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An Integrated Vehicle Routing and Vehicle Sequencing Problem at the Cross-Docking Centre: A Genetic Algorithm Approach

S. R. Gnanapragasam[1*] and W. B. Daundasekera[2]

[1]*Department of Mathematics, The Open University of Sri Lanka, Sri Lanka*
[2]*Department of Mathematics, University of Peradeniya, Sri Lanka*

Abstract

Cross-docking is one of the logistic strategies in the supply chain. To improve the efficiency of a supply chain, the literature review recommends jointly considering operational level problems together on cross-docking. Therefore, in this study, the vehicle routing problem with moving shipments and vehicle sequencing problem at the cross-docking center (CDC) which has only single-receiving and single-shipping door is integrated and abbreviated as VRSP-SD. On the one hand, the integrated VRSP-SD differs from the literature by considering internal operations such as unloading, moving and reloading shipments not only at suppliers/customers but also at the

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Correspondence should be addressed to* ***Dr S. R. Gnanapragasam**, Department of Mathematics, Faculty of Natural Sciences, The Open University of Sri Lanka, Sri Lanka*

Email: srgna@ou.ac.lk

https://orcid.org/0000-0003-1411-4853

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CDC. On the other hand, the novelty of VRSP-SD in sequencing vehicles by minimising the waiting-time of vehicles is based on the ‘arrival-time’ of inbound vehicles to the CDC and also based on the ‘route-quantity’ of outbound vehicles. Therefore, the objective of this study is to test the accuracy of the proposed genetic algorithm (GA) based meta-heuristic approach to solve VRSP-SD by optimising the total transportation cost which incur by routing vehicles, moving shipments and sequencing vehicles. A mixed integer quadratic programming model is developed to solve the integrated VRSP-SD. Since the numerical experiments reveal that the accuracy of the proposed GA is over 94% against the exact-optimal solution obtained by branch and bound algorithm, it is recommended to employ the proposed GA to solve VRSP-SD. Therefore, the industries which apply cross-docking strategy may benefit by utilizing this proposed GA to schedule the vehicles to the routes and to the doors of CDC.

Keywords: *cross-docking, genetic algorithm, vehicle routing, vehicle sequencing.*

Introduction

In order to survive in the globalised industrial environment, the efficiency of supply chain is crucial. To satisfy the requirements of customers in terms of time, quality, and cost, industries adopt the innovative logistic strategy ‘cross-docking’ in their supply chain. Also, the cross-docking center (CDC) is an intermediate destination in a supply chain network, and it is exclusively dedicated to the transhipment of shipments. Therefore, these CDCs not only receive shipments from inbound vehicles but also dispatch them to outbound vehicles. Moreover, the doors at these CDCs are limited and most of the time, the number of doors is less than the number of vehicles used to tranship the shipments. Moreover, the ‘vehicle routing problem’ and ‘vehicle sequencing problem’ are two of the operational level decisions at the CDC. A CDC can have different layouts in its structure but the basic layout has only a single-receiving door and a single-shipping door. Therefore, in the basic layout of the CDC, scheduling vehicles to either the receiving door or the shipping door is a matter of sequencing vehicles to the door. The literature survey (Van Belle et al., 2012) on the cross-docking recommends jointly consider the operational level problems. Consequently, integrating 'vehicle routing problem' and 'vehicle sequencing problem' will improve the efficiency of the supply chain. Therefore, in this study, these two problems are integrated.

In 1959, Dantzig & Ramser (1959) introduced the vehicle routing problem. Now, it has become one of the well-studied combinatorial optimisation problems in operations research. It is an extended version of the 'travelling salesman problem' by utilising multiple vehicles to satisfy the requirements of the suppliers or customers in a specified time-horizon. Capacitated vehicle routing problem is one of the basic variants of the vehicle routing problems (Toth & Vigo, 2002). There are ample research conducted on vehicle routing problems and cross-docking, sequentially. In 2006, Lee et al. (2006) initiated a study on integrating vehicle routing problems with cross-docking strategy (VRPCD). Thereafter, it became very popular among the practitioners. Also, researchers conducted several studies by incorporating various characteristics of the vehicle routing problem on VRPCD. For instance, characteristics such as time windows, open network configuration, multi-commodities, splitting shipments, environmental factors, and heterogeneous vehicles were considered in the following studies: Hasani-Goodarzi & Tavakkoli-Moghaddam, 2012; Moghadam et al., 2014; Nikolopoulou et al., 2016; Tarantilis, 2013; Wen et al., 2009; Yin & Chuang, 2016.

Initially, not all the CDCs had multiple-receiving and multiple-shipping doors but mostly in the small-size CDCs; only a single-receiving door and a single-shipping door were designed in its layout. Consequently, properly sequencing vehicles to the corresponding door at the CDC plays an important role in the efficiency of the supply chain. On the one hand, after collecting products from suppliers, those collected products need to be unloaded at CDC. If the CDCs have only one receiving door, the inbound vehicles must wait in the parking yard located near the CDC until they get their turn to unload the accumulated products. On the other hand, when the CDCs have only a single-shipping door, the outbound vehicles must wait until they get their turn to reload the products which are to be distributed to the customers. This 'waiting' creates an additional cost to the system, and to cut down the cost, the idle time of each vehicle in the queue needs to be reduced. Therefore, a proper mechanism to sequence the vehicles in the optimum order to the doors of CDC is essential. Consequently, vehicle sequencing problems are also one of the key problems in operations research. In 2004, Li et al., (2004) introduced the vehicle scheduling problem based on the just-in-time concept by considering the machine scheduling problem. After the study by Yu & Egbelu (2008), the vehicle sequencing problem to a single-receiving door and a single-shipping door at CDC became a focal area of research among researchers. The common objective of the following studies on vehicle sequencing problem was to minimize the 'makespan' only at the CDC: Boloori Arabani et al., 2011; Boysen et al., 2010; Liao et al., 2012; Soltani & Sadjadi, 2010; Vahdani & Zandieh, 2010. However, this study attempts to minimise the total waiting time of all the vehicles.

