Evaluating on-demand warehousing via dynamic facility location models

Kaan Unnu and Jennifer Pazour*
Rensselaer Polytechnic Institute, Troy, NY 12180
*Corresponding Author, 110 8th Street, Troy, NY 12180; 1 (518) 276-6486; pazouj@rpi.edu

Abstract: On-demand warehousing platforms match companies with underutilized warehouse and distribution capabilities with customers who need extra space or distribution services. These new business models have unique advantages, in terms of reduced capacity and commitment granularity, but also have different cost structures compared to traditional ways of obtaining distribution capabilities. This research is the first quantitative analysis to consider distribution network strategies given the advent of on-demand warehousing. Our multi-period facility location model – a mixed-integer linear program – simultaneously determines location-allocation decisions of three distribution center types (self-distribution, 3PL/lease, on-demand). A simulation model operationally evaluates the impact of the planned distribution strategy when various uncertainties can occur. Computational experiments for a company receiving products produced internationally to fulfil a set of regional customer demands illustrate that the power of on-demand warehousing is in creating hybrid network designs that more efficiently use self-distribution facilities through improved capacity utilization. However, the business case for on-demand warehousing is shown to be influenced by several factors, namely on-demand capacity availability, responsiveness requirements, and demand patterns. This work supports a firm's use of on-demand warehousing if it has tight response requirements, for example for same day delivery; however, if a firm has relaxed response requirements, then on-demand warehousing is only recommended if capacity availability of planned on-demand services is high. We also analyse capacity flexibility options leased by third-party logistics companies for a premium price and draw attention to the importance of them offering more granular solutions to stay competitive in the market.

Keywords: warehouse, distribution, on-demand, supply chain network design, facility location models

1. Introduction

The proliferation of e-commerce has fundamentally altered demand characteristics and order profiles: the handlings units are smaller, the delivery locations are more dispersed, and the customers expect faster low-cost or free deliveries. Consequently, nearly half of all US retailers offer same-day delivery (Saleh, 2018). This has increased investments in distribution centers (DCs) and warehouses closer to large populations (Breedam, 2016). Traditionally increasing the number of DC locations has also increased total facility, infrastructure, inventory, and operational costs. Binding outsourcing agreements for distribution services or investing in facility ownership are long-term commitments that come with overflow or underutilization

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risks due to demand variability and volatility. Small and medium-sized enterprises often do not have the capital needed to own and operate such complex distribution networks (Dunke et al., 2016). Finally, the availability of warehouses and DCs is currently limited (Hudson, 2019). To address these challenges, innovative and more flexible business models (Grant, 2017) and new approaches to classic supply chain designs are required (Breedam, 2016). Rather than design distribution networks only through facility ownership or long-term partnerships, this study focuses on how a company can incorporate on-demand warehousing into their distribution network design decisions.

On-demand warehousing platforms operate marketplaces to match companies with underutilized warehouse and distribution capabilities with customers who need extra space or distribution services (Forger, 2018; Pazour & Unnu, 2018; *Supply Chain Digest*, 2019; Tornese et al., 2020; Van der Heide et al., 2018). Several companies worldwide operate such platforms, including US-based platforms Flexe, Warehouse Exchange, Flowspace, and Ware2Go; European platforms, Stowga, OneVAST, Stockspots and Waredock; and African-based platform Logistify AI.

An on-demand warehousing system consists of three primary actors. **The supply owners (lenders)** are the primary holders of the resources (e.g., warehouse space, fulfillment capabilities). They differ from traditional suppliers because, generally in on-demand models, outsourcing is not the supplier's core business. Instead, the suppliers derive additional values from sharing access to their underutilized warehousing resources, and also, in some cases, benefit from a more stable workload (O'Brien, 2017). **The demand requests** are indicated needs for warehousing resources made by **customers**. The customers' need for the service is mostly short term, for a small resource amount and required to be fulfilled immediately (on-demand). **The platform** is a third-party organization responsible for managing the interactions between the supply owners and the demand requests. The platform operates a marketplace and provides access and visibility to both suppliers and customers. Such systems create spatial and temporal resource elasticity by matching underutilized resources on-demand, where and when needed (Pazour & Unnu, 2018).

On-demand warehousing platforms are open, available on-demand, and priced on a per-use basis; thus, they embody the principles of open supply webs (Montreuil, 2011) and the Physical Internet (Pan et al., 2017). As on-demand warehousing provides unique advantages, but also have different cost structures, dynamics and risks, than traditional ways to acquire warehouse space and distribution capabilities, quantitative research is needed to aid in understanding who, when, and how to utilize these systems. The contributions of this paper – which take a customer viewpoint - are summarized as follows. Our paper is the first to formulate an optimization model incorporating on-demand system properties into distribution network design problems. We extend the dynamic facility location problem (DFLP) to simultaneously decide between three types of distribution capabilities (self-distribution, 3PL, on-demand), deciding which of these alternatives to use at which locations to meet demand over multiple locations and time periods. This requires a new optimization model capturing varying commitment granularity and capacity granularity properties, as well as varying cost structures, of the distribution center alternatives. Secondly, our model is used to evaluate and provide insights on how a firm's distribution strategy should change with the advent of on-demand warehousing alternatives. Our design of experiment (DOE) captures different environmental and company factors to answer the open question: under what circumstances is on-demand warehousing beneficial for customers? The developed optimization model is used to evaluate network design decisions with and without the on-demand alternative being available. Then, to evaluate performance operationally, these network designs are fed into a Monte-Carlo simulation that incorporates uncertainty in customer demand and on-demand capacity availability. These extensive computational experiments allow us to quantify the impact of the on-demand alternative on total distribution costs and to provide managerial insights on which factors affect distribution network design decisions and performance.

2. Distribution Types

Companies have three main ways to increase their distribution and storage capabilities. They can (1) build and operate their own self-distribution facility, (2) outsource distribution operations to a third-party logistics provider (3PL) via a long-term lease agreement, or (3) access on-demand capabilities for short-term use.

Each distribution type has unique advantages and disadvantages, which we compare in **Table 1** (Unnu & Pazour, 2019). From a distribution network design perspective, critical differences exist in terms of capacity granularity, commitment granularity, and access to scale (Pazour & Unnu, 2018).

Table 1: Comparison of advantages and disadvantages of the distribution center types

Type	Advantages	Disadvantages
Self Distribution	-Low variable operational costs if operated at high-capacity utilization. -Ownership allows control	-Highest investment costs, creating the longest commitment duration. -Less flexible to demand variability and volatility -Highest latency from the decision to operation
3PL	-More flexible than self-distribution -Shorter latency from decision to operation -Lower initial investments than self-distribution	-Higher operational costs -Start-up time required for contract negotiations -Commitment with binding contracts -Potential trust, quality, and performance concerns
On-Demand	- Highest flexibility -Lowest latency between decision and implementation -No initial investment or fixed costs	- Highest per unit variable costs -Without a contract, potential uncertainty in available capacities period to period. -Potential trust, quality, and performance concerns

Capacity granularity is defined as the minimum capacity that can be acquired by a given distribution type. Capacity granularity is measured for self-distribution in full building units (e.g., number of warehouses). Most 3PLs require firms to commit up front to contracted capacity for the duration of the contracting period, with capacity granularity typically in square feet or number of storage units per period. A common 3PL policy is to enable temporary use of extra capacity beyond this contracted capacity (at a premium charge). For on-demand, minimum capacity requirements are either non-existent or very low.

Commitment granularity is defined as the minimum commitment (in time units) a firm must maintain its decision. The commitment granularity of self-distribution is related to the payback period planned for the company's return on investment, which is often at least 5 years but can be much longer, e.g., 30 years. For 3PL it is 1 to 3 years because of the lengthy decision lead times, negotiation periods, contracting, and minimum leasing periods. Due to *on-demand's* short, predefined leasing periods, its commitment granularity is typically monthly, but some platforms offer weekly commitments.

Access to Scale is defined as the percent of demand reachable within a given distance of distribution resources. When companies own their distribution resources, high investment costs can lead to operating only a handful of facilities. This has low access to scale and long last leg deliveries and transportation costs.

Alternatively, access to scale can be increased by accessing distribution resources through an on-demand system, which does not have high fixed investment costs of ownership. These three attributes are interrelated; if a company decides to build a facility, this is a strategic decision, in which initial significant fixed costs drive long commitment granularity, but if used at full capacity, results in lower variable costs (Unnu & Pazour, 2019). Whereas with on-demand warehousing, distribution resources can be acquired at the pallet level and for short one-month commitment periods. Adoption of this alternative can lead to improved flexibility and agility, as well as access to scale, but also has higher variable costs for per pallet handling and holding, and the use of multiple companies' resources creates more complex operations. Thus, given the different cost structures and operating attributes, many tradeoffs exist. Consequently, an open research question includes, "Is there a business case to be made for the use of on-demand systems, and if so, in what environments?"

3. Literature Review

On-demand resource-sharing research is proliferating, including work focused on the logistics sector (Carbone et al., 2017; S. Melo et al., 2019; Mourad et al., 2019; Yu & Shen, 2020). The vast majority focuses on transportation and delivery, using crowd shipping or crowdsourced logistics (Kafle et al., 2017; Le et al., 2019; Mofidi & Pazour, 2019). On-demand business models remain underexplored for warehouse and distribution services, and research incorporating on-demand warehousing into distribution network modeling, as well as quantitatively analyzing on-demand warehousing's suitable applications have not yet been addressed. Recently Rogers et al. (2020) argue that on-demand distribution systems (a) improve customer service and reduce costs, (b) enable dynamically reconfigurable distribution networks and (c) enable companies to adopt multiple distribution channels for their different products. The work is empirical, using survey data and use cases to support their propositions. They also advocate for the need of new quantitative models, and in this paper, we address many of their proposed future research suggestions.

