represents the vehicle load, A_d represents the average distance travelled by vehicle, E_f and represents the average carbon dioxide emission factor per ton kilometer by vehicle.

3. Block recombination algorithm

In this paper, we use a block recombination approach to calculate the minimum distance and minimum carbon dioxide emission. To get the better block, the angel and capacity based allocation method are applied to generate the better artificial chromosomes. We select the best 25 chromosomes and generate the blocks using the dependent matrix. The number of blocks depends on the number of vehicles used in each data set. Pseudo Code for the proposed methodology is as follows:

1. Arrange the city in clock wise and anti-clock wise uses the polar angles.
2. Create initial population based on the weight.
3. For $i=0$ to every initial population
4. For $j=0$ to every cluster
5. Create the structured chromosome using nearest neighbor algorithm.
6. End for
7. End for
8. //Reverse order
   Arrange the initial population in descending order.
9. Repeat the steps 3 to 7.
10. Combined the entire cluster to form the chromosome.
11. Create better chromosome using dependent matrix.
12. Use genetic algorithm for all cluster to find better chromosome.
13. Block recombination
14. Calculate the final fitness.
15. End

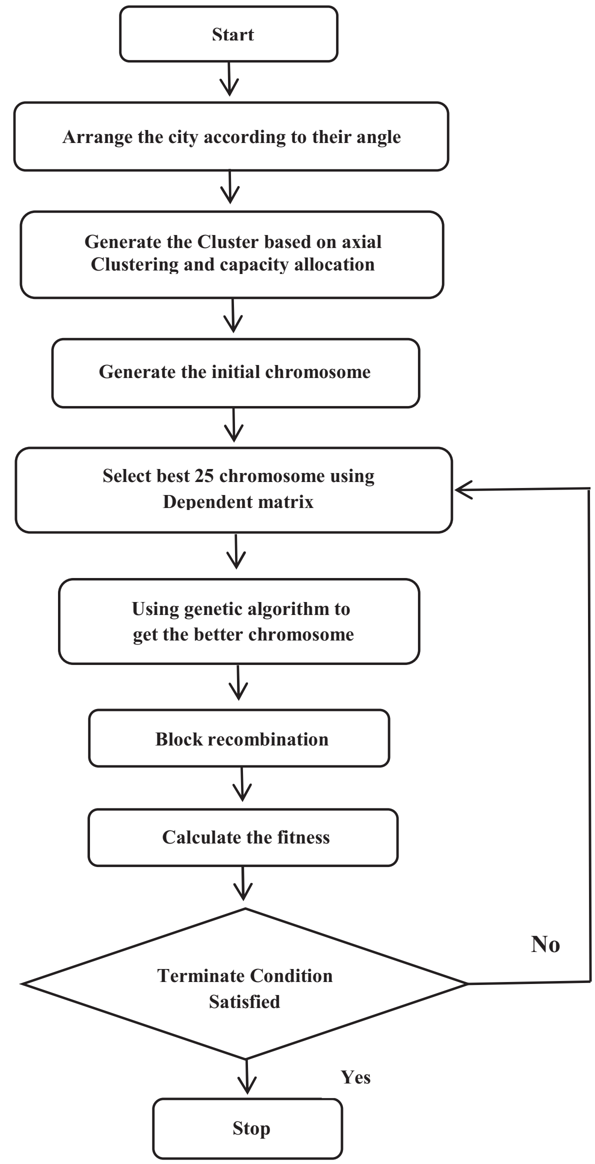

Fig. 1. The flow diagram of the block recombination approach.

The flow diagram of the block recombination approach is shown in Fig. 1.

3.1. Arrangement of the city according to angel

Wang and Lu (2009) proposed a hybrid genetic algorithm that optimizes capacitated vehicle problem. In this paper author used an angel based approach to find the different cluster.

To arrange the city according to angel, first we calculate the coordinate (X, Y) points for all the distribution point. The X,Y coordinate for all the distribution point relative to their depot area are calculated as follows:

$$\begin{cases} X_i = x_i - x_0 \\ Y_i = y_i - y_0 \end{cases} \tag{9}$$

where (X_i,Y_i) the x and y is coordinates of the ith distribution point relative to the depot (X_0,Y_0) is the coordinate of the depot and (x_i,y_i) is original coordinated of x and y for the ith distribution point.