In the literature of the supply chain, several operational level problems related to cross-docking have been conducted separately. However, it was recommended in a literature review (Van Belle et al., 2012) to jointly consider several operational level problems together. Subsequently, there are a few studies which integrate vehicle routing and sequencing problems together. In this regard, Musavi et al. (2017) and Yazdani et al. (2017) can be named a few. A bi-objective model for a green VRSP-SD at a cross-docking center was presented in Musavi et al. (2017) to consider the environmental factor of the network and an archived multi-objective simulated annealing was used to solve it. Another integrated VRSP-SD cross-docking center was formulated in Yazdani et al. (2017) as a MILP model and two meta-heuristics, reactive tabu Search with path relinking and a generational genetic algorithm with a local search and restart phase, were proposed to solve the problem. Furthermore, another literature review, Buakum & Wisittipanich (2019), recommended incorporating some of the internal operations at the CDC to the problems involved with cross-docking. Therefore, in the study Gnanapragasam & Daundasekera (2022), a mathematical model for the VRPCD was developed by incorporating a few internal operations that take place at the CDC. Nevertheless, in the current study, vehicle routing and vehicle sequencing problems are integrated with some internal operations at the CDC.

Since the vehicle routing problem is classified as NP-hard in strong sense (Lenstra & Rinnooy Kan, 1981), integrating the sequencing of the vehicles to the CDC makes the problem more challenging and hence, a meta-heuristic method is more suitable to solve the problem. Therefore, in the current study, a genetic algorithm is proposed to solve the integrated vehicle routing problem and vehicle sequencing problem at the CDC. Furthermore, this study is an extension of the research by Gnanapragasam & Daundasekera (2022) on vehicle routing problem with moving shipments at the cross-docking center (VRPCD-MS). Though a meta-heuristic method was utilized in the study by Gnanapragasam & Daundasekera (2024) to the simplified version of the VRPCD-MS, sequencing vehicles problem is not integrated in it. In the current study, VRPCD-MS is integrated with the vehicle sequencing problem at the CDC which has single-door at either side and abbreviated by VRSP-SD.

Since properly sequencing vehicles to the limited doors at the CDC optimises the total transportation cost, Yu & Egbelu (2008) initiated sequencing vehicles to the CDC with 'single-receiving door and single-shipping door' layout. The integrated model in this study differs from the literature in three-fold. Firstly, the following internal operations in the consolidation process are taken into consideration: unloading shipments at the receiving door, 'moving shipments' internally and 'reloading shipments' at the shipping door at the CDC. Secondly, loading/unloading shipments' at the suppliers/customers are also taken into account. Thirdly, sequencing vehicles by minimising the 'waiting time' of vehicles based on two different aspects. One aspect is based on the 'arrival-time' of inbound vehicles to CDC. The other aspect is based on the 'route-quantity' of outbound vehicles. Finally, the integrated VRSP-SD problem is developed by incorporating all three features. Therefore, the objective of this study is to test the accuracy of the proposed genetic algorithm based on meta-heuristic approach to solve VRSP-SD in terms of total transportation cost which is incurred generally by routing vehicles, moving shipments and sequencing vehicles.

The problem under investigation in this study amalgamates the sequencing vehicles at CDC and routing vehicles with moving shipments at the CDC. In addition to the characteristics assumed in the study Gnanapragasam & Daundasekera (2024) on VRPCD-MS, the following characteristics are also assumed in the integrated vehicle routing and sequencing with moving shipments:

- Single-CDC is considered with single-receiving and single-shipping doors.
- All the vehicles are available at the initial time of the time horizon.
- The temporary storage area inside the cross-docking centre is not limited.
- The delivery process should start after receiving all the products to the shipping door of CDC.
- Changeover cost (and time) at the door of the center is fixed for all the vehicles.
- Each door processes one vehicle at a time and is assumed to be sufficiently equipped with equipment and labourers.

The components of the total transportation cost considered in the current problem are defined in the equations from (21) to (28) given in the following section.

Methodology

A mixed integer quadratic programming (MIQP) model is developed to solve the integrated VRSP-SD. The mathematical model and the solution methods are described below:

Mathematical model for VRSP-SD

Indices and variables

i, j : Indices for suppliers/customers

d : Index for receiving or shipping door at the CDC

k, l : Indices for inbound/outbound vehicles

q_i : Shipments at supplier (or customer) i

Q_S : Capacity of vehicles used for suppliers

Q_C : Capacity of vehicles used for customers

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

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

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

$D = \{o, o'\}$: Set of receiving-door (o) and shipping-door (o') at the CDC

tc_{ij} : Travelling-cost between supplier (or customer) i and supplier (or customer) j

OC_S^k : Operations-cost of the vehicle k used for suppliers

OC_C^k : Operations-cost of the vehicle k used for customers

SC_i^k : Service-cost at supplier (or customer) i by vehicle k

SC_d^k : Service-cost at receiving (or shipping) door d by vehicle k

A_c : Fixed-preparation cost for serving at suppliers (or customers) or doors

B_c : Variable-serving cost for serving of a unit of shipment

C_c : Fixed-vehicle changeover cost

tt_{ij} : Travelling time from supplier (or customer) i to supplier (or customer) j

