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Research Article

Integrated mutation strategies in a biologically inspired algorithm to solve the vehicle routing problem with moving shipments at the cross-docking centre

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Abstract

This study is an extended version of previously developed model for the Vehicle Routing Problem with Moving Shipments at the Cross-Docking Centre (VRPCD-MS). In the earlier study, some internal operations at the cross-docking centre were integrated and only the small-scale instances were used to obtain the exact-optimal solution. Nevertheless, in this study a biologically inspired approach to reach near-optimal solution to the large-scale instances of VRPCD-MS is proposed. Therefore, Genetic Algorithm (GA) with integrated-mutation strategies ‘SWAP’ and ‘REVERSION’ to solve VRPCD-MS is employed in the current study. The ‘SWAP’ mutation strategy was already applied in the literature of VRPCD-MS and the current solutions by ‘REVERSION’ mutation strategy is compared with it. When the GA with SWAP, and GA with REVERSION mutation strategies are applied separately, the solutions of the benchmark problems reveal that there is no strong evidence to recommend any of those two approaches is better than the other. The two-sample t-test also confirms the similar result that, there is no significant difference in solutions by applying these two mutation strategies alone. The numerical experiments conclude that, up to 30% improvement in the solution can be achieved by the integrated mutation strategies in the proposed biologically inspired approach which is nearly 15% on average.

Keywords: Cross-docking, Genetic Algorithm, REVERSION mutation, SWAP mutation

1. Introduction

The background of the research with the past studies and the description of the problem under investigation are presented in this section.

1.1. Background

The Vehicle Routing Problem is one of the well-studied optimization problems in the field of Operations Research. It is an extended version of the Travelling Salesman Problem. In 1959, Dantzig and Ramser introduced the vehicle routing problem [1] and thereafter it got more attention among the researchers. The capacitated vehicle routing problem is one of the variants of vehicle routing problems [2]. Moreover, the Cross-Docking is an innovative logistic technique in a supply chain and it has created a significant attention among the practitioners. A transhipment centre in a transportation network of a supply chain that uses cross-docking is called the Cross-Docking Centre (CDC). Therefore, CDC not only collects shipments from the suppliers but also dispatches them to the customers. Vehicle routing problem is an operational level decision problem in the cross-docking technique. Before 1980s, a lot of research on Vehicle Routing Problem and Cross-Docking were conducted sequentially. However, only Lee et al. (2006) initiated the integrated study on Vehicle Routing Problem with Cross-Docking (VRPCD) [3]. Thereafter, it became a well celebrated field among the researchers as well as the practitioners.

In the first integrated study [3], mainly two conditions: (I) two separate fleets of vehicles, one for each pickup and delivery processes and (II) the inbound vehicles arrive the CDC simultaneously; were assumed. A few variants of vehicle routing problem by incorporating different characteristics with the study [3] were developed in the literature of VRPCD. The open network configuration, the heterogeneity in vehicle capacities, multi-commodities, some environmental factors, multi-sources and split shipments were considered in the studies [4-9]. Moreover, in the past various methods of solution were employed to the model developed in [3]. For instance, Simulated Annealing [9-10], Adaptive Memory Artificial Bee Colony [5], Tabu Search algorithm [11], Hybrid method [12], Matheuristic algorithm [13], Adaptive Large Neighbourhood Search [14] to name a few.

In the study [15], on the one hand, two main conditions (I and II) assumed in [3] were relaxed. On the other hand, the dependency rule and consolidation decision were introduced to generalize the VRPCD. Additional characteristics to the study [15] such as split shipments, correspondence between many suppliers to one customer, profit maximization, customer satisfaction, correspondence between many suppliers to many customers, heterogeneity in vehicle capacities, time windows and simultaneous arrivals of inbound vehicles to CDC were included in the studies [16-21]. Furthermore, diverse methods to solve the model developed in [15] were applied in the literature of VRPCD and for instance: Branch & Price algorithms [22-23], Column Generation [24], Hybrid Algorithms [16,18], Constructive Heuristics [17,25], Meta-Heuristic [19], Matheuristic [26] can be referred.

