Optimization of Green Logistic Distribution Routing Problem with Multi Depot Using Improved Simulated Annealing

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Abstract. The traditional vehicle routing problems (TVRP) are suited for cost minimization. In this study, Green VRP with Multi Depot (G-VRPMD) is addressed. The G-VRPMD, an extension of TVRP, is NP-hard which creates eco-friendly distribution system starting and destination to multiple depots. In the present study, modified probability of accepting criteria (MPAC) has been developed. Clustering of consumer was done based on nearness' to depot using distance saving method. Depot's number, customer number and optimal distance used as performance measures. Comparison of output result with state-of-the-art shows that the performance of Improved Simulated Annealing (ISA) is effective in solving G-VRPMD. The emission rate is proportional to age; therefore in designing distribution network path has to incorporate vehicle age prior to optimization.

Keywords: G-VRPMD · MMAC · Vehicle age · ISA

1 Introduction

Effective logistic distribution requires an efficient delivery system of items from source origin to end consumer. A single origin delivery is called single problem. A multiple problem if the delivery has more than one source origin (Yoshiike and Takefuji 2002). Green routing means designing an eco-friendly distribution system. The green (G-VRPMD) examine the delivery network impacts on transportation environment and cost.

The traditional VRP does not consider delivery impact on environment (Paulo et al. 2018). However, environmental issue becomes a competitive factor for companies and in their corporate social responsibility policy (Lyon and Maxwell 2008). Thus in developing distribution system, impacts on environment has to incorporated. In the present study, G-VRPMD model helps organizations to achieve environmental and cost concern in their distribution system. Under this perspective consumers clustered based distance saving method before distribution assignment and optimization. The aim of study is to design an eco-friendly goods distribution system. A minimum cost attended

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using distance saving whereas the emission model descried in terms of EU 2020 regulation emission factor and vehicle age.

The remainder of this paper is organized as follows: In Sect. 2, literature review on G-VRPMD. Section 3 presents the model development and solution methodology. Section 4 reports the computational study, followed by results and discussion. Section 5 describes illustrative example considered in the work. Finally, the conclusion is given in Sect. 6.

2 Literature Review

Research on routing problem has gain more attention (Lahyani et al. 2015). An extension of TVRP having a constraint including (1) environmental; (2) backhauls; (3) Periodic; (4) maximum route; (5) time window; (6) split delivery (Figliozzi 2010) (see Fig. 1).

Based on addressed problem can be categorized into two such as: - (i) Energy saving models (Erdoğan and Miller-Hooks 2012; Xiao et al. 2012; Ćirović et al. 2014; Kara et al. 2007; Figliozzi 2010; Jabali et al. 2012). (ii) Emission reduction models (Huang et al. 2012; Lin. et al. 2014; Demir et al. 2014; Bektaş and Laporte 2011; Soysal et al. 2015), CMEM (Comprehensive Modal Emission Model) considered by (Bektaş and Laporte 2011; Soysal et al. 2015; Demir et al. 2012), MEET (Emissions and Energy consumption) model used by (Jabali et al. 2012), relate fuel consumption and emissions speed (Figliozzi 2010; Palmer 2007; Jabali et al. 2012), to load and distance (Huang et al. 2012), develop special function (Zhang et al. 2015), speed (Suzuki 2011; Fagerholt et al. 2010), alternative fuel vehicle (Qian and Eglese 2016; Li et al. 2015; Erdoğan and Miller-Hooks 2012; Taha et al. 2014).