3.2. Generate the cluster based on axial clustering and capacity allocation

We calculate the polar angel of different distribution points. The X and Y coordinate of all distribution points are converted to polar angel using the formula proposed by Wang and Lu (2009).

$$\phi_i = \begin{cases} \tan^{-1}\frac{y_i}{x_i}, & X_i > 0, Y_i > 0 \\ \pi + \tan^{-1}\frac{y_i}{x_i} & X_i < 0 \\ 2\pi + \tan^{-1}\frac{y_i}{x_i} & X_i > 0, Y_i > 0 \end{cases} \tag{10}$$

where ϕ_i represents the polar angel of the ith distribution point. We sort the distribution points in both ascending and descending to get better distribution points in each cluster. We sort the distribution points based on ϕ_i calculated from Eq. (10). The polar angel is as follows:

$$\phi_{j-1} < \phi_j < \phi_{j+1} \tag{11}$$

In this problem, we consider the load as an important factor, we generate the initial chromosome based on the capacity allocation, and each vehicle have a minimum and maximum capacity limit. After getting the distribution points from polar angel we generate the new distribution point based on capacity allocation, we used nearest neighborhood method to get the minimum distance between the two distribution points. The capacity allocation of the distribution points is as follows from the equation proposed by Wang and Lu (2009).

$$\sum_{j=r_{k-1}+1}^{r_k} c_j \le C \le \sum_{j=r_{k-1}+1}^{r_k+1} c_j \quad j = 1, \ldots, n, \quad k = 1, \ldots, m, \tag{12}$$

where C represents the vehicle capacity constraint, c_j is the demand of the jth distribution points, k is the number of vehicle, r_k is the last distribution point after sorting according to polar angel. Fig. 2 represents the procedure of angel based clustering and chromosome representation.

3.3. Generating of initial chromosome

We use the different clusters to generate the initial chromosomes. Initial chromosome is the combination of all clusters. We start from the first cluster to the last cluster. Fig. 3 explains the procedure of the generation of initial chromosome.

3.4. Generating better chromosomes using dependent matrix

To generate the better chromosome we use the dependent matrix. The dependency matrix is applied to store the information related to the sequence of each city. Each element of the dependent matrix and the dependency probability matrix is defined in Eq. (13). To generate the dependency matrix, we select the m chromosome (C^1,C^2,C^3,…,C^m) from initial population from the current generation t, Y_{ij}^k is a binary variable which can be treated like a gene with chromosome C^k.

$$Y_{ij}^k = \begin{cases} 1 & \text{if job i is next to job } j \\ 0 & \text{othersise} \end{cases}$$
$$i = 1, \ldots, n; \quad j = 1, \ldots, n; \quad k = 1, \ldots, m \tag{13}$$

The θ_{ij} in Eq. (14) represents the number of times that city j is before city i. It is calculated from the summation of all the statistic information in all m chromosomes, i.e., sum of Y_{ij}^k. The total number of generation is G.

$$\theta_{ij} = \sum_{k-1}^{m} Y_{ij}^k, \quad i = 1, \ldots, n; \quad j = 1, \ldots, n; \quad k = 1, \ldots, m, \tag{14}$$

We get the dependency probability matrix from the dependent matrix. Each element of dependency matrix is defined as follows:

$$P_{ij} = \frac{\theta_{ij}}{m} \quad i = 1, \ldots, n, \quad j = 1, \ldots, n \tag{15}$$

A systematic diagram of the dependency matrix to dependency matrix is as shown in Fig. 4.

To generate the better chromosome we use dependent matrix, the city which never change their position have the better chance to be selected. In this way we generate the dependent matrix for every generation.

3.5. Using genetic algorithm for each cluster

In this paper we use simple genetic algorithm to get the better cluster. We used the chromosome from depending matrix as an initial chromosome and roulette wheel selection is applied to select the better chromosome. After selecting the better chromosome we use two point crossover and one point mutation. We use crossover probability 0.3 and mutation probability 0.05. Since the chromosome size of each cluster is small, so only small size of population is generated and the iteration is set up to 30. A better cluster then can be further derived using genetic algorithm.

3.6. Generation of blocks and artificial chromosome

We generate the better cluster using the genetic algorithm, which provides the better artificial chromosomes. We use each cluster as a block. In this paper we use the block recombination techniques to get the final artificial chromosome. In Block recombination technique first we generate 100 chromosomes and calculate the fitness value of the entire chromosome. We select best 20 chromosomes for the block recombination techniques. We rank the entire cluster and calculate the fitness value of each cluster. Then, select the entire cluster with higher fitness and combine it according to their ranking. The block recombination technique provides a best chromosome with minimum fitness value. Fig. 5 describes the block recombination approach.

