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ScienceDirect

Procedia Engineering 97 (2014) 2176 – 2185

Procedia Engineering

www.elsevier.com/locate/procedia

12th GLOBAL CONGRESS ON MANUFACTURING AND MANAGEMENT, GCMM 2014

Solving Multi-objective Vehicle Routing Problem with Time Windows by FAGA

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Abstract

The vehicle routing problem with time windows (VRPTW) is a complex transportation issue. In this paper, multi objective VRPTW is considered in which the total distance travelled, total number of vehicles used and route balance are minimized. Genetic algorithm with fitness aggregation approach and specialized operators like selection based on aggregate fitness value, best cost route crossover called Fitness Aggregated Genetic Algorithm (FAGA) is introduced for solving the multi objective problem. The algorithm was tested on large number of Solomon's benchmarks for bi-objective model that is minimization of total distance travelled and total number of vehicles used. The results produced by FAGA are highly competitive to best known results reported in the literature. After validation the third objective that is route balance is incorporated into bi-objective model and it is observed that FAGA produces better balanced routes without affecting the total distance travelled and total number of vehicles used.

Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014

Keywords: Vehicle Routing Problem with Time Windows; Vehicle Routing Problem with Route balance; Multi Objective Optimization; Genetic Algorithm; Fitness Evaluation for Multi Objectives;

1. Introduction

Transportation of raw materials and finished products is an important responsibility for manufacturing industries and huge amount of money is expended for it in present scenario. The vehicle routing problem (VRP) is a complicated transportation problem in the field of distribution, operations research and manufacturing management.

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1877-7058
Selection and peer-review under responsibility of the Organizing Committee of GCMM 2014
doi:10.1016/j.proeng.2014.12.461

Nomenclature

D	total distance travelled by all vehicles
K	total number of vehicles or routes
RB	route balance
n	number of objective functions
C	vehicle capacity
N	total number of customers
N_j	number of customers delivered in route j
d_j	distance or length of route j
d_{max}	maximum distance or length among all routes
d_{min}	minimum distance or length among all routes
t_{max}	maximum route time for vehicles
$a_{(i,j)}$	arrival time at node i in route j
$w_{(i,j)}$	waiting time at node i in route j
$s_{(i,j)}$	service time at node i in route j
$e_{(i,j)}$	ready time or lower time bound at node i in route j
$l_{(i,j)}$	due time or upper time bound at node i in route j
$q_{(i,j)}$	demand at node i in route j
$d_{(i, i+1), j}$	distance travelled by vehicle from node i to i+1 in route j
$t_{(i, i+1), j}$	travel time of vehicle from node i to i+1 in route j
Z	population size
max gen	number of generations
$F_{(1,v)}$	individual fitness of total distance travelled in solution v
$F_{(2,v)}$	individual fitness of total number of vehicles used in solution v
$F_{(3,v)}$	individual fitness of route balance in solution v
AFV	aggregate fitness value
D_{max}	maximum total distance travelled among Z solutions in a population
D_{min}	minimum total distance travelled among Z solutions in a population
K_{max}	maximum total number of vehicles used among Z solutions in a population
K_{min}	minimum total number of vehicles used among Z solutions in a population
RB_{max}	maximum route balance among Z solutions in a population
RB_{min}	minimum route balance among Z solutions in a population
P_c	crossover probability
P_m	mutation probability
σ	standard deviation

The VRP can be defined as the process of determining economical routes for vehicles to deliver the required products to each and every customer [1]. The vehicle routing problem with time windows (VRPTW) is a type of VRP, in which each customer has time windows within which the deliveries must be done. Though a lot of research has used single objective optimization for resolving this VRPTW, it has infrequently been considered on multi objective optimization front.

