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Vehicle routing problem with cross docking: A simulated annealing approach

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Abstract

Cross docking is a valuable logistics strategy given that it provides less inventory holding costs, less transportation costs and fast customer deliveries. Cross docking should also be considered in strategic planning since it provides competitive advantage by reducing firm costs. An efficient vehicle routing may even increase the benefits of the cross docking. This study presents a vehicle routing problem in a cross docking setting with heterogeneous vehicles having different capacities. All the routes begin and end at the cross dock and all the pickup and delivery sites are visited by only one vehicle. The aim of this study is to find the routes that minimize total transportation costs and the fixed costs of the vehicles. A simulated annealing algorithm is proposed to solve the problem. The proposed simulated annealing heuristic presents reasonable solutions in terms of computational time, best cost values and the convergence pattern on the best cost.

Keywords: Logistics strategy, cross docking, vehicle routing problem, heterogenous vehicles, simulated annealing

1. Introduction

Supply chain and logistics management in contemporary markets is a vital function of operations management since consumers want to access diversified and quality goods in quick and easy ways. To efficiently deliver goods to customers it is insufficient to minimize costs for each supply chain member separately. Upper stream and downstream members of the supply chain should be considered as integrated in cost minimization since minimizing system wide

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cost will improve supply chain performance as a whole and provide better delivery performance to customers (Simchi-Levi, Kaminsky, & Simchi-Levi, 2007). Cross docking is one of the methods that establish integration between upper stream and downstream members of the supply chain.

Cross docking can be generally defined as the transfer of goods and materials from an inbound carrier to an outbound carrier while materials and goods do not actually enter into the warehouse or stored in a predetermined depot (Kulwiec, 2004). With cross docking policy, inventory holding role of a traditional warehouse is eliminated and at the same time products are still subject to consolidation meaning classification according to demand patterns and loading to delivery vehicles (Wen, Larsen, Clausen, Cordeau, & Laporte, 2008). Cross docking center should not be regarded as a storage point since products are stored for a short duration only for the consolidation process. Right after the consolidation, products will be transmitted to their corresponding customers according to product destinations (Moghadam, Ghomi, & Karimi, 2014).

Cross docking has various benefits for especially large scale supply chains working with massive amounts of products. Significant inventory savings due to no storage compose an important part of cross docking benefits. There is no routing to stationary storage areas and rerouting back to dock areas. Without the storage unit, inventory holding costs and inventory handling costs are severely reduced. In addition to benefits to the supply chain firms, crossdocking provides enhanced customer service by speeding up customer deliveries (Kulwiec, 2004).

Advantages of cross docking may even be enhanced by an efficient vehicle routing (Hasani-Goodarzi & Tavakkoli-Moghaddam, 2012). The vehicle routing problem (VRP) plays an essential role in the field of supply chain management and logistics. The costs related to operating vehicles used for transfer of goods to customers constitute an important part of total supply chain costs (Barbarosoglu & Ozgur, 1999). In VRP there are differentially located customers that have diverse demands for a product. They are served by some identical vehicles with a limited capacity from one depot. The aim of VRP is to determine a set of vehicle routes that brings minimum total cost in a single period given that (i) each route starts and ends at a depot; (ii) each customer is served by only one vehicle; and (iii) the total demand on each route does not exceed the vehicle capacity. (Lahyani, Khemakhem, & Semet, 2015).

Strategic management literature has not given much attention on supply chain management and benefits of supply chain management on strategic management is not well explored (Gonzalez-Loureiro, Dabic and Kiessling, 2015). Logistics management should be considered as a part of strategic management since it provides competitive advantage to the companies by focusing on low cost delivery performance, a key success factor in most of the industries. To make costs lower and gain competitive advantage distribution decisions should be considered in the strategic planning. Although, there are some arguments stating replenishment decisions such as transportation patterns are not at the strategic level and should not be discussed in the strategic planning, taking transportation costs out of consideration can indicate sub-optimality (Max Shen & Qi, 2007). A successful logistics strategy not only includes integration with other departments such as marketing and production, it also should be linked to overall corporate strategy (Meade & Sarkis, 1998). Sum, Teo and Ng (2001), showed that for strategic companies logistics plays a key role in strategic planning process. In their study they investigated how different departments influence strategic planning of the firms. Their findings showed logistics have a larger influence on strategic planning than marketing and production (Sum, Teo, & Ng, 2001).