1.2. Research problem

A literature survey [27] on Cross-Docking recommends considering the internal operations at the CDC to develop the models for the VRPCD. Consequently, some of the internal operations taken place inside the CDC to model the VRPCD with Moving Shipments (VRPCD-MS) were considered in the study [28]. However, only the small-scale instances of the VRPCD-MS were used to obtain the exact-optimal solution. The purpose of using small-scale instances was to validate the developed mathematical model for the VRPCD-MS. Since Vehicle Routing Problem is classified as a NP-hard problem [29], it was mentioned in the study [28] that VRPCD-MS is also a NP-hard problem. Therefore, it was recommended to apply a suitable meta-heuristic approach to reach near-optimal solutions to the large-scale instances of VRPCD-MS. Consequently, a population based meta-heuristic method based on Genetic Algorithm to solve the VRPCD-MS was applied in [30]. In this recent study [30], only the 'SWAP' mutation method was applied to the structure of the algorithm. Nevertheless, in the current study, the 'REVERSION' mutation method is employed and the solutions are compared with the results obtained in the existing study [30]. Only two approaches were found in the literature to solve the VRPCD-MS; the Branch and Bound algorithm, which is an exact method, in the study [28] and, Genetic Algorithm, which is a meta-heuristic method, in the study [30].

This study attempts to employ a biologically inspired meta-heuristic method based on Genetic Algorithm with multiple mutation strategies to solve the VRPCD-MS. The genetic operators of a Genetic Algorithm have to be decided when the structure of the algorithm is designed. Mutation is one of the genetic operators of a common Genetic Algorithm and it has a few different strategies to be chosen. In this study, two mutation strategies 'SWAP' mutation and 'REVERSION' mutation are taken into consideration of the proposed Genetic Algorithm (GA). Initially, these two mutation strategies are incorporated into the method as two separate algorithms to solve the large-scale instances of the VRPCD-MS. Subsequently, those two mutation strategies are integrated into a single algorithm to solve the VRPCD-MS. Consequently, three Genetic Algorithms; GA with 'SWAP' mutation strategy, GA with 'REVERSION' mutation strategy and GA with merged mutation strategy are employed. Therefore, the objective of this study is to apply Genetic Algorithm with two different mutation strategies and to recommend a better mutation strategy after comparing the quality of the solution to the VRPCD-MS.

2. Material and Methods

The similar characteristics in the previous study [28] are assumed in this study as well. Consequently, model considered in this study is a simplified version of the model developed in the previous study [28] for the VRPCD-MS by relaxing the time-related constraints. However, all the cost-related constraints are included and the relevant cost components of the Total Transportation Cost taken into account in the respective process are mentioned as follows:

In the pickup process: Travelling cost between suppliers including CDC, loading cost at suppliers which includes preparation to load the shipments and inbound vehicles operations cost.

In the consolidation process: Unloading cost at the receiving doors at the CDC, cost of moving shipments from receiving doors to the shipping doors of the CDC and re-loading cost at the shipping doors at the CDC.

In the delivery process: Travelling cost between customers including the CDC, unloading cost at the customers which includes preparation to unload the shipments and outbound vehicles' operations cost.

Subsequently, the model for the study in hand is formulated as described in the section 2.1.

2.1 Mathematical Model for the VRPCD-MS

A single-objective Mixed Integer Linear Programming model is formulated in order to minimize the Total Transportation Cost of the VRPCD-MS.

2.1.1 Notations

i, j : Indices for suppliers and customers

h : Index for receiving or shipping doors of CDC

k : Index for inbound or outbound vehicles

$S = \{S_1, S_2, ..., S_n\}$: Set of n suppliers

$C = \{C_1, C_2, ..., C_{n'}\}$: Set of n' customers

$N = S \cup C$: Set of $(n+n')$ suppliers and customers

$V_S = \{v_1^S, v_2^S, ..., v_m^S\}$: Set of m inbound vehicles used for pickup process

$V_C = \{v_1^C, v_2^C, ..., v_{m'}^C\}$: Set of m' outbound vehicles used for delivery process

$V = V_S \cup V_C$: Set of $(m+m')$ inbound and outbound vehicles

$O = \{o, o'\}$: Set of receiving (o) and shipping (o') doors of CDC

tc_{ij} : Travelling cost between suppliers (or customers) i and j
q_i : Supply of supplier (or demand of customer) i
Q_S : Inbound vehicle capacity
Q_C : Outbound vehicle capacity
OC_S^k : Operations cost of the inbound vehicle k
OC_C^k : Operations cost of the outbound vehicle k
SC_i^k : Service cost at supplier (or customer) by vehicle k
SC_h^k : Service cost at receiving (or shipping) door h by vehicle k
A_c : Fixed preparation cost for loading (or unloading) products
B_c : Variable shipping cost for loading (or unloading) a unit of product

$$x_{ij}^k = \begin{cases} 1, & \text{if vehicle } k \text{ travels from supplier (or customer)} \\ & i \text{ to supplier (or customer) } j \\ 0, & \text{otherwise} \end{cases}$$

2.1.2 Constraints of the VRPCD-MS

The set of constraints [from Eq. (1) to Eq. (9)] that relevant to routing the vehicles in both pickup and delivery processes with explanations are reported as follows:

Initially any inbound (or outbound) vehicle should leave from CDC to suppliers (or customers):

$$\sum_{j\in N} x_{hj}^k \le 1 \qquad \forall k \in V,\ \forall h \in O \tag{1}$$

Ultimately all the inbound (or outbound) vehicles should arrive from suppliers (or customers):

$$\sum_{i\in N} x_{ih}^k \le 1 \qquad \forall k \in V,\ \forall h \in O \tag{2}$$

Only a single vehicle has to satisfy the supply of a supplier:

$$\sum_{i\in N\cup O}\sum_{k\in V} x_{ij}^k = 1 \qquad \forall j \in N \tag{3}$$

Only a single vehicle has to satisfy the demand of a customer:

$$\sum_{j\in N\cup O}\sum_{k\in V} x_{ij}^k = 1 \qquad \forall i \in N \tag{4}$$

Repetitive routes should be prevented:

$$x_{ii}^k = 0 \qquad \forall i \in N\cup O,\quad \forall k \in V \tag{5}$$

Backward movements in routes should be prevented:

$$x_{ij}^k + x_{ji}^k \le 1 \quad \forall i,\ j \in N\cup O,\ \forall k \in V \tag{6}$$

Total supply in the pickup process and total demand in the delivery process are the same:

$$\sum_{i\in S} q_i = \sum_{i\in C} q_i \tag{7}$$

Accumulated supply cannot exceed the capacity of the one set of homogeneous inbound vehicles:

$$\sum_{\substack{i\in S\\ j\in S\cup\{o\}}} q_i x_{ij}^k \le Q_S \qquad \forall k \in V_S \tag{8}$$

Accumulated demand cannot exceed the capacity of the another set of homogeneous outbound vehicles:

$$\sum_{\substack{i\in C\\ j\in C\cup\{o'\}}} q_i x_{ij}^k \le Q_C \qquad \forall k \in V_C \tag{9}$$

2.1.3 The components of the Total Transportation Cost

In order to determine the Total Transportation Cost, the following components [from Eq. (10) to Eq. (15)] should be obtained while satisfying all the constraints presented in the sub-section 2.1.2 above:

Travelling Cost (*TC*) at the pickup and delivery processes:

$$TC = \sum_{k\in V}\sum_{i,\,j\in N\cup O} tc_{ij} x_{ij}^k \tag{10}$$

Service Cost (*SC*) at the suppliers or customers places:

$$SC = \sum_{k\in V}\sum_{\substack{i\in N\cup O\\ j\in N}} SC_j^k x_{ij}^k, \qquad \text{where}$$

$$SC_j^k = A_c + B_c\, q_j x_{ij}^k \quad \forall i \in N\cup O,\ \forall j \in N,\ \forall k \in V \tag{11}$$

Unloading Cost (*UC*) at the receiving doors of CDC:

$$UC = \sum_{k\in V_S}\sum_{i\in N} SC_o^k x_{io}^k, \qquad \text{where}$$

$$SC_o^k = A_c + B_c \sum_{\substack{i\in N\\ j\in N\cup\{o\}}} q_i x_{ij}^k \qquad \forall k \in V_S \tag{12}$$

Loading Cost (*LC*) at the shipping doors of CDC:

$$LC = \sum_{k\in V_C}\sum_{i\in N} SC_{o'}^k x_{o'i}^k, \qquad \text{where}$$

$$SC_{o'}^k = A_c + B_c \sum_{\substack{i\in N\\ j\in N\cup\{o'\}}} q_i x_{ij}^k \qquad \forall k \in V_C \tag{13}$$

Moving shipments Cost (*MC*) internally at CDC:

$$MC = \sum_{k\in V_S}\sum_{\substack{i\in S\\ j\in S\cup\{o\}}} q_i x_{ij}^k \tag{14}$$

Operations Cost (*OC*) of number of inbound and outbound vehicles:

$$OC = \sum_{k\in V_S}\sum_{i\in S} OC_S^k x_{io}^k + \sum_{k\in V_C}\sum_{j\in C} OC_C^k x_{o'j}^k \tag{15}$$

After formulating the aforementioned components of the Total Transportation Cost (*TTC*), the objective function [in Eq. (16)] of the formulated model can be expressed as follows:

$$Minimizing\ TTC = TC + SC + UC + LC + MC + OC \tag{16}$$

2.2 Genetic Algorithm to solve the VRPCD-MS

Genetic Algorithm which belongs to the family of Evolutionary Algorithms is inspired by the natural selection and genetics. From this meta-heuristic process of Genetic Algorithm, high-quality solutions can be expected for optimization problems. Genetic Algorithm was initially proposed by John Holland in 1975 with the concept of survival of the fittest from Darwinian revolution [31]. Then in 1989, it was popularized by Goldberg [32].

