Supply Chain Scheduling using a Transportation System Composed of Vehicle Routing Problem and Cross-Docking Approaches

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Abstract

This study considers a combination of cross-docking and vehicle routing problem (VRP) approaches to transport raw material and parts in a supply chain. The supply chain is composed of some suppliers which are spread in different geographical zones and multiple shared vehicles with different speeds and capacities for transporting orders from the suppliers to a manufacturer. After proposing a mathematical model of this new problem, a developed version of genetic algorithm based on a psychological theory, named Reference Group Genetic Algorithm (RGGA) is used to solve the problem. The originality of this research is proposing a new method in integrated production and transportation scheduling in supply chain by combination of cross-docking and VRP approaches, presenting the mathematical model of the problem and adapting RGGA to solve it. To evaluate RGGA performance, we develop a genetic algorithm proposed for the nearest problem in literature and compare these two algorithms. Moreover, RGGA results are compared with optimum solutions by some low size test problems. The result shows the good performance of RGGA.

Keywords: Transportation, vehicle routing problem; cross-docking, scheduling; supply chain

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1. Introduction

A supply chain consists of all the stages that add value to the product. The role of supply chain management is integrating all enterprises in the supply chain and synchronizing them to fulfill customer quests to achieve competitiveness in the supply chain. With the emergence of the globalization phenomenon, one of the attractive subjects for both industry and academic researchers is integration between production and transportation in supply chain.

To survive in the current competitive environment of global markets, manufacturers have been forced to choose an appropriate supply chain network for cost reduction in their inventory systems [Ghasimi et al., 2014]. This article investigates the scheduling problem in a transportation system composed of cross-docking and Vehicle Routing Problem (VRP) approaches in a supply chain to minimize total delays in orders' delivery. The supply chain consists of some suppliers who are spread in different geographical zones and an integrated transportation system consisting of multiple vehicles. This hybrid transportation fleet transports orders from the suppliers to a manufacturer. It is assumed that suppliers use shared vehicles to reduce transportation costs.

Vehicle sharing between suppliers has various benefits for suppliers, such as reducing transportation costs, increasing the vehicles' performance, etc. VRP is a common approach in vehicle sharing between suppliers, in which a vehicle travels between suppliers and picks up orders (Figure 1-b). However, in some cases, the vehicles' travel between suppliers may be a very time consuming and inefficient task. For instance, suppose a case where a vehicle should travel in urban areas with heavy traffic, or a case in which there are restricted areas for heavy vehicles. In such case, the Cross-docking approach could be used, in which suppliers convey their own finished orders by low capacity vehicles to a Cross-Docking Terminal (CDT), in a place out of town. Thereafter, the orders are traveled to the manufacturer using heavy vehicles with high capacity (Figure 1-c).

Figure 1 illustrates the considered problem in this research with 6 orders and 4 suppliers. Here order 6 is assigned to supplier 1, order 3 and 2 to supplier 2, order 1 to supplier 3 and order 4 and 5 to the supplier 4. In Figure 1-a suppliers transfer their orders to the manufacturer independently. Figure 1-b shows the situation where suppliers use shared transportation to transfer orders to the manufacturer. Suppliers' corporation method in using shared transportation is VRP. In Figure 1-c, again suppliers use shared transportation for delivering orders to the manufacturer but with the cross-docking method of corporation. Figure 1-d shows the situation whereby suppliers use a combination of VRP and cross-docking method.