Ombuki et al. (2006) [5] represented VRPTW as multi objective problem by minimizing the number of vehicles and total distance travelled. Genetic algorithm (GA) with pareto ranking technique was introduced for resolving the problem. The algorithm produced set of unbiased solutions for both objectives against large number of standard benchmark instances. Jozefowiez et al. (2007, 2009) [7,8] developed a model for bi objective capacitated vehicle routing problem (CVRP), where minimization of total route length and route balance are considered. They have implemented a multi objective genetic algorithm with target aiming pareto search and multi objective evolutionary algorithm (MOEA) with Elitist diversification method to solve the problem. The result shows that the methods were quite effective as compared to other heuristics. Ghoseiri et al. (2010) [9] derived a multi objective VRPTW, in which total distance travelled and number of vehicles used are minimized. GA with Goal programming approach for problem formulation is used for solving the problem. The algorithm was tested on huge number of Solomon's benchmark instances, and the results validate the effectiveness of the algorithm. Muller (2010) [10] described multi objective VRP with soft time window where a penalty is imposed for violation of the time window. Minimization of total cost (sum of costs for distance travelled and number of vehicles used) and total penalty amount are considered as the objectives. Heuristic method was used for solving this problem; results prove that allowance of penalty scheme makes considerable reductions in total cost. Minocha et al. (2011) [11] developed a model for multi objective VRPTW, in which minimization of total distance travelled and number of vehicles used are the objectives. GA with local search heuristics (Replacing next neighbour and Reinserting random customer) was introduced to solve the problem. The results show that incorporation of local search heuristics improved the efficiency of GA. Najera et al. (2011) [12] considered minimization of total distance travelled, total delivery time and number of vehicles used for multi objective optimization of VRPTW. MOEA with similarity measurement was recommended to resolve the problem. The results display that introduction of similarity measurement improves the quality of solutions. Banos et al. (2013) [13,14] described multi objective VRPTW by considering minimization of total distance travelled and workload imbalance in terms of distance and load. They have introduced hybrid algorithm (combination of evolutionary computation and simulated annealing) and the results shows the good performance of suggested approach [13]. And implemented multiple temperature pareto simulated annealing algorithm (MT-PSA), the results show the outperformance of MT-PSA against Strength pareto evolutionary algorithm [14]. Nahum et al. (2014) [15] developed model for multi objective VRPTW, where total distance travelled and number of vehicles used are minimized. Artificial bee colony algorithm with vector evaluated approach was proposed to solve the problem. Results display that the algorithm was superior than existing heuristics methods. It is observed from the above review that multi objective optimization beyond two objectives has very rarely been considered for VRPTW due to the following reason; the determination of non dominated solutions is a hard process when number of objectives increases, because the proportion of non dominated solutions increases exponentially with the number of objectives [4]. But in real world scenario, majority of the routing problems has many objectives in nature [2]. In this paper, multi objective VRPTW is considered in which three objectives namely total distance travelled, total number of vehicles used and route balance are minimized.

2. Mathematical Formulation

In VRPTW, there are N number of customers and one central department. Each customer is geographically situated at coordinates (x, y), and has a specific demand, time window and service time. The demand at each customer should be greater than zero. Central department is denoted by the symbol 0, from which all customers are treated by homogeneous delivery vehicles. In order to formulate multi objective VRPTW the following equations are derived.

$$\mathrm{Min}\, D = \sum_{j=1}^{K} d_j \tag{1}$$

where $d_j = \sum_{i=0}^{N_j} d_{(i,\, i+1),\, j}$

$$\mathrm{Min}\, K \tag{2}$$

$$\mathrm{Min}\ RB = d_{max} - d_{min} \tag{3}$$

where $d_{max} = \max[d_j] \qquad \forall\, j = 1,2,......,K.$

where $d_{min} = \min[d_j] \qquad \forall\, j = 1,2,......,K.$

Subject to

$$\sum_{i=1}^{N_j} q_{(i,j)} \le C \qquad \forall\, j = 1,2,......,K. \tag{4}$$

$$e_{(i,j)} \le (a_{(i,j)} + w_{(i,j)}) \le l_{(i,j)} \qquad \forall\, j = 1,2,......,K. \tag{5}$$

$$\sum_{i=0}^{N_j} \left[t_{(i,\, i+1),\, j} + w_{(i,j)} + s_{(i,j)} \right] \le t_{max} \qquad \forall\, j = 1,2,......,K. \tag{6}$$