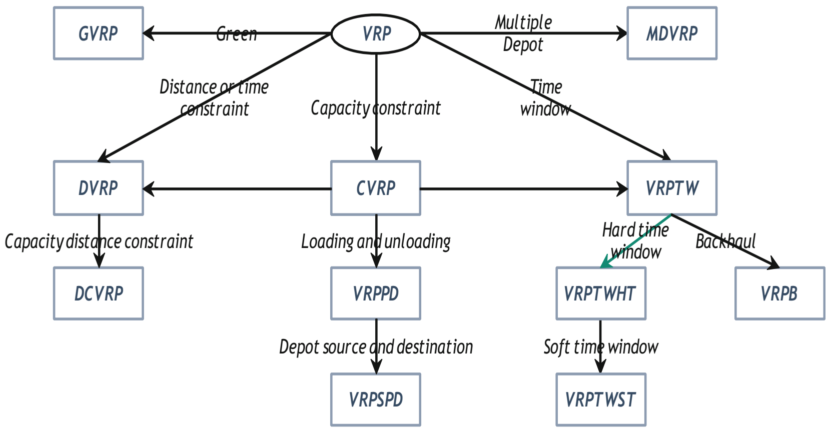


Fig. 1. Different VRP types

Routing problems based on solution approaches categorized into three such as: (i) Exact (ii) Heuristics (iii) Meta-heuristics. Exact methods such as branch and bound

(Laporte and Nobert 1987; Baldacci and Mingozzi 2009; Fischetti et al. 1994), branch and cut (Cordeau 2006), branch and price (Martinelli et al. 2010).

Heuristics such as two-phase heuristics (Beasley 1983), construction heuristics (Clarke and Wright 1964), Iterative heuristics (Gendreau et al. 2001). Meta-heuristics such as simulated annealing, tabu search (Renaud et al. 1996; Li et al. 2012; Prins et al. 2007; Wu et al. 2002; Cordeau et al. 1997), GA (Lacomme et al. 2001; Oliveira et al. 2017; Jorgensen et al. 2007; Haghani and Jung 2005), Ant colony (Donati et al. 2008; Yu et al. 2011), Variable neighborhood search (Hemmelmayr et al. 2009; Affi et al. 2018; Polacek et al. 2004).

Exact methods are only convent for a limited problems in lesser CPU (Kellehauge 2008). The limitation of exact method geared researcher towards heuristic and meta-heuristics for large problems (Kellehauge 2008).

Meta-heuristics suitable for large problems with short CPU time (Zachariadis et al. 2007). This paper deals improved SA performance on green goods distribution system. The contribution is to address logistic supply problems and improve SA convergence mechanism.

3 Methodology

3.1 Mathematical Formulation and Problem Description

A single product supply from m multi-depots to n consumer has been studied. Demand sharing and consumer demand are less than depot storage capacity. In a supply chain a consumer has a successor and predecessor route. The supply route assignment was done using distance saving method. The total cost comprises supply cost and emission cost. Model assumptions are:

(a) A determined demand, vehicle and depot storage
(b) A shortest path b/n depot and consumer is known
(c) Depots location and consumer is known
(d) Origin and destination at depot
(e) A single vehicle visit a depot and a customer exactly once
(f) Homogeneous vehicles are used (capacity, speed and emission parameters are same)

3.2 Model Parameters

Sets	***Parameters***
F – All depot set	N – Number of vehicles
E – All consumer set	V_i – Product available at f
K – All vehicle set	D_j – Demand at e
Indices	Q_K – Capacity at k
f – depot index	e_{ij} – Co_2 emissions cost between point i to j
e – consumer index	X_{ij} = 1, if the arc (i, j) is traveled by vehicle k; 0 otherwise
k – vehicle index	Z_{ij} = 1, if customer j is allotted to depot i; 0 otherwise

(*continued*)

(*continued*)

Sets	***Parameters***
d_{ij} – Distance between point i to j	U_{Ik} – auxiliary variable for sub-tour elimination constraints in route k C_{ij} – Distribution cost between point i to j

3.3 Model Development

G-VRPMD descried in terms of graph, G = (A, E). Node j ∈ A indicates consumer or depot and an edge e ∈ E represent a path in routes. Where $E = \{1, \ldots, n\}$ be consumer set and $F = \{1, \ldots, m\}$ set of depots. Consumer need, $D_j(j \in \{1, 2, 3, \ldots n\})$ to be delivered using a vehicle k. G-VRPMD reduces both cost and Co_2 emissions. G-VRPMD model is shown below:

$$\mathrm{Min} \; = \sum_{i \in F \cup E} \sum_{j \in F \cup E} \sum_{k \in K} C_{ij}.X_{ij} + \sum_{i \in K} \sum_{J \in F \cup E} e_{ij} \tag{1}$$