According to Fig. 5, we calculate the entire selected block (1–5) fitness value. We select the best fitness valued block and combine it. Selected bocks provide the minimum the fitness value.

4. Results and discussion

To test the performance of our block based recombination approach we used the benchmark test problem from Benchmark problems obtained from international VRP Websites (http://neo.lcc.uma.es/radi-aeb/WebVRP/). Each instance is executed for at least ten runs. The number of city is represented by n. The population size is set to be 100 and number of generation is 100. As we proposed the carbon di oxide emission based on weight and distance. So we compare our first objective with minimum distance with hybrid genetic algorithm. To check the validity of

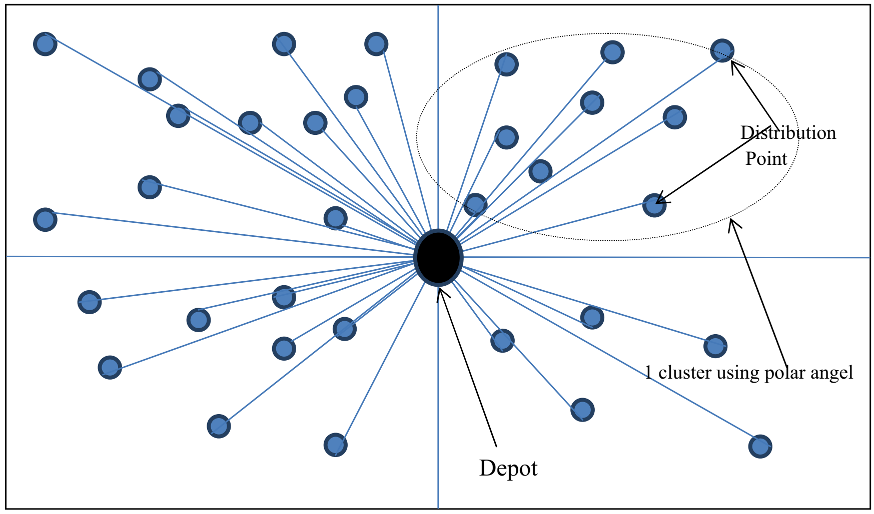

Fig. 2. Representation of distribution point based on polar angel.

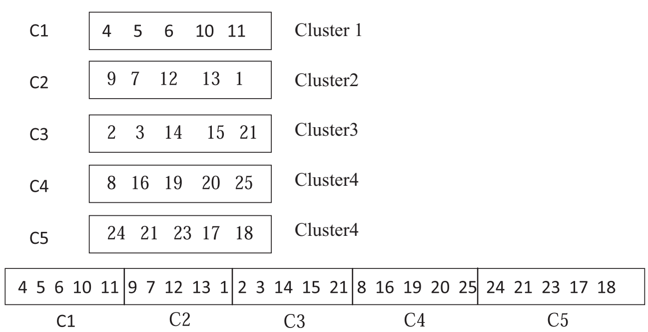

Fig. 3. Generation of initial chromosome.

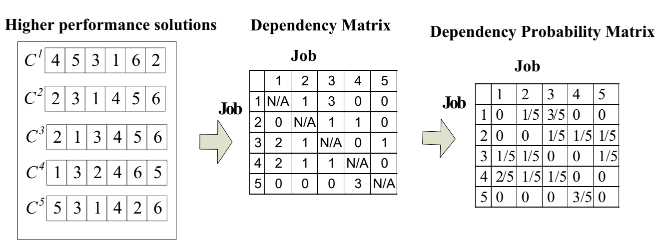

Fig. 4. Dependency matrix and dependency probability matrix.