Both dynamic and static facility location models have been extensively used for locating DCs/warehouses and assigning demand points to them, as well as supporting other tactical/operational decisions such as inventory and routing. A detailed taxonomy of these models can be found in the review papers (Boloori Arabani & Farahani, 2012; Daskin et al., 2005; Klose & Drexl, 2005; Seyedhosseini et al., 2016). Dynamic facility location problems (DFLP) are multi-period models where the input parameters, such as costs, demands, and capacities, vary over time, and multiple decisions are allowed throughout a given planning horizon (Klose & Drexl, 2005). A vast literature exists for DFLPs, which includes papers studying DFLP's with capacity adjustments at production facilities (Bayram et Al., 2019; Bhat & Krishnamurthy, 2015; Malladi et al., 2020; Zhao et al., 2018). Focusing our review on DFLP for distribution, we identify a scarcity in research capturing different DC/warehouse types with varying commitment, capacity, and cost structures.

Jena et al. (2015) classifies capacity adjustment options into three groups: (1) capacity is adjusted by changing the capacity levels of an existing single facility; (2) adjustments are realized by adding/removing modular capacities or opening/closing the same type of facilities; and (3) facilities with different capacities are opened/closed. Our work does not fit into any of these existing categories as we consider capacity adjustments for multiple locations, and those adjustments can be achieved by combining multiple types of facilities, and/or changing the capacity of an open facility and/or opening and closing facilities. Thus, we introduce a new option, which represents the combination of the previous three capacity adjustments based on the warehouse type.

Most DFLP with capacity adjustment papers restrict opening and closing decisions for ease of solution approaches. For example, Dias et al. (2007) constrain the maximum number of facilities operating at the same location in the same period. Wilhelm et al. (2013) highlight facility opening-closing decision flexibility; however, these decisions are still limited by a maximum number of open facilities and a restriction on re-opening facilities. In Hinojosa et al. (2000), new facilities can be opened in any period, but closing is only allowed for the facilities opened in the first period and once a facility is closed, it cannot be re-opened. Other papers consider modular capacity adjustment options. Antunes and Peeters (2001) add or remove a capacity module. Jena et al. (2015) also study modular capacities for facility closing and re-opening and for capacity expansion and reduction. In their models, only one facility is allowed to be opened on the selected candidate location, and the capacity adjustment or opening-closing decisions are considered for these individual facilities. Recently Jena, Cordeau, and Gendron (2017) studied its multi-commodity version. Other work considers interconnected but restricted time periods for strategical and tactical decisions. The tactical decisions are made in each period and might include production, inventory, and routing decisions. Whereas strategic decisions, including the location, opening/closing, or capacity adjustment decisions, can only be realized at predefined strategic periods (Bashiri et al., 2012; Correia & Melo, 2016; Fattahi et al., 2016).

Related is work considering different warehouse types with unique capacity, cost and commitment properties (Bashiri et al., 2012; Fattahi et al., 2016; Thanh et al., 2008; Vila et al., 2006). In Vila et al. (2006), the facility locations are initially defined. Then, dynamic decisions are made related to production and distribution capacities. The cost structure of the three types of warehouses (owned, rented, public) and also their approach to consider expansion and reduction are similar to our model; however, they do not consider any commitment constraints. In Bashiri et al. (2012), public warehouses have no initial setup or closing costs but relatively higher operational costs and are uncapacitated. On the other hand, private warehouses have setup costs and lower operational costs and are restricted to be closed once opened. For open private warehouses, capacity expansion can be considered; however, capacity contraction is not allowed. Similarly, in Fattahi et al. (2016) public warehouses do not have restricted opening and closing decisions. In contrast, the private warehouses can only be opened once and are not allowed to be closed. Thanh et al. (2008) start with all facility locations and capacities known, and decide facility closing, opening, and capacity expansions over time. In their model, private warehouses should be kept open or closed for the entire planning horizon after a decision is made. However, a public warehouse can be opened and closed multiple times, but there should be at least a two-period gap between the decision points. This property is like our commitment duration (granularity), but we capture it for different types of warehouses. To the best of our knowledge, Thanh et al. (2008) is the only existing paper introducing such an approach

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to decision periods. However, they do not incorporate a 3PL warehouse type with a commitment duration between totally flexible (public) and totally constrained (private), nor do they consider location decisions.

To model a firm's decision of simultaneously having the option to utilize three different warehouse types over multiple unrestricted time periods, we need to incorporate multiple types of facilities and their unique characteristics into a multi-period facility location-allocation optimization model. The model needs to capture (a) multiple decision periods, (b) the ability for multiple facility types to be located in a given location, (c) the ability to open facilities during any period, (d) the ability to capture different cost structures associated with the different facility types, and (e) varying commitment and capacity granularities of different facility types. Despite the vast amount of distribution system and supply chain network design literature, none have all of these unique properties.

4. Optimization Model to Plan a Firm's Distribution Strategy

In this section, we introduce a deterministic mixed-integer linear model for our DFLP with capacity adjustment and commitment options. All notations used in the model are defined in **Table 2**.

Table 2: Notations for sets, input parameters, and decision variables

Sets	
I	: Set of supply locations; indexed on i
J	: Set of candidate DC locations; indexed on j
D	: Set of customer locations; indexed on d
U	: Superset (union) of all location points $U = \{ I \cup J \cup D \}$; indexed on u
T	: Set of time periods; indexed on p
A	: Set of distribution center alternatives indexed on a where $A = \{A^o \cup A^l \cup A^s\}$. The subsets of A are disjoint, i.e., i.e., $A^o \cap A^l = \emptyset$; $A^o \cap A^s = \emptyset$; $A^l \cap A^s = \emptyset$.
A^o	: Set of on-demand type DCs, $A^o \subset A$
A^l	: Set of 3PL type DCs, $A^l \subset A$
A^s	: Set of self-distribution type DCs, $A^s \subset A$
A^c	: Set of DCs without the on-demand type, $A^c = \{A^l \cup A^s\}$
A^{lo}	: Set of 3PL and on-demand type DCs, $A^{lo} = \{A^o \cup A^l\}$
O	: Set of whole numbers capturing the operating facility quantity O ={1..|A|*|J|}; indexed on f
Input Parameters	
N_a	: Commitment granularity in number of periods for an alternative a $(a \in A)$
K_{ajp}	: Capacity of a DC at location j for alternative a at time period p $(a \in A^c, j \in J, p \in T)$
F_{ajp}	: Cost of initial set-up of an alternative a DC at location j at time period p $(a \in A^c, j \in J, p \in T)$
H_{ajp}	: Cost of holding one unit in an alternative a DC for period p $(a \in A^o, j \in J, p \in T)$
R_{ajp}	: Fixed cost of keeping open an alternative a DC for period p $(a \in A^c, j \in J, p \in T)$
G_{ajp}	: Cost of handling one unit in an alternative a DC at location j at time period p $(a \in A^{lo}, j \in J, p \in T)$
C_{ijp}	: Freight cost per mile per unit between supply point i and DC at location j at time period p $(i \in I,\ j \in J, p \in T)$
CF_{ijp}	: Freight cost per unit between supply point i and DC at location j at time period p $(i \in I,\ j \in J, p \in T)$

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E_{jdp}	: Freight cost per mile per unit between DC at location j and customer d at time period p $(j \in J, d \in D, p \in T)$
EF_{jdp}	: Freight cost unit between DC at location j and demand d at time period p $(j \in J, d \in D, p \in T)$
λ_{dp}	: Expected demand at customer d in time period p $(d \in D, p \in T)$
$\theta_{u_1 u_2}$	: Distance between location point u_1 and location point u_2; $(u_1, u_2 \in U)$
α	: Max distance (range) allowed to assign a demand point d to a DC at location j
γ	: Sales price of the product
φ	: Loss of sales cost in percentage of product sales price
ρ	: Cost increase factor defining the premium cost for extra capacity usage of 3PL facilities
β	: Extra capacity ratio allowed additional to the capacity of 3PL facilities $(\beta \leq 1)$
SS_p	: amount of safety stock for the distribution system if a single centralized location is used at period p $(p \in T)$
M	: A large positive number (Big-M)

Decision Variables	
Z_{ajp}	: $\begin{cases} 1 \text{ if alternative } a \text{ at location } j \text{ is } \textbf{first} \text{ opened at period } p, \\ 0 \text{ otherwise } (a \in A, j \in J, p \in T) \end{cases}$
OC_{ajp}	: $\begin{cases} 1 \text{ if a 3PL alternative } a \text{ at location } j \text{ uses an extra capacity option (at a premium costs) in period } p \\ 0 \text{ otherwise } (a \in A, j \in J, p \in T) \end{cases}$
X_{aijp}	: Units delivered from supply location i to alternative a at location j at period p $(i \in I,\ j \in J, a \in A,\ p \in T)$
W_{ajdp}	: Demand ratio fulfilled by alternative a at location j to demand d at period p $(d \in D,\ j \in J, a \in A,\ p \in T)$
S_{ajp}	: Amount of inventory in alternative a at location j at the end period p $(a \in A, j \in J, p \in T)$
LS_{dp}	: Ratio of demand not fulfilled (Loss of sales) at demand point d at period p $(d \in D, p \in T)$
Q_{fp}	: $\begin{cases} 1 \text{ if } f \text{ number of DCs are operating at period } p \\ 0 \text{ otherwise} \end{cases}$

We model three echelons, in which the supply and demand locations are given input parameters, and we decide where to locate DCs. Given each DC type can have multiple alternative capacities and costs, we use subsets over the DC alternative set $A = \{A^o \cup A^l \cup A^s\}$ to denote DC alternatives of each type: on-demand (A^o), 3PL (A^l), and self distribution (A^s). These subsets are disjoint, i.e., $A^o \cap A^l = \emptyset$; $A^o \cap A^s = \emptyset$; $A^l \cap A^s = \emptyset$. For a multi-period planning horizon ($p \in T$), the model decides whether to open a DC of alternative a in location j at period p with the binary variable Z_{ajp} and for 3PL alternatives $a \in A^l$ whether temporary extra capacity (at a premium cost) in location j at period p is planned with the binary variable OC_{ajp}. Additional continuous decisions made every period (see Table 2) include the units delivered from supply locations to DCs, the ratio of fulfilled demand from DCs to assigned customer locations, the ratio of unfulfilled demand at a customer location, and the inventory at each alternative and location. We also capture the number of open DC facilities at a given period to approximate network safety stock impacts. We model a single commodity problem, and the model can be extended by adding a new index representing different commodities with different properties.