In strategic planning, logistics strategies should be well-thought-out while deciding overall strategies of the firms. Logistics strategies are beneficial to the firms in terms of achieving overall corporate strategies, since one of the most important features of logistics strategies should be finding the ways of minimizing total cost in the distribution phase. Minimizing distribution costs can be achieved by determining best vehicle routing while serving to the customer. Cross docking is a technique that provides low inventory and transportation cost in the supply chain. In this aspect VRP with cross docking (VRPCD) can be considered as a vital logistics strategy during strategic planning of the organization and should take more attention from the strategic management point of view.

In the supply chain literature VRP has been intensively studied for the last decades in various contexts. First study of a VRPCD is conducted by Lee, Jung, and Lee (2006). They studied VRP in an environment including a number of pickup nodes and a number of delivery nodes connected by a cross dock. Shipments are conducted by homogenous vehicles chosen from a set. Routes of the vehicles start and end at the cross dock and all the vehicles return to the cross dock simultaneously. The objective is to minimize total cost including distribution costs and fixed costs of the vehicles. They used a tabu search algorithm to find the minimum total cost. Wen, Larsen, Clausen, Cordeau, & Laporte (2007) studied VRPCD in a setting where the vehicles after pickup do not have to come to the cross dock simultaneously.

Different from Lee et al. (2006) they considered consolidation time for each delivery in mathematical modeling. They also used a tabu search metaheuristic embedded in an adaptive memory procedure to find the best routes producing minimum distribution costs. Liao, Lin, & Shih (2010) used same setting with the same parameters as Lee et al. (2006). They proposed a different tabu search algorithm and compared their results with Lee et al. (2006). Their solution provided lower costs than the solution of Lee et al. (2006).

Santos, Mateus, & Salles da Cunha (2011) proposed a VRPCD in which costs to load/unload trucks at cross dock are introduced. They ignored time windows constraints at suppliers, consumers and cross dock. They implemented a Branch-and-price algorithm to solve the proposed problem. Dondo & Cerdá, (2013) defined a VRPCD with some additional assumptions to the formulations. They assumed vehicles can serve more than one supplier or one customer. They considered service time at supply and delivery nodes and at the cross dock as Wen et al. (2007) did. They also assumed goods picked up and delivered by the same vehicle are not unloaded at the cross-dock. They compared an exact algorithm with a sweep based heuristic for solution of the problem. Their results showed the sweep based heuristic performed good in a short computational duration. Hasani-Goodarzi & Tavakkoli-Moghaddam (2012) studied VRPCD in a multi-product environment. They allowed split deliveries in their model meaning a customer can be served by more than one vehicle. Mixed-integer linear programming (MILP) is used to find the best vehicle routes.

VRP is an NP-hard problem and to solve the problem optimally, exact algorithms can only work fully for small scale problems. Since many real life problems include large scale distribution networks, heuristics and metaheuristics are often more appropriate for such NP hard problems (Braekers, Ramaekers, & Van Nieuwenhuyse, 2015). Recently, Moghadam et al.(2014) proposed a similar VRPCD as Wen et al. (2009) including service times at cross docks and time windows in the whole problem. Additionally they allowed split deliveries in their model. They proposed a hybrid metaheuristics formed with Ant Colony optimization and Simulated Annealing to solve the problem. Morais, Mateus and Noronha (2014) also used same problem as Wen et al. (2009). To solve the problem they proposed three Iterated Local Search heuristics. One of their solutions outperformed the solution of Wen et al. (2009). Ahmadizar, Zeynivand and Arkat (2015) formulated a two level VRPCD with multiple cross docks and multiple products. Best routing was tried to be found between suppliers and the cross docks in pickup and between the cross docks and the retailer in the delivery. A hybrid metaheuristic including genetic algorithm and local search is utilized in their study. Yu, Jewpanya and Redi (2016) studied open VRPCD. In an open VRP, a vehicle does not obliged to start from the cross dock or return to the cross dock after delivery. They proposed a simulated annealing heuristic to solve the problem. They compared the results of the proposed algorithm with the tabu search algorithms of Lee et al. (2006) and Liao et al. (2010). The proposed algorithm outperformed the two known tabu search algorithms.