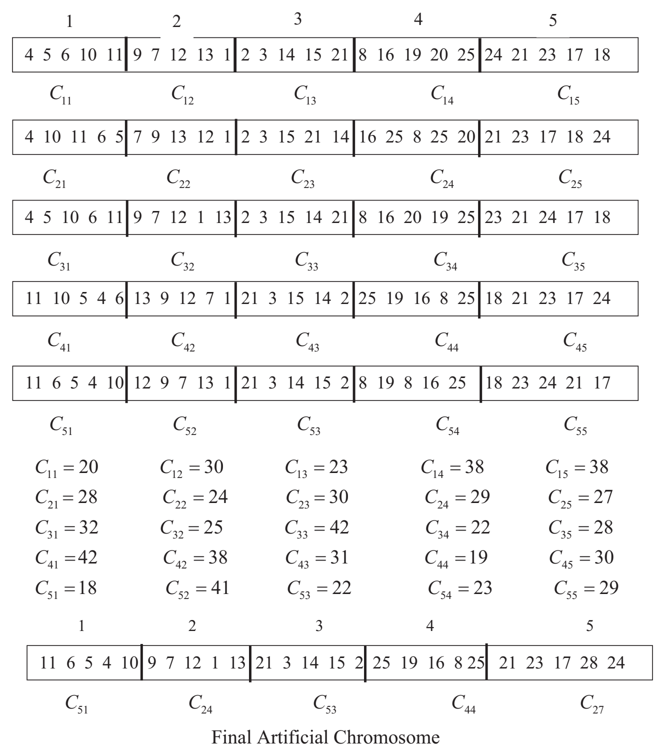

Fig. 5. Block recombination process.

our approach for the benchmark problems, results are compared to the well-known hybrid genetic algorithm. We used the same number of population and same number of generation for both algorithms. To avoid the bias in result, hybrid genetic algorithm was run for various values of parameters. And the set of values with best output were considered for final experiments.

Hybrid genetic algorithm for vehicle routing problem was proposed by Chung et al. (2009). In this proposed HGA author used three stages. First author used nearest addition method (NAM) was incorporated into sweep algorithm (SA) that simultaneously accounts for axial and radius relationship among distribution points to generate the initial chromosome. Second stage was response surface methodology was employed to optimize crossover and mutation probability. Third stage author used improved sweep algorithm which was incorporated into the GA.

To calculate the second objective we used distance based methodology. According to Eq. (8) weight is a measure factor which has a large impact on carbon dioxide emission factor. We allot each truck a minimum and maximum capacity for different instances. Each truck has a different weight and has to deliver according to the demand of different customers. We calculated the carbon dioxide emission for each truck between two cities and sum it.

As shown in following Table 1, we used the instance E-n33-k4 to show the effect of weight on carbon dioxide emission. In Table 1, we can say that the weight have a very strong effect on carbon dioxide emission.

As shown in Table 1, we consider 4 vehicles to deliver the goods on different distribution center. We can see the in from the depot area vehicle carry more weight, because of the heavy weight the carbon dioxide emission is more. Carbon dioxide also depends upon the distance travelled by the vehicle. When the vehicle is empty then it has 40% carbon dioxide emission due to the truck weight.

We test our problem on different instances. In our experiments we check all the possible instances. From the table we can say that using block recombination techniques and considering weight as a

Table 1
En-33 K-4 D, effect of weight on CO_2.

Vehicle 1			Vehicle 2		
Distance	Weight	CO_2 (g)	Distance	Weight	CO_2 (g)
11.1803398874989 23	3625	2495.451863	15.8113883008419 19	3700	3529.101869
34.1803398874989 10	3325	4741.45	55.6360038043217 6	3300	8148.116332
37.7858911629629 11	3225	787.9932313	63.6360038043217 1	3150	1760.8
39.200104725336 12	2275	234.5473193	71.2517769101856 24	2850	1605.404971
47.2623624736346 8	2150	1749.509931	77.0827288050309 25	2350	1156.860856
50.2623624736346 14	1700	590.55	82.4678936121654 29	1550	968.2526323
58.8646877406772 9	1550	1853.370979	96.4678936121654 27	550	2343.6
62.9877933662949 17	1250	849.9782247	119.813128672023 28	450	5210.656465
80.0171797322213 7	1150	3721.77239	137.277377868596 26	300	3843.881248
92.0587743110136 13	1000	2594.361552	184.1495444	0	3269.333619
95.6643255864776 16	850	776.8160223			
101.988880906814 15	700	1362.625444			
130.273152154276 18	150	5392.396313			
139.7599851	0	661.7066004			
Vehicle 3			**Vehicle 4**		
Distance	**Weight**	**CO_2**	**Distance**	**Weight**	**CO_2 (g)**
26.1725046566048 22	3925	5841.703039	23.1948270094864 21	1500	2157.118912
56.1891666962121 2	3825	6699.718967	46.38965402	0	1617.839184
69.6055745612108 5	725	935.7944486			
79.6554501823317 4	525	2243.132239			
92.693854992737 3	425	2910.171954			
115.953261691963 20	300	5191.499575			
134.9269277	0	1323.413201			

Table 2
Summary of the calculation of the benchmark problems.