The previously introduced capacity and commitment granularities of DC alternatives correspond to the input parameters K_{ajp} and N_a, respectively. Self-distribution and 3PL alternatives ($a \in A^c$) have finite capacities K_{ajp} and can be opened at any period p and location j but an opened DC stays operational until the end of their commitment duration of N_a periods. To capture a common 3PL practice, we allow the temporary capacity of 3PL alternatives ($a \in A^l$) in location j at period p to exceed their contracted capacity K_{ajp} with up to an extra capacity level (β) at a premium cost (ρ). In the optimization model, we assume the on-demand type is uncapacitated and can be opened and closed without any restrictions ($N_a = 1, \forall a \in A^o$). Access to scale is captured via a parameter for the allowed maximum distance (α) between a demand location and the DC that satisfies the demand.

The DC types have different cost structures, which we break into four cost parameters that can vary based on their location j and time period p. For self-distribution and 3PL alternatives $a \in A^c$, initial costs (F_{ajp}) are one-time costs required before becoming operational. Operational costs (R_{ajp}) are fixed per period recurring expenses required to keep the self-distribution or 3PL DC functioning, regardless of the satisfied demand amount. On-demand alternatives $a \in A^o$ incur holding costs (H_{ajp}), which are variable costs of one unit storage per each time period. On-demand and 3PL alternatives $a \in A^{lo}$ also incur handling costs (G_{ajp}), which are per unit costs every time a unit is handled for receiving, put-away, and picking.

Aligned with common freight practices, transportation costs have two components. The first (CF_{ijp}, EF_{jdp}) is the fixed (per unit delivery cost) independent of the distance between two locations and the second (C_{ijp}, E_{jdp}) are per unit distances. Additionally, the transportation costs capture differences in more efficient inbound (CF_{ijp}, C_{ijp}) versus outbound (EF_{jdp}, E_{jdp}) loads. The inventory at the beginning of the first period at each DC location and alternative is set to zero ($S_{aj0} = 0, \forall a \in A,\ \forall j \in J$).

The objective function minimizes the total costs related to the complete distribution system design, where (1)-(a) is the total first-mile costs captured as the sum of the delivery costs from supply locations to DCs, (1)-(b), (1)-(c) and (1)-(d) incorporate DC opening costs, handling costs, and inventory holding costs, respectively. We assume that a holding cost for one period occurs for the fulfilled demand quantity

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$\left(W_{ajdp}\lambda_{dp}\right)$ and (1)-(e) is this additional holding cost. The total operational costs of DCs are calculated by (1)-(f) and (1)-(g). The former is used when the commitment duration's last period is within the planning horizon ($p \leq |T| - N_a$), and (1)-(g) when the remaining planning horizon is shorter than the commitment period. We also assume that when the extra capacity option is triggered for a 3PL alternative, the premium cost for the entire expansion ratio is added to the objective function at that period, as shown in (1)-(h). Finally, the last mile delivery costs and the costs regarding the unfulfilled demand are incorporated into the objective function with expressions (1)-(i) and (1)-(j). In reporting results, we denote the sum of (1)-(b) to (1)-(h) as *DC Costs* and the sum of (1)-(a) and (1)-(i) as *Transportation Costs*.

$$\begin{aligned}
Minimize \Bigg\{ & \underbrace{\sum_{i\in I}\sum_{j\in I}\sum_{p\in T}\sum_{a\in A} X_{aijp}\left(\theta_{ij}C_{ijp} + CF_{ijp}\right)}_{a} + \underbrace{\sum_{j\in J}\sum_{p\in T}\sum_{a\in A^c} Z_{ajp}F_{ajp}}_{b} + \\
& \underbrace{\sum_{i\in I}\sum_{j\in J}\sum_{p\in T}\sum_{a\in A^{lo}} X_{aijp}G_{ajp}}_{c} + \underbrace{\sum_{j\in J}\sum_{p\in T}\sum_{a\in A^o} S_{ajp}\,H_{ajp}}_{d} + \\
& \underbrace{\sum_{j\in J}\sum_{d\in D}\sum_{p\in T}\sum_{a\in A^o} W_{ajdp}\lambda_{dp}H_{ajp}}_{e} + \underbrace{\sum_{j\in J}\sum_{p\in T:\, p\leq(|T|-N_a)}\sum_{a\in A} Z_{ajp}\,N_a R_{ajp}}_{f} + \\
& \underbrace{\sum_{j\in J}\sum_{p\in T:\, p>(|T|-N_a)}\sum_{a\in A} Z_{ajp}\left(|T|-p\right)R_{ajp}}_{g} + \underbrace{\sum_{j\in J}\sum_{p\in T}\sum_{a\in A^l}\left(OC_{ajp}\,R_{ajp}\right)\beta\,\rho}_{h} + \\
& \underbrace{\sum_{j\in J}\sum_{d\in D}\sum_{p\in T}\sum_{a\in A} W_{ajdp}\lambda_{dp}\left(\theta_{jd}E_{jdp} + EF_{jdp}\right)}_{i} + \underbrace{\sum_{d\in D}\sum_{p\in T} LS_{dp}\lambda_{dp}\gamma\varphi}_{j} \Bigg\}
\end{aligned} \tag{1}$$

While multiple alternatives can be operating at the same location, opening the same alternative DC at the same location is not allowed. This is defined by constraint (2), which also enforces that once a decision to open an alternative a warehouse at location j, it will stay open during the entire commitment period.

$$\sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} \leq 1 \qquad \forall j \in J\,;\ \forall p \in T\,;\ \forall a \in A \tag{2}$$

In (3) and (4) the distribution facility capacity constraints limit the inbound and outbound deliveries. As the self-distribution and 3PL alternatives are capacitated, and the on-demand alternatives are uncapacitated, the capacity constraints only consider the alternative subset A^c.

$$\sum_{i\in I} X_{aijp} + S_{ajp-1} \leq \left(\sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} K_{ajp} \right) + \left(OC_{ajp} K_{ajp} \beta \right) \quad \forall j \in J; \ \forall a \in A^c; \ \forall p \in T \tag{3}$$

$$\sum_{d\in D} W_{ajdp} \lambda_{dp} + S_{ajp} \leq \left(\sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} K_{ajp} \right) + \left(OC_{ajp} K_{ajp} \beta \right) \quad \forall j \in J; \ \forall a \in A^c; \ \forall p \in T \tag{4}$$

The extra capacity option is limited only to the opened 3PL alternatives with constraints (5) and (6). Constraint (7) guarantees demand locations must be assigned a DC within the maximum distance allowed (range). The model allows lost sales and demand quantities can be fulfilled from more than one DC; the total demand fulfillment and lost sales are linked to each other with constraint (8).

$$OC_{ajp} = 0 \qquad \forall j \in J; \ \forall p \in T; \ \forall a \in (A^s U A^o) \tag{5}$$

$$OC_{ajp} \leq \sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} \qquad \forall j \in J; \ \forall p \in T; \ \forall a \in A^l \tag{6}$$

$$W_{ajdp}\left(\alpha - \theta_{jd}\right) \geq 0 \qquad \forall a \in A; \ \forall p \in T; \ \forall j \in J; \ \forall d \in D \tag{7}$$

$$LS_{dp} + \sum_{a\in A} \sum_{j\in J} W_{ajdp} = 1 \qquad \forall d \in D; \ \forall p \in T \tag{8}$$

The capacity constraint (3) incorporates the inventory at the end of each period. Thus, to keep inventory at the end of a period $(p-1)$ the subject DC should be open with available capacity on the following period (p). In addition, (9) constrains the inventory kept in an open facility for the last period $p = |\mathrm{T}|$ to be less than its capacity. Constraints (10) and (11) link the on-demand alternative's inventory keeping decisions to the opening decisions. Constraints (12) assure the inventory is balanced at each DC.

$$S_{aj|T|} \leq \left(\sum_{z=\max\{1,(|T|-N_a+1)\}}^{|T|} Z_{ajz} K_{aj|T|} \right) + \left(OC_{aj|T|} K_{aj|T|} \beta \right) \qquad \forall j \in J; \ \forall a \in A^c \tag{9}$$

$$S_{aj(p-1)} \leq Z_{ajp} M \qquad \forall j \in J; \ \forall a \in A^0; \forall p \in T \tag{10}$$

$$S_{aj|T|} \leq Z_{aj|T|} M \qquad \forall j \in J; \ \forall a \in A^0 \tag{11}$$

$$S_{aj(p-1)} + \sum_{i\in I} X_{aijp} = \sum_{d\in D} W_{ajdp} \lambda_{dp} + S_{ajp} \qquad \forall j \in J; \forall a \in A; \forall p \in T \tag{12}$$