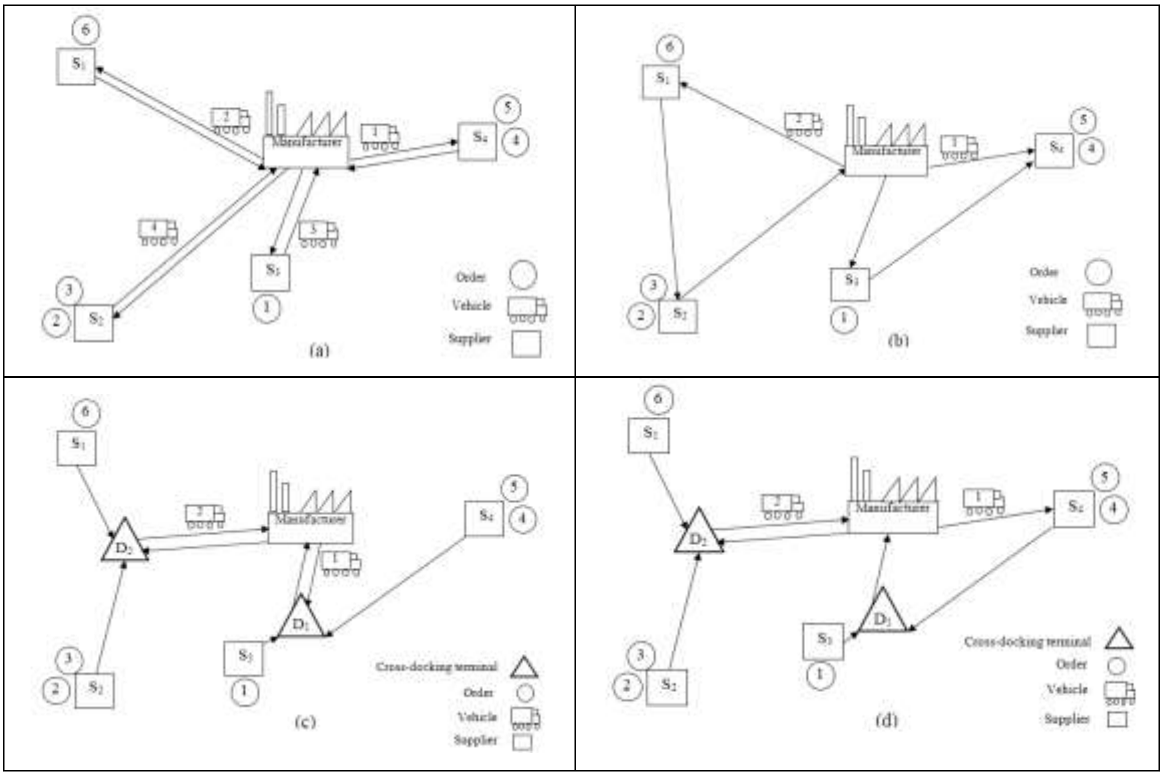

Figure 1. Different logistic methods

Integration in decisions in supply chain increases the productivity. Separation in production planning for suppliers and transportation, for instance, may keep us from achieving the global optima [Zegordi et al., 2010].

This paper studies a transportation system, which is a combination of VRP and cross-docking methods. Additionally, the orders' assignment to the suppliers and orders' production sequence in suppliers are considered as decision variables.

After proposing the mathematical model of the problem, a developed version of genetic algorithm based on a psychological theory, named Reference Group Genetic Algorithm (RGGA) introduced by [Beheshtinia et al., 2018] is adapted to solve the problem.

The rest of the paper is organized as follows. In Section 2, the literature review of the problem is mentioned. In Section 3, the problem is explained and a new mathematical model for the problem is presented. The adapted RGGA is described in Section 4 to solve the problem. In Section 5 the computational results obtained by solving various problems with RGGA is investigated. Finally, in the last section, conclusion and the future research spaces are presented.

2. Literature Review

Supply chain scheduling is investigated by various researchers. Each research has studied an integration level in the supply chain. Some researches integrate the relation between a manufacturer and some suppliers such as [Yan et al., 2008] and [Gaudreault et al., 2009] Also, a supply chain with two levels of suppliers and a manufacturer was discussed considering economic batch size and scheduling in the supply chain [Osman and Demirli, 2012]. [Ren et al., 2013] discussed the complexity of a scheduling problem at supply chain, considering some suppliers at the first stage and a manufacturer at the second one. [Sawik, 2014] presented a mixed integer model for a supplier selection and scheduling problem considering two kinds of suppliers to minimize costs and maximum service level. The first kind of supplier is placed in the manufacturer region and the others are placed out of the manufacturer region.

Moreover, some researches integrate the relation between a manufacturer and some distributers such as [Mahdavi Mazdeh et al., 2008] and [Selim et al., 2008].

Integration of the relation between some parallel manufacturers is considered by some papers such as [Nishi et al., 2007] and [Moon et al., 2008]. Finally, some researches consider a combination of the mentioned integrations, for example [Caner Taşkın and Tamer Ünal, 2009] and [Silva et al., 2009]. Similarly, [Selvarajah and Zhang, 2014] proposed a lower bound and a heuristic for solving a supply chain scheduling problem to minimize the sum of orders flow and delivery costs. They considered some suppliers, a manufacturer and some customers.

Some papers do not consider the transportation fleet in their problem. For example, [Thomas et al., 2014] considered some sub-problems in a coal supply chain scheduling problem and proposed a mixed integer programming model for each case. Then column generation technique was employed to each model.

Although many researches use time as continuous parameter, some of them use time as discrete parameter and consider multiple time periods. For example, [Kabra et al., 2013] developed [Shaik and Floudas, 2008] work and discussed supply chain scheduling problem in multi-period, multi-stage and multi-products mode. [Mousavi et al., 2014] study the location of cross-docking centers and vehicle routing scheduling considering multiple time periods and propose two deterministic mixed-integer linear programming (MILP) models for the problems. They convey the deterministic models to fuzzy ones to consider the uncertainty in the problems.

On-line approach is considered by some papers. Various cases of on-line production–distribution scheduling problems were discussed by [Averbakh, 2010]. [Averbakh and Baysan, 2013] investigated a supply chain with multiple customers and proposed an algorithm for an online scheduling problem to minimize orders flow and delivery costs.

From another perspective, some papers dealt transportation resources in production scheduling. [Zegordi and Beheshti Nia, 2009a] considered a heterogeneous transportation fleet in a supply chain and used a genetic algorithm with different chromosome structure. Also, [Zegordi and Beheshti Nia, 2009b] presented a multi-population genetic algorithm for the problem in which a predetermined quota is assigned for each supplier. [Zegordi et al., 2010] introduced a gendered genetic algorithm for the problem, when the suppliers are located in a similar zone. [Yeung et al., 2011] discussed minimization of inventory and transportation costs in a supply chain scheduling problem. They use multiple time windows for products delivery. [Ullrich, 2013] considered time window for products delivery in a two-echelon supply chain and discussed the integration of production and transportation scheduling problems. [Beheshtinia et al., 2017] used RGGA to solve integrated production and transportation scheduling problem in a supply chain with multiple manufacturers. [Wang and Gunasekaran, 2017] proposed a dynamic programming based algorithm to minimize total shipping and penalty costs plus order fulfilment lead time in an integrated operations scheduling problem in reverse supply chains. [Karaoğlan and Kesen, 2017] developed a branch-and-cut algorithm to minimize the required time to produce and deliver all

customer demands in a single production facility and its customers using the concept of limited shelf life.
[Devapriya et al. 2017] developed a mixed integer programming model and an evolutionary algorithm to minimize costs in an integrated production and distribution supply chain scheduling problem. In their problem, the products have limited lifetime and the total demand must be satisfied within a planning horizon.