Subject to;

$$\sum_{k \in K} \sum_{i \in F \cup E} X_{ijk} = 1, j \in E \tag{2}$$

$$\sum_{j \in E} D_j \sum_{j \in F \cup E} X_{ijk} \le Q_k, k \in K \tag{3}$$

$$\sum_{i \in F \cup E} X_{ijk} = \sum_{j \in F \cup E} X_{jik}, \; k \in K, i, j \in F \cup E \tag{4}$$

$$\sum_{i \in F} \sum_{j \in E} X_{ijk} \le 1, k \in K \tag{5}$$

$$\sum_{j \in E} D_j Z_{ij} \le V_i, i \in F \tag{6}$$

$$-Z_{ij} + \sum_{u \in F \cup E} \left(X_{iuk} - X_{ujk}\right) \le 1, i \in F, j \in E, k \in K \tag{7}$$

$$U_{Ik} - U_{Jk} + Nx_{ijk} \le N - 1, l, j \in J, k \in K \tag{8}$$

$$e_{ij} = \delta.d_{ij}.V_f[(V_A F_V + MF_M).(W_L P_{co2})] \tag{9}$$

Constraint (2) allocated vehicle to customer. Constraint (3) shows the vehicle capacity constraint for all set. Constraint (4) describes vehicles starting and returns point.

(5) Indicates route can serve at once. Constraint (6) states depot capacity. Constraint (7) specifies that a consumer served by depot if there a route exist. Constraint (8) describes sub tour elimination. Constraint (9) Co_2 emission from node i to node j.

3.4 Steps in Simulated Annealing Algorithm (SA)

STEP 1 Select random feasible solution, X_o, randomly, staring temperature (t_o), current solution $(X_i = X_o)$, iteration step (k = 0) and temperature at k^{th} step $(t_k = t_o)$.

STEP 2 Select temperature if satisfies the loop stop condition, go to (3); if not, choose a neighborhood, X_j, randomly and calculate; $\Delta E_{ji} = E(X_j) - E(X_i)$. If $\Delta E_{ji} \leq 0$, thus $(X_i) = (X_j)$; otherwise if $\exp(-\frac{\Delta E_{ji}}{t} > rand(0,1))$ go to step 2.

STEP 3 Temperature control function; $k = k + 1, t_{k+1} = \alpha t_k$, $\alpha \in (0.8 - 0.99)$. If it meets the termination conditions, go to step 4; if not, go to (2).

STEP 4 Terminate SA algorithm after all consumers assigned to route

3.5 Modified Simulated Annealing (ISA)

A modified SA is developed to address logistic supply problem. The plugged improvements are shown below:

(1) Distribution representation
A distribution network solution may contain a multiple distribution paths. Loops start and terminate at depot centre (0). For instance a route solution: 0-1-2-0-3-4-0, tells that a route contains two paths, 0-1-2-0 and 0-3-4-0. A route initial solution process is generated using three basic steps: clustering, routing and path optimization (see Fig. 2).

Fig. 2. SA grouping

(a) Clustering – consumers are grouped based on the distance computation according to the following rule:

$$D_{(c,0)} = \sqrt{(X_c - X_0)^2 + (Y_c - Y_0)^2} \quad (13)$$

Where, $D_{(c,0)}$ represent the distance between consumer (c) and depot (0).

(b) Routing – each consumers allotted to depot using distance saving matrix $(S_{ci,cj})$ between two consumer c_i and c_j in the same link. The distance saving matrix is shown below;

$$S_{ci,cj} = D_{(0,ci)} + D_{(0,cj)} - D_{(ci,cj)} \tag{14}$$

(c) Optimization – starting from closest consumer to depot, the logistic supply is sequenced. Logistic supply route optimization is repeated until all unselected customers are sequenced.

(2) Neighborhood. The traditional SA algorithm is $2 - \text{opt}$ exchange to nodes at a time. However, at each temperature, it takes a longer CPU time to get an optimal solution space. In this paper neighborhood switching in-circuit is implemented with randomly using $2 - \text{opt}$ and $3 - \text{opt}$ method to produce a new feasible solution.