For a (Q, r) inventory policy that moves from centralized stocking to one where stock is kept amongst f facilities, then the total safety stock will increase with a ratio of $\sqrt{f}$ (assuming same parameters, fill rate,

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and demand being independent and identically distributed) (Eppen, 1979). In any given period, the number of open facilities can be up to $|J| * |A|$ which can increase the required system safety stock drastically. As the direct use of the square root rule requires non-linear constraints, the model considers the safety stock changes at the echelon level and then decides the distribution of the inventory to the open DCs. Using a set of linear constraints (13)-(15), a stepwise function captures safety stock being the square root of the total number of open DCs at a given period. Finally, (16)-(22) capture non-negativity and binary conditions.

$$\sum_{f \in O} Q_{fp} = 1 \qquad \forall p \in T \qquad (13)$$

$$\sum_{f \in O} Q_{fp} f = \sum_{a \in A^c} \sum_{j \in J} \sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} + \sum_{a \in A^o} \sum_{j \in J} Z_{ajp} \qquad \forall p \in T \qquad (14)$$

$$\sum_{f \in O} Q_{fp} SS_p \sqrt{f} \le \sum_{a \in A} \sum_{j \in J} S_{ajp} \qquad \forall p \in T \qquad (15)$$

$$Z_{ajp} \in \{0,1\} \qquad \forall a \in A, \forall j \in J, \forall p \in T \qquad (16)$$

$$OC_{ajp} \in \{0,1\} \qquad \forall a \in A, \forall j \in J, \forall p \in T \qquad (17)$$

$$Q_{fp} \in \{0,1\} \qquad \forall f \in O, \forall p \in T \qquad (18)$$

$$X_{aijp} \ge 0 \qquad \forall a \in A, \forall i \in I, \forall j \in J, \forall p \in T \qquad (19)$$

$$W_{ajdp} \ge 0 \qquad \forall a \in A, \forall j \in J, \forall d \in D, \forall p \in T \qquad (20)$$

$$S_{ajp} \ge 0 \qquad \forall a \in A, \forall j \in J, \forall p \in T \qquad (21)$$

$$LS_{dp} \ge 0 \qquad \forall d \in D, \forall p \in T \qquad (22)$$

Valid inequalities (23) and (24) connect the demand fulfillment variables with the opening decisions, and are added to improve solution times (Jena et al., 2015); e.g., such valid inequalities have reduced the computational time on other DFLPs by a ratio of 1.2-2 (Jardin et al., 2006).

$$W_{ajdp} \le \sum_{z=\max\{1,(p-N_a+1)\}}^{p} Z_{ajz} \qquad \forall j \in J;\ \forall p \in T;\ \forall d \in D;\ \forall a \in A^c \qquad (23)$$

$$W_{ajdp} \le Z_{ajp} \qquad \forall j \in J;\ \forall p \in T;\ \forall d \in D;\ \forall a \in A^0 \qquad (24)$$

5. Description of the Design of Experiments

Using representative input parameters from industry and a design of experiments (DOE), we provide new understanding of which DC alternatives should be selected when and where and quantify the influence of different factors on distribution network design with and without on-demand warehousing. The

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optimization model presented in Section 4 is helpful as a strategic planning tool to determine facility alternative and location decisions, especially as deciding to build a DC or committing to a 3PL contract requires some lead time to implement. Like aggregate planning in manufacturing, these facility decisions (i.e., $Z_{ajp} = 1$ values) would be made using a forecast for demand across locations and time periods. We assess operational performance of this plan using a Monte Carlo simulation (see supplemental materials for details) that updates operational decision variables due to (i) demand variability or (ii) on-demand warehousing capacity variability (as there are no long-term contacts, the amount and location of on-demand warehousing capacity can vary period to period beyond what was expected). In the simulation, demand quantities ($\bar{\bar{\lambda}}_{dp}\ \forall d \in D, \forall\ p \in T$) and on-demand warehousing capacities ($\bar{\bar{K}}_{ajp}\ \forall a \in A^o, \forall\ j \in J, \forall\ p \in T$) are now random variables, which influences the units supplied, units delivered, demand ratios fulfilled, lost sales, and inventory levels. Due to insufficient capacity, a firm may need to return some inventory and these return costs are incorporated into the total cost values reported in the simulation.

In the DOE, first, the deterministic optimization model is used to find optimal/near-optimal network designs for the first full factorial design given in **Table 3-(1).** Then each of these optimization solutions are evaluated operationally via a simulation model, with a second full factorial design conducted on factors in **Table 3-(2).** A full factorial set of experiments based on these factors requires 96 optimization runs and for each optimization run we run 32 simulation runs (based on a full factorial experiment for factors (2-1) through (2-5)), for a total of 3072 simulation runs. For each simulation run, we report results using 100 replications.

Table 3: (1) Optimization and (2) Simulation Model Design of Experiment Factors and Levels

No	Factor (Short Description)	Factor Level Definitions	
(1-1)	On-demand Alternative (Opt_OnDemand)	(OD) - With on-demand alternative	
		(NOD) -Without on-demand alternative	
(1-2)	Demand Trend (Opt_Trend)	(TDown) - Increasing Demand (trend upwards)	Opt_Trend= +0.01
		(TNone) - No trends in demand	Opt_Trend= 0
		(TDown) - Decreasing Demand (trend downwards)	Opt_Trend = -0.01
(1-3)	Seasonality (Opt_Season)	(SNone) - No seasonal effect ($OptSeason_p = 0 \quad \forall p \in T$	
		(SMajor) - Major Seasonal effects based on quarters ($OptSeason_p$)	Opt_Season_p= -4.70% $\forall p \in \{1,5,9,13,17\}$
			Opt_Season_p= -0.90% $\forall p \in \{2,6,10,14,18\}$
			Opt_Season_p= -1.30% $\forall p \in \{3,7,11,15,19\}$
			Opt_Season_p= 6.90% $\forall p \in \{4,8,12,16,20\}$
(1-4)	Response requirement (Opt_Range)	(100) miles range (same day delivery)	$\alpha = 100$
		(250) miles range (one day delivery)	$\alpha = 250$
(1-5)	3PL option capacity expansion (Opt_ ExtraCapacity)	(NOC) - No capacity expansion	$\beta = 0$
		(OC) - Capacity expansion w/ penalty	$\rho = 0.2$ $\beta = 0.1$
(1-6)	Safety Stock (Opt_SafetyStock)	(NSS) - No Safety stock at DC echelon	$SS_p = 0\,;\ \forall p \in T$
		(SS) - Safety stock in DCs	$SS_p = 0.025 \sum_{d \in D} \lambda_{dp}\,; \forall p \in T$

(2-1)	Demand Variability (Sim_DemandVariability)	(0.1) - Low variability	$Sim\_DemandVariability = 0.10$
		(0.3) - High variability	$Sim\_DemandVariability = 0.30$
(2-2)	Time dependent forecast uncertainty (Sim_TimeVariability)	(0) - Time independent	$Sim\_TimeVariability = 0$
		(0.1) - Yes	$Sim\_TimeVariability = 0.10$
(2-3)	New On-Demand alternative (Sim_NewOndemand)	(0-NO) - No new on-demand DCs (only optimization results)	
		(1-YES) - Allow additional on-demand DCs	
(2-4)	New 3PL alternative capacity expansion (Sim_NewExtraCapacity)	(0-NO) - No capacity expansion (only optimization results)	
		(1-YES) - Allow additional capacity expansion for opened 3PL facilities	
(2-5)	On-Demand alternative available capacity (Sim_OnDemandCapacity)	(0-NO) - No capacity constraints	
		(1-YES) - Variable Capacity	$K_{10jp} = K_{4jp} U[0,1]$

The factor (1-1)'s no on-demand decision (NOD) level is enforced in the optimization formulation with an additional constraint $Z_{10jp} = 0 \; \forall j \in J; \forall p \; in \; T$. The factors (1-4), (1-5) and (1-6) are tested by changing the input parameter values as given in **Table 3-(1).** To generate the demand quantities for the entire planning horizon ($\forall p \in T$) at each demand location ($\forall d \in D$), the optimization and simulation models use the initial demand input parameter based on city populations (see Section 6 for detailed calculations of λ_{d1}) and equation (25). For a given demand location, the demand quantity is a function of its initial demand in the first period, adjusted for trends, seasonal factors, and variability (noise). Expected

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demand forecast values, used in the optimization model, are created for different trend (1-2) and seasonality (1-3) factors using (25)-a. Specifically, the seasonality factors replicate the retail sector and emphasize the impact of the holiday season. Then the second part, denoted as (25)-b, incorporates demand variability (2-1) and forecasting errors (2-2) factors and simulates demand uncertainty with a randomly generated coefficient ($U[-1,1]$). For the optimization model, (25)-b is assumed to take on a value of zero, whereas in the simulation model, a random demand generation is created due to the Uniform random variable.

$$\lambda_{dp} = \lambda_{d1} \left(\underbrace{1 + Opt\_Trend(p-1) + Opt\_Season_p}_{a} + \underbrace{\left(Sim\_DemandVariability + Sim\_TimeVariability \frac{p}{|T|} \right) U[-1,1]}_{b} \right) \forall\, d \in D, \forall\, p \in T: p > 1 \tag{25}$$

Opt_Trend	: (1-2) trend; demand increase/decrease in each period
Opt_Season_p	: (1-3) seasonality factor for period p ($\forall p \in T$)
$Sim\_DemandVariability$	: (2-1) demand variability; uncertainty
$Sim\_TimeVariability$	: (2-2) forecast error at the end of planning horizon (linearly increasing over time)
$U[\,]$	: uniform distribution

The on-demand alternative capacity factor (2-5), used in the simulation, is based on the smallest 3PL alternative size. The factors (2-3) and (2-4) consider whether new capacity decisions can be made period to period or if the firm must stick with the capacity decisions planned with the optimization model. The simulation model does not allow reducing planning capacities, i.e., opened facility locations and alternatives and extra capacity decisions determined by the optimization model are directly adopted. We do explore the impact of operationally obtaining on-demand DCs and 3PL extra capacity in *addition* to the planned capacity from the optimization model (see the factors in Table 3). Specifically, when the factor Sim_NewOndemand = 1, then if there is not enough capacity at an opened 3PL or self-distribution facility, a new on-demand DC is opened at that location and period (with this new capacity decision denoted as $\bar{\bar{Z}}_{ajp}\ \forall a \in A^o, j \in J, p \in T$). This adjusts the available in-bound capacity to include $\bar{\bar{Z}}_{ajp}\bar{\bar{K}}_{ajp}$. Further, if the factor Sim_NewExtraCapacity = 1, then new 3PL extra capacity is executed when there is insufficient 3PL capacity at a location and period (and this new decision is denoted as $\overline{\overline{OC}}_{ajp}\ \forall a \in A^l, j \in J, p \in T$).