[Alinezhad et al., 2018] discussed Vehicle Routing Problem (VRP) considering simultaneous delivery and pickup and time windows. After presenting the mixed binary integer programming of the problem, they used an Improved Particle Swarm Optimization (PSO) algorithm to solve it. [Borumand and Beheshtinia, 2018] used a developed genetic algorithm by merging genetic algorithm with VIKOR method to solve integrated production and transportation scheduling problem with multiple objective functions. [Beheshtinia and Ghasemi, 2017] used a new meta-heuristic algorithm named Multiple League Championship Algorithm (MLCA) that inspired by championship matches to solve integrated production and transportation scheduling problem in a supply chain with multi-site manufacturers.

Some researches consider routing problems in various cases.
[Ghatreh Samani and Hosseini-Motlagh, 2017] proposed a hybrid algorithm by combination of simulated annealing (SA) algorithm and genetic algorithm (GA) to solve a two-echelon location-routing problem with simultaneous pickup and delivery under Fuzzy Demand. [Nikkhah Qamsari et al., 2017] used a hybrid heuristic method by combination of variable neighborhood search algorithm (VNS) and simulated annealing (SA) for a multi-depot inventory-routing problem
[Cheraghi and Hosseini-Motlagh, 2017] proposed a fuzzy-stochastic mixed integer linear programming model to design blood supply chain network for disaster relief. They employed the model in a real-life case study in Iran.

The literature review indicates that transportation scheduling in a supply chain considering a combination of VRP and cross-docking methods for transportation has not been studied until now.

In this research we study this problem and merge the transportation scheduling with transportation one. Using time as continuous parameter, the material flow between some suppliers and a manufacturer is determined to minimize total tardiness in delivering a set of orders. Briefly, the innovations in this study are as follow:

- Considering transportation scheduling problem in a hybrid transportation system composed of cross-docking and VRP approaches
- Merging the mentioned transportation scheduling problem with the production scheduling problem
- Presenting a mathematical model for this new problem
- Adapting RGGA to solve the problem

3. Research Method

In this section after presenting the problem definition, the research steps are described.

3.1 Problem Description

In this article production scheduling in suppliers is merged with that of transportation in a supply chain. This type of integration is considered by some previous researches such as [Zhong et al., 2007], [Zegordi and Beheshti

Nia, 2009b], [Zegordi and Beheshti Nia, 2009a] and [Zegordi et al. 2010].

Moreover, it is assumed that the transportation system used by the suppliers is a combination of VRP and cross-docking methods.

Other hypothesizes of the problem are as follows:

- It is assumed that there are n orders, which need to be assigned for processing to *m* suppliers located in different geographical places.
- Some of the suppliers may have more equipment and machinery that leads to faster production compared to other suppliers. In other words, each supplier has a different production speed.
- Orders should be transferred from suppliers to a manufacturer with a transportation fleet that consists of *l* vehicles.
- Vehicles in the transportation fleet could have different transfer speed, which is considered constant in the entire rout. If vehicle *k* travels distance of *dis*, the time would be calculated by *dis/ vk*, in which *vk* is transfer speed of vehicle *k*.
- Suppliers have different production speeds. If supplier *s* process order *i* with pt_i required processing time, the real processing time would be calculated by pt_i/SS_s, in which SS_s is production speed of supplier *s* [Zegordi et al., 2010].
- After transferring goods from the suppliers to the manufacturer no vehicle would be deleted from the problem and they could be reused.
- Any order can occupy different capacity of vehicles.
- Capacity of each vehicle could be different from the others. The capacity is defined as the volume or weight of orders that is carried in a batch of a vehicle. If the total volume of orders assigned to a vehicle is more than its capacity, it should be divided in multiple batches where each is not more than the vehicle capacity.
- If orders assigned to one vehicle come from different suppliers, the vehicle should load orders from the suppliers as in VRP method and deliver them to the manufacturer.
- There are *f* Cross-Docking Terminals (CDT) that are spread out in different geographical places.
- Suppliers can use cross-docking terminals for transporting the orders. If a supplier uses a cross-docking terminal, assigned orders to this supplier would be transferred to the nearest cross-docking terminal by the small capacity vehicles. In this situation, ready time of an order for loading on the high capacity vehicles is the sum of its completion time in its assigned supplier and transportation time by the assigned small capacity vehicle.
- Each order has a predetermined due date and if delivery time of each order to the manufacturer is longer than its due date, then the order has tardiness. In this case, the tardiness is equal to the difference between due date and delivery time of the order.
- The problem determines the following decisions as output to minimize the total tardiness of orders:
- Orders assignment to each supplier
- Orders production sequence for orders assigned to each supplier

- Suppliers which are better to use cross-docking terminals
- Orders assignment to each vehicle
- Orders transportation priority for orders assigned to each vehicle

After determining the above items and considering input data, scheduling in different stages (suppliers and vehicles) can be calculated.