$$w_{(i,j)} = \begin{cases} 0 & \text{if } e_{(i,j)} \le a_{(i,j)} \le l_{(i,j)} \\ e_{(i,j)} - a_{(i,j)} & \text{if } a_{(i,j)} \text{ is less than } e_{(i,j)} \end{cases} \tag{7}$$

$$a_{(i,j)} = a_{(i\text{-}1,\, j)} + w_{(i\text{-}1,\, j)} + s_{(i\text{-}1,\, j)} + t_{(i\text{-}1,\, i),\, j} \tag{8}$$

$$d_{(i,\, i+1),\, j} = t_{(i,\, i+1),\, j} = \left[(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2 \right]^{\frac{1}{2}} \tag{9}$$

$$q_{(0,j)} = a_{(0,j)} = w_{(0,j)} = s_{(0,j)} = 0 \qquad \forall\, j = 1,2,......,K. \tag{10}$$

$$N_j + 1 = 0 \qquad \forall\, j = 1,2,......,K. \tag{11}$$

Eq. (1), (2) and (3) gives the three objective functions namely minimization of total distance travelled by all vehicles, total number of vehicles used and route balance respectively. The aim of this multi objective VRPTW is to determine a set of K routes without violating the following three constraints.

- Capacity constraint – summation of all customer demands in a route must not exceed the vehicle capacity as given in Eq. (4).
- Time window constraint – all the customers must be delivered within the time window as given in Eq. (5).
- Maximum route time constraint – all the vehicles must return to the central department within the upper time bound of the central department as given in Eq. (6).

Orders are strictly rejected if the vehicle reaches the customers beyond the time window. If the vehicle reaches the customers before the time window, orders are accepted but the vehicle has to wait till the ready time for the customer is reached. Waiting time of the vehicle is zero if it reaches the customers within the time window else waiting time is calculated by taking the difference between arrival time and ready time as illustrated in Eq. (7) and (8). The distance and time taken for travels between two customers are simply considered by Euclidean distances as shown in Eq. (9). The demand, arrival time, waiting time and service time at the central department is zero as represented in Eq. (10). Eq. (11) ensures each route should start and finish at the central department.

3. Proposed Methodology

GA is the most preferable approach for multi objective optimization subjects because large number of multi objective genetic algorithms like vector evaluated genetic algorithm, non-dominated sorting genetic algorithm (NSGA), NSGA II etc., have been generated in the recent years [3]. But when number of objectives increases, the convergence ability and efficiency of pareto based multi objective GA can be affected [4]. In this paper, GA with fitness aggregation approach and specialized genetic operators called fitness aggregated genetic algorithm (FAGA) is introduced to solve the multi objective problem. The FAGA involves three main modules namely initialization, fitness aggregation and GA operators. The following sections explain each module in detail.

3.1. Initialization module

In this module initial population is created and GA parameters like population size, number of generations, crossover probability and mutation probability are assigned. Initially the population is generated by selecting a random customer to be the first customer on the first route. In an iterative process customers are added to first route without violating all the constraints. New routes are created if a constraint is violated by a customer when placed in any of the previous routes. This procedure is repeated till all customers in a problem are assigned to routes. The entire procedure is repeated until Z numbers of solutions are created in the initial population.

3.2. Fitness aggregation module

The aim of this module is to evaluate fitness function value for multiple objectives. This method eliminates the problems associated with the selection of weight vectors for multi objectives in the weighted sum approach. Hence the confusions and distractions for decision makers while deriving weight vectors for multi objectives are avoided. Initially the objective values namely total distance travelled by all vehicles, total number of vehicles used and route balance for all solutions in a population is calculated by Eq. (12).

$$F_{(1,v)} = \frac{D_{max} - D_v}{D_{max} - D_{min}} ; \quad F_{(2,v)} = \frac{K_{max} - K_v}{K_{max} - K_{min}} ; \quad F_{(3,v)} = \frac{RB_{max} - RB_v}{RB_{max} - RB_{min}} \qquad \begin{cases} \forall\, v = 1,2,\ldots\ldots,Z. \\ \forall\, v = 1,2,\ldots\ldots,\text{max gen.} \end{cases} \tag{12}$$

$$AFV_v = \frac{\sum_{u=1}^{n} F_{(u,\, v)}}{n} \qquad \begin{cases} \forall\, v = 1,2,\ldots\ldots,Z. \\ \forall\, v = 1,2,\ldots\ldots,\text{max gen.} \end{cases} \tag{13}$$