A_t : Fixed-preparation time for serving at suppliers (or customers) or doors

B_t : Variable-serving time for serving of a unit of shipment

ST_i^k : Service-time at supplier (or customer) i by vehicle k

CT^k : Fixed-changeover time of vehicle k

AT_i^k : Arrival-time of vehicle k at supplier (or customer) i

DT_i^k : Departure-time of vehicle k at supplier (or customer) i

PT_d^k : Processing-time of vehicle k at door d at the CDC

BT_d^k : Beginning-time of vehicle k to serve at door d at the CDC

ET_d^k : Ending-time of vehicle k after serving at door d at the CDC

$RT_{o'}^k$: Ready time of the shipments to be reloaded through shipping door o' to vehicle k

WT_d^k : Waiting-time of vehicle k to serve at the door d at the CDC

M : Relatively a large number

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

$$x_d^k = \begin{cases} 1, & \text{if vehicle } k \text{ assigns to the receiving door (or shipping door) } d \\ 0, & \text{otherwise} \end{cases}$$

$$z_d^{kl} = \begin{cases} 1, & \text{if vehicle } k \text{ precedes vehicle } l \text{ in the vehicle sequence at receiving door (or} \\ & \text{shipping door) } d \text{ when } k \neq l \text{ or if vehicle } k \text{ is the first vehicle in receiving door} \\ & \text{(or shipping door) } d \text{ when } k = l \\ 0, & \text{otherwise} \end{cases}$$

Constraints of the MIQP model for VRSP-SD

The constraint (1) represents that all the inbound (or outbound) vehicles start their tours from the CDC to suppliers (or customers):

$$\sum_{i \in N} x_{di}^k \leq 1 \qquad \forall k \in V$$

(1)

The constraint (2) represents that all the inbound (or outbound) vehicles end their tours at the CDC from suppliers (or customers):

$$\sum_{j \in N} x_{jd}^{k} \leq 1 \qquad \forall k \in V$$

(2)

Only a single vehicle has to arrive to a supplier (or customer) and depart from a supplier (or customer) are respectively indicated by the constraints (3) and (4):

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

(3)

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

(4)

Loops in the pickup (or delivery) routes are prevented by the constraint (5):

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

(5)

The constraint (6) prevents the backward movements in the pickup (or delivery) routes:

$$x_{ij}^{k} + x_{ji}^{k} \leq 1 \quad \forall i,\ j \in N \cup D\ , \forall k \in V$$

(6)

The constraints (7) and (8) confirm that at any given time, the accumulated shipments from suppliers or loaded shipments to the customers cannot exceed the capacity of an inbound or an outbound vehicle respectively:

$$\sum_{\substack{i \in S \\ j \in S \cup \{o\}}} q_i x_{ij}^{k} \leq Q_S \qquad \forall k \in V$$

(7)

$$\sum_{\substack{i \in C \\ j \in C \cup \{o'\}}} q_i x_{ij}^{k} \leq Q_C \qquad \forall k \in V$$

(8)

The calculation of the service-time at suppliers (or customers), the departure-time from a supplier (or customer) and the arrival-time to a supplier (or customer) are represented respectively by the constraints (9), (10) and (11):

$$ST_j^k = A_t + B_t q_j x_{ij}^k \qquad \forall i \in N \cup D,\ \forall j \in N, \forall k \in V$$

(9)

$$DT_j^k = \left(DT_i^k + tt_{ij} + ST_j^k\right) x_{ij}^k \qquad \forall i \in N \cup D,\ \forall j \in N, \forall k \in V$$

(10)

$$AT_j^k = \left(tt_{ij} + DT_i^k\right) x_{ij}^k \qquad \forall i \in N \cup D,\ \forall j \in N, \forall k \in V$$

(11)

The constrain (12) ensures that every inbound (or outbound) vehicle is assigned to either the receiving door (or shipping door):

$$\sum_{d \in D} x_d^k = 1 \quad \forall k \in V$$

(12)

The constraint (13) shows the relationship between the variables x_d^k, x_d^l and z_d^{kl} for the inbound (or outbound) vehicles:

$$x_d^k + x_d^l - 1 \le z_d^{kl} + z_d^{lk} \quad \forall k, l \in V, k \ne l, \forall d \in D$$

(13)

The condition that either vehicle k precedes vehicle l or vehicle l precedes vehicle k at the receiving door (or shipping door) d is prevented by constraint (14):

$$z_d^{kl} + z_d^{lk} \le 1 \ \ \forall k, l \in V, \forall d \in D$$

(14)

The constraint (15) specifies that the Beginning -time of each vehicle is at least the arrival-time of that vehicle:

$$BT_d^k \ge AT_{id}^k \ \ \forall k \in V, \forall d \in D$$

(15)

The processing-time of each inbound (or outbound) vehicle at the receiving door (or shipping door) is calculated by constraint (16):

$$PT_d^k \ge CT^k + B_t \sum_{i \in N \cup D} q_i x_{id}^k \ \ \forall k \in V, \forall d \in D$$

(16)

The constraint (17) determines the ending-time of each vehicle after processing at the receiving (or shipping) door:

$$ET_d^k \geq AT_{id}^k + PT_d^k \quad \forall k \in V, \forall d \in D$$

(17)

The ending-time of each inbound (or outbound) vehicle which predecessors plus vehicle changeover-time is shown in the constrain (18):

$$BT_d^l \geq ET_d^k + CT^k - M(1 - z_d^{kl}) \quad \forall k, l \in V, \forall d \in D$$

(18)

The time at which orders are ready to be reloaded in their corresponding outbound vehicle is determined by constraint (19):

$$RT_{o'}^k = \max_k \left\{ AT_{o'}^k + UT_{o'}^k + \sum_i q_i \right\}$$

(19)

The constraint (20) exposes the waiting time of each inbound (or outbound) vehicle at the parking yard of the CDC:

$$WT_d^k \geq BT_d^k - AT_{id}^k \qquad \forall k \in V, \quad \forall d \in D$$

(20)

All the decision variables defined in the model are non-negative.