3.2 Research Steps

In this research the following steps are used to solve the problem:
Step1: Presenting the mathematical model of the problem.
Step 2: Giving a developed version of genetic algorithm called Reference Group Genetic Algorithm (RGGA) to solve the problem.
Step 3: Generating a set of test problems to evaluate the performance of RGGA.
Step 4: Comparing the obtained result by RGGA and a Classical Genetic Algorithm (CGA).
In the next section the obtained results by implementing the research steps are mentioned.

4. Results

In this section the results of implementation of research steps are described.

4.1 Presenting the Mathematical Model

The mathematical model of the problem is introduced in this section. Before presenting the model, we introduce the used notation for the mathematical model of the problem as follows:

Sets

Set of *No* orders (*No:* Total number of orders)
Set of *Nv* vehicles (*Nv:* Total number of vehicles)
Set of *Ns* suppliers (*Ns*: Total number of suppliers)
Set of *Nc* cross-docking terminals (*Nc*: Number of cross-docking terminals)

Indices

q,i:	Order index, $i, q = 1, 2, ..., No$
s, s' :	Supplier index, $s, s' = 1, 2, ..., Ns$
b:	Batch index, $b = 1, 2, ..., No$
m:	Vehicle index, $m = 1, 2, ..., Nv$
c:	Cross-docking terminals index, $c = 1, 2, ..., Nc$
p:	Priority index for transportation of orders of a batch, $p = 1, 2, ..., No$

Parameters

Due_i:	Due date of order
SS_s:	Speed of supplier s
VS_m:	Speed of vehicle m
$Size_i$:	Occupied size of a vehicle by order i
Cap_m:	Transfer capacity of vehicle m
pt_i:	Processes time of order i
Use_s:	1 if supplier s uses a CDT, otherwise 0

$dis_{ss'}^{cc}$: Distance from supplier s to s' when both of the uses CDTs. In this case it is equal to distance from CDT of supplier s to CDT of supplier s'.

$dis_{ss'}^{cs}$: Distance from supplier s to s' when supplier s uses CDT, while supplier s' does not use it.

$dis_{ss'}^{sc}$: Distance from supplier s to s' when supplier s does not uses CDT, while supplier s' uses it.

$dis_{ss'}^{ss}$: Distance from supplier s to supplier s' when none of them use CDT.

$disms_s$: Distance from the manufacturer to supplier s

$dismc_s$: Distance from the manufacturer to the related CDT of supplier *s*

$discm_s$: Distance from the related CDT of supplier *s* to the manufacturer

$dissm_s$: Distance from supplier s to the manufacturer

$ttsc_s$: Transportation time between supplier *s* and its related CDT

A: A $No \times Ns$ matrix, $A(i,s)=1$ if assigning of order *i* to supplier *s* is allowed, else 0

BIG: A big positive number

Variables

co_i: Completion time of order *i* at supplier stage

$Delivery_i$: Delivery time of order *i*

$Tardiness_i$: Tardiness of order *i*

$Load_i$: Loading time of order *i* by a vehicle

Av_{mbi}: Availability of vehicle *m* to transfer order *i* in batch *b*

x_{si}: It is 1, If order *i* is assigned to supplier *s*; otherwise it is 0

y_{iq}: If order *i* has higher production priority than order *q* at supplier stage

V_{mbip}: If order *i* have *f*th transfer priority in *b*th batch of vehicle *m*

$rdis_{ss'}$: Real traversed distance by a vehicle, when it loads an order from supplier *s* and another from supplier s', consecutively

The mathematical model of the problem is as follows:

$$Min\, Z = \sum_{s=1}^{No} Tardiness_i \qquad (1)$$

S.t.:

$$\sum_{s=1}^{Ns} x_{si} = 1 \qquad \forall i \qquad (2)$$

$$\sum_{m=1}^{Nv}\sum_{b=1}^{No}\sum_{p=1}^{No} V_{mbip} = 1 \qquad \forall i \qquad (3)$$

$$\sum_{i=1}^{No} V_{mbip} \le 1 \qquad \forall m, b, p \qquad (4)$$

$$\sum_{i=1}^{No}\sum_{p=1}^{No} size_i \times V_{mbip} \le Cap_m \qquad \forall m, b \qquad (5)$$

$$co_i \ge \frac{pt_i}{SS_s} - BIG \times (1 - x_{is}) \qquad \forall i, s \qquad (6)$$

$$\begin{aligned} & co_i + BIG \times (2 + y_{iq} - x_{si} - x_{sq}) \ge co_q + \frac{pt_i}{SS_s} \\ & co_q + BIG \times (3 - y_{iq} - x_{si} - x_{sq}) \ge co_i + \frac{pt_q}{SS_s} \end{aligned} \qquad \forall i, q, s \mid i < q \qquad (7)$$

$$y_{iq} = 0 \qquad \forall i, q \mid i \ge q \qquad (8)$$

$$\sum_{i=1}^{No} V_{mbi(p+1)} \le \sum_{i=1}^{No} V_{mbip} \qquad \forall m, b, p \mid p < No \qquad (9)$$