(3) Modified probability of accepting criteria (MPAC)

Metropolis accepting criteria determine probability of the accepting a worse solution (see Fig. 3). Suppose there are n times that worse solution is accepted as current solution, we use $\left(\Delta E_{ji}\right)_k$, the difference of potential energy state values and AC_p as probability of accepting where k = 1 … n, and the relation between $\left(\Delta E_{ji}\right)_k$ and AC_p as shown in Eq. (15).

$$AC_p = \begin{cases} 1, & \text{if } \Delta\left[E_{ji}\right]_k \le 0 \\ \exp^{-\left(\frac{\Delta[E_{ji}]_k}{t_k}\right)}, & \text{if not} \end{cases} \tag{15}$$

The standard SA accepting criteria is given in Eq. (16).

$$\exp^{-\left(\frac{\text{new soultion} - \text{current solution}}{t_k}\right)} > r_k \epsilon [0, 1] \tag{16}$$

In present study, modified accepting criteria constructed are given in Eq. (17).

$$\text{MPAC} = \exp^{-\left(\frac{\text{new soultion} - \text{current solution}}{\log[t]_k}\right)} > r_k \epsilon [0, 1], t_k = \frac{-\Delta\left[E_{ji}\right]_k}{\ln[r]_k} \tag{17}$$

The MPAC accepting criteria value becomes larger negative us $\log[t]_k$ goes up Therefore; modified accepting criteria of bad solution becomes drastically reduced at high temperature.