The general structure of a Genetic Algorithm contains the genetic operators such as selection operator, crossover operator and mutation operator. In this study, two different strategies on mutation operator are applied sequentially as well as a combined operator. Also any Genetic Algorithm has population size, number of generations, termination count, crossover rate, mutation rate and elitism rate as its parameters. The following procedure depicts the structure of the proposed Genetic Algorithm with chosen genetic operators to solve VRPCD-MS:

2.2.1 Structure of the proposed Genetic Algorithm

Step 1: Generating *random* initial population.
Step 2: Evaluating *initial population* generated in step 1.
Step 3: Selecting chromosomes (parents) by *tournament* method.
Step 4: Creating offspring (children) by applying *order-crossover* method.
Step 5: Employing *swap-mutation* method to make offspring within the search-space.
Step 6: Employing *reversion-mutation* method to make new offspring within the search-space.
Step 7: Choosing the best chromosomes from the previous generation by *elitism method*.
Step 8: Setting new population by performing steps 3 to 7.
Step 9: Evaluating giant chromosome of *new population* set in step 8.
Step 10: Going to step 12, if sufficient *number of generations* met, otherwise repeat steps 1 to 9.
Step 11: Going to step 12, if it satisfies *termination count*, otherwise repeat step 10.
Step 12: Receiving the *best giant chromosome* with minimized cost.
Step 13: Identifying *routes* from the results of step 12.
Step 14: Calculating the *components of costs* and *run time* by performing all 14 steps and terminating.

The step-by-step procedure described in the sub-section 2.2.1 is designed as a self-explanatorily flowchart in the Figure 1. It must be emphasized that, initially the parameters of the proposed Genetic Algorithm are tuned by following the Taguchi's method of parameter estimation presented in the study [33].