Objective of the MIQP model for VRSP-SD

The single-objective function of the MIQP model, which is to minimise the total transportation cost, is formulated by considering the cost components: travelling Cost (*TC*) between suppliers/customers, service Cost (*SC*) at suppliers/customers, unloading cost (*UC*) of shipments at receiving door, moving cost (*MC*) of shipments inside CDC, loading cost (*LC*) at shipping door, operations cost (*OC*) of the vehicle, changeover cost (*CC*) of the vehicle, and waiting cost (*WC*) of the vehicle.

$$\begin{matrix} Minizing\,Total \\ Transportation\,Cost \end{matrix} = \begin{cases} (Travelling\,Cost) + (Service\,Cost) + (Unloading\,Cost) + \\ (Moving\,Cost) + (Loading\,Cost) + (Operations\,Cost) + \\ (Changeover\,Cost) + (Waiting\,Cost) \end{cases}$$

The components of the total transportation cost are defined in the following equations from (21) to (28):

- $$Travelling\ Cost\ (TC) = \sum_{k\in V}\sum_{i,j\in S\cup D} tc_{ij}x_{ij}^{k}$$ (21)
- $$Service\ Cost\ (SC) = \sum_{k\in V}\sum_{\substack{i\in S\cup D\\ j\in S}} A_c + B_c\, q_j x_{ij}^{k}$$ (22)
- $$Unloading\ Cost\ (UC) = \sum_{k\in V}\left[A_c + B_c\sum_{i\in S} q_i x_{io}^{k}\right]$$ (23)
- $$Moving\ Cost\ (MC) = \sum_{k\in V}\sum_{\substack{i\in S\\ j\in S\cup\{o\}}} B_c q_i x_{ij}^{k}$$ (24)
- $$Loading\ Cost\ (LC) = \sum_{k\in V}\left[A_c + B_c\sum_{i\in S} q_i x_{o'i}^{k}\right]$$ (25)
- $$Operations\ Cost\ (OC) = \sum_{k\in V}\sum_{j\in S} OC_S^k\, x_{io}^{k} + \sum_{k\in V}\sum_{j\in S} OC_C^k\, x_{o'j}^{k}$$ (26)
- $$Changeover\ Cost\ (CC) = \sum\left(m + m'\right)C_t$$ (27)
- $$Waiting\ Cost\ (WC) = \sum_{k\in V}\sum_{\substack{i\in S\cup O\\ h\in D}}\left[BT_d^k - AT_{id}^k\right]$$ (28)

The costs of travelling at the pickup (or delivery) process are presented in (21). From equation (22), the costs of loading (or unloading) at the suppliers (or customers) are calculated. This method of calculation is new to the literature as the preparation costs as well as the unit cost of loading (or unloading) shipments are newly taken into account. Cost of unloading at the receiving door, cost of moving shipments from receiving door to shipping door, and cost of reloading at the shipping door are respectively represented by (23), (24), and (25). These three different cost components are relevant to the internal operations taking place inside the cross-docking centre, which is a novel concept to the literature. The vehicle operations cost mainly for maintenance and cost of vehicle changeover to the door are measured by (26) and (27), respectively. Finally, the costs of vehicle waiting at the parking yard of the cross-docking centre are determined by (28). These waiting costs (proportionate to waiting times) are to be minimised in the problem under investigation. Also minimising waiting time in sequencing vehicles to the doors at cross-docking centre based on two different aspects is another novel idea in the literature of VRSP-SD.

Exact-optimal solution to VRSP-SD by branch and bound (BB) algorithm

Generally, the branch and bound algorithm is applied not only to obtain the optimal-solutions to integer programming problems but also to obtain the optimal-solutions for certain other optimisation problems. Moreover, the algorithm provides optimal-solution to NP-hard problems by exploring the complete search space by partitioning the feasible solution space into smaller subsets of solutions. Since VRPCD-MS is classified as a NP-hard problem (Gnanapragasam & Daundasekera, 2022), incorporating the vehicle sequencing problem to it makes the problem even harder to solve; hence, the integrated VRSP-SD is also a NP-hard problem. Moreover, branch and bound algorithm is capable of solving small-scale instances of NP-hard problems. Therefore, only the small-scale instances of the integrated VRSP-SD are considered to obtain the exact-optimal solution. The developed MIQP model described above is coded in the *LINGO* (version 18) optimization software and the branch and bound algorithm is chosen to obtain the exact-optimal solution.

Near-optimal solution to VRSP-SD by genetic algorithm (GA)

It can be observed that methods based on the genetic algorithm were applied in some of the studies in the literature to solve VRPCD (Hasani Goodarzi et al., 2018; Kargari Esfand Abad et al., 2018; Baniamerian et al., 2018; Hasani Goodarzi et al., 2022). Besides, there is no study found in the literature using genetic algorithm to minimise the total cost with a single objective. Furthermore, different solution methods were tried out in the literature of sequencing vehicles to single-door cross-docking centre. Boloori Arabani et al. (2011) employed five meta-heuristic methods, namely genetic algorithm, tabu search, particle swarm optimization, ant colony optimization and differential evolution. The efficiencies of these five algorithms were compared and concluded that except tabu Search, other algorithms have a relatively similar behaviour. Also a genetic algorithm based meta-heuristic approach was proposed to solve VRSP-SD in Mohtashami (2015) by considering the repetitive pattern for shipping vehicles. A lower bound was developed in Golshahi-Roudbaneh et al. (2017) and five meta-heuristics, namely simulated annealing, genetic algorithm, Keshtel algorithm, stochastic fractal search algorithm along with one hybrid simulated annealing-particle swarm optimisation method were proposed in it. Pan et al. (2021) formulated a mixed-integer mathematical model to represent VRSP-SD and proposed a solution framework based on the genetic algorithm. It is observed from the previous studies in the literature of VRSP-SD that, none of these models considered the waiting time of the vehicles. Therefore, in this study, minimising the waiting time of the vehicles is considered as the objective of the vehicle sequencing problem. Subsequently, a genetic algorithm based meta-heuristic approach is proposed here to sequence the vehicles to single-door cross-docking centre.

