

different scenarios and the results accordingly. Finally, conclusions and further research are presented in section VI.

2 Literature Review

Starting from the earliest research that tackled cross-docking simulation problems, Rohrer [1] explained how simulation helps ensuring the success of cross-docking operations. The paper that targeted simulation practitioners introduces metrics that may help analyzing cross-docking problems efficiently. The problem of allocating the incoming and outgoing trucks to the doors of a CDF has been previously studied by simulation approaches. In 1999, Gue [4] proposed a rule where a rank of doors is assigned to each incoming truck based on the load's weight and the distances to each door. Regan et al [5] proposed a rule based on the transfer time of the order from incoming to outgoing door. This problem has been studied in the Optimization area as well by several researchers. Several scheduling problems have been indentified and different approaches have been proposed to solve it, see for example [5], [6], and [7].

Maglabehe et al. [8] introduced a simulation model of a CDF having several suppliers and destinations. The study focuses on the internal CDF operations (inbound and outbound trucks, consolidation, loading/unloading, etc) but does not address the aspects of the policies concerning the scheduling and the assignment decisions made by the dispatcher.

Cross-docking problems have been addressed by many researchers, but mostly in a deterministic fashion and with several strong assumptions. Deterministic cross-docking optimization problems were studied by [9] and [10]. This study proposes a discrete-event simulation model to attempt solving the cross-docking problem and evaluate different scenarios where some of the assumptions found in the literature are relaxed.

3 Model Description

In cross-docking, orders with specific load size are placed by customers from specific warehouses, where trucks pick the orders and unload them at the CDFs. At the warehouses, the orders are generated according to uniform schedules (depending on the scenario being modeled). Additionally, order attributes are assigned to each order upon generation. The attributes are: order id, order size, order due date, order destination, and order release time. The orders are then sorted and consolidated at the CDF to be ready for pick up by outgoing trucks to the destination of the customer who placed the order initially. At the CDF, the orders remaining slack time are updated (by subtracting current time t from order release time). The orders are finally shipped to the final destination according to the orders' attribute "order destination", and by priority depending on the updated slack time.

In our model, we are assuming three warehouses (origins), and a number of CDFs and a number of trucks that change according to the scenario being studied. Additionally, we are assuming three different standard truck sizes of 20, 40, and 53 units and truck types will be used according to the scenario chosen. A truck cannot be preempted during its trip to a certain CDF, origin, or destination, and becomes available right after offloading its carried load at a CDF or a destination.

The assumptions used in our model are the following:

1. Truck availability is taken into consideration. After offloading a load, the truck becomes available and free to be assigned to any other location.
2. All the products being transported are assumed to have a similar shape.
3. The origins and CDFs have infinite capacity (i.e. no queuing delays will occur at these locations) – as this assumption may seem unrealistic, the next version of our study will relax this assumption and focus on studying the overall behavior with queuing delays occurring at the CDFs.
4. The loading/unloading delays at the warehouse and CDFs are considered to be negligible.

5. The inventory at the warehouses is considered infinite. The demand is always met without any production delay.
6. All order sizes are generated according to a triangular distribution where orders vary from 5 units (minimum) to 53 units (maximum). In the case of an order size being equal to the requested truck size, the order is shipped directly to its final destination without passing through CDFs.
7. The three truck types have three different sizes.

4 Discrete Event Simulation Model

In our cross-docking simulation model, we use discrete event simulation in order to capture the effects of the chronological sequence of events occurring at specific times, and discretely changing states. The simulation model proposed was created using the simulation package Arena 10.0 that uses a graphical user interface (GUI) for SIMAN.

Our simulation model consists of three warehouses (or origins) and five customers (or destinations). Trucks carrying requested loads from origins to destinations pass through CDFs which can be 0, 2, or 4 CDFs depending on the scenario being studied. Trucks can move directly from origin to destination (and vice versa), from origin to CDFs (and vice versa), and from CDFs to destinations (and vice versa), as shown in Fig 1.