$$\sum_{i=1}^{No} V_{m(b+1)i1} \le \sum_{i=1}^{No} V_{mbi1} \qquad \forall m, b \mid b < No \qquad (10)$$

$$Load_i \ge Av_{mbi} - BIG \times (1 - \sum_{p=1}^{No} V_{mbip}) \qquad \forall m, b, i \qquad (11)$$

$$Load_i \ge co_i \qquad \forall i \qquad (12)$$

$$Load_i \ge co_i + ttsc_s - BIG \times (2 - x_{is} - Use_s) \qquad \forall i, s \qquad (13)$$

$$\begin{aligned} & av_{m1i} \ge \frac{dismc_s}{VS_m} - BIG \times (3 - V_{m1i1} - x_{is} - Use_s) \\ & av_{m1i} \ge \frac{disms_s}{VS_m} - BIG \times (2 - V_{m1i1} - x_{is} + Use_s) \end{aligned} \qquad \forall m, s, i \qquad (14)$$

$$\begin{aligned} & av_{mbi} \ge delivery_q + \frac{dismc_s}{VS_m} - \\ & BIG \times (4 - V_{mbi1} - V_{m(b-1)q1} - x_{is} - Use_s) \\ & av_{mbi} \ge delivery_q + \frac{disms_s}{VS_m} - \\ & BIG \times (3 - V_{mbi1} - V_{m(b-1)q1} - x_{is} + Use_s) \end{aligned} \qquad \forall i, q, m, s, b \mid b \ne 1 \qquad (15)$$

$$rdis_{ss'} \geq dis_{ss'}^{cc} - BIG \times (2 - Use_s - Use_{s'})$$
$$rdis_{ss'} \geq dis_{ss'}^{cs} - BIG \times (1 - Use_s + Use_{s'})$$
$$rdis_{ss'} \geq dis_{ss'}^{sc} - BIG \times (1 + Use_s - Use_{s'}) \qquad \forall c, s, s' \qquad (16)$$
$$rdis_{ss'} \geq dis_{ss'}^{ss} - BIG \times (Use_s + Use_{s'})$$

$$av_{mbi} \geq Load_q + \frac{rdis_{ss'}}{VS_m} - BIG \times (4 - V_{mbqp} - V_{mbi(p+1)} - x_{qs} - x_{is'}) \qquad \forall i, q, m, s, s', b, p \mid p < No \qquad (17)$$

$$delivery_i \geq Load_q + \frac{discm_s}{VS_m} - BIG \times (4 - \sum_{p=1}^{No} V_{mbip} - \sum_{p=1}^{No} V_{mbqp} - x_{qs} - Use_s)$$
$$delivery_i \geq Load_q + \frac{dissm_s}{VS_m} - BIG \times (3 - \sum_{p=1}^{No} V_{mbip} - \sum_{p=1}^{No} V_{mbqp} - x_{qs} + Use_s) \qquad \forall m, b, i, q, s \qquad (18)$$

$$Tardiness_i \geq delivery_i - Due_i \qquad \forall i \qquad (19)$$

$$Xsi = 0 \qquad \forall i, s \mid A(i,s) = 0 \qquad (20)$$

$$co_i \geq 0,\ Delivery_i \geq 0,\ Tardiness_i \geq 0,\ Load_i \geq 0 \quad \forall i \qquad Av_{mbi} \geq 0 \quad \forall i, m, b$$
$$rdis_{ss'} \geq 0 \quad \forall s, s' \qquad y_{iq} \in \{0,1\} \quad \forall i, q \qquad (21)$$
$$x_{si} \in \{0,1\}\ \forall i, s \qquad V_{mbip} \in \{0,1\}\ \forall i, m, b, p$$

Constraint set 2 indicates that each order should be assigned to exactly one supplier. Constraint set 3 shows that each order should be assigned to one position of one batch of one vehicle. Constraint set 4 forces that two orders do not assigned to a position of a batch. Constraint set 5 indicates that total occupied size by the assigned orders to each batch of a vehicle should not exceed the vehicle capacity. Constraint set 6 links the completion time of each order with its processing time. Constraint set 7 demonstrations that each supplier could not process two orders simultaneously. Some extra variables are eliminated by Constraint set 8. Constraint set 9 specifies that if there is no assignment to position p of a batch, then it is not possible to assign an order to position p+1 of the batch. Constraint set 10 shows that if there is no assignment to batch b, then it is not possible to assign an order to batch b+1.

Constraint sets (11-13) determine loading time of an order. The loading is done when both of order and vehicle are available. Constraint set (11) considers the availability time of the related vehicle, while constrain sets (12) and (13) consider availability time of the order. The availability time of an order is equal to its completion time. Nevertheless, when its related supplier uses CDT, it is equal to summation of its completion time and the time of reaching to the related CDT. Constraint set 14 determines the availability time of a vehicle to transport the first order of its first batch considering using or not using CDT. The availability time of a vehicle to transport the first order of its other batches considering using or not using CDT is determined by constraint set 15. The real distance between two suppliers based on using or not using a CDT is determined by constraint set 16. Constraint set 17 links the availability time of a vehicle to transport an order and loading time of the previous assigned order. Constraint set 18 indicates that delivery time of the assigned orders to a batch should be identical. The tardiness of each order is specified by constraint set 19. Constraint set 20 prevents assigning an order to an allowable supplier. Constraint set 21 shows the sign and type of the used variables.