The structure given below depicts all the necessary details about the proposed meta-heuristic approach based on the genetic algorithm:

Structure of the proposed meta-heuristic approach

Step 1: Initialise the configuration of parameters of the genetic aalgorithm

Step 2: Generate initial population of suppliers *randomly*

Step 3: Calculate the fitness values of giant chromosome of the initial population of suppliers

Step 4: Select chromosomes (solutions for suppliers) using *tournament-selection* method

Step 5: Apply *order-crossover* to create offspring as new solutions for suppliers

Step 6: Employ *swap- mutation* to create offspring as new solutions for suppliers

Step 7: Select best chromosomes (solutions for suppliers) using *elitism* method

Step 8: Set new population of suppliers after Genetic Algorithm operations from steps 4 to 7

Step 9: Calculate the fitness values of giant chromosome for new population of suppliers

Step 10: Go to step 12, if sufficient *number of generations* met, otherwise repeat steps 2 to 9

Step 11: Go to step 12, if it satisfies *termination count*, otherwise repeat step 10

Step 12: Obtain the best giant chromosome (solutions for suppliers) with its fitness value

Step 13: Identify the pickup routes based on the inbound vehicle capacity

Step 14: Sort inbound vehicles based on *arrival-time*

Step 15: Send inbound vehicles to receiving door in *ascending order of arrival-time*

Step 16: Go to step 17, if the *ending-time* of precedence inbound vehicle is at most the *arrival-time* of the next inbound vehicle sorted in step 14, otherwise wait until the inbound vehicle with next lowest ending-time completes the unloading at the CDC

Step 17: Assign inbound vehicle to the receiving door of the CDC

Step 18: Unload collected shipments at the receiving door of the CDC

Step 19: Move shipments from the receiving door to the shipping door of the CDC

Step 20: Repeat steps 2 to 12 to obtain the best giant chromosome (solutions for customers in the delivery process) with its fitness value

Step 21: Identify the delivery routes based on the outbound vehicle capacity

Step 22: Consolidate the shipments based on the orders of customers

Step 23: Sort outbound vehicles based on delivery route-quantity

Step 24: Send outbound vehicles to the shipping door in *ascending order of route-quantity*

Step 25: Go to step 26, if the *ending-time* of precedence outbound vehicle is at most the *ready-time plus route-quantity* of the next outbound vehicle sorted in step 23, otherwise wait until the outbound vehicle with next lowest ending-time completes the loading at the CDC

Step 26: Assign outbound vehicle to the shipping door of the CDC

Step 27: Reload consolidated shipments to the outbound vehicles at the shipping door of the CDC

Step 28: Calculate the cost components of the total transportation cost

A flowchart (Figure 1) describing the structure of the proposed genetic algorithm is also given in Figure 1 to capture the algorithm flow visually. It must be emphasised that, initially at step 1, the parameters of the genetic algorithm in the structure above are tuned by the *Taguchi's* parameter estimation scheme by following a similar method presented in the study by Vahdani et al. (2010). To attain the best robustness of meta-heuristic algorithms, their parameters have to be designed. Tuning the parameters not only can lead to a relative improvement in the quality of solutions and quicker convergence of the algorithms, but also avoid prohibitively large run times. In this study, Taguchi's parameter estimation scheme is used to tune the following five parameters of the proposed genetic algorithm:

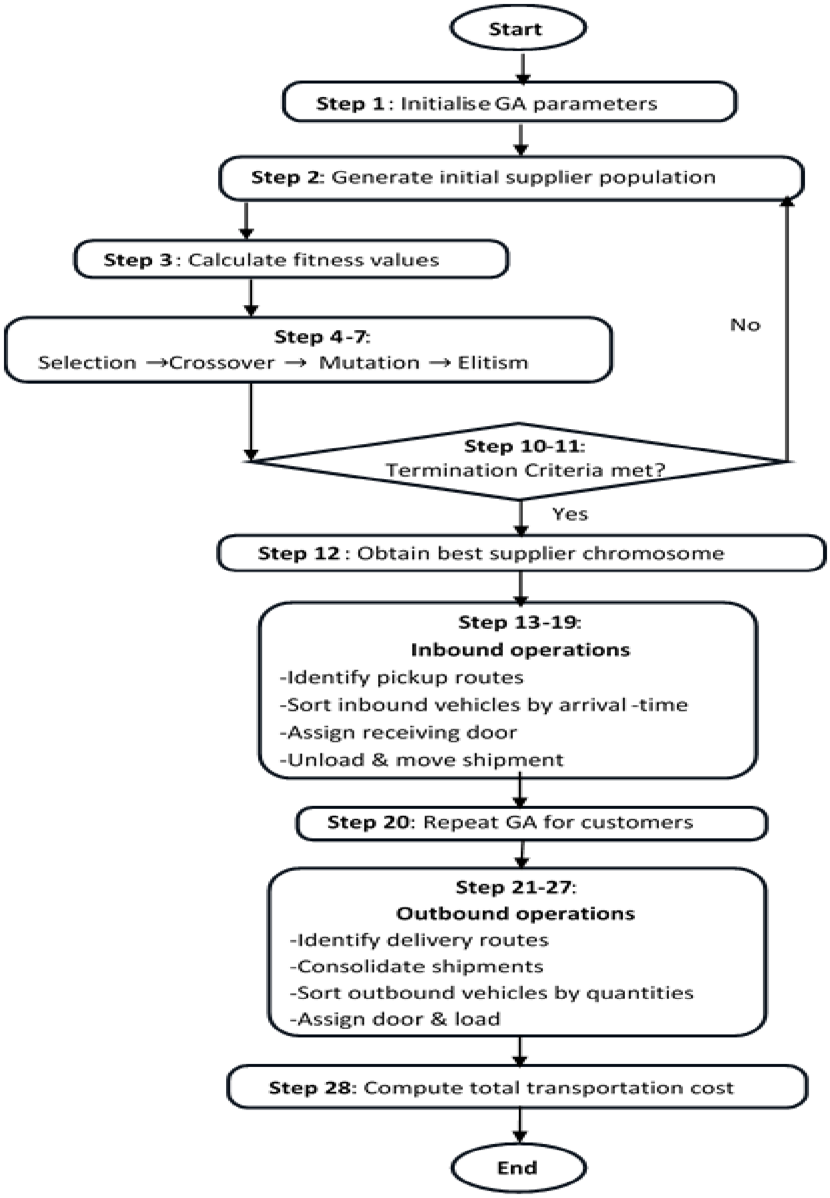

Figure 1. Flowchart of the Proposed Genetic Algorithm

Size of the population : Total number of members in the population that can have at any generation
Number of generations: Total number of populations to be generated
Termination count : Number of same solutions obtained to a particular population
Crossover rate : Number of chromosomes to be crossover in a population
Mutation rate : Number of chromosomes to be mutated in a population

Three levels in each of the parameters of the genetic algorithm are indexed in Table 1 given below.

Table 1. *Parameter levels of the genetic algorithm*

Parameters of the genetic algorithm	Index of levels 1	2	3
Size of the population	**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**

After following the procedure which is mentioned in Vahdani et al. (2010), the estimated parameter values are obtained and they are highlighted in bold in Table 1. Therefore, it can be concluded that the tuned parameters of the genetic algorithm are 100, 150, 50, 0.7, and 0.3, respectively, for the size of the population, number of generations, termination count, crossover rate, and mutation rate. Moreover, the proposed genetic algorithm is coded in the *MATLAB* platform to obtain near-optimal solutions to the VRSP-SD. The data are extracted from the benchmark instances from Wen et al. (2009) in the literature of vehicle routing problem with cross-docking. Eventually, the near-optimal solution to the VRSP-SD reached by genetic algorithm is compared with the exact-optimal solution obtained by the branch and bound algorithm.

Results and Discussion

The instances to check the feasibility of the developed MIQP model for the VRSP-SD are extracted from a benchmark problem in the literature of VRPCD. The optimal-solution obtained by the branch and bound algorithm and near-optimal solution reached by the proposed genetic algorithm are compared in the following sub-section.

Test of accuracy of the results obtained by solving VRSP-SD using the genetic algorithm

The purpose of test the accuracy is to observe that 'how far the near-optimal solution reached by genetic algorithm (GA) against the exact optimal solution obtained by branch and bound (BB) algorithm'. In this regard, the relative percentage deviation measure is utilised in this study. The most prominent results of ten small-scale instances of VRSP-SD reached by both BB algorithm and GA are summarised in Table 2.

Table 2. *Comparison of solutions between BB algorithm and GA for VRSP-SD*

Instance number	Instance size		Required vehicles		BB	GA		RPD in %
	No. of suppliers	No. of customers	Inbound	Outbound	Optimal solution	Best solution	Average solution	
01	03	03	1	1	1,087.91	1,087.9	1,087.90	0.00
02	03	04	1	1	1,122.63	1,122.6	1,122.60	0.00
03	03	05	1	1	1,172.66	1,172.7	1,172.70	0.00

04	04	04	1	1	1,20 0.54	1,200. 5	1,200 .50	0.00
05	04	05	1	1	1,21 0.58	1,210. 6	1,210 .60	0.00
06	04	06	1	2	1,60 0.52	1,600. 5	1,624 .68	1.51
07	05	05	1	2	1,72 5.77	1,725. 8	1,733 .00	0.42
08	05	06	1	2	1,70 7.51	1,705. 5	1,728 .66	1.24
09	05	07	2	2	1,81 8.55	1,892. 1	1,917 .30	5.43
10	**06**	**06**	**2**	**2**	**1,98 1.20**	**2,009 .2**	**2,052 .48**	**3.60**

In each instance, its size (in terms of number of suppliers and customers) and required number of vehicles (inbound and outbound) are included from the 2nd column to the 5th column. In addition, exact-optimal solution obtained by the BB algorithm is reported in the 6th column. Moreover, the best solution and average solution of 10 repetitive execution (of the same instance) of the genetic algorithm are respectively exhibited in the 7th and the 8th columns of Table 2. Since the individual values of the cost components are not compared for the small-scale instances of the VRSP-SD, only the total transportation costs obtained by both BB and GA approaches are presented in Table 2. Eventually, in the last column of Table 2, the relative ppercentage deviation (RPD) value is calculated according to the following formula:

$$\text{RPD} = \left[\frac{\begin{pmatrix} \text{Average Near Optimal} \\ \text{Solution by GA approach} \end{pmatrix} - \begin{pmatrix} \text{Exact Optimal} \\ \text{Solution by BB approach} \end{pmatrix}}{(\text{Exact Optimal Solution by BB approach})} \right] \times 100$$

It can be observed from the results presented in Table 2 that when the size of the instance is less than 10 (in the first 5 instances), the proposed genetic algorithm also reaches the same exact-optimal solution obtained by the branch and bound algorithm. This can be clearly seen in Figure 2 given below as well. In Figure 2, both bars in the first five instance numbers have exactly the same value.