Then the aggregate fitness value (AFV) for each solution in the population is determined by Eq. (13). Since it is a minimization problem a solution with high AFV is the best solution in the population is shown in Table 1. At the end of each generation a best solution is identified by fitness aggregation approach and saved as the overall best individual during the generation. Finally at the completion of required number of generations, the same fitness aggregation approach is applied to all the best solutions across the generations, the solution with highest AFV is the ultimate best solution for the problem.

3.3. GA operators module

This module encompasses three operators namely selection based on AFV, best cost route crossover and swap mutation. The aim of the first operator is to select or reproduce best solutions (solutions with high AFV) for next stage and to extremely reduce the reproduction of solutions with low AFV. Table 1 shows the example for selection procedure. The solution No.2 in Table 1 has high AFV and which is selected for four times is shown in bold. Overall, out of ten selected solutions eight solutions have high AFV.

Table 1. Example for selection procedure.

Solution No.	D	K	RB	$F_{(1,v)}$	$F_{(2,v)}$	$F_{(3,v)}$	AFV	Probability	Cumulative Probability	Random numbers	Selected Solution for Crossover
1	512	5	0.88	0.828	0.5	0.381	0.569	0.116	0.116	0.253	**2 – best fit**
2	518	4	0.79	0.621	1	0.595	$\boxed{0.739}$	0.151	0.267	0.499	4 – best fit
3	522	6	0.64	0.483	0	0.952	0.478	0.098	0.365	0.632	7
4	507	5	0.81	1	0.5	0.548	0.683	0.139	0.504	0.301	**2 – best fit**
5	531	5	1.02	0.172	0.5	0.048	0.24	0.049	0.553	0.082	1 – best fit
6	525	6	0.97	0.379	0	0.167	0.182	0.037	0.59	0.568	5
7	536	5	0.80	0	0.5	0.571	0.357	0.073	0.663	0.199	**2 – best fit**
8	511	4	1.04	0.862	1	0	0.621	0.127	0.79	0.822	8 – best fit
9	529	5	0.62	0.241	0.5	1	0.58	0.118	0.908	0.931	9 – best fit
10	530	5	0.77	0.207	0.5	0.643	0.45	0.092	1	0.212	**2 – best fit**
						Total	4.899	1			

Ghoseiri and Ghannadpour [9] stated that standard crossover operators like one-point crossover, two-point ordered crossover, uniform ordered crossover etc, may produce infeasible solutions for VRPTW. Due to the above reason a specialized genetic operator called best cost route crossover (BCRC) is employed in this paper. The main advantage of the BCRC is its capability to simultaneously minimize the total distance travelled by all vehicles and total number of vehicles used as shown in Fig.1. The BCRC is applied with a crossover probability of P_c. The procedure of BCRC contains the following steps. First couple of solutions is selected from the population and they are called as parents.