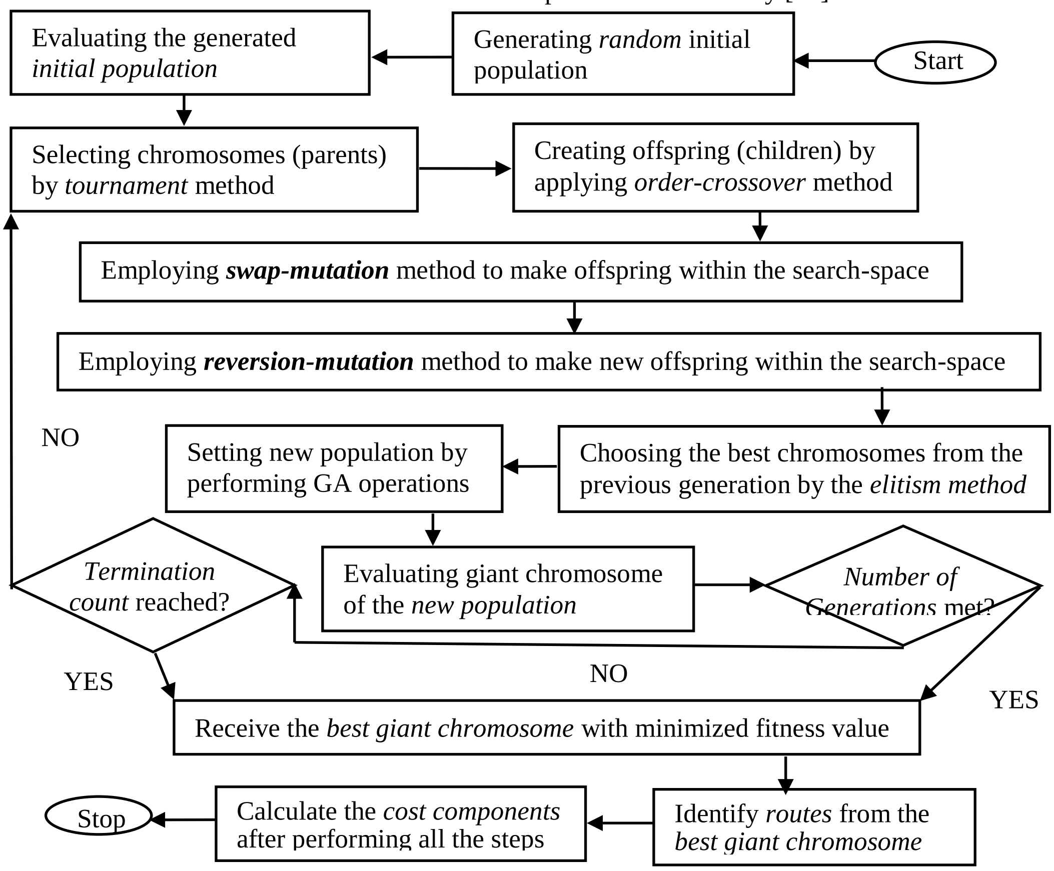

Fig. 1. Flowchart of the proposed Genetic Algorithm

2.2.2 Taguchi's method of parameter estimation

Based on the parameter design scheme introduced by Dr. Taguchi in early 1960s, a method to tune the parameters of Genetic Algorithm were proposed in the study [33]. A similar method to configure the parameters of the proposed Genetic Algorithm is followed in this study as well. Accordingly, the solutions of the model $\left(y_l\text{'}s\right)$ of quality characteristics obtained through the experiments are transformed into signal/noise:

$$S/N\ ratio = -10\log\left(\frac{1}{r}\sum_{l=1}^{r} y_l^2\right),$$ where r is the number of observations. (17)

Then based on the highest average value of *S/N* ratios [in Eq. (17)], the best combination of control factors is selected.

2.2.3 Mutation Operator

Generally to search a nearest solution in the space, the mutation operator is used by selecting a random chromosome from the current generation of the population to the next generation as an offspring. In this study, for mutation operator, 'SWAP' strategy and 'REVERSION' strategy are respectively employed at step 5 and step 6. The details about those strategies are as follows:

2.2.3.1 SWAP Mutation Strategy: Two positions in a chromosome are chosen randomly. The genes of chosen positions in the current chromosome are *exchanged* their positions in the new chromosome. The SWAP mutation strategy is illustrated in the Figure 2 given below (The changes before and after the mutation are highlighted in bold and italic):

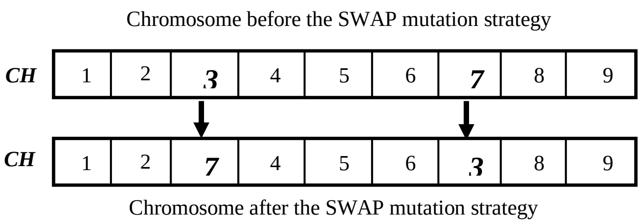

Fig. 2. SWAP mutation strategy to a chromosome

2.2.3.2 REVERSION Mutation Strategy: Two positions in a chromosome are chosen randomly. The genes between those two chosen positions are *reversed* in order in the new chromosome. The REVERSION mutation strategy is illustrated in the Figure 3 given below (The changes before and after the mutation are highlighted in bold and italic):

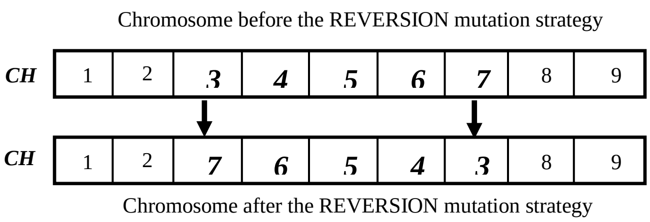

Fig. 3. REVERSION mutation strategy to a chromosome

2.3 Statistical Tests

In this study, for convenience, the Genetic Algorithm with SWAP mutation strategy and Genetic Algorithm with REVERSION mutation strategy are denoted by GA_S and GA_R respectively. To compare the results obtained by both approaches, they are tested using some suitable statistical tests which are reported as follows:

2.3.1 Analysis of Variance (ANOVA)

ANOVA is employed to determine the most influential parameters of the Genetic Algorithm which have significant impact on the robustness of the Genetic Algorithm to solve the VRPCD-MS.

2.3.2 F-test for Equality of Two Variances

The F-test is applied to test whether the variances of solutions between the two approaches, GA_S and GA_R, are equal or not. In view of that, the null-hypothesis $H_0:\sigma^2_{Approach1}=\sigma^2_{Approach2}$ against the alternative hypothesis $H_1:\sigma^2_{Approach1}\neq\sigma^2_{Approach2}$ are taken into consideration.

2.3.3 Two-sample t-test for Equal Variances

The t-test is applied to test whether the average solutions by GA_S and GA_R are equal or not. Accordingly, the null-hypothesis $H_0:\mu_{Approach1}=\mu_{Approach2}$ against the alternative hypothesis $H_1:\mu_{Approach1}\neq\mu_{Approach2}$ are stated.

2.3.4 Relative Percentage Deviation (RPD)

The performances of the results of any of the two approaches are compared using the following formula [in Eq. (18)] for the Relative Percentage Deviation (RPD):

$$RPD=\frac{\left(Solution\ by\ Approach1-Solution\ by\ Approach2\right)}{Solution\ by\ Approach2}\times 100 \quad (18)$$

3. Results and Discussion

The instances for the numerical experiments in this study are extracted from the benchmark problem [15] in the literature of the Vehicle Routing Problem with Cross-Docking. The proposed Genetic Algorithm is programmed in MATLAB (R2013a) platform and the programs are run on Intel Core i5 with 2.30 GHz CPU and 4 GB RAM.