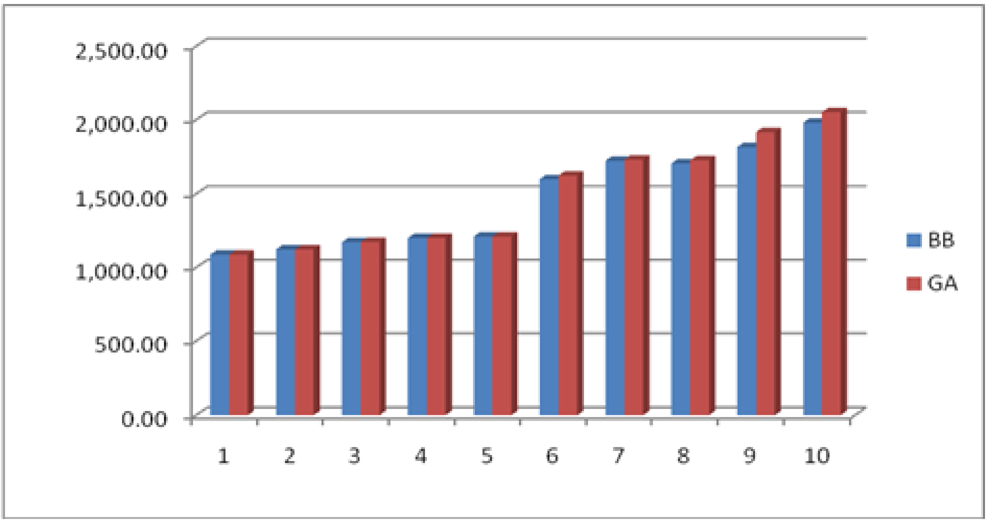

Figure 2. Bar Chart of Solution to VRSP-SD by BB and GA Approaches

Moreover, in the instances from 6th to 8th in Table 2, although there is a small deviation (from 0.5% to 1.5% in RPD) in the average-solution by the GA, the best-solution among the 10 replicates reaches the exact-optimal solution. However, in the last two instances (9th and 10th), only a near-optimal solution is reached by the proposed GA with about 5.5% RPD. Furthermore, on average, among the 10 instances, the solution reached by the GA deviates only about 3.6%. Therefore, it can be concluded that, the accuracy of the proposed GA to solve the VRSP-SD is over 94% and on average which is over 96%.

Optimal routes to an instance with 6-suppliers and 6-customers in VRSP-SD

The results of the best-solution reached by the GA to the last instance (highlighted in bold in the Table 2) with 6-suppliers (labelled as S_1 to

S_6) and 6-customers (labelled as C_1 to C_6) are discussed in this subsection. Figure 3 depicts the optimal routes in both pickup and delivery processes from the cross-docking centre. The triangle , circle and rectangle in Figure 3, respectively indicate the amount of supply (or demand) by each supplier (or customer), accumulated quantity by each route (vehicle) and travelling time between suppliers (or customers or cross-docking centre).

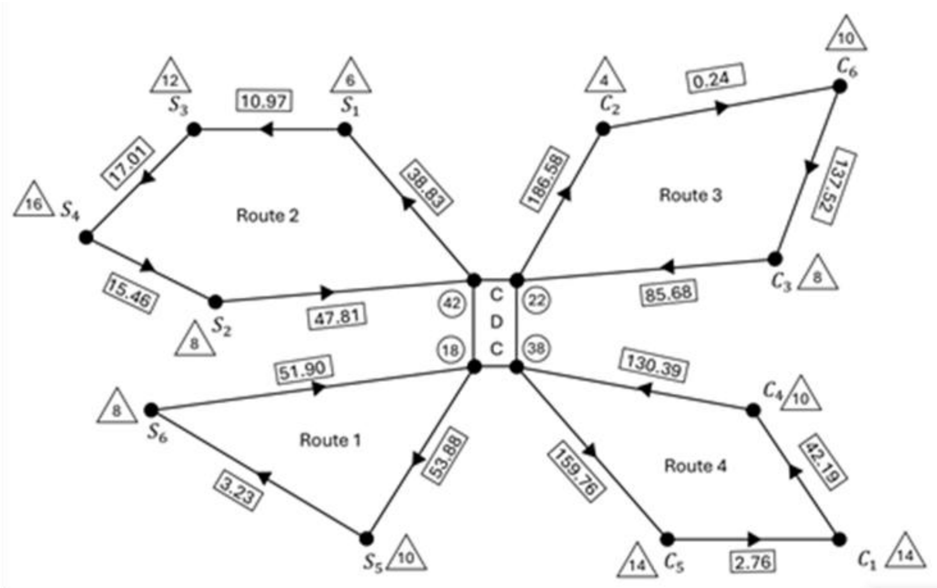

Figure 3. Optimal Routes of an Instance with 6-Suppliers and 6-Customers

Figure 3 reveals that, two-inbound and two-outbound vehicles are needed to fulfil the requirements of suppliers and customers in this particular instance. Furthermore, the sequence of the suppliers (or customers) in each route with the quantity is pointed out in a self-explanatory way in the Figure 3. It can be determined that the inbound vehicles, for Route 1 and Route 2, arrive at the cross-docking center in 147.01- and 212.08-time units, respectively. After the consolidation process inside the cross-docking center, the ready time to reload the shipments is observed as 306.08-time units. The sequencing vehicles to the cross-docking center in this particular instance are discussed in the following sub-section.