In this study VRP in a cross docking setting is proposed and solved where goods are taken from several suppliers and consolidated in a cross docking. After the consolidation goods are distributed to the customers based on their priory known demands. Different from other studies, vehicles operated in the proposed setting are heterogeneous. Heterogeneous means the vehicles in the distribution network have different capacities. VRP implementation with cross docking includes two vehicle routing problems which should be considered together. First is the pickup in which the best route between suppliers and a cross dock is decided. Then to deliver the products to the customers, best route between the cross dock and the customers should be determined. The aim of the proposed setting is to minimize total distribution costs in the system including pickup and delivery. A simulated annealing (SA) metaheuristics is proposed to find the best solutions that reveal minimum distribution costs estimated by summing total transportation costs and fixed costs of the vehicles.

The remainder of the paper is organized as follows: In the second section the problem is defined with mathematical formulations. The proposed SA metaheuristic is explained in Section 3. Section 4 covers the proposed problem parameters and the results of the computations. Finally section 5 consists of the conclusions about this study.

2. Problem Definition

The problem in this study consists of two parts. In the first part goods are taken from the suppliers which are the pickup nodes and then delivered to the cross dock where they will be consolidated for customer delivery. In the second part, consolidated products are delivered to the customers whose demand is previously known. Vehicles are chosen from a set of heterogeneous vehicles meaning each vehicle has a different capacity. The problem in this study is similar to Lee et al. (2006) and Liao et al. (2010) problem except in this study heterogeneous vehicles are utilized and time horizon is not used for the computational simplicity. All the routes begin and end at the cross dock and no split deliveries are allowed. Pickup and delivery sites are represented by a node. For pickup and delivery, all the nodes are visited by only a one vehicle. Delivery immediately begins after all the pickup routes are finished. Fig. 1 represents the problem. The objective is to find the best routes that minimize total transportation costs and the fixed costs of the vehicles. For the calculation simplicity length of a visit in a node (including cross dock) is assumed to be zero. Notation that is used in this study and mathematical formulations that summarizes the problem is provided in the following.

Parameters

P	pickup nodes for suppliers
D	delivery nodes for customers
0	node for the cross dock
n	number of all nodes
V	number of available vehicles
m	index for vehicles from 1 to V
Q_m	maximum capacity for the vehicle m
p_i	quantity to be picked up in node i
d_i	quantity to be delivered to node i
tc_{ij}	transportation cost from node i to node j
c_m	operational cost of the vehicle m

Decision variables

x_{ijm}	1, if vehicle m moves from node i to node j ; 0, if otherwise
y_{ij}	amount to be transported from node i to node j in the pickup process
z_{ij}	amount to be transported from node i to node j in the delivery process

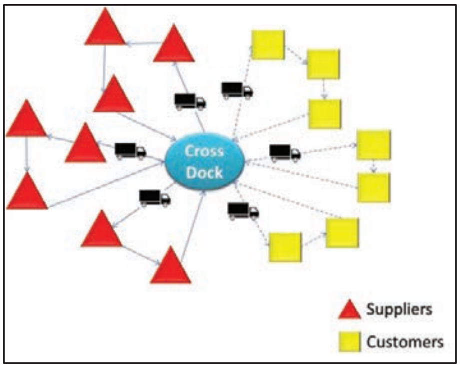

Fig. 1: Proposed cross dock environment.

The objective function in this study computes total distribution costs acquired in pickup and delivery processes including total transportation costs between nodes and the total operational costs of the vehicles as shown in Eq. 1. The mathematical representation of the proposed problem is described as the following.

$$Min\left(\sum_{i=0}^{n}\sum_{j=0}^{m}\sum_{m=1}^{V}tc_{ij}x_{ijm}+\sum_{m=1}^{V}\sum_{j=1}^{n}c_m x_{0jm}\right) \tag{1}$$

s.t

$$\sum_{i=0}^{n}\sum_{m=1}^{V}x_{ijm}=1 \qquad \forall j \tag{2}$$

$$\sum_{j=0}^{n}\sum_{m=1}^{V}x_{ijm}=1 \qquad \forall i \tag{3}$$

$$\sum_{i=0}^{n}x_{ibm}=\sum_{j=0}^{n}x_{bjm} \qquad \forall b,m \tag{4}$$

$$\sum_{j=1}^{n}x_{0jm}\le 1 \qquad \forall m \tag{5}$$

$$\sum_{i=1}^{n}x_{i0m}\le 1 \qquad \forall m \tag{6}$$

$$\sum_{m=1}^{V}\sum_{j=1}^{n}x_{0im}\le V \qquad \forall m \tag{7}$$

$$y_{ij}\le Q_m.x_{ijm} \qquad \forall m,\forall i,j \tag{8}$$

$$z_{ij}\le Q_m.x_{ijm} \qquad \forall m,\forall i,j \tag{9}$$

$$\sum_{i=1}^{n}p_i=\sum_{i=1}^{n}d_i \tag{10}$$

$$y_{ij}-y_{jb}=\begin{cases} p_j, & if\ \ j\in P,\forall i,b \\ 0, & if\ \ j\in D,\forall i,b \\ -\sum_{i=1}^{n}p_i, & if\ \ j\in 0,\forall i,b \end{cases} \tag{11}$$