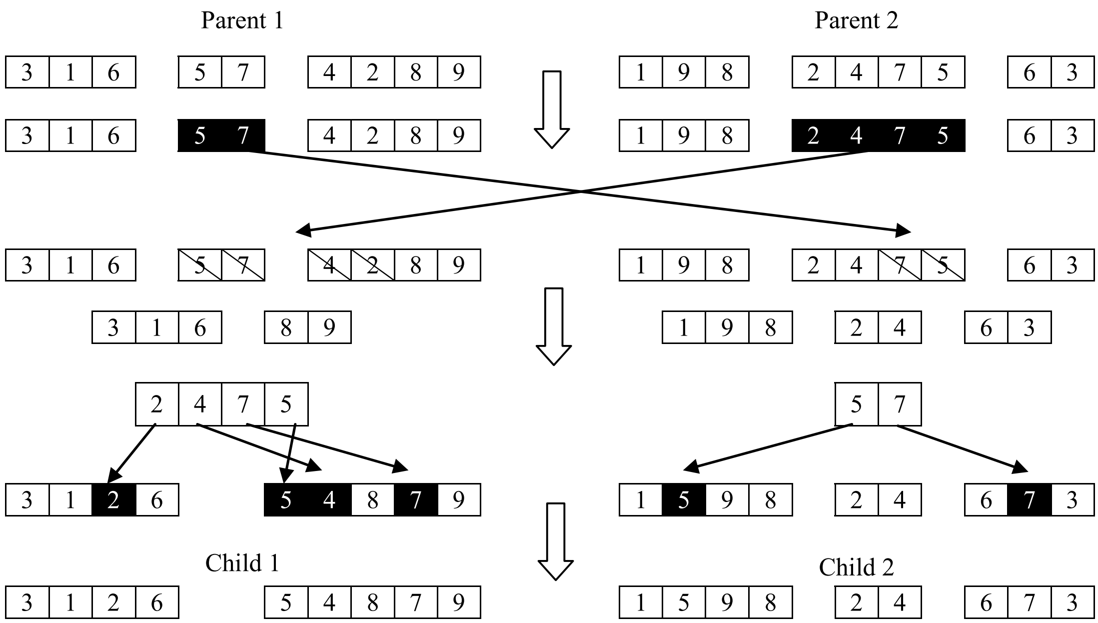

Fig. 1. Example for BCRC procedure.

Then a random route is selected from both the parents. All the customers from the chosen route of the first parent are deleted from second parent and vice versa. Finally the BCRC replaces each removed customers in the same parent in best cost (total distance) and route (number of vehicles) position without violating all the constraints. The last operator in this module is swap mutation (SM). It is applied with a mutation probability of P_m. In SM, single solution is selected from the population and one customer each from any two routes is randomly chosen and their location is exchanged without violating all the constraints. Thereafter, any customer from any route of the same solution is selected randomly and it is removed from its original location and reinserted into rest of any one route without violating all the constraints.

4. Computational Results

The statistical analysis is carried out to study the performance of the multi objective genetic algorithm FAGA. The algorithm was coded in MATLAB and run on a PC with 2.93GHz CPU and 3GB RAM. The experiments use the standard Solomon's benchmark problem instances for VRPTW. The problems vary with geographical locations of customers, demands at each customers, vehicle capacity, time windows and service times for different test cases. The parameters used for experimental analysis are given below:

$Z=50$, max gen=500, $N=25$, $P_c=0.9$, $P_m=0.2$

Table 2. Results produced by FAGA for bi-objective model.

Problem No.	BK			Results produced by FAGA (Number of runs = 10)						
				Best		Worst		Mean		σ
	D	K	Ref	D	K	D	K	D	K	D
C101	191.81	3	[6]	191.81	3	217.33	3	194.37	3	8.07
C105	191.81	3	[6]	191.81	3	193.04	3	192.18	3	0.59
C106	191.81	3	[6]	191.81	3	217.33	3	194.37	3	8.07
C107	191.81	3	[6]	191.81	3	236.66	3	204.05	3	19.76
C108	191.81	3	[6]	194.40	3	233.87	3	203.58	3	11.45
R101	617.10	8	[11]	629.95	8	659.65	8	646.43	8	9.90
R102	547.10	7	[11]	571.29	7	588.94	7	579.04	7	6.91
R104	417.96	4	[6]	438.99	4	461.84	4	450.10	4	9.39
R105	530.50	6	[11]	543.56	6	593.24	6	574.84	6	16.47
R106	466.48	5	[6]	472.19	5	510.19	5	486.99	5	12.24
R107	425.27	4	[6]	429.20	4	470.20	4	446.97	4	12.68
R108	398.30	4	[6]	427.59	4	445.67	4	435.50	4	6.26
RC101	462.16	4	[6]	478.52	4	485.49	4	482.60	4	2.59
RC102	352.74	3	[6]	356.44	3	362.69	3	359.21	3	2.34
RC103	333.92	3	[6]	333.92	3	338.52	3	335.37	3	1.61
RC104	307.14	3	[6]	307.14	3	329.62	3	311.87	3	6.45
RC105	411.30	4	[11]	420.50	4	433.26	4	426.73	4	4.74
RC106	345.50	3	[11]	353.52	3	362.24	3	358.54	3	2.91
RC107	298.95	3	[6]	302.24	3	322.72	3	316.64	3	6.08
RC108	294.99	3	[6]	300.93	3	312.96	3	309.26	3	3.79