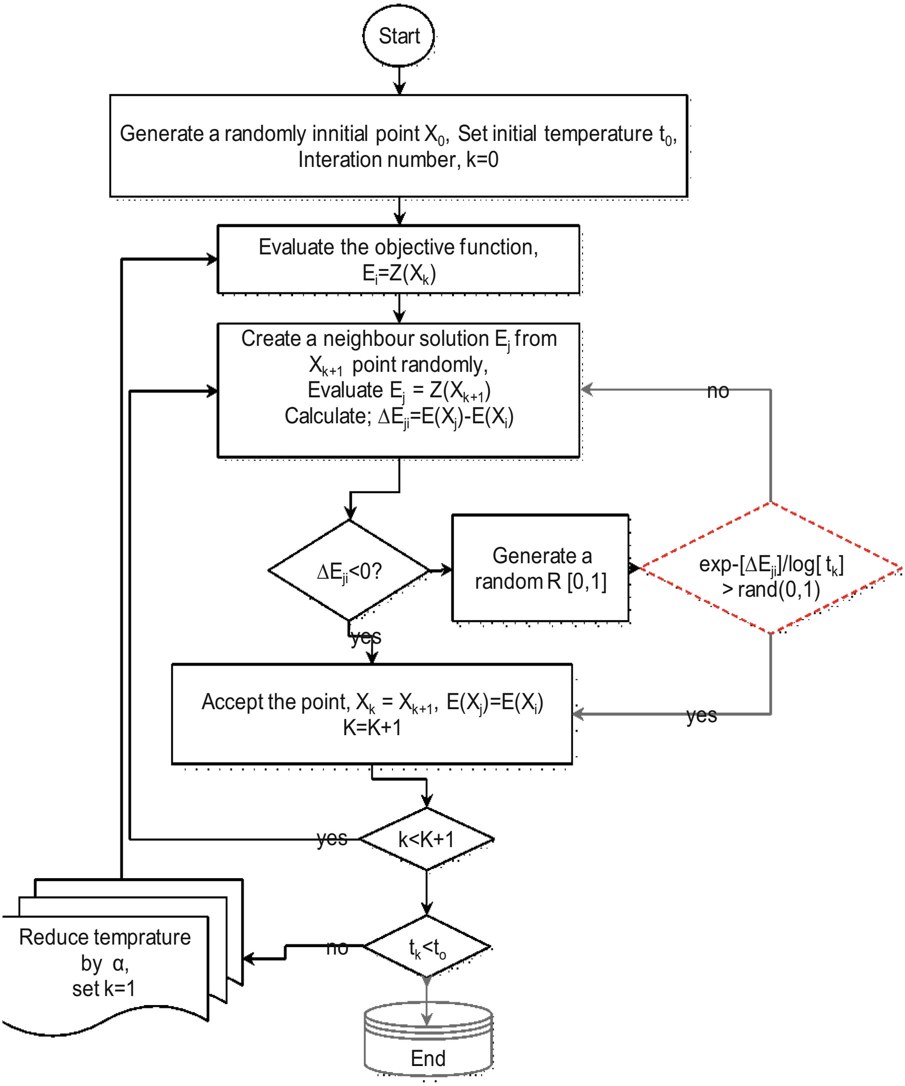


Fig. 3. Proposed flowchart of simulated annealing algorithm

4 Result and Discussion

An Improved Simulated Annealing (ISA) algorithm code was implemented in MATLAB R2016a on Intel core 5 Duo (1.73 GHz), 3 GB RAM PC. A set of test has been carried out to examine ISA performance on problem instance (P03, P05, P06 and P07) known as Cordeaux's instances. These instances are listed in Table 1 where:

I- Problem instance	M- Depot number
N- customer no.	D- Maximum distance traveled

Table 1. Problem instances

I	N	M	D
P03	75	3	∞
P05	100	2	∞
P06	100	3	∞
P07	100	4	∞

4.1 Result Analysis

Clustering – consumers categorized based on depot nearness. Consumer located in same depot route distribution path developed using distance saving method. Blue color indicates consumer geographical location whereas red colors indicate depot location (see Fig. 4).

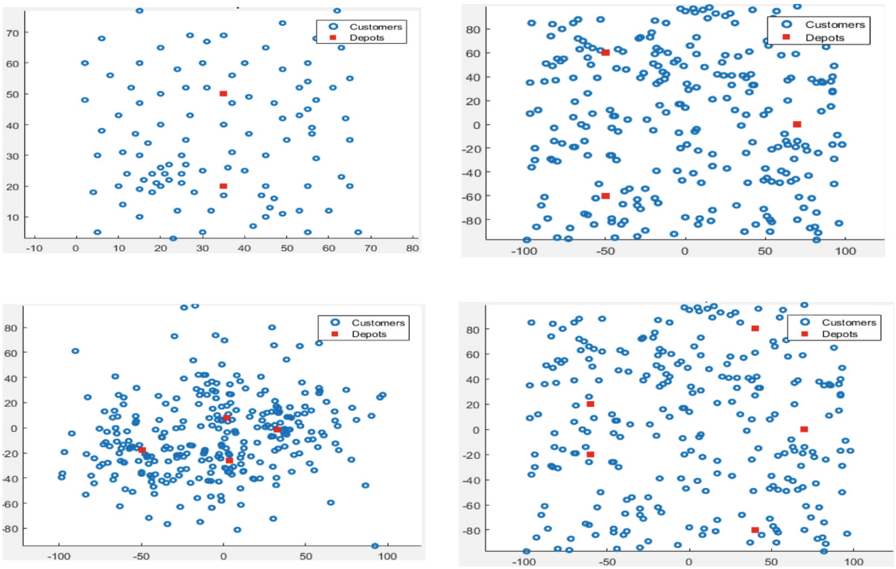


Fig. 4. Illustration of initial consumer location with respect to depot (Color figure online)

Distribution route optimization – consumers with higher distance saving method plugged into same depot (Tables 2, 3, 4 and 5).

Table 2. Distribution network path assignment for P03

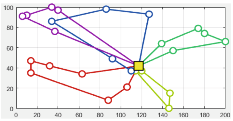
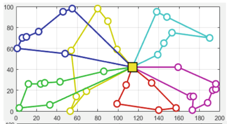
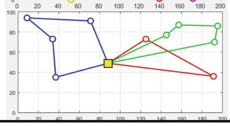
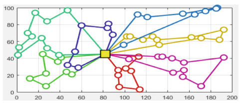
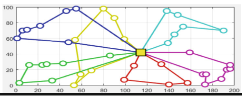
Depot	Optimal dist. path	Best opt. distance	Served consumer	No. vehicles
B(30,40)		330.48	25	5
D(10,20)		232.2926	40	6
C(20,10)		101.9574	10	3