Best solution on sequencing vehicles in the instance of VRSP-SD

The relevant information on the best solution by the GA to the specific instance with 6-suppliers and 6-customers of VRSP-SD are summarized in Table 3.

Table 3. *Best solution by the GA to the instance with 6-suppliers and 6-customers of VRSP-SD*

Route	Route Quantity	Arrival Time / Ready Time	Beginning Time	Processing Time	Ending Time
1: CDC-S_6-S_5-CDC	18	147.01	147.01	33	180.01
2: CDC-S_2-S_4-S_3-S_1-CDC	42	212.08	212.08	57	269.08
3: CDC-C_2-C_6-C_3-CDC	22	306.08	306.08	37	343.08
4: CDC-C_5-C_1-C_4-CDC	38	**306.08**	**343.08**	53	396.08

In the first column of Table 3, the closed vehicle tours to collect shipments from the designated suppliers are presented in the first two routes (1 and 2), whereas, to distribute the collected shipments to corresponding customers reported in the last two routes (3 and 4). The accumulated shipments in each route are represented by the 'route-quantity' in the 2nd column. Moreover, the 'arrival-time' of inbound vehicles to the CDC and the 'ready-time' of shipments to be loaded to outbound vehicles are included in the 3rd column of Table 3. Besides, the 'Beginning-time' to process at the doors is added in the 4th column. In addition, the 5th-column contains the 'processing-time' of each vehicle. Finally, at the last-column of Table 3, the 'ending-time' of each vehicle is mentioned.

It can be observed from Table 3 that the 1st-route vehicle arrives at the CDC at 147.01 time units and starts to unload at its arrival. It finishes its job at 180.01 time units with 33 (which equals to 18 *(accumulated units of shipments)* plus 15 *(vehicle changeover-time)*) units of processing-time. Also, the 2nd-route vehicle arrives well later 180.01 time units and that time the receiving door is not occupied by any vehicle. Therefore, without waiting, it starts its job at 212.08 time units. It stops its unloading at 269.08 time units with 57 units of processing-time. Therefore, there is no waiting time for both inbound vehicles. Moreover, it can be observed in Table 3 that the 'ready-time' of shipments at the CDC is 306.08 but the 3rd-route vehicle has the least 'route-quantity' and therefore it is assigned first to the shipping door. It finishes its loading at 343.08 time units with 37 units of processing-time. However, the 4th-route vehicle has to wait until the 3rd-vehicle finishes its job, and therefore, at about 343.08 time units only it can start its loading. Hence, the waiting-time of the 4th-vehicle is 37 (which is equal to 343.08 minus 306.08) time units. Finally, it completes its job at 396.08 time units with 53 units of processing-time. In fact, only the 4th-route vehicle has to wait in this particular instance. Therefore, with 37 cost units of the waiting, the total transportation cost is 2009.20 cost units which is the best-solution of 10 executions of the last instance reported in Table 2. Furthermore, the breakdowns of all the components of total transportation cost are summarised in Table 4.

Table 4: *The cost components to the instance with 6-suppliers and 6-customers*

Route	**Components of total transportation cost**								**Route-wise cost**
	TC	***SC***	***UC***	***MC***	***LC***	***OC***	***CC***	***WC***	
1: CDC-S_6-S_5-CDC	79.69	38	28	18	N/A	150	15	0	**328.69**

2: CDC-S_2-S_4-S_3-S_1-CDC	159.39	82	52	42	N/A	150	15	0	**500.39**
3: CDC-C_2-C_6-C_3-CDC	335.10	52	N/A	N/A	32	100	15	0	**534.10**
4: CDC-C_5-C_1-C_4-CDC	378.02	68	N/A	N/A	48	100	15	37	**646.02**
Component-wise total cost	**952.20**	**240**	**80**	**60**	**80**	**500**	**60**	**37**	**2009.20**

It must be emphasised from Table 4 that the shipment loading and unloading costs are respectively relevant only to pickup (first 2 vehicles) and delivery (last 2 vehicles) routes. Also, the moving shipments (from receiving door to shipping door) costs are applicable only to the shipments collected by the pickup routes. From Table 4, it can be observed that the route-wise cost (highlighted in the final-column) which sums up all the components relevant to each route. Ultimately, the component-wise total cost is also highlighted at the last-row of Table 4. Accordingly, the total transportation cost is 2009.20 cost units which is the best-solution of 10 executions of the last instance reported in Table 2.

Conclusions and Recommendation

The vehicle routing problem with moving shipments and vehicle sequencing problem at the cross-docking centre which has only a single-receiving and single- shipping door (VRSP-SD) are integrated in this study. The GA based meta-heuristic approach is proposed to the mixed integer quadratic programming model developed to solve the integrated VRSP-SD. From the numerical experiments to the benchmark instances in the literature, it can be concluded that the accuracy of the proposed GA shows over 94% against the exact-optimal solution obtained by the BB algorithm which is over 96% on average. Consequently, it can be recommended to employ the proposed GA to solve the VRSP-SD even to the large-scale instances. Therefore, the industries which apply cross-docking strategy in their supply chain may benefit by utilising this proposed GA to schedule the vehicles to the route as well as to the cross-docking centre with single-receiving and single-shipping door layout. Moreover, in the future studies, the integrated problem on the vehicle routing and sequencing at the single-door cross-docking centre can be extended to a cross-docking centre with multi-doors. Also, in the extension studies of the aforementioned problem, multiple cross-docking centres can be taken into account in the supply chain.

Conflict of interest

The authors have no conflicts of interest to declare information that are relevant to the content of this article.

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