$$z_{ij}-z_{jb}=\begin{cases} d_j, & if\ \ j\in D,\forall i,b \\ 0, & if\ \ j\in P,\forall i,b \\ -\sum_{i=1}^{n}d_i, & if\ \ j\in 0,\forall i,b \end{cases} \tag{12}$$

Constraints 2 and 3 ensure that only one vehicle can come to and leave from one node. Constraint 4 guarantees that vehicles move successively. Constraint 5 states whether a vehicle enters the cross dock. Constraint 6 shows whether a vehicle leaves the cross dock. Constraint 7 ensures that all the vehicles leaving cross dock must be less than the total number of vehicles. Constraints 8 and 9 guarantees that transported amount of goods in the vehicle should not exceed the vehicles capacity for both pickup and delivery process. Constraint 10 states that all the goods that are picked up from the suppliers must be delivered to the customers. Constraints 11 and 12 shows how the amounts of transported goods between nodes are calculated for pickup and delivery processes.

3. Simulated Annealing Algorithm

SA algorithm is a metaheuristic used to solve combinatorial optimization that repeatedly improves initial solution by making small local changes until no improvement occurs in the solution or a ending condition is satisfied (Chiang & Russell, 1996). Simulated annealing finds solutions by representing annealing of substances. SA uses several parameters including initial temperature, allowed iteration numbers at each temperature, the cooling rate, and the final temperature meaning the ending condition for the search (Borges, Eid, & Bergseng, 2014).

In SA search is started from initial solution with the aim of finding better solutions. When a solution outperforms the current solution then the new solution is updated as the current solution. If the new solution is worse than the current solution it is accepted based on a probability value which is calculated by using the values of the current temperature and the difference between the current and the candidate solution. Accepting worse solutions in some conditions allows SA to escape from local optimum.

3.1. Initial Solution

The initial solution of the SA algorithm in this study is a modified version of the algorithm used by Şirin (2010). In this study tolerance value used in Şirin (2010) is omitted. The steps of the initial solution algorithm are as follows:

Step 1: Select a vehicle to route.

Step 3: Add cross dock as the starting point of the route.

Step 4: Determine a random combination of the cities.

Step 5: Add the first city in the random combination to the route.

Step 6: Add demand of the selected city to the vehicle's capacity.

Step 7: Check if the vehicle's capacity is full. If it is not full, increment the city number and repeat steps 5 and 6. If the vehicle is full send vehicle back to the cross dock.

Step 8: Repeat steps1 to 8 until all cities has been visited.

3.2. Solution Representation

Each solution is composed of a set of numbers representing a node and a route change. A solution set in the pickup process includes pickup nodes of P={1,2,…,p} and the numbers representing a route change R={p+1,p+2,…,p+V). Similarly a solution set in the delivery process includes delivery nodes of D={1,2,…,d} and the route change numbers of R'={d+1,d+2,…,d+V}. In every solution the route starts and finishes with the cross dock. A solution set with p=4, d=5 and V=3, and its graphical representation can be seen in fig.2.

3.3. Neighborhood Search Mechanisms

SA algorithm in this study employs three different neighborhood search mechanisms to find better route combinations. These neighborhood search mechanisms are swap, reversion and insertion as used in Yu and Lin (2016). To find a new solution each neighborhood search mechanism will be used with a 1/3 probability. Explanations for the neighborhood search mechanisms are as follows:

- Swap: In this technique two nodes in a solution are randomly selected and their positions are exchanged in the new solution.
- Reversion: In this technique two nodes in a solution are randomly selected and the nodes between the selected nodes are reversely sorted in the new solution.

- Insertion: In this technique two nodes in a solution are randomly selected and the node which has the smallest position is inserted into the position just before the other node.