Instance	Block recombination approach	CO_2 (g)	HGA solution	Best known	Vehicle capacity
E-n30-k3	568.56	91992.74617	568.56	568.563	4500
E-n33-k4	505	88568.92938	508.14	538.958	4500
E-n51-k5	845	256024.1771	845.24	838.721	8000
E-n51-k5	524.61	3930.832769	524.61	524.944	160
E-n76-k7	701.28	6816.146455	701.28	687.603	220
E-n76-k8	750.48	5958.608851	750.48	735	180
E-n76-k10	853.05	5390.838835	853.05	832	140
E-n76-k14	1057.7	4061.023914	1057.7	1032	100
E-n101-k8	847.5	7479.43902	847.5	817	200
E-n101-k14	1121.3	6001.300386	1121.3	1077	112
E-n484-k19	1755.37	80183.07	–	1137.176	1000

factor we reduce the weight as well as emitted carbon dioxide. Table 2 shows the result.

In Table 2, the results from the proposed approach are better than Hybrid genetic algorithm. We calculate the results for all instances. The proposed methodology work well than the other proposed approach (HGA). In the instances, each truck has a minimum and maximum loading capacity. Each vehicle allotted a different distribution area with different demand. For example in instance E-n30-k3, number of trucks are 3 and number of distribution areas are 30. Each distribution area has different demands. So we divide the entire city in three different clusters and each cluster contains different distribution area. According to our objectives, we distribute the vehicle load in this way that we get minimum carbon di-oxide emission. In Table 2, the best know value is the optimal value for all the instances. Vehicle capacity is the minimum capacity for each instance.

Table 3 shows the optimal path which provides the minimum distance and minimum carbon dioxide. Table 3 presents the optimal path with minimum distance and correspondence demands. According to Table 3, if vehicle follow the following route, the carbon di-oxide emission will be minimum. We have mentioned the optimal route for all the instances.

Table 3 represents the route table for all the instances. From the above table we can see the vehicle capacity as well as emitted carbon dioxide emission. Fig. 6 describes the relationship between distances; weight and CO_2 emission for instance **En101-k14**. In Fig. 6, we can see that, carbon di oxide emission is varying according to weight and distance. If distance is less and weight is more, the emitted carbon di-oxide is higher. If distance is more and weight is less, the emitted carbon di-oxide is more. For example we consider vehicle 7 which travels the largest distance with maximum weight and emitted maximum carbon di-oxides.

5. Conclusion

In this paper we propose a block recombination approach to solve the Green vehicle routing problem. The main objective of this paper is to minimize the emitted carbon di-oxide by vehicle during the transportation of goods from depot area to customer. The second objective of this paper is to minimize the total distance travelled by the vehicle. We propose a new model to calculate the emitted carbon dioxide. In this paper we also consider weight as a measure factor which has a large impact on emitted carbon dioxide. We attempt to schedule the weight loading in each vehicle along with the distance travelled in such a combination such that the total carbon dioxide emission is minimized. To find the initial cluster we schedule the city according to their demand.

Table 3
The route Corresponding distance and truck capacity.