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This adjusts the available in-bound capacity to include $\overline{\overline{OC}}_{ajp}K_{ajp}\beta$ and can occur only when and where the opened 3PL alternative with insufficient capacity had not planned to execute the extra capacity option.

6. Description of Input Parameters

We introduce our remaining input parameters, which are representative of a company that receives pallets of products produced outside of the US into the Newark, NJ port to fulfill the US Northeast region's demand. Cost expressions capture DC and freight costs associated with storing, handling and delivery of a 40x48 inch standard GMA pallet as the smallest stock-keeping unit (SKU). We use quarters as the periods and five years (20 periods) as the planning horizon. In the optimization model, the total demand is normalized for all instances. Therefore, regardless of the trend and seasonality factors, the total expected demand quantity for each location summed over the planning horizon is kept the same for all instances.

DC Data: Alternatives, capacities, commitment durations, and costs used in the computational experiments are presented in **Table 4**. This represents ten total alternatives, with three capacity levels for self-distribution, six for 3PL, and one uncapacitated on-demand alternative. As given in **Table 4**, these capacities are set based on a max capacity assumption as presented in equation (26). After generating the demand quantities for the model run, the maximum demand quantity over the entire planning horizon are summed over the demand locations and divided by *0.6P,* where *P* is the minimum number of DCs required to cover all locations, found by solving a classical set covering model based on the selected response requirement α. To accommodate for spatial demand variations that require some DCs to need additional capacities to fulfill the requirements, we incorporate a safety coefficient of 0.6 when setting capacities.

$$\max(K) = \frac{\sum_{d \in D} \max_{p \in T}(\lambda_{dp})}{0.6P} \tag{26}$$

For self-distribution alternatives, the commitment covers the entire planning horizon (20 periods or five years), whereas 3PL alternatives have a commitment of 4 quarters (one year), and the on-demand alternative's commitment is one quarter (see **Table 4**). The DC cost input parameter values are calculated for each DC alternative using formulations, assumptions, and cost references in Unnu & Pazour, 2019. We assume alternative capacities and costs are the same for all locations over the entire planning horizon, and thus we drop the index for location and period for the cost input parameters. We validate the cost relations between the alternatives and confirm that they incorporate the economies of scale and the ownership cost advantages (see supplemental materials for details).

Table 4: Capacities and costs of the 10 alternatives used in the computational studies

a	Type	Capacity (K_a)	Capacity (units) (K_a)	Commitment (period) (N_a)	Initial Costs ($) ($F_a$)	Operational Costs ($/period) ($R_a$)	Holding Costs ($/period/unit) ($H_a$)	Handling Costs ($/unit) ($G_a$)
1	Self	0.20 * Max(K)	10,000	20	1,030,000	368,550	0	0
2	Self	0.50 * Max(K)	25,000	20	2,400,000	897,000	0	0
3	Self	Max(K)	50,000	20	4,700,000	1,691,000	0	0
4	3PL	0.05 * Max(K)	2,500	4	7,000	115,000	0	6.33
5	3PL	0.08 * Max(K)	4,000	4	8,100	175,000	0	6.00
6	3PL	0.10 * Max(K)	5,000	4	8,900	210,000	0	5.67
7	3PL	0.20 * Max(K)	10,000	4	13,000	405,000	0	5.33
8	3PL	0.50 * Max(K)	25,000	4	24,500	975,000	0	5.00
9	3PL	Max(K)	50,000	4	45,000	1,900,000	0	4.33
10	On-Demand	Infinite	Infinite	1	0	0	33.00	15.00

Locations: The 49 metropolitan areas with populations more than 50,000 in the US Northeast region are used as demand points (*US Census, 2018*). The center of each of the metropolitan area is set as the center of its most populated county (*US Census,* 2019). The great-circle distances between the locations' centers ($\theta_{u_1 u_2}$), calculated with the Haversine formula, are used as surrogates for the transportation costs and are gathered from the US Census and National Bureau of Economic Research's County Distance Databases (US *Census, 2010; County distance database*). One of US's largest ports is located at Newark, NJ, and is used as a single supply point in our model (McCahill, 2017).

To set candidate DC locations, we rely on the 14 publicly available locations of Amazon, Walmart and Target's DCs in the Northeast US region. Two maximum ranges ($\propto$) represent customer delivery expectations, with $\propto$=250 miles capturing next day delivery and $\propto$=100 miles capturing same day delivery. The feasibility of meeting these maximum range constraints using the 14 identified locations was tested using a set covering model with the 49 demand points being candidate locations and with an additional constraint to keep the identified 14 DC locations open. The set covering model solution required 3 additional candidate DC locations (for the 100 miles range) and we adopted these 17 candidate locations in our models for both values of $\propto$.

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Demand Quantity: The population of each metro (*Metropolitan and Micropolitan Statistical Areas Totals*, 2019) divided by 1000 are used to set the initial demands λ_{d1} = ($\frac{metro\ population}{1000}$).

Freight Cost Data: Data from transportation resources (*Lojistic*, 2020; *National van Rates*, 2020; Keller, 2017) are used to estimate freight costs based on truck deliveries. The inbound and outbound costs are different due to capacity utilization, number of stops on the route, and distances traveled. Inbound trucks are assumed, on average, 75% utilized, and trucks from DCs to demand locations are assumed 60% utilized (Mathers, 2015). A logistic practice is to use the weight cost or cost per unit delivery in addition to distance-based costs to estimate the freight costs (*2020 UPS Rate & Service Guide*, 2019; *FedEx Freight Zone-Based Rates*, 2018). Accordingly, these values are used in our computational studies: C_{ijp}: 0.083 $/mile/unit, CF_{ijp}: 3.00 $/unit, E_{jdp}: 0.251 $/mile/unit, and EF_{jdp}: 15.00 $/unit.

Other Data: The lost sales cost ($\gamma * \varphi$) is 200 $/unit, which is higher than the unit distribution cost, and thus in the optimization model, for all experiments, it will be optimal to have no lost sales.

7. Computational Results

This section summarizes the computational results from the previously introduced datasets, assumptions, and factor levels. The *optimization models* are solved with IBM ILOG CPLEX 12.9 with a maximum time limit based on the model characteristics. The optimization solution times varied between 30 seconds up to of 22 hours and returned optimality gaps between 0% and 1.15%. All 96 optimization runs were solved using 154 hours of solve time. The *simulation models* are coded with Python 3.7.3 and results are based on 100 replications per simulation run. 516 hours of computational time were required to solve the 3072 simulation runs explained in Table 4. This number of replications is selected based on confidence interval calculations and variability analysis of the total distribution costs (see supplemental materials for details).

Optimization Model Results

Figure 1 provides the box plots of the optimization objective function values grouped by factor levels if the total distribution cost difference between factor levels was greater than one million dollars. Factors having the largest impact at the planning stage are whether on-demand warehousing is considered or not, the response requirement range value, and whether safety stock is planned for or not.

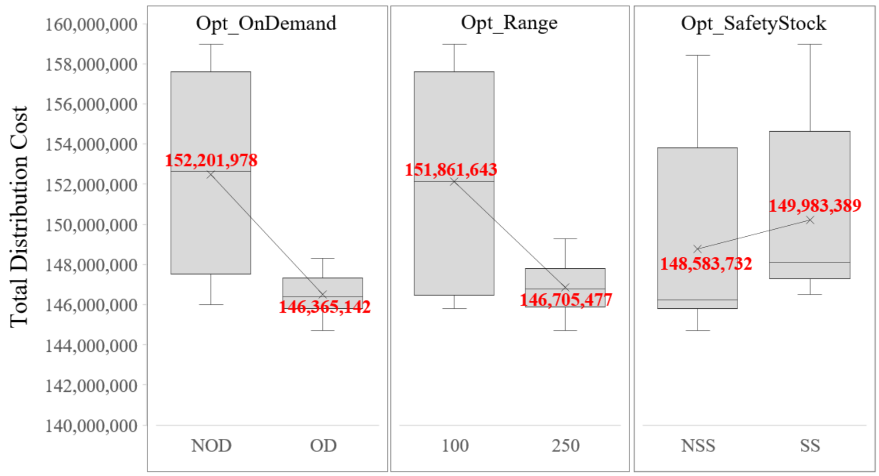

Figure 1: Optimization model factors' box plots of the total distribution costs for factor levels that have a difference greater than or equal to $1Million.