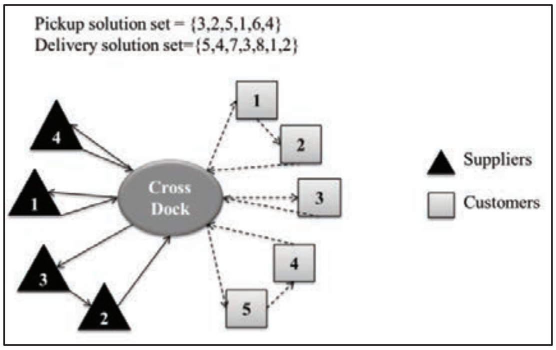

Fig. 2 – Representation of a solution.

3.4. Simulated Annealing Method

The SA algorithm in this study uses initial temperature (T_0), final temperature (T_f), temperature reduction rate (α) and the acceptance criteria for the non-improving solutions (P) as the main heuristic parameters. T_0 states the temperature at which the algorithm will start. In the beginning current temperature (T) is set to T_0. At each iteration current temperature is reduced by the ratio α. When T is below T_f the algorithm stops. When the new solution does not improve the best solution, it may be accepted with a condition depending on the value P. The steps of the proposed SA algorithm can be seen in the following.

Step 1: Set parameters T0, Tf and α
Step 2: Generate an initial solution (S) as explained in section 3.1.
Step 3: Update best solution: Best Solution=S;
Step 4: Set current temperature as the initial temperature: T=T0;
Step 5: Main body of the SA:

```
  while T>TF
 Create Neighbor solutions: use swap, reversion and insertion with a 1/3 probability
 if cost of New Solution<=Cost of S
          Accept new solution: S= New Solution;
      else
      delta= (Cost of New Solution) – (Cost of S)
      P=exp(-delta/T);
      Generate a random number between 0 and 1
          if random number<=P
            Accept new solution:  S= New Solution;
     if (Cost of S)<=(Cost of Best Solution) & Vehicle capacities are not exceed
   Update Best Solution: Best Solution=S;
    T= α*T
```

4. Numerical Example

To test the proposed model and the algorithms, instances were generated from the dataset of problem 1 adapted from Lee et al. (2006) Liao et al. (2010) and Yu et al. (2016) except two differences. Firstly the vehicle capacities were a constant of 70 in their dataset. In this study capacities of the vehicles were randomly distributed between 65 and 75. Secondly time parameters are not used in this study. The dataset contains a problem with 10 nodes. For each test instance transportation cost values between nodes are generated asymmetrically. Fixed cost of vehicles are 1000 in each instance. All the parameters used in this study is shown in table 1. Among SA parameters T0, Tf, and alpha were set to 100, 0.01 and 0.99 respectively.

The proposed SA algorithm was implemented on Matlab r2015b. In order to see the performance of the proposed algorithm, the SA procedure was run for 30 instances for each data set. Every run is performed on a Mac with a 2.6 Ghz Intel Core i5 Processor and 8 GB of RAM under the OS X El Capitan operating system The best cost obtained from instances in the dataset is listed in table 2. To assess the performance of the proposed algorithm average computational time values are also reported in table 2. Results show that each test instance is completed in a reasonable amount of time. Except one instance, each test instance was finalized before 2 seconds. For 30 instances average computational time recorded as 1.7434 seconds. To see how the proposed algorithm converges on the best solution three instances are chosen and convergence on best solutions are plotted in figures 3a, 3b and 3c . Figure 3a, 3b and 3c shows that SA is working as expected and after a certain number of iterations the SA algorithm converges on the best solution. For instance 1 as can be seen in figure 3a, after iteration 400 solution converges on the best cost. Figure 3b show that for instances 12 the algorithm converges on the best solution around iteration 150. For instance 26 the best solution is found after the first iterations as shown in figure 3c. By examining the convergence patterns SA algorithm can be regarded as fast in terms of finding the best solution.