Table 2 presents a summary of results produced by FAGA with first two objective functions i.e. total distance travelled and total number of vehicles used for several Solomon's benchmark problems of VRPTW and compare the findings with the best known solutions (BK). The experiments use twenty benchmark problems taken differently from clustered sets (C sets, geographical data are clustered), randomly generated sets (R sets, geographical data are randomly created) and combination of randomly generated and clustered sets (RC sets). It is observed from Table 2 that out of five C set problems, the proposed FAGA produce four problems with exactly same results for both objectives as compared to BK. And out of eight RC set problems, the algorithm produce two problems with exactly same results and five problems with approximately close results to BK. In R sets the FAGA produce very close results for three problems out of seven. Totally out of twenty problems, the proposed algorithm produces fourteen problems with competitive results for both objectives as compared to BK. The minimum range (difference between best value and worst value) for the first objective produced by FAGA is 1.2279. Out of twenty problems, the algorithm produces five problems with the range less than ten for first objective. Based on the standard deviation (σ), the FAGA produce seven problems with σ less than five for first objective and fifteen problems with σ less than ten. The range and σ for second objective is zero for all problems which means the proposed algorithm produce exactly same results for second objective for all problems and in all test runs. From the above comparisons, it is observed that the proposed FAGA is highly competitive and effective one for multi objective optimization field.

Table 3. Results produced by FAGA for Tri-objective model.

Problem No.	Best results produced by FAGA based on high AFV in 10 runs						Average results produced by FAGA in 10 runs					
	Bi-objective model			Tri-objective model			Bi-objective model			Tri-objective model		
	D	K	Associated RB	D	K	RB	D	K	Associated RB	D	K	RB
C101	191.81	3	59.44	265.46	3	12.35	194.37	3	57.81	251.23	3	24.90
C105	191.81	3	59.44	273.84	3	3.96	192.18	3	59.44	267.38	3	11.70
C106	191.81	3	59.44	253.09	3	16.81	194.37	3	57.81	249.49	3	25.83
C107	191.81	3	59.44	273.61	3	10.60	204.05	3	52.46	274.70	3	17.23
C108	194.40	3	58.09	286.59	3	7.47	203.58	3	62.27	262.96	3	19.86
R101	629.95	8	107.12	666.28	8	35.87	646.43	8	74.68	694.34	8.5	38.80
R102	571.29	7	72.76	617.02	7	31.28	579.04	7	93.66	623.05	7	39.95
R104	438.99	4	40.76	446.26	4	19.49	450.10	4	46.79	484.87	4	19.38
R105	543.56	6	58.49	608.87	6	32.47	574.84	6	84.44	625.42	6.4	37.87
R106	472.19	5	84.11	502.29	5	33.64	486.99	5	85.74	506.22	5	33.71
R107	429.20	4	56.57	464.39	4	3.68	446.97	4	64.74	465.38	4	5.36
R108	427.59	4	44.36	432.66	4	12.14	435.50	4	61.28	474.28	4	11.67
RC101	478.52	4	14.55	494.77	4	8.95	482.60	4	19.81	496.11	4.5	16.93
RC102	356.44	3	26.09	374.28	3	8.25	359.21	3	30.41	379.92	3	6.43
RC103	333.92	3	18.80	358.56	3	1.07	335.37	3	19.90	354.13	3	3.66
RC104	307.14	3	13.49	332.12	3	0.19	311.87	3	14.19	328.75	3	2.59
RC105	420.50	4	58.87	450.97	4	26.52	426.73	4	59.06	456.96	4	22.64
RC106	353.52	3	10.39	360.90	3	2.69	358.54	3	10.74	365.24	3	5.07
RC107	302.24	3	8.47	320.44	3	1.51	316.64	3	7.55	324.29	3	2.26
RC108	300.93	3	3.21	316.78	3	0.14	309.26	3	5.29	317.34	3	2.03