Utilizing the on-demand alternative yields nearly a 4% decrease, on average, in total planned distribution costs. The optimal decision variable values indicate that solely using on-demand warehousing to fulfill customer requests is not justified; instead, hybrid solutions, utilizing a mix of self-distribution, 3PL, and on-demand alternatives, are recommended. Companies should consider on-demand warehousing (in addition to self distribution and 3PL facilities) when designing their distribution network to reduce total costs. To understand the reasons for the distribution cost differences, we analyze the average number of open facilities at each period by type. There are 17 candidate locations, with each location having the opportunity to open 10 alternatives (if the on-demand alternative is considered, and only 9 alternatives if on-demand warehousing is not considered). Therefore, considering on-demand warehousing, the optimization model has 170 candidate facilities across 17 locations available per period. As presented in Table 5, with the advent of on-demand warehousing, the average number of total open locations per period increased, both through use of on-demand facilities but also by increasing the number of self-distribution facilities. Yet, the reliance on lease facilities (at least with 3PL's current commitment granularities and cost structures) decreased.

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Table 5: The average number of open facilities per period and the transportation, DC and total costs of the optimization runs, segregated into when the on-demand alternative is not available (NOD) and when on-demand warehousing is available (OD)

Opt_OnDemand	Average Number of Open Facilities per Period				Transportation Costs	DC Costs	Total Costs
	Total	Self	3PL	On-demand			
NOD	10.08	2.52	7.56	0.00	94,106,294	58,095,684	152,201,978
OD	12.00	2.92	2.63	6.45	94,673,816	51,691,326	146,365,142
				Diff	**-0.60%**	**12.54%**	**3.99%**

When the number of facilities increases, we would traditionally expect an increase in total DC costs. However, with on-demand warehousing, the DC costs decrease by 12.54%, even though the number of facilities has increased, and on-demand warehousing has higher costs. This cost reduction is due to on-demand warehouses being only opened for one period at a time, which creates more efficient demand fulfillment and better capacity utilization amongst the opened DCs (of all types). As presented in Table 6, with on-demand warehousing, the average capacity utilization for both self-distribution and 3PL alternatives increases (94% to 98% and 85% to 98%, respectively). Also, the demand fulfilled by self-distribution increases (71% to 80%). Thus, on-demand warehousing's reduced granularity enables better capacity utilization and decreased DC costs of the opened self-distribution and 3PL facilities.

Table 6: Broken down by DC type, the optimization model results of total costs, percent demand fulfilled and capacity utilization, without and with on-demand warehousing.

	Opt_OnDemand				Opt_OnDemand NOD					Opt_OnDemand OD				
	NOD	OD			% Demand Fulfilled			Capacity Utilization		% Demand Fulfilled			Capacity Utilization	
	Total Costs		Diff		Self	3PL	OnD	Self	3PL	Self	3PL	OnD	Self	3PL
Mean	**152,201,978**	**146,365,142**	**5,836,836**	**3.99%**	71%	29%	0%	94%	85%	80%	13%	7%	98%	98%
StDev	***4,883,296***	***981,810***	***4,432,216***											

As shown in Table 7, in scenarios with a maximum 100-mile range, using on-demand warehousing decreases the costs by 6.93% compared to when on-demand was not considered. Yet, the savings with on-demand is only 1.03% with looser response requirements of 250-miles. Thus, on-demand warehousing has the most value when a firm has tight responsiveness requirements. For both response requirements, on-demand warehousing changes the alternative selected, as well as how many and where facilities are located. Using on-demand warehousing in looser response requirement environments led to a greater increase in the average number of facilities opened per period than for the tighter response requirement environments.

Table 7: For both response requirements, the mean, min, and max open facilities per period and the optimization's total costs, when on-demand is not available (NOD) versus available (OD).

		Opt_OnDemand										
		NOD				OD						
		Open Facilities per Period			Total Costs	Open Facilities per Period			Total Costs	Diff		
		Mean	Min	Max		Mean	Min	Max		%	Mean	*Stdev*
Opt Range	**100**	13.1	12	16	**156,944,553**	13.2	12	17	**146,778,733**	6.93%	10,165,819	*908,475*
	250	7.1	5	11	**147,459,403**	10.8	7	17	**145,951,551**	1.03%	1,507,852	*456,166*
		Diff		**%**	6.43%	**Diff**		**%**	0.57%			
				Mean	9,485,150			**Mean**	827,182			
				Stdev	*1,054,812*			***Stdev***	*224,552*			

To observe how the optimization model decisions affect specific DC-to-demand location assignments, capacity utilization and costs, with and without on-demand warehousing, we examine an instance in detail. This instance has demand with a downward trend and seasonality, allows 3PL extra capacity at a premium, has safety stock depending on the number of open DCs, and a 100 miles maximum range. Figure 2 illustrates how demand is fulfilled differently with and without on-demand warehousing. Similar DC locations are selected, but different DC alternative combinations are used. Figure 3 illustrates that with the inclusion of on-demand warehousing, most of the 3PLs are replaced with on-demand alternatives and the number of self-distribution types also increased. As shown in **Table 8**, when we analyze DC type capacities and demand fulfillments over the planning horizon, the capacity utilization of 3PL option is 79% on average without the on-demand alternative. With on-demand warehousing, the 3PL capacity utilization increases to 95% and self-distribution to 99%. Thus, the on-demand alternative's reduced granularity and commitment, allows for changing capacity levels over time that better match with demand requirements and enables better capacity utilization for the other DC alternative types.

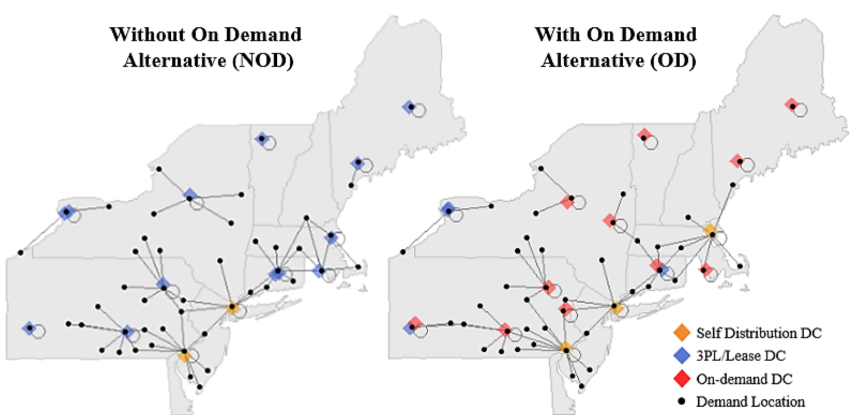

Figure 2: Location allocation decisions of a selected example

Table 8: Cost and demand fulfilment details of the selected example

	Without On-demand (NOD)			With On-demand (OD)			Diff
DC Types	Fulfilled Demand		Capacity Utilization	Fulfilled Demand		Capacity Utilization	
Self-Distribution	633,243	60.8%	93%	825,994	79.3%	99%	
3PL	408,456	39.2%	79%	118,915	11.4%	95%	
On-Demand				96,790	9.3%		
Across all DC Types	1,041,700	100.0%		1,041,700	100.0%		
Total Costs			156,364,049			147,830,309	5.8%
Transportation Costs			91,818,793			93,864,946	-2.2%
DC Costs			64,545,256			53,965,363	19.6%

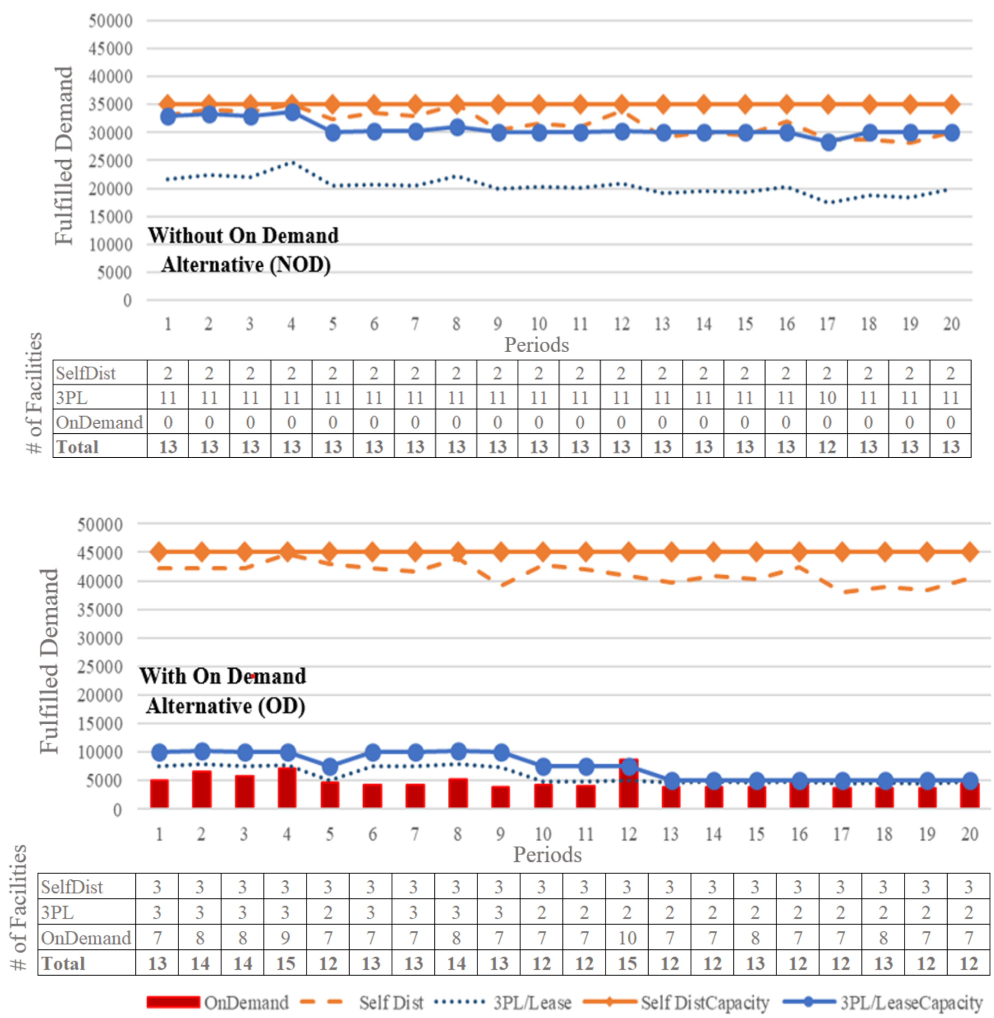

Figure 3: DC type capacity, demand fulfilment and number of facilities per period of the selected example, with and without on-demand warehousing