3.1 Parameters of the proposed Genetic Algorithm

The travelling cost (tc_{ij}) between suppliers (or customers), the supply (q_i) at each supplier and demand (q_i) at each customer are determined from the data available in the study [15]. The values of the rest of the parameters in the instances are assigned randomly and are summarized in the Table 1 given below:

Table 1
Parameter values in the instances of VRPCD-MS.

Notation	Description	Value
Q_S	Capacity of an inbound vehicle	60 units
Q_C	Capacity of an outbound vehicle	40 units
A_c	Fixed preparation cost for loading (or unloading) products	10 units
B_c	Variable shipping cost for loading (or unloading) a unit of product	1 unit
OC_S^k	Operations cost of an inbound vehicle	150 units
OC_C^k	Operations cost of an outbound vehicle	100 units

To apply the Taguchi's method, the following parameters with their levels of the proposed Genetic Algorithm are summarized in the Table 2 given below:

Table 2
Levels of the parameters of the Genetic Algorithm.

Parameters	Levels		
	1	2	3
Population size	100	150	200
Number of generations	150	200	250
Termination count	50	100	150
Crossover rate	0.7	0.8	0.9
Mutation rate	0.1	0.2	0.3

Table 2 shows the three-levels in each of the parameters of the Genetic Algorithm. If the full factorial design is considered, it requires 3^5=243 experiments for the Genetic Algorithm. However, this kind of experimental design is not economical especially in terms of time. Therefore, the method like Taguchi's parameter estimation scheme is more appropriate and chosen in this study. The averages of *S/N* ratios of each level of every parameter are plotted in the Figure 4. In each parameter of the Genetic Algorithm, the average of *S/N* ratios of each of the three levels are calculated separately and plotted in the Figure 4. The highest average value of *S/N* ratio is selected as the best estimate for the parameter.

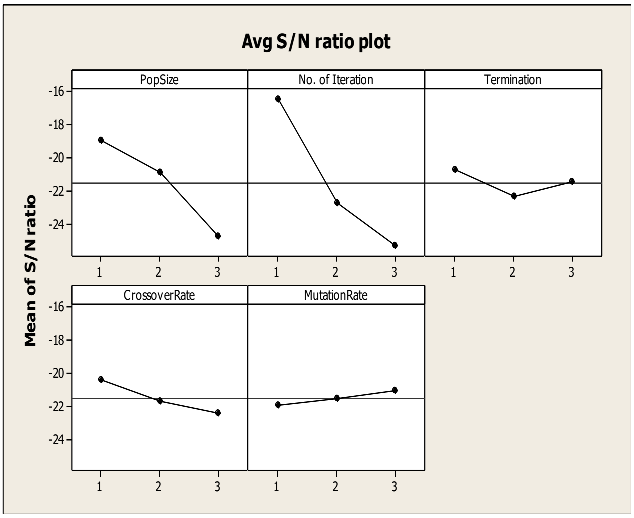

Fig. 4. The plot of the mean of *S/N* ratios

It can be observed from the Figure 4, level 1 is selected as the best level for Population size, Number of generations, Termination count and Crossover rate parameters. However, for Mutation rate, level 3 is chosen as the best level. Accordingly, the tuned parameters of the proposed Genetic Algorithm to solve the VRPCD-MS are as follows:
Population size – 100; Number of generations – 150;
Termination count – 50; Crossover rate – 0.7;
Mutation rate – 0.3:

Based on the *S/N* ratios (defined under the sub-section 2.2.2), the ANOVA for the parameters of the Genetic Algorithm are represented in the Table 3 given below:

Table 3
ANOVA for the *S/N* ratios of the parameters of the Genetic Algorithm.

Source	df	SS	MS	F-value	p-value
Population size	2	57.25	28.62	21.68	0.007
Number of generation	2	143.34	71.67	54.29	0.001
Termination count	2	5.25	2.62	1.98	**0.252**
Crossover rate	2	5.35	2.67	2.02	**0.247**
Mutation rate	2	1.36	0.68	0.52	**0.633**
Error of parameters of the GA	4	5.28	1.32	-	-
Total of parameters of the GA	14	217.83	-	-	-

As per the p-values (at 5% level of significance) in the Table 3, it can be concluded that, among the five parameters of the Genetic Algorithm, the ones which impact on the robustness of the proposed Genetic Algorithm are only the Termination count, Crossover rate and Mutation rate. Therefore, in this study, one of the impact parameters of the Genetic Algorithm, mutation operator is taken into consideration. Subsequently, two different strategies on mutation, 'SWAP' and 'REVERSION' are employed as better strategies to solve the VRPCD-MS.