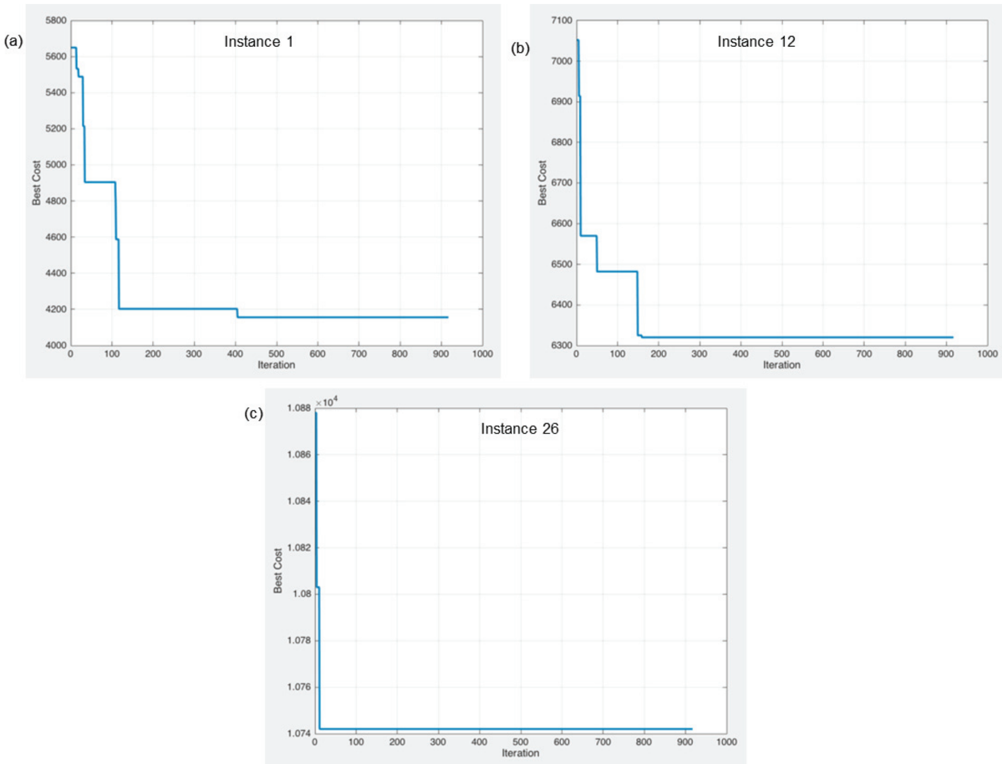

Figure 3 (a); (b); (c) Selected convergence patterns of the algorithm

Table 1. Parameters in the problem set

	Parameters
n	10
m	10
Qm	U(65,75)
cm	1000
tcij	U(48,560)
pi,di	U(5,50)
No. of suppliers	4
No. of customers	6

Table 2. Numerical results from the problem set

instance	Best cost	Total Computational time(sec)	instance	Best cost	Total Computational time(sec)	instance	Best cost	Total Computational time(sec)
1	4156	1.588	11	9731	1.819	21	8448	1.681
2	3992	1.537	12	6320	1.864	22	7524	1.864
3	9229	1.843	13	7237	1.605	23	7971	1.724
4	8761	1.933	14	10807	1.758	24	9541	1.584
5	11368	1.723	15	12210	1.704	25	8828	1.735
6	7319	1.839	16	3668	1.585	26	10742	1.712
7	6975	1.692	17	9775	1.832	27	7942	1.725
8	7172	1.797	18	8716	1.712	28	8123	1.753
9	8160	1.756	19	9276	1.771	29	5286	2.062
10	7142	1.751	20	10352	1.611	30	8692	1.742
						Average	8182.1	1.7434

5. Conclusion and future research avenues

Cross docking is an integration tool in logistics management that unites upper stream and downstream members of the supply chain. In cross docking there is a transfer center which is called the cross dock that consolidates the products picked up from a supplier. The consolidated products are then delivered to the customer according to customer demands. Since the cross dock is not an actual warehouse, firms in the integration bear less inventory costs.

In this study a cross docking setting with pickup and delivery sites were modeled mathematically. In the proposed setting the goods picked up from the suppliers. The same amounts of goods that are picked up are delivered to the customers. During the pickup and delivery processes heterogeneous vehicles that have different capacities are used. A SA algorithm is proposed to solve the problem. Proposed algorithm is tested with 30 instances that are randomly generated from a dataset used in Lee et al. (2006). In summary, the proposed SA algorithm showed solutions that are reasonable in terms of computational time, best cost values and the convergence pattern on the best cost. The results indicate that the proposed SA algorithm is applicable and effective in solving VRPCD problems.

This study may address several future research avenues for VRPCD. A time horizon may be added to the mathematical model to reflect a different supply chain setting. Split deliveries and multiple products may also be adapted to the proposed problem. Finally, the proposed algorithm may be modified such that more complicated problems with a bigger distribution network can be solved.

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