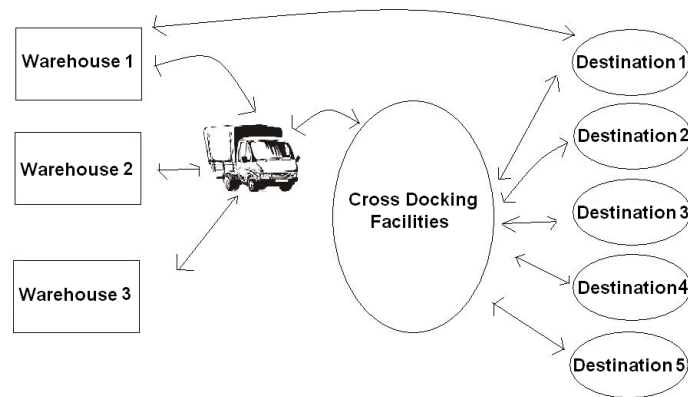


Fig. 1. The different routings of a truck.

When an order is placed by a customer, the order size, the supplier, and the due date are assigned as order's attributes. Following assumption number 5 in section 3, no delay occurs in generating the order and the load is ready to be picked up by a truck as soon as the order is placed. Orders are picked up by the closest available trucks according to the closest due date (orders with earlier due dates have higher priority). Once a load is picked up, if the load size is less than the truck size, it is transferred to the cross-dock representing the shortest route between origin and destination. Our assumption in choosing the cross-dock solely based on distance is that the origins, destinations, and CDFs are static in nature, thus, the distance between them remains the same throughout the entire model's lifecycle. If the load size is equal to the truck size, then the order is shipped directly from origin to destination without passing through CDFs. Note that the distances are generated randomly between each node in our system, following a general rule that the direct distance from origin to destination is larger than the total distance from origin to destination through an optimal cross-dock. The generated distances and the optimal cross-docks are discussed in more details in section 5.

When orders reach the CDFs, they are unloaded and batched with other orders according to the final destination. As soon as a truck is unloaded, it becomes available for other requests. Following our third and fourth assumptions in section 3 respectively, the CDFs have infinite capacities (i.e. no queuing delays will occur resulting from a CDF oversaturation) and loading/unloading delays are negligible.

When orders reach their final destination, they are disposed from the system, and necessary statistics are recorded. The orders at the CDFs are decided according to a priority rule using the following Slack function:

$$\text{Slack} = \text{DueDate} - \text{CurrentTime} \quad (1)$$

where DueDate is the due date of the order placed by the customer, and CurrentTime is the current time of the simulation clock. Higher priority is given to orders with smaller slack. Note that the CDFs and origins compete for the same resources which are the available trucks.

Controlling the flow of operations is critical in cross-docking. Cross-docking demands that an order must be delayed (intentionally) at the CDF, in order to wait for other incoming orders that could be scheduled to be shipped to the same destination. In that case, the orders are batched together in the same truck (according to their final destination) and depart from the CDF to the customer. Therefore, we delay the truck at the CDF using the following intended delay formula:

$$\text{Intended delay} = \text{DueDate} - \text{CurrentTime} - \text{SafetyFactor} \quad (2)$$

where SafetyFactor is the time amount that can be tolerated before a truck must depart the CDF in order to avoid missing the order's due date.

5 Experiments and Results

The experiments and different scenarios are conducted with the same distances and same average truck velocity of 55 miles per hour. All distance units are in miles and time units are in hours. In the first scenario, we assumed a constant rate of 4 orders per hour placed through each of the three warehouses. This excessively high order rate was chosen deliberately in order to test our system in the worst case scenario. We present in Table 1 the order size and the orders' due dates placed by each customer that are generated according to triangular distributions (i.e., TRI (minimum, most likely, maximum)). We used triangular distributions for the order sizes and due dates since there is only limited sample data concerning those parameters. The values of the distributions (minimum, most likely, maximum), were chosen based on a knowledge of the minimum and maximum possible values, or simply by "inspired guess" [1].

Table 1. Orders Generation Attributes

| Destination (customer) | Order Size | Due Date |
|------------------------|---------------|---------------|
| 1 | TRI(11,21,33) | TRI(25,30,50) |
| 2 | TRI(10,40,53) | TRI(25,30,50) |
| 3 | TRI(5,10,20) | TRI(25,30,50) |
| 4 | TRI(8,25,35) | TRI(25,30,50) |
| 5 | TRI(20,40,53) | TRI(25,30,50) |

In Table 2, we present the optimal cross-docks selection according to randomly generated distances in the case of having four CDFs. The optimal cross-docks in the case of having two CDFs are presented in Table 3.