3.2 Comparison of the solutions reached by GA_S and GA-R approaches

The results of fifteen different instances (ranging the problem size from 10 to 200) of the VRPCD-MS reached by GA_S (GA with SWAP mutation strategy) and GA_R (GA with REVERSION mutation strategy) approaches are summarized in the Table 4. It must be emphasized that, the method applied in the previous study [30] is adapted to obtain the solutions by GA_S. Moreover, it is to compare the solution reached by GA_R in the current study with the existing method found in the literature. Furthermore, every instance is executed 10 times and accordingly the best and the average solutions among those 10 executions are obtained for both approaches and reported accordingly. Moreover, by comparing the results, better average solutions among the two approaches are highlighted in bold in the Table 4:

Table 4
Solution of VRPCD-MS using GA_S and GA_R approaches.

Problem Number	Problem Size		GA_S ([30])			GA_R		
	Suppliers	Customers	Best Solution	Average Solution	Average Time (s)	Best Solution	Average Solution	Average Time (s)
01	5	5	1,694.80	1,695.64	5.33	1,694.80	**1,695.34**	7.85
02	6	6	1,757.40	1,773.51	5.17	1,756.10	**1,765.88**	5.67
03	7	7	2,165.30	**2,183.15**	5.81	2,164.00	2,188.39	8.04
04	8	8	2,376.90	2,407.61	3.55	2,339.40	**2,400.32**	6.19
05	9	9	2,726.00	2,787.87	3.51	2,776.30	**2,836.99**	5.95
06	10	10	2,815.90	2,895.80	5.58	2,812.10	**2,871.73**	9.47
07	20	20	6,030.70	6,248.25	5.77	5,769.70	**6,214.99**	8.01
08	30	30	9,320.10	**9,483.66**	6.10	9,361.20	9,545.47	6.37
09	40	40	12,088.00	**12,429.30**	6.16	12,529.00	12,674.00	14.78
10	50	50	15,551.00	**15,874.70**	6.35	15,364.00	15,885.40	11.90
11	60	60	17,759.00	17,999.30	7.10	17,670.00	**17,971.10**	12.79
12	70	70	20,861.00	21,335.00	6.82	20,867.00	**21,177.90**	13.11
13	80	80	24,266.00	24,583.30	5.37	23,931.00	**24,407.80**	12.49
14	90	90	27,519.00	27,998.10	4.59	27,519.00	**27,850.00**	13.12
15	100	100	30,975.00	31,517.30	7.92	31,230.00	**31,439.10**	12.42

It can be observed from the Table 4 that approximately 75% of the time (in fact, 11 out 15 instances) GA_R provides better near-optimal solutions than that of from GA_S in the existing study [30]. It further reveals that, GA_R takes more computational-time to reach solutions compared to GA_S approach. Since, for some instances, GA_S also provides better near-optimal solutions compared to GA_R, there is no strong evidence to recommend one of the two approaches over to other to solve VRPCD-MS. Furthermore, statistical tests are also conducted to verify the performance of both approaches and those results are reported as follows:

The F-test is conducted to test whether the variances among the average solutions by both GA_S and GA_R approaches are equal or not. Besides equal-variance two-sample t-test is also conducted to test whether the average solutions by both approaches are equal or not. Accordingly, the test-statistic and the relevant p-value of both F-test (*Null hypothesis*: variances are equal) and t-test (*Null hypothesis*: Solutions are equal) are presented in the Table 5.

Table 5
Test results of the solutions by GA_S and GA_R approaches.

Statistical Test	Test-Statistic Value	Probability Value (p-value)
F-test	1.01	0.985
Two-sample t-test	0.01	0.996

According to the test-results reported in the Table 5, it can be accepted at 5% level of significance that, the variances of the solutions by both approaches GA_S in the previous study [30] and GA_R are equal as the p-value of F-test is 0.984. Moreover, the p-value (0.996) of two-sample t-test for equal variances also strongly confirms that, there is no significant difference of the results of both approaches at 5% level of significance. Therefore, this study recommends merging both approaches (in steps 5 and 6 in the structure of the proposed GA in the sub-section 2.2.1) and using as an integrated method of mutation. The multiple (or merged /integrated) mutation strategies in the Genetic Algorithm is referred it hereafter as GA_M.