Vehicle number	Route	Distance	Capacity	CO_2
	Instance: E-n23-k3			
V1	0→21→4→5→8→9→7→0	210.52	2575	28418.90
V2	0→18→19→20→22→17→14→15→16→3→2→1→6→11→12→0	290.10	3264	53554.77
V3	0→13→10→0	67.94	4350	10019.06
	Total	568.56	10189	91992.74
	Instance: E-n30-k3			
Vehicle number	Route			
V1	0→23→10→11→12→8→14→9→17→7→13→16→15→18	139.75	3625	27812.52
V2	0→19→6→1→24→25→29→27→28→26→0	184.14	3700	31836.00
V3	0→22→2→5→4→3→20→0	134.92	3925	25145.43
V4	0→21→0	46.38	1500	3774.95
	Total	505.19	12750	88568.9
	Instance: E-n33-k4			
Vehicle number	Route			
V1	0→11→18→19→21→20→22→23→24→25→17→13→0	262.07	8000	56229.32
V2	0→3→2→12→32→10→9→8→7→6→5→4→0	175.05	7620	44720.04
V3	0→1→30→31→14→15→1→0	166.97	6950	44720.04
V4	0→1→29→28→16→27→26→0	241.13	6800	69919.42
	Total	845.22	29370	215588.82
	Instance: E-n51-k5			
Vehicle number	Route			
V1	0→46→5→49→10→39→33→45→15→44→37→12→0	99.25	160	743.67
V2	0→8→26→31→28→3→36→35→20→22→1→32	118.51	149	878.58
V3	0→11→2→29→21→16→50→34→30→9→38→0	99.33	159	702.04
V4	0→18→13→41→40→19→42→17→4→47→0	109.05	157	803.26
V5	0→27→48→23→7→43→24→25→14→6→0	98.45	152	717.51
	Total	524.59	777	3845.06
	Instance: E-n76-k7			
Vehicle number	Route			
V1	0→17→51→16→63→23→56→49→24→18→50→32→44→3→0	120.04	217	1162.55
V2	0→30→48→47→36→70→60→71→69→21→61→28→74→75→0	122.80	210	1317.57
V3	0→6→33→73→1→43→41→42→64→22→62→2→68→0	97.43	208	1008.63
V4	0→46→8→19→54→13→57→15→20→37→5→29→45→0	102.24	199	1008.33
V5	0→26→12→72→58→10→31→55→25→9→39→40→0	116.96	206	1170.25
V6	0→7→35→53→14→59→11→66→65→38→0	105.29	209	943.33
V7	0→4→27→52→34→67→0	36.48	115	205.46
	Total	701.24	1364	6816.12
	Instance: E-n76-k8			
Vehicle number	Route			
V1	0→45→29→5→37→20→70→60→71→69→36→47→48→0	103.65	177	798.91
V2	0→75→51→16→63→23→56→49→24→3→44→17→0	103.09	174	870.99
V3	0→6→33→73→1→43→41→42→64→22→62→0	96.75	172	726.56
V4	0→46→8→19→54→13→57→15→27→52→34→0	83.79	163	684.28
V5	0→12→39→9→25→55→18→50→32→40→0	96.35	178	773.44
V6	0→11→66→65→38→10→31→72→58→0	110.66	180	864.31
V7	0→68→2→28→61→21→74→30→4→0	76.35	170	635.39
V8	0→67→35→14→59→53→7→26→0	79.80	150	604.69
	Total	750.44	1364	5958.57
	Instance: E-n76-k10			
Vehicle number	Route			
V1	0→74→21→47→36→69→71→60→70→20→29→0	109.50	139	671.98
V2	0→51→16→63→23→56→49→24→3→17→0	96.35	137	627.97
V3	0→73→1→43→41→42→64→22→61→68→0	110.58	133	727.24
V4	0→30→48→5→37→15→57→13→46→0	81.75	138	514.33
V5	0→8→54→19→59→14→53→35→0	97.60	134	586.510
V6	0→44→50→18→55→25→32→40→0	94.63	134	586.48
V7	0→58→10→31→9→39→72→12→0	87.37	134	540.65
V8	0→7→11→66→65→38→26→0	76.47	140	493.89
V9	0→6→33→62→28→2→75→0	58.82	139	392.93
V10	0→4→45→27→52→34→67→0	39.91	136	248.80
	Total	852.98	1364	5390.78
	Instance: E-n76-k15			
Vehicle number	Route			
V1	0→36→69→71→60→70→20→37→29→0	103.06	96	446.07
V2	0→43→41→42→64→22→61→0	109.64	99	419.52
V3	0→16→49→24→56→23→63→0	91.14	94	354.10
V4	0→45→5→15→57→13→27→0	69.39	93	279.04
V5	0→32→25→55→18→3→51→0	94.86	85	396.96
V6	0→74→21→47→48→30→0	62.10	99	255.22
V7	0→33→1→73→62→28→0	67.17	98	245.06

Table 3 (*continued*)