The running time for the simulation was set at 168 hours (7 days a week, 24 hours a day). After running the experiments for 100 replications, we obtained the results shown in Table 4. Two metrics are used in all of our experiments to investigate the model's performance of Truck Utilization and the order's Service Level. Note that orders received on Sundays are supposed to be produced and transported for the next week (i.e. their statistics were ignored in our study).

Table 2. Optimal cross-dock allocation in the case of 4 CDFs.

| Origin | Destination | Optimal CDF | Total Distance |
|--------|-------------|-------------|----------------|
| 1 | 1 | 4 | 56 |
| 1 | 2 | 1 | 67 |
| 1 | 3 | 1 | 72 |
| 1 | 4 | 4 | 62 |
| 1 | 5 | 2 | 65 |
| 2 | 1 | 3 | 80 |
| 2 | 2 | 2 | 70 |
| 2 | 3 | 3 | 65 |
| 2 | 4 | 3 | 67 |
| 2 | 5 | 2 | 60 |
| 3 | 1 | 3 | 60 |
| 3 | 2 | 4 | 74 |
| 3 | 3 | 3 | 45 |
| 3 | 4 | 3 | 47 |
| 3 | 5 | 3 | 50 |

Table 3. Optimal cross-dock allocation in the case of 2 CDFs.

| Origin | Destination | Optimal CDF | Total Distance |
|--------|-------------|-------------|----------------|
| 1 | 1 | 1 | 62 |
| 1 | 2 | 1 | 67 |
| 1 | 3 | 1 | 72 |
| 1 | 4 | 1 | 87 |
| 1 | 5 | 2 | 65 |
| 2 | 1 | 1 | 85 |
| 2 | 2 | 2 | 70 |
| 2 | 3 | 1 | 95 |
| 2 | 4 | 2 | 87 |
| 2 | 5 | 2 | 60 |
| 3 | 1 | 1 | 74 |
| 3 | 2 | 1 | 79 |
| 3 | 3 | 1 | 84 |
| 3 | 4 | 2 | 97 |
| 3 | 5 | 2 | 70 |

When having a small number of trucks (i.e. 2 trucks available), the truck utilization tends to be at its highest. For the case of having no CDFs, the average service level is low with two trucks being scheduled, and tends to increase when we assign more trucks with larger size. For instance, the service level increased from 57.52% (two size-20 trucks scheduled) to 100% (four size-40 or size-53 trucks scheduled). In the case of having two CDFs available, having chosen the safety factor variables according to the quality of the results generated, we basically notice an improvement in the system as the service level increases (82.52% if two size-20 trucks were scheduled and 100% if four trucks were scheduled of size-40 or size-53). If we average the service level results according to the number of CDFs, the best scenario would be to have 2 CDFs, having an average service level of 91.49%, compared to a service level of 91.11% (with 4 CDFs), and 81.52% (with 0 CDFs).

For all the cases in scenario 1 in Table 4, the truck utilization was extremely high resulting in more gas spending and higher level of carbon emissions (due to the excessive demand). However, the truck utilization was lower in cases having active CDFs especially with higher number of trucks. In the 2 active CDFs case, the truck utilization was 80.46% when scheduling 4 trucks. In the 4 active CDFs case, the truck utilization was 80.1% when scheduling 4 trucks. However, in the 0 active CDFs case, the truck utilization stayed high at 97.07% when having the same number of trucks scheduled.

Table 4. Scenario 1 results (constant rate of 4 orders/hour).