[Zegordi et al., 2010] have proved that when there is not cross-docking approach and the all distances between suppliers are zero, the problem is NP-Hard. Since the problem considered in this study is an extension of the mentioned problem, then it is at least the NP-Hard kind. So, finding an optimum solution in a reasonable time is impossible for all problems and heuristic or meta-heuristic solutions should be used. In this paper RGGA is adapted to solve the problem.

4.2 Reference Group Genetic Algorithm

In recent years, genetic algorithms have been commonly used for solving scheduling problems. In GA, each solution is transformed to a chromosome. After generating a population of chromosomes, two operators, namely crossover and mutation are used to increase the population size by generating the new chromosomes. Then, some chromosomes are selected to create a new population. The procedure is repeated on the new population until the termination criterion is satisfied.

In this paper, to solve the problem a developed version of genetic algorithm based on a psychological theory, named Reference Group Genetic Algorithm (RGGA) introduced by [Beheshtinia et al. 2017] is adapted to solve the problem.

The sociologist Robert K. Merton introduced a concept named “role mode” [Calhoun, 2010]. The role models are reference groups that people in society imitate. A hero, a sport athlete or a movie superstar could be a role model. Reference groups influence the behaviors and manners of the people.

In this algorithm a set of chromosomes that have the best objective function values are considered in a collection called Good Role Models (GRM) set and a list of chromosomes that have the worst objective function values are considered in a collection called Bad Role Models (BRM) set. Chromosomes in a population try to make themselves more similar to GRM members and different from the BRM members. In the mutation operator of RGGA, one chromosome is randomly chosen and the mutation is operated on in two phases. In the first phase, one chromosome is randomly chosen from GRM set and the studied chromosome by mutation tries to make himself similar to the good model. In the second phase one chromosome is randomly chosen from BRM and the studied chromosome by mutation tries to be different from the bad chromosome. Furthermore, in the proposed genetic algorithm it is assumed that the population would be influenced by each other as well as by the good and bad role models. This situation is considered in the crossover operator. In this crossover operator two chromosomes are chosen randomly and each one of them is influenced by the other one and tries to make himself similar to that. The flowchart of RGGA is presented in Figure 2.

4.2.1 Chromosomes Structure

In RGGA, each chromosome structure consists of two parts. The first part is a binary array whose length is equal to the number of suppliers. This array, that we call Cross-Usage string, shows if any suppliers use a CDT or not. If the value corresponding to a supplier in Cross-Usage array is 1, it means that specific supplier is using a cross-docking terminal and vice versa.

The next part is a two-dimensional matrix. The vertical dimension is related to the suppliers and vehicles and the horizontal dimension is related to assigned orders to the suppliers and vehicles. For each supplier (vehicle) there is a string that the length and the elements order indicate the number of assigned order to the supplier

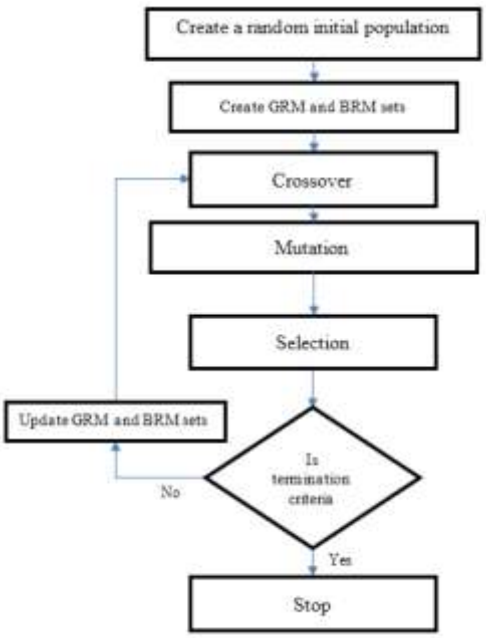

Figure 2. Flowchart of RGGA

Cross-Usage string	0	1	0
Supplier 1	4		
Supplier 2	3	2	
Supplier 3	5	1	
Vehicle 1	4	3	5
Vehicle 2	2	1	

Figure 3. Chromosome structure in RGG

Table 1. Assigned orders and their sequences

	Assigned orders and their priorities		
Supplier 1	O_4	Cross-docking use	No
Supplier 2	$O_3 \rightarrow O_2$		Yes
Supplier 3	$O_5 \rightarrow O_1$		No
Vehicle 1	$O_4 \rightarrow O_3 \rightarrow O_5$	Batch assignment	O_4 and $O_3 \rightarrow B_{11}$, $O_5 \rightarrow B_{12}$
Vehicle 2	$O_2 \rightarrow O_1$		O_4 and $O_3 \rightarrow B_{21}$

(vehicle) and their production (transportation) priority. If the number of tasks assigned to suppliers or vehicles is changed, the length of related string would be changed as well. To explain further, consider a problem with 3 suppliers, 2 vehicles and 5 orders. A chromosome for this problem is demonstrated in Figure 3. The related solution of this chromosome is presented in Table 1.

Considering the orders size and vehicles capacity, the orders are assigned to the batches.

4.2.2 Fitness Function

Fitness function for each chromosome is $\frac{MaxT - T}{Max\ T}$,where T is obtained from the chromosome scheduling and $Max\ T$ is the highest value of objective function in current population.