Vehicle number	Route	Distance	Capacity	CO_2
	Instance: E-n23-k3			
V8	0→58→38→10→31→72→0	86.78	97	339.12
V9	0→46→8→19→54→52→0	59.88	93	239.48
V10	0→7→11→66→65→0	76.13	98	252.65
V11	0→26→12→40→17→0	33.76	87	120.98
V12	0→35→14→59→53→0	77.78	87	273.38
V13	0→39→9→50→44→0	68.50	84	237.56
V14	0→6→2→68→75→0	32.51	75	117.32
V15	0→4→34→67→0	24.91	79	84.49
	Total	1057.61	1364	4061.02
	Instance: E-n101-k8			
Vehicle number	Route			
V1	0→27→69→1→70→30→20→66→32→90→63→10→62→88→31→0	113.93	199	1011.12
V2	0→52→7→82→48→19→11→64→49→36→47→46→8→83→18→0	138.79	199	1269.00
V3	0→76→77→3→79→78→34→35→65→71→9→51→81→33→50→0	118.79	199	1062.68
V4	0→28→12→80→68→29→24→54→55→25→39→4→40→53→0	107.43	188	1029.25
	0→6→96→99→93→61→16→86→17→45→84→5→60→89→0			
V5	0→26→21→72→75→56→67→23→41→22→74→73→58→0	92.64	181	845.40
V6	0→59→98→85→91→44→38→14→100→37→92→94→0	108.94	189	1018.92
V7	0→13→95→97→87→42→43→15→57→2→0	88.78	188	796.02
	Total	769.3	1343	7032.39
	Instance: E-n101-k14			
Vehicle number	Route			
V1	0→96→99→5→84→17→45→83→60→89→0	72.53	100	361.52
V2	0→52→7→19→49→64→11→62→88→0	103.78	110	495.50
V3	0→27→69→70→32→90→63→10→31→0	78.39	106	366.94
V4	0→76→78→34→35→9→81→33→50→0	89.51	104	429.82
V5	0→13→87→42→43→15→57→2→58→0	73.22	101	360.45
V6	0→53→40→73→41→22→74→72→21→0	63.38	99	275.36
V7	0→30→20→66→65→71→51→1→0	105.48	110	523.68
V8	0→82→48→47→36→46→8→18→0	90.00	106	427.11
V9	0→93→91→44→38→14→100→97→0	87.84	106	416.99
V10	0→68→80→24→29→79→3→77→0	75.01	104	336.91
V11	0→26→4→25→55→54→12→28→0	72.17	97	348.50
V12	0→94→59→98→37→92→95→0	44.19	95	175.00
V13	0→61→86→16→85→6→0	71.36	111	333.78
V14	0→75→23→67→39→56→0	94.37	109	397.11
	Total	1121.23	1458	5248.67

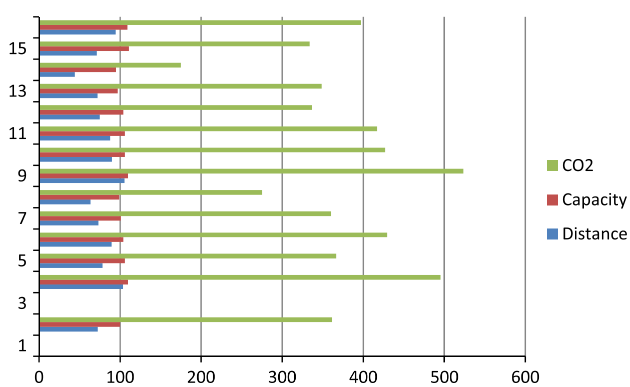

Fig. 6. The CO_2 emission considering the factors of weight and distance.

Then, a block recombination approach is applied to solve the green vehicle routing problem. We use the dependent matrix to generate the better cluster which helps to get the final blocks and we recombine the blocks based on their fitness. The proposed approach is tested on different instances. Instances contain some small number of city problems and some big number of city problems. It can be evidently concluded that the proposed technique to calculate the emitted carbon dioxide can be used in real life problem. In future, we will implement a new model and a new approach to reduce the emission of carbon dioxide. We are planning to calculate the carbon di-oxide emission based on vehicle speed, vehicle capacity and traffic flow. The new model is expected to control the average speed of vehicle in real time manner that the total carbon dioxide emission is minimized.

References

Adiba, B.I., Elhassania, M., Ahemed, H., 2013. A hybrid ant colony system for green capacitated vehicle routing problem in sustainable transport. J. Theor. Appl. Inf. Technol. 54, 198–208.

Baker, B.M., Ayechew, M.A., 2003. A genetic algorithm for the vehicle routing problem. Comput. Oper. Res. 30, 787–800.

Bauer, J., Bektas, T., Crainic, T.G., 2010. Minimizing greenhouse gas emissions in intermodal freight transport: an application to rail service design. J. Oper. Res. Soc. 61, 530–542.

Chang, Pei-Chann, Chen, Meng-Hui, 2014. A block based estimation of distribution algorithm using bivariate model for flow shop scheduling problems. Soft Comput. 18 (6), 1177–1188.