| Number of CDFs | Truck Size | Number of Trucks | Safety Factor | Avg. Order Cycle | Truck Utilization | Service Level |
|----------------|------------|------------------|---------------|------------------|-------------------|---------------|
| 0 | 20 | 2 | n/a | 36.9 | 100 | 57.53 |
| 0 | 40 | 2 | n/a | 30.78 | 100 | 66.52 |
| 0 | 53 | 2 | n/a | 30.78 | 100 | 66.52 |
| 0 | 20 | 3 | n/a | 21.87 | 99.89 | 79.77 |
| 0 | 40 | 3 | n/a | 18.43 | 99.69 | 84.44 |
| 0 | 53 | 3 | n/a | 18.43 | 99.69 | 84.44 |
| 0 | 20 | 4 | n/a | 12.17 | 99.23 | 94.42 |
| 0 | 40 | 4 | n/a | 4.89 | 96.07 | 100.00 |
| 0 | 53 | 4 | n/a | 4.89 | 96.07 | 100.00 |
| 2 | 20 | 2 | 12 | 21.66 | 100 | 82.52 |
| 2 | 40 | 2 | 12 | 19.45 | 100 | 83.92 |
| 2 | 53 | 2 | 30 | 25.45 | 99.91 | 74.32 |
| 2 | 20 | 3 | 30 | 14.73 | 99.7 | 91.55 |
| 2 | 40 | 3 | 30 | 9.4 | 98.91 | 99.07 |
| 2 | 53 | 3 | 30 | 12.79 | 98.2 | 96.17 |
| 2 | 20 | 4 | 15 | 12.5 | 98.9 | 95.90 |
| 2 | 40 | 4 | 12 | 4.97 | 89.11 | 100.00 |
| 2 | 53 | 4 | 12 | 6.33 | 80.46 | 100.00 |
| 4 | 20 | 2 | 30 | 23.43 | 99.85 | 81.06 |
| 4 | 40 | 2 | 30 | 16.36 | 99.77 | 89.98 |
| 4 | 53 | 2 | 15 | 25.34 | 98.79 | 78.99 |
| 4 | 20 | 3 | 15 | 17.1 | 98.63 | 90.08 |
| 4 | 40 | 3 | 15 | 11.1 | 98.66 | 94.92 |
| 4 | 53 | 3 | 30 | 15.12 | 98.36 | 90.54 |
| 4 | 20 | 4 | 15 | 11.91 | 97.02 | 95.20 |
| 4 | 40 | 4 | 15 | 7.99 | 83.99 | 99.22 |
| 4 | 53 | 4 | 15 | 10.66 | 80.18 | 100.00 |

In the second scenario in Table 5, the same experiments are conducted but according to a uniform schedule of 3 to 6 orders per day (no orders are placed on Sundays). Clearly, in this scenario, the demand is less than the previous scenario. The results are shown in Table 5.

The service level in this scenario is evidently higher than the previous scenario since the demand is significantly less. In the experiments where two trucks were available, the system having active CDFs outperformed the one without any active CDFs. In the experiments of having three or four trucks available, the results varied depending on the number of active CDFs and the safety factor parameter.

It is worthy to note that in both scenarios, when having 0 active CDFs, the results did not vary between assigning trucks of size-40 and size-53. However, it was noticed that having larger truck types assigned always yields better results.

6 Conclusions and Future Research

The proposed discrete event simulation model of cross-docking operations, where trucks must be routed from origins to destinations, is presented. The stochastic nature of the system allows us to analyze different scenarios and to reveal the importance of the model's parameters such as the safety factor, the number of trucks assigned, the types of the trucks (according to their size), and the number of active CDFs.

Two scenarios were conducted, one having a constant rate of 4 orders/ hour requested through each supplier, and a second scenario having a uniform schedule of 3 to 6 orders per day (excluding Sundays). The results of the experiments conclude that the use of cross-docking configurations produces higher service levels if the right safety factor was chosen. Additionally, truck utilizations tend to be lower when using CDFs, which according to our assumptions will result in lower level of trucks' carbon emissions. Finally, we conclude that larger trucks result in better service levels and overall better performance of the system.

Table 5. Scenario 2 results (schedule of 3 to 6 orders per day).