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Simulation Model Results

To assess operational performance of the distribution networks created by our optimization model, in this section we analyze the mean total distribution cost from using 100 replications for each of the 3072 simulation runs. Figure 4 presents box plots of the simulation's mean total distribution costs between main factor levels that change available capacity; this includes in the planning stage whether on-demand warehousing as well as whether premium extra 3PL capacity was considered or not, as well as in the simulation whether new on-demand facilities could be opened, whether new extra 3PL capacity can be obtained, and whether on-demand capacity is available as planned.

Figure 4: Boxplots of the simulation runs' mean distribution cost values for factors that change available capacity

Even when demand operationally varies from the estimates used to create the distribution network and only limited adjustments to the planned decisions are allowed, the presence of on-demand warehousing can decrease total distribution costs. Yet, in general, the impact is small. As we explore in this section, the business case for on-demand warehousing is influenced by several interactions.

As displayed in Figure 5 **(a)**, if there is a demand trend (opt_Trend - either upward or downward), using on-demand warehousing can reduce distribution costs. However, if no trend exists, traditional ways of obtaining distribution capacity are sufficient. Capacity sizing decisions, specifically whether to plan to obtain extra capacity over expected demand during the network design planning stage, is investigated through the safety stock factor (Opt_SafetyStock) in Figure 5 (b). If a company does not plan to use on-demand warehousing in its distribution network, it is better not to incorporate an extra demand buffer (NSS

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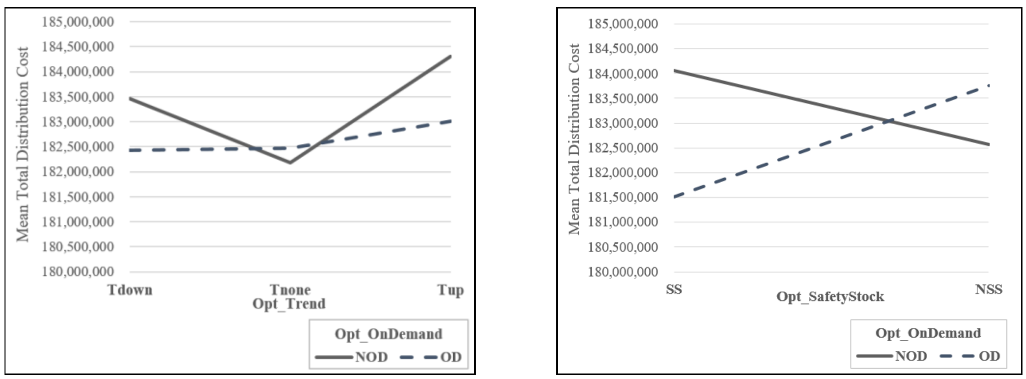
– No safety stock). This is because of the larger capacity granularities of the self-distribution and 3PL DCs, which already have a built-in capacity buffer due to their higher capacity granularities. However, due to on-demand's low capacity granularity and higher capacity utilization of 3PL and self-distribution options when on-demand is present, less of such buffers exist with hybrid distribution networks using on-demand warehousing. Therefore, firms planning to utilize on-demand alternatives are advised to incorporate an extra capacity buffer during distribution network design planning.



(a) Demand Trend **(b)** Safety Stock

Figure 5: Evaluation of the mean total costs with and without on-demand warehousing for (a) different demand trends, and (b) whether safety stock is considered at the planning stage or not.

The business case for on-demand warehousing is influenced by a firm's response requirements (Opt_Range) and whether on-demand capacity is always available when and where a firm needs it (Sim_OnDemandCapacity). Figure 6**(a)** displays the interaction effects of response requirements and whether the network is designed considering on-demand warehousing. If a firm has a tight service requirement (maximum 100-miles of service range), then on-demand warehousing is useful. However, if a company has less stringent response requirements of 250 miles, then on-demand warehousing's higher per unit costs are not justified because the longer-range enables self-distribution and 3PL type DCs to better utilize their larger capacity granularities to serve multiple demand locations. On-demand warehousing does not have long-term contracts, resulting in a risk that the on-demand alternative is not always available period to period as planned. This risk is captured in the simulation factor, with Sim_OnDemandCapacity=1. If on-demand warehousing needs are always met as planned (Sim_OnDemandCapacity=0), Figure 6(b) illustrates network designs with on-demand warehousing are beneficial in both response ranges, and the impact is

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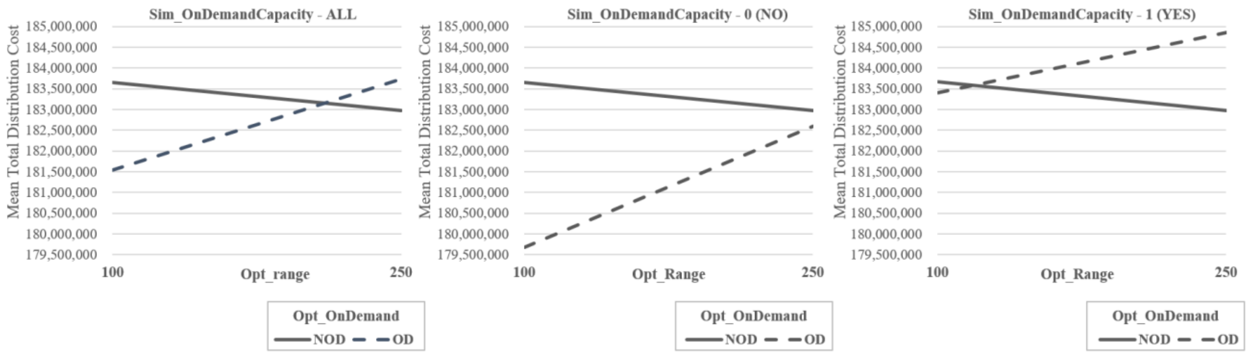
greater with tighter response times. Yet, as shown in Figure 6(c), when on-demand capacity is not always available (Sim_OnDemandCapacity=1), on-demand warehousing's benefits are minor for tight response times, and not justified for relaxed response requirements.



(a) (b) (c)

Figure 6: Evaluation of mean total costs with and without on-demand warehousing and for different response requirements over (a) all simulation cases, (b) when on-demand warehousing is available as planned, and (c) when on-demand warehousing is not always available as planned.

Finally, we analyze the impact of on-demand warehousing on the business model of 3PLs. As shown in Figure 4, costs increase when firms use 3PLs extra capacity at a premium price if they do not have enough capacity to fulfill their demand (Sim_NewExtraCapacity=1). In Table 9, we display the mean total distribution costs for the different cases of obtaining extra capacity in the simulation. Planning and operating the distribution network without on-demand warehousing (opt_Ondemand=NOD, sim_newOndemand=NO) and adding 10% more 3PL capacity for a 20% premium cost, increases the overall distribution costs because the firm pays for unused premium capacity. As a reminder, the contract simulated was that 3PL capacity is increased by 10% once a unit arrives over the contracted amount. Such 3PL premium capacity expansion clauses are found not cost effective for the lost sale parameters tested because of both the higher costs and the requirement of paying for 10% capacity, even when the firm does not need all this extra capacity. Without 3PL capacity expansions (Sim_NewExtraCapacity=0), and instead both planning the network to use on-demand warehousing and operationally having a firm add new on-demand facilities if capacity is insufficient (opt_Ondemand=OD, sim_newOndemand=YES) are better at reducing costs and returns the lowest cost value in Table 9.

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Table 9: The mean total costs of using 3PL premium capacity expansion or adding new on-demand warehousing, by whether the firm planned to use on-demand warehousing or not. (Highest and lowest values are shaded.)

Opt OnDemand	Sim NewOndemand	Sim_NewExtraCapacity	
		0	1
NOD	NO	183,034,724	**184,006,420**
	YES	182,364,909	183,856,086
OD	NO	182,533,362	183,036,588
	YES	**182,047,985**	182,919,942

8. Conclusions and Future Research

On-demand warehousing matches companies with underutilized warehouse and DC capabilities with customers who need extra space or distribution services. Via reduced capacity and commitment granularities, they create flexibility and increase responsiveness for customers, but also have different cost structures, with much higher variable per-pallet costs, than traditional types of DCs. Given these tradeoffs, this work is motivated by the following open question, "Is there a business case to be made for the use of on-demand warehousing, and if so, in what environments?" Answering this question requires development of a dynamic facility location model able to simultaneously consider the location and allocation decisions of three DC types (self-distribution, 3PL, on-demand). A mixed-integer linear program captures the three DC types' varying commitment granularities, capacity reduction-expansion policies, and cost structures, across multiple periods and locations. Through a comprehensive design of experiments based on industry data, we evaluate the impact of having the on-demand alternative available.