Initial population: chromosomes of the initial population are randomly created. Size of the first population is specified with parameter *popsize.* For creation of each random chromosome the following algorithm is used:

Step 1: specify randomly Cross-Usage string elements with zero and one.

Step 2: for each order select a supplier and a vehicle randomly.

Step 3: create a random permutation from orders.

Step 4: assign orders based on the permutation of step 3 to the selected suppliers and vehicles.

In the following section, other parameters and operators of RGGA are described.

4.2.3 Crossover and Mutation

In a society people try to imitate the good models and distinguish themselves from the bad models. This behavior is implemented in the mutation procedure of RGGA. Also, the impression of people to each other is considered in the crossover operator of RGGA.

4.2.3.1 Mutation

To explain the mutation operator, consider a randomly selected chromosome from the population, namely X, a randomly selected chromosome from the good models, namely Y and a randomly selected chromosome from the bad models, namely Z.

Chromosome X tries to imitate Y and inherits some characteristics of Y. To simulate this behavior in RGGA, a random order is selected. If the allocated supplier and vehicle of the selected order in X is different from Y, then they should be converted to be the same as Y. But, if allocated supplier and vehicle of the selected order in X is the same as Y, then no change occurs.

Chromosome X tries to distinguish itself from Z. To simulate this behavior in RGGA, a random order is selected. If allocated supplier and vehicle of the selected order in X is different from Z, then no change occurs. But, if allocated supplier and vehicle of the selected order in X is the same as Z, then the selected order is allocated to another supplier or vehicle, randomly.

When the allocation of supplier or vehicle is changed, then its position in the string of new supplier or vehicle is determined randomly.

4.2.3.2 Crossover

As mentioned previously, the impression of people to each other is considered in the crossover operator of RGGA. To explain the crossover operator, consider two randomly selected chromosomes from the population, namely A and B. Chromosome A inherits some characters of B and B inherits some characters of A. To simulate this behavior in RGGA, the allocated supplier and vehicle for a randomly selected order in chromosome A should be converted to be the same as B, and vice versa.

In RGGA, a fraction of the population with the highest fitness function value is transferred directly to the next generation. This fraction is shown by *best* and it is one of the genetic algorithm parameters. The rest of the chromosomes for the next population are chosen based on the roulette wheel criterion from the previous population.

If the current best fitness function of RGGA does not improve in sequential generations, the algorithm terminates. The number of these consecutive repeats is specified by *termination* parameter.

Based on the performed examinations and empirically, 100 is considered a proper value for the population size. Similarly, 5 for size of GRM and BRM sets, 100 for *termination*, 0.6 for the crossover rate, 0.8 for the mutation rate and 0.1 for *best*.

4.3 Numerical Experiment

Because the discussed problem has not been investigated previously in the literature, to assess the performance of RGGA, it was compared with a genetic algorithm proposed for the nearest problem in the literature to ours by [Zegordi and Beheshti Nia, 2009b] namely dynamic genetic algorithm (DGA). An attempt was made to define the characters and parameters of RGGA and DGA as identically as possible such as chromosome structure, population size, selection operator, crossover and mutation rates and termination criterion. Furthermore, the performance of RGGA is evaluated by comparison between its results and the optimum solutions.

4.3.1 Test Data

To generate the test problems, the following parameters of the test problems are changed: 1) No, 2) Ns and Nv, 3) process times and distances, 4) Cap_m, 5) Nc, 6) SS_s and VS_m, 7) $Size_i$, 8) and Due_i.

To generate a wide spectrum of test problems, three cases are considered for No as 10, 50, and 100. Also, three cases for Ns and Nv. In the first case, Ns and Nv are selected from the uniform distribution U[11,15]. In the second case Ns~U[6,10], but Nv~U[16,20]. In the third case, Nv~U[6,10], but Ns~U[16,20]. In fact, we have a balance between Ns and Nv in the first case. In the second case, we have a bottleneck in the production stage, but in the third case, we have a bottleneck in the transportation stage.

A similar scenario, is considered for the processing times of orders and distances. In the first case, both parameters follow from uniform distribution of U[10,30]. In the second case, processing times~U[1,20], while the distances ~U[20,40], and in the third case, processing times~U[20,40], while the distances ~U[1,20]. For Cap_m two cases are considered. In the first case, the Cap_m~U[8,13] while in the second case Cap_m~U[13,23]. Also, two cases are considered for Nc. In the first case, Nc~U[1,0.5*Ns] and in the second one Nc~U[0.5*Ns, Ns].

For the other parameters, only one case is considered as follows: SS_s and VS_m ~U[1,4], $Size_i$~U[1,8] and Due_i~U[0,0.2P] in which P is a destination for delivery time of the last delivered order and is obtained from the following relation:

$$P = \frac{\sum_{i=1}^{No} pt_i}{\sum_{s=1}^{Ns} SS_s} + \frac{No\,\bar{d}is}{\sum_{m=1}^{Nv} VS_m} \qquad (22)$$

In which, $\bar{d}is$ is mean of all distances.

108 test problems are generated when the mentioned parameters are varied. (3*3*3*2*2*1*1*1= 108). These 108 problems have been solved by RGGA and DGA and the results are assessed in the next section.