Table 3. Distribution network path assignment for P05

Depot	Optimal dist. path	Best opt. distance	Served consumer	No. vehicles
A(20,20)		381.2767	60	7
B(30,40)		370.2926	40	6

Performance – a modified SA performance testing was done with existing literature such as Genetic Clustering (GC) (Thangiah and Salhi 2001) and Genetic Algorithm (GA) (Ombuki-Berman and Hanshar 2009). Performance metrics and output is shown in Table 6. Percentage gap (%GAP) is calculated by,

$$\%\mathrm{GAP} = \frac{C_{bod} - C_{bkd}}{C_{bkd}} \mathrm{x} 100$$

Where; C_{bod}, best optimal path using modified SA and C_{bkd}, best known path (Cordeaux instances). The total path distance is closer to optimal distance reported in the literature.

Table 4. Distribution network path assignment for P06

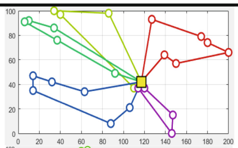
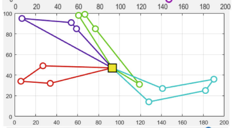
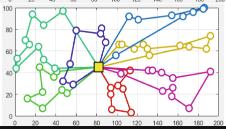
Depot	Optimal dist. path	Best opt. distance	Served consumer	No. vehicles
A(20,30)		324.601	25	5
B(30,20)		275.4021	14	4
C(30,40)		381.2767	60	7

Table 5. Distribution network path assignment for P07

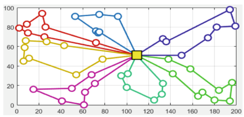
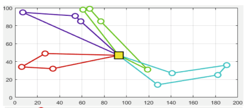
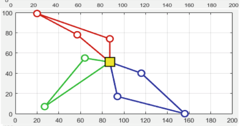
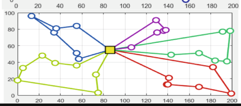
Depot	Optimal dist. path	Best opt. distance	Served consumer	No. vehicles
A(10,10)		257.5058	50	7
B(10,30)		245.4021	14	4
C(20,10)		124.1634	8	3
D(15,25)		294.1318	30	5

Table 6. Comparative analysis for problem instances

I	N	M	Best known distance (km)	Distance reported in literature (km)		Best optimal distance (km) ISA	Best optimal distance (km) SA	% Deviation
				GC (Thangiah and Salhi. 2001)	GA (Ombuki-Berman and Hanshar 2009)			
P03	75	3	641.19	694.49	706.88	664.73	732	3.67
P05	100	2	750.03	-	-	751.5693	794	0.205
P06	100	3	876.5	976.02	908.88	957.1493	1137	9.2
P07	100	4	885.8	-	-	921.2031	1248	3.99

5 Illustrative Example

A depot (O) from its central hub supplies fresh product to n consumer. In order to keep the quality freshness till consumed and minimize cost. The firm requires designing the logistic supply network. Fresh agricultural products are, generally, transported from central to local hub and finally delivered to consumers (see Fig. 5). Costs of vehicle are fixed and variable cost. Fixed cost is 30$ which includes personnel salary and refrigeration equipment. Variable cost includes gasoline price spent 8$ per kilometer. The firm in consideration deliver fresh product from its local warehouse (W_1, W_2, W_3 and W_4) located at Cordeaux coordinate (P03, P05, P06 and P07) respectively to geographically distributed n consumer through assigned m depots.