| CDF | Truck Size | Number of Trucks | Safety Factor | Avg. Order Cycle | Truck Utilization | Service Level |
|-----|------------|------------------|---------------|------------------|-------------------|---------------|
| 0 | 20 | 2 | n/a | 28.11 | 99.83 | 66.99 |
| 0 | 40 | 2 | n/a | 24.15 | 99.68 | 77.65 |
| 0 | 53 | 2 | n/a | 24.15 | 99.68 | 77.65 |
| 0 | 20 | 3 | n/a | 15.39 | 98.34 | 89.88 |
| 0 | 40 | 3 | n/a | 10.19 | 95.86 | 97.15 |
| 0 | 53 | 3 | n/a | 10.19 | 95.86 | 97.15 |
| 0 | 20 | 4 | n/a | 7.35 | 88.63 | 99.10 |
| 0 | 40 | 4 | n/a | 5.02 | 79.59 | 99.99 |
| 0 | 53 | 4 | n/a | 5.02 | 79.59 | 99.99 |
| 2 | 20 | 2 | 15 | 18.04 | 99.78 | 87.07 |
| 2 | 40 | 2 | 15 | 13.38 | 99.69 | 92.12 |
| 2 | 53 | 2 | 15 | 17.35 | 98.93 | 88.65 |
| 2 | 20 | 3 | 15 | 13.06 | 98.07 | 94.01 |
| 2 | 40 | 3 | 15 | 8.23 | 88.66 | 98.69 |
| 2 | 53 | 3 | 15 | 9.87 | 88.42 | 99.57 |
| 2 | 20 | 4 | 17 | 7.03 | 87.57 | 99.66 |
| 2 | 40 | 4 | 17 | 5.37 | 58.77 | 100.00 |
| 2 | 53 | 4 | 10 | 8.16 | 56.68 | 100.00 |
| 4 | 20 | 2 | 30 | 18.29 | 99.4 | 86.12 |
| 4 | 40 | 2 | 15 | 12.69 | 97.65 | 93.45 |
| 4 | 53 | 2 | 15 | 20.55 | 97.61 | 88.36 |
| 4 | 20 | 3 | 15 | 15.76 | 95.21 | 91.60 |
| 4 | 40 | 3 | 15 | 9.9 | 87.45 | 97.95 |
| 4 | 53 | 3 | 15 | 12.36 | 79.69 | 99.08 |
| 4 | 20 | 4 | 15 | 10.96 | 84.21 | 96.64 |
| 4 | 40 | 4 | 15 | 8.70 | 64.51 | 99.32 |
| 4 | 53 | 4 | 15 | 9.86 | 62.28 | 100.00 |

Note that in both scenarios, the service level and truck utilization varied depending on the following variables of the model: number of CDFs, number of trucks available, value of the safety factor, and the type of trucks used. This implies that a more extensive study is needed in order to choose the optimal safety factor, the optimal number of trucks assigned, and the most favorable truck assignment of truck types (depending on their sizes) in the system.

As for future research, the authors plan to extend the proposed simulation model by making it more generic allowing the user to control the number of CDFs, the number of warehouses, and the number of customers at the initiation of the simulation. As a second step, more assumptions are to be relaxed making the model more realistic. Possible follow-on work for the model includes the possibility of adding different product types and different due dates.

References

1. Rohrer, M.: Simulation and Cross Docking. In: 27th conference on Winter Simulation Conference, pp. 846--849. IEEE Computer Society Washington, DC. (1995).
2. Apte, U.M., S. Viswanathan: Effective Cross Docking for Improving Distribution Efficiencies. *International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management*, 3(3), 291—302 (2000)
3. Li, Y., Lim, A., Rodrigues, B.: Crossdocking - Jit scheduling with time windows. *Journal of the Operational Research Society*, 55, 1342--1351. (2004)
4. Gue, K.R.: The effects of trailer scheduling on the layout of freight terminals. *Transportation Science*, 33, 419--428 (1999)

5. Wang, J.F., Regan, A.: Real-time trailer scheduling for crossdock operations. *Transportation Journal*. 47(2), 5--20 (2008)
6. Soltani, R., Sadjadi, S.J.: Scheduling trucks in cross-docking systems: A robust meta-heuristics approach. *Transportation Research Part E*. To be published.
7. Ley, S., Elfayoumy, S.: Crossdock scheduling using genetic algorithms. In: 7th IEEE Int. Symposium in Computational Intelligence in Robotics and Automation, pp. 416--420. Jacksonville, FL, (2007)
8. Magableh, G. M., Rossetti, M. D., Mason, S. Modeling and analysis of a generic cross-docking facility. In: 37th Conference on Winter Simulation, pp. 1613--1620. Orlando, FL (2005)
9. Derbes, D. Rabadi, G., Musa, R., Transportation problem for a cross-dock network with time constraints. In: *Industrial Engineering Research Conference*, pp. 1393--1398. Miami, FL, (2009)
10. Musa, R., Arnaout, J.-P., Jung, H.: Ant Colony Optimization algorithm to solve for the transportation problem of cross-docking Network. *Computers & Industrial Engineering*. To be published.
11. Weisstein, E.W., Triangular Distribution, *MathWorld*.