After the validation of proposed algorithm the third objective function i.e. route balance is incorporated into bi-objective model and Table 3 presents summary of best and average results produced by FAGA for tri-objective model and compares the results produced with results of bi-objective model. The same values for parameters like Z, max gen, etc., are used for tri-objective optimization also. It is observed from Table 3 that out of twenty problems the FAGA produce solutions with great reduction in route balance as compared to associated route balance determined in bi-objective model without affecting the second objective i.e. total number of vehicles used for all the problems. Similarly, in average results produced by FAGA, seventeen problems produce better balanced solutions without affecting the number of vehicles. The results prove that inclusion of third objective does not affect the performance of the proposed algorithm in identifying the optimal total number of vehicles

Table 4. Percentage deviations in results produced by FAGA for Tri-objective model as compared to Bi-objective model.

Problem No.	Best Results			Average Results			Problem No.	Best Results			Average Results		
	D ↑	K ↑	RB ↓	D ↑	K ↑	RB ↓		D ↑	K ↑	RB ↓	D ↑	K ↑	RB ↓
C101	38.39	0	79.22	29.26	0	56.93	R107	**8.20**	**0**	**93.49**	4.12	0	91.72
C105	42.77	0	93.34	39.13	0	80.32	R108	**1.19**	**0**	**72.63**	8.90	0	80.96
C106	31.95	0	71.72	28.36	0	55.32	RC101	**3.40**	**0**	**38.49**	2.80	12.5	14.54
C107	42.64	0	82.17	34.63	0	67.16	RC102	**5.01**	**0**	**68.38**	5.77	0	78.86
C108	47.43	0	87.14	29.17	0	68.11	RC103	**7.38**	**0**	**94.31**	5.60	0	81.61
R101	**5.77**	**0**	**66.51**	7.41	6.25	48.04	RC104	**8.13**	**0**	**98.59**	5.41	0	81.75
R102	**8.00**	**0**	**57.01**	7.60	0	57.35	RC105	**7.25**	**0**	**54.95**	7.08	0	61.67
R104	**1.66**	**0**	**52.18**	7.73	0	58.58	RC106	**2.09**	**0**	**74.11**	1.87	0	52.79
R105	12.02	0	44.49	8.80	6.67	55.15	RC107	**6.02**	**0**	**82.17**	2.42	0	70.07
R106	**6.37**	**0**	**60.00**	3.95	0	60.68	RC108	**5.27**	**0**	**95.64**	2.61	0	61.63

The next analysis is based on the effect of the introduction of third objective on first objective i.e. total distance travelled. It is clear from Table 4 that large percentage of reduction in route balance leads to very small amount of increment in total distance travelled. It is observed from Table 4 that out of twenty problems four problems have less than five percent increment in total distance with great reduction in route balance shown by rectangular box representation and four problems with almost equal to hundred percent reduction in route balance with less than ten percent increment in total distance shown by shaded box representation. Overall, fourteen problems show minimal increase in objective one when route balance is introduced shown in bold. The above experimental analysis proves that the proposed algorithm is able to determine better balanced routes for VRPTW without affecting the optimal total distance travelled and total number of vehicles used.

5. Conclusions

This paper considered multi objective VRPTW in which total distance travelled by all vehicles, total number of vehicles used and route balance are considered. Genetic algorithm with fitness aggregation approach and specialized operators called fitness aggregated genetic algorithm is introduced to solve the multi objective VRPTW. The proposed algorithm was initially formulated as bi-objective model i.e. total distance and total number of vehicles. The proposed algorithm was validated with the help of standard Solomon's benchmark problems and best known results reported in the literature for bi-objectives. After validation the third objective i.e. route balance is incorporated into bi-objective model and the proposed algorithm determines better balanced routes without affecting the total distance travelled and number of vehicles used.

Acknowledgement

The authors would like to thank the management of K.L.N. College of Engineering for providing necessary facilities and resources to accomplish this research work.

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