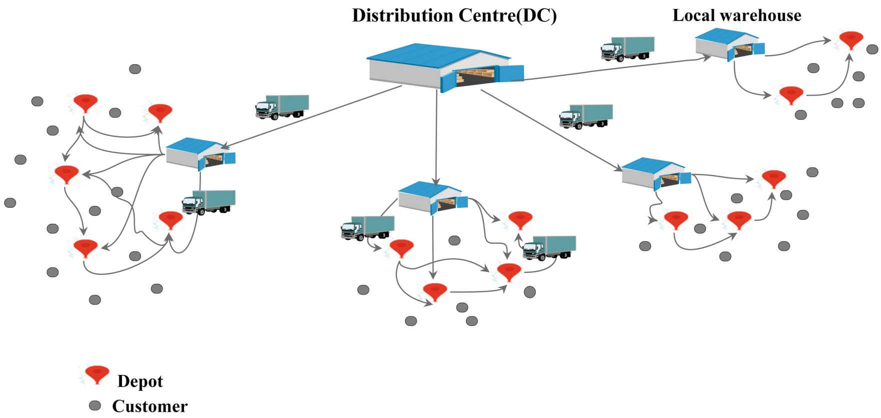


Fig. 5. Illustration of two-echelon logistic distribution

Table 7. Performance metric results

Local warehouse	No. Customer	No. depot	Route	Best optimal distance (km)	Transportation cost	Emission cost/route	Emission cost	Total cost
W_1	75	3	14	664.73	5347.84	155.513	2177.18	7525.02
W_2	100	2	13	751.5693	6042.55	175.829	2285.77	8328.32
W_3	100	3	16	957.1493	7687.19	223.924	3582.78	11269.97
W_4	100	4	19	921.2031	7399.63	215.514	4094.77	11494.40

The total Co_2 emission cost (e_{ij}) from point i to j with distance (d_{ij}) is given by Eq. 18.

$$e_{ij} = \delta . d_{ij} . V_f [(V_A F_V + M F_M).(W_L P_{co2})] \tag{18}$$

Where δ, is vehicle carbon emission factor, V_A is vehicle age, F_V is vehicle constant, M is vehicle mass, W_L is co_2 emission per liter (W_L = 0.216 $kgco_2$/Lt), P_{co2} is average fuel price per unit Co_2 ($P_{co2} = 12\$/kgco_2$), V_f is fuel consumption per unit distance per vehicle ($V_f = 0.614$ Lt/km) and F_M is a road constant. In this study, Co_2 emission as function of age and distance travelled was analyzed by taking other (F_V, M and F_M) parameters constant as shown in Table 7. Emission factor taken for light vehicle as per EU2020 targets as 0.147 kg Co_2/km and Eq. 18 becomes: $e_{ij} = 0.147.d_{ij} V_f [(V_A F_V + M F_M).W_L P_{co2})]$.

The age in [A] region ranges 1 up to 5 years shows an average 8% emission, whereas in [B] region ranges 5 up to 15 years emission increases continually by 27.85%. In [C] region more than 15 ages and afterwards emission increased drastically by 42.31% (see Fig. 6). Therefore using very aged (>15 year) vehicle have more environmental impact than the services it provides. In Developed there is age limitation with a range of 15 year and imposed carbon foot print taxation. But in developing countries like India, Brazil and Ethiopia vehicle used as long as it serve. Therefore decision maker has to consider age prior to path optimization.

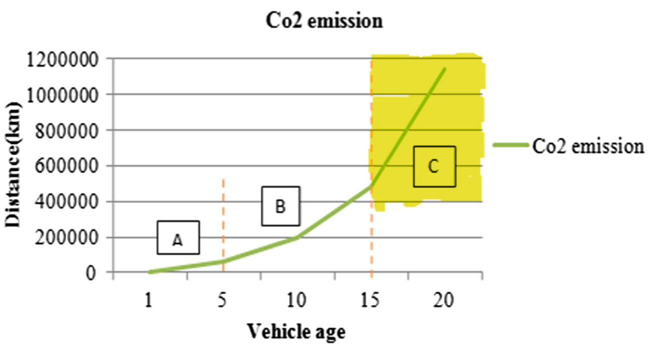


Fig. 6. Co_2 emission per distance travelled

6 Conclusion

A logistic supply network in green vehicle route problem with multi depot (G-VRPMD) is considered. A bi-objective model developed that minimizes emission of vehicles and total cost. Modified accepting criteria have been developed and performance analysis verified using instance. A comparison of modified SA with existing optimal reported results in the literature, ISA performs a better quality solution than other meta-heuristics. A 4.27% gap was found in modified SA, which is smaller than that of GC (9.834%) and GA (6.97%). Utilizing modified SA for G-VRPMD can help organization managers to design eco-friendly distribution network. Emission rate is proportional to vehicle age. Therefore in designing distribution network path vehicle aged has been given priority before route.

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