4.3.2 Comparison of RGGA and DGA

The generated test problems are solved by RGGA and DGA and results are shown in Table 2 in which the mean results and mean CPU times of both algorithms is accessible. Also, the gap of the obtained solutions (Gap), the percentage of success of RGGA than DGA (PS) and the percentage of defeat of RGGA from DGA (PD) are shown.

All algorithms are coded in Matlab and run by a PC with Intel Core i3, 1.70 GHz CPU with 4 GB of Ram.

Table 2 indicates that RGGA outperforms DGA in all of the cases. The results show that an increase in *No* causes increase in mean of the results and CPU times as well. Considering the *Ns* and *Nv*, it is obvious better results are obtained when the Ns is high (Case 3) and the worse result is achieved when the *Ns* is low and there is a bottleneck in the supplier stage (Case 2). It means that *Ns* is more critical than the *Nv*. Also, when process times in supplier stage is high (Case 3) the worse result is obtained than the case the distances are high (Case 2). It is confirmed that having a bottleneck in the supplier stage causes the worse results compared with the case in which there is a bottleneck in the transportation stage.

Table 2.Performance study of RGGA and DGA algorithms

		Mean of RGGA answers	Mean DGA answers	Gap	PBR	PER	Mean RGGA cpu-time	Mean DGA cpu-time
Number of orders	10	132.99	145.37	12.38	75	0	21.97	40.23
	50	1825.52	3219.53	1394	100	0	670.94	738.62
	100	3769.59	8329.69	4560.1	100	0	2453.48	1798.74
Number of suppliers and vehicles	Case 1	1844.41	3925.49	2081.1	91.66	0	1019.39	862.6
	Case 2	2360.53	4097.58	1737.1	100	0	1030.09	835.1
	Case 3	1523.16	3671.52	2148.4	83.33	0	1096.92	879.89
Distance and processing time	Case 1	1956.33	3970.15	2013.8	94.44	0	1077.3	839.86
	Case 2	1056.55	2184.42	1127.9	91.66	0	1052.01	868.85
	Case 3	2715.21	5540.03	2824.8	88.88	0	1017.09	868.88
Vehicles capacity	U[8,13]	1960.3	4003.9	2043.6	94.64	0	1072.1	912.13
	U[13,23]	1858.44	3792.5	1934.1	88.67	0	1025.49	806.27
Number of cross-dock	Case 1	2020.01	3973.11	1953.1	90.74	0	976.36	790.02
	Case 2	1798.72	3823.29	2024.6	92.59	0	1121.24	928.37
All problems results		1909.37	3898.2	1988.8	91.66	0	1048.8	859.2

Table 2 shows increasing the *Capm*, causes decrease in mean of both algorithms results. Also, increasing the *Nc* leads to decrease in the mean of both algorithms results.

For more evaluation of the RGGA performance, we compare its results with optimum solutions for some low size randomly generated problems. We use CPLEX solver to obtain optimum solution. Table 3 shows the problems in which each problem is identified by three parameters. The parameters are *No*, *Ns* and *Nv*, respectively and other parameters of the problems are considered randomly. The results show RGGA provide the optimum solution in some cases, having the lower CPU time. In the other cases, the differences between RGGA and the optimum results is not high. Subsequently, we could conclude the superiority of RGGA.

5. Summary, Conclusion and Future Studies

Using a shared transportation system causes more effective use of vehicles and reduction in transportation costs. This paper studies an integration scheduling supply and production in a supply chain considering a shared transportation system. It is assumed that the shared transportation system combines VRP and cross-docking methods.

After proposing a new mathematical model of the problem, an innovative genetic algorithm based on a psychological theory, named Reference Group Genetic Algorithm (RGGA) is introduced to solve the problem. The sociologist Robert K. Merton introduced a concept named “role mode” [Calhoun, 2010]. Role models are persons that people in society imitate. A hero, a sport athlete or a movie superstar could be a role model. Role models influence the behaviors and manners of the people. Because the problem has not been studied previously in the literature, RGGA performance is compared with a genetic algorithm proposed by [Zegordi and Beheshti Nia, 2009a] for the nearest problem in the literature to ours, namely dynamic genetic algorithm (DGA). An attempt was made to define the characters and parameters of RGGA and DGA as identically as possible such as chromosome structure, population size, selection operator, crossover and mutation rates and termination criterion.

Table 3. Comparison between RGGA and optimum solution

Problem	Optimum solution		RGGA	
	Result	CPU time (second)	Result	CPU time (second)
5×1×1	13.56	46	15.51	40
5×2×2	12.34	48	12.34	33
5×3×3	10.47	61	10.47	34
6×1×1	24.21	2374	27.37	34
6×2×2	20.45	627	20.45	36
6×3×3	18.35	822	18.35	61
6×4×2	15.09	638	15.09	26
6×2×4	14.67	3546	14.67	0
7×2×1	25.6	455	27.3	48
7×1×2	26.86	490	28.82	27

The results show the better performance of RGGA. Comparison between RGGA results and optimum solution certificates the superiority of RGGA.

Developing the problem for a situation in which the customer distribution channel is also considered in the supply chain integration could be a field for future studies.

Adding other objective functions such as minimizing total traveled distances or *CO2* emission could be another scope for the future studies. Another avenue for future studies is merging other psychological concepts with genetic algorithm.

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