3.3 Results of the Multiple-mutation strategies in the Genetic Algorithm (GA_M)

The results of the multiple-mutation strategies in the Genetic Algorithm (GA_M) are summarized in the Table 6: The Relative Percentage Deviation (RPD) values between SWAP (method followed in the previous study [30] found in the literature) and REVERSION strategies, between SWAP (existing method in the literature of VRPCD-MS) and MERGED strategies, between REVERSION and MERGED strategies are respectively denoted by RPD_SR, RPD_SM and RPD_RM in the Table 6. Hence, the pair-wise comparison of these three methods are summarised in the Table 6. Similarly like in the other two approaches, the same instance is executed 10 times and the relevant best and the average solution by GA_M approach are appended in the Table 6 given below:

Table 6
Comparison of solutions of VRPCD-MS using multiple GA_M approach.

No.	GA_M			RPD_SR	RPD_SM	RPD_RM
	Best Solution	Average Solution	Average Time (s)			
01	**1,694.80**	**1,694.80**	11.73	0.02	0.05	0.03
02	**1,756.10**	**1,756.10**	11.78	0.43	0.99	0.56
03	**2,161.70**	**2,161.70**	12.63	-0.16	1.07	1.23
04	**2,312.70**	**2,312.70**	14.16	0.30	4.10	3.79
05	**2,667.30**	**2,667.30**	15.25	-1.73	4.52	6.36
06	**2,716.10**	**2,716.10**	16.64	0.84	6.62	5.73
07	4,896.90	4,953.19	36.82	0.54	26.15	25.47
08	7,150.20	7,338.43	39.70	-0.65	**29.23**	**30.08**
09	9,993.80	10,039.78	38.61	-1.93	23.80	26.24
10	12,501.00	12,783.70	41.72	-0.07	24.18	24.26
11	14,852.00	15,087.00	40.19	0.16	19.30	19.12
12	17,546.00	17,793.30	39.80	0.74	19.90	19.02
13	20,392.00	20,624.90	39.84	0.72	19.19	18.34
14	23,259.00	23,554.70	41.90	0.53	18.86	18.24
15	26,357.00	26,561.00	43.99	0.25	18.66	18.37
Average Relative Percentage Deviation				**0.00**	**14.44**	**14.46**

Since, the best and average solutions in the first six instances in the Table 6 are the same, it shows that they are the exact-optimal solutions and also, those optimal-solutions are much better than that of from the best solutions obtained by other two approaches, GA_S and GA_R, as given in the Table 4. It can be clearly seen from the Table 6 that, the computational time to reach a solution in each instance is relatively high in GA_M approach compared to other two approaches as exhibited in the Table 4. Since GA_M should go through both mutation operations in its algorithm, it requires more computational time than the algorithm with individual mutation operation. However, much better solutions can be reached by GA_M. The zero value of the average RPD_SR in the Table 6 again confirms that, there is no significant difference in solutions by applying SWAP and REVERSION mutation strategies alone. The values of RPD_SM and RPD_RM reveal that, up to 30% improvement in the solution can be achieved by the GA_M approach. Based on the average RPD_SM and average RPD_RM values, it can be concluded that, nearly 15% improvement in solutions are reached by the Genetic Algorithm with multiple-mutation strategies (GA_M) approach.

4. Conclusion

A population-based meta-heuristic Genetic Algorithm with two different mutation strategies (SWAP and REVERSION) is proposed to solve the integrated Vehicle Routing Problem with Moving Shipments at the Cross-Docking Centre (VRPCD-MS). Moreover, the parameters of the proposed Genetic Algorithm are tuned using Taguchi's estimation method. Furthermore, it is shown that mutation operator is one of the impact parameters of the Genetic Algorithm. Subsequently, two different strategies on mutation operator, 'SWAP' and 'REVERSION' are employed to recommend a better mutation strategy to solve the VRPCD-MS. However, the 'SWAP' mutation strategy was already applied in the literature of VRPCD-MS. Based on the results of the instances from a benchmark problem, it can be concluded that, there is no significant difference in solutions by applying SWAP and REVERSION mutation strategies when applying alone. Further, it concludes that, up to 30% improvement in the near-optimal solution can be reached by the merged-mutation strategies in the Genetic Algorithm. Moreover, it can be concluded that, on an average, by using the integrated-mutation strategies in the proposed Genetic Algorithm approach, nearly 15% improvement can be obtained in reaching the near-optimal solutions. Therefore, this study recommends employing the Genetic Algorithm with multiple-mutation strategies together to reach promising near-optimal solutions to the VRPCD-MS problem. Moreover, it is recommended to apply other biologically inspired or population based meta-heuristic methods to reach better near-optimal solutions to the large-scale instances of the VRPCD-MS.

Conflicts of Interest

No conflicts of interest to declare.

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