As the first quantitative approach to understanding when and how to utilize on-demand warehousing in a firm's network design, we provide insights valuable to supply chain managers, especially those at companies receiving products produced outside of the US to fulfill a set of regional customer demands. Even with on-demand warehousing's higher per unit costs, a company can reduce its distribution costs by adopting on-demand warehousing as part of its network design strategy. The power of on-demand warehousing's reduced commitment and capacity granularity is in creating network designs that can meet tight response requirements and more efficiently use owned and 3PL/leased facilities through improved capacity utilization. Thus, on-demand warehousing can be a good supplement to more traditional forms of acquiring fulfillment services. With the advent of on-demand warehousing, we expect firms to increase the number of DC locations, both using on-demand facilities but also by increasing the number of self-distribution facilities. Companies planning to utilize on-demand warehousing should incorporate an extra capacity buffer during distribution network planning

Evaluating the network designs obtained from the optimization model using a simulation model to capture demand and on-demand warehousing capacity uncertainty, we find that the business case for on-demand warehousing is influenced by several operational factors. With no long-term contracts, the availability of on-demand capacity where and when a firm needs it depends on the markets' supply-demand relations. Therefore, a risk, which is not widely discussed in practice, is that the on-demand alternative may not always be available as planned. We recommend considering on-demand warehousing if your firm has tight response requirements, for example for same day delivery; however, if your firm has relaxed response requirements, then on-demand warehousing is only recommended if capacity availability of planned on-demand services is high. Lastly, 3PLs should consider offering more granular solutions to their customers to stay competitive in the market.

This research opens several future research directions. The current model only captures truck delivery, future research can incorporate multiple transportation modes into the model. In addition to deciding what mode to select for each demand point and time period, an extended model could also relax the maximum range constraint, capturing different transportation mode costs in the objective function. The current optimization model is useful for planning, but additional tactical or operational models would be useful to adjust and adapt a firm's network strategy to changes dynamically. Another direction is to incorporate the varying time of the different DC types required between a facility opening decision and the facility being operational. On-demand systems enable quick access to the market, which is a competitive advantage that should be captured in a dynamic model. Finally, future research also includes developing specialized solution methods and heuristics for large scale networks. These large-scale dynamic facility location problems could help to better model tight response requirements for national use cases.

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Data Availability Statement: The reproducibility report is available in the supplemental material; Data and computer files that support the findings are available at https://jenpazour.wordpress.com/research-2/

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Biographies: Kaan Unnu is a Data Scientist of the Development Supply Chain group at Amgen. He received his Ph.D. degree in decision sciences and engineering systems from Rensselaer Polytechnic Institute in 2020.

Jennifer Pazour is an Associate Professor and the Undergraduate Coordinator of Industrial and Systems Engineering at Rensselaer Polytechnic Institute (RPI). Her research and teaching develop and use mathematical models to guide decision making for logistics and supply chain challenges.

Supplemental Materials for

Evaluating on-demand warehousing via dynamic facility location models

by Unnu and Pazour

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Outline of Supplemental Material

1. **Cost Structural Differences between the different DC Types**
2. **Monte Carlo Simulation Model Details**
3. **Data Input Validation to Confirm Economies of Scale and Ownership Cost Advantages**
4. **Additional Simulation Results**
5. **Reproducibility Report**
6. **Simulation Pseudo Code**

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1. **Cost Structural Differences between different DC types.**

Supplemental Table 1: Cost Structures of the Different DC Types (Unnu & Pazour, 2019)

Cost Type / DC Type	**Initial Costs ($)** (F_{ajp})	**Operational Costs ($/period)** (R_{ajp})	**Holding Costs ($/unit/period)** (H_{ajp})	**Handling Costs ($/unit)** (G_{ajp})
Self Distribution (A^s)	- Construction or acquisition - Equipment (handling, storage, etc.) - Closing costs, due diligence	- Labor (direct labor, common, management, etc.) - Equipment rental (e.g. forklift) - Other charges (insurance, outsourced services, etc.)	-	-
3PL (A^l)	- Security deposit, legal fees (contract review), account setup fees	- Contractual payments per period - Other charges (insurance, outsourced services, etc.)	-	Variable (per use) handling costs
On-Demand (A^o)	-	-	Variable storage cost	Variable (per use) handling costs

Reference:

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2. Monte Carlo Simulation Model Description

The optimization model presented in Section 4 is helpful as a strategic planning tool to determine facility alternative and location decisions, especially because deciding to build a DC or committing to a 3PL contract requires some lead time to implement. Like an aggregate planning problem in manufacturing, these facility decisions (i.e., $Z_{ajp} = 1$ values) would be made using a forecast for demand across locations and time periods. We assess operational performance of this plan using a Monte Carlo simulation that updates the remaining operational decision variables due to (i) demand variability or (ii) on-demand warehousing capacity variability (as there are no long-term contacts, the availability of on-demand warehousing capacity where and when a firm may want it can vary period to period beyond what was expected). Specifically, in the simulation, demand quantities ($\bar{\bar{\lambda}}_{dp}\ \forall d \in D, \forall\, p \in T$) and on-demand warehousing capacities ($\bar{\bar{K}}_{ajp}\ \forall a \in A^o, \forall\, j \in J, \forall\, p \in T$) are now random variables. As we illustrate in Supplemental Figure 1, such uncertainty can result in a firm updating their units supplied, units delivered, demand ratios fulfilled, lost sales, and inventory levels. Further, due to insufficient capacity, a firm may need to return some inventory back to supply locations, which requires introducing two additional variables, $\overline{\overline{returnC}}_{ajp}$ and $\overline{\overline{returnOff}}_{ajp}$.

In all our experiments, if the optimization model sets $Z_{ajp} = 1$, then in the simulation model a facility of alternative a is opened in location j in period p and the available capacity associated with this decision is K_{ajp}. Similarly, if the optimization has set $OC_{ajp} = 1$, then in the simulation model the extra capacity for a 3PL alternative a is executed in location j at period p, providing $K_{ajp}\beta$ available capacity. For some of the computational factors (described in our design of experiments in Section 6), additional capacity can be made available in limited situations. Specifically, in the case of a period having insufficient capacity, we explore the value of a firm being able to add additional 3PL extra capacity options or to add additional on-demand warehousing options for that period.

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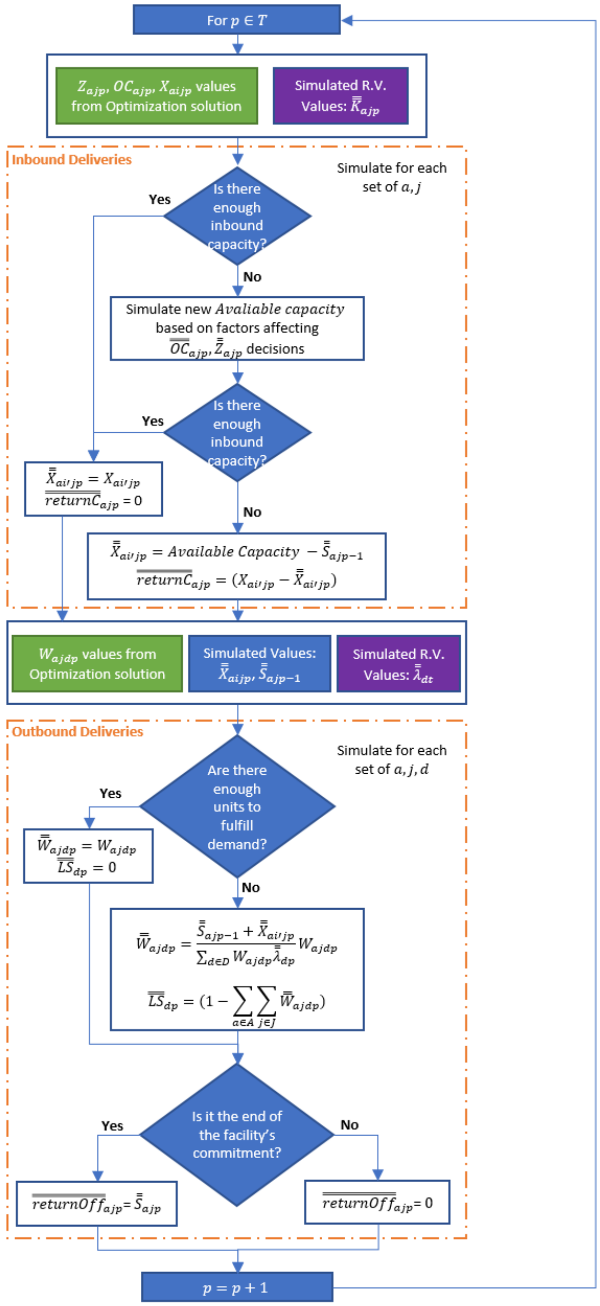

Supplemental Figure 1: Simulation model decision flow chart.

For each period $p \in T$, the simulation takes the optimization model's optimal decision variable values for DC opening, 3PL over capacity, inbound deliveries from supply location to DCs and demand fulfill ratios (Z_{ajp}, OC_{ajp}, X_{aijp} and W_{ajdp}, respectively) as inputs. Then after observing values for the simulated demand ($\bar{\bar{\lambda}}_{dp}$) and on-demand DC capacities ($\bar{\bar{K}}_{ajp}$), an associated value for the simulated

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decision variables: new inbound deliveries, new