Erdoğan, S., Miller-Hooks, E., 2012. A green vehicle routing problem. Trans. Res. E 48, 100–114.

Figliozzi, M.A., 2010. Vehicle routing problem for emissions minimization. Trans. Res. Rec. 2197, 1–7.

González-Torre, P.L., Adenso-Dıáza, B., Artib, H., 2004. Environmental and reverse logistics policies in European bottling and packaging firms. Int. J. Prod. Econ. 88 (1), 95–104.

Govindan, K., Jafarian, A., Khodaverdi, R., Devika, K., 2014. Two-echelon multiple-vehicle location routing problem with time windows for optimization of sustainable supply chain network of perishable food. Int. J. Prod. Econ. 152, 9–28.

Jaber, J., Manel, Z., Khaled, M., 2012. NSGA-II Algorithm for the Green Vehicle Routing Problem, Evolutionary Computation in Combinatorial Optimization 2012, LNCS 7245, pp. 37–48. Springer, Heidelberg.

Joumard, R., 1998. Methods of Estimation of Atmospheric Emissions from Transport: European Scientist Network and Scientific State-of-the-art Action COST 319. Final Report. INRETS, Bron Cedex, France.

Konur, V., 2014. Carbon constrained integrated inventory control and truckload transportation with heterogeneous freight trucks. Int. J. Prod. Econ. (Available online 17 March 2014).

Kunz, N., Reoner, G., Gold, S., 2014. Investing in disaster management capabilities versus pre-positioning inventory: a new approach to disaster preparedness. Int. J. Prod. Econ. 157, 261–272.

Kuo, T.C., Chen, G.Y.H., Wang, M.L., Ho, M.W., 2014. Carbon footprint inventory route planning and selection of hot spot suppliers. Int. J. Prod. Econ. 150, 125–139.

Malandraki, C., Daskin, M.S., 1992. Time-dependent vehicle-routing problems—formulations, properties and heuristic algorithms. Trans Sci 26 (3), 185–200.

Mirzapour Al-e-hashem, S.M.J., Rekik, Y., 2014. Multi-product multi-period inventory routing problem with a transshipment option: a green approach. Int. J. Prod. Econ. 157, 80–88.

Montané, F.A.T., Galvão, R.D., 2002. Vehicle routing problems with simultaneous pick-up and delivery service. Oper Res Soc India (OPSEARCH) 39 (1), 19–33.

Paksoy, T., Ozceylan, E., Weber, G.W., 2010. A multi-objective model for optimization of a green supply chain network. In: Proceedings of PCO, Third Global Conference on Power Control and Optimization, Gold Coast, Queensland, Australia.

Palmer, A., 2007. The Development of an Integrated Routing and Carbon Dioxide Emissions Model for Goods Vehicles. (Ph.D. Thesis). School of Management. Cranfield University. Cranfield, UK.

Prins, C., 2004. A simple and effective evolutionary algorithm for the vehicle routing problem. Comput Oper Res 31, 1985–2002.

Rexeis, M., Hausberger, S, Riemersma, I., 2005. Emissions and Fuel Consumption from Heavy Duty Vehicles (Final Report of Action COST346/ARTEMIS). Graz University of Technology, Institute for Internal Combustion, Engines and Thermodynamics.

Sbihi, A., Eglese, R.W., 2007. Combinatorial optimization and green logistics. Q. J. Oper. Res. 5 (2), 99–116.

Soysal, M., Bloenhof-Ruwaard, J.M., Van der Vorst, j.G.A.G., 2014. Modelling food logistic networks with emission consideration: case of international beef supply chain. Int. J. Prod. Econ. 152, 57–70.

Srivastava, S.K., 2007. Green supply chain management: a state-of-the-art literature review. Int. J. Manage. Rev. 9 (1), 53–80.

Ubeda, S., Arcelus, F.J., Faulin, J., 2011. Green logistics at Eroski: a case study. Int. J. Prod. Econ. 131 (1), 44–51.

Wang, H.F., Chen, Y.Y., 2013. A coevolutionary algorithm for the flexible delivery and pickup Problem with time windows. Int. J. Prod. Econ. 141 (1), 4–13.

Wang, C.H., Lu, J.Z., 2009. A hybrid genetic algorithm that optimizes capacitated vehicle routing problems. Expert Syst. Appl. 36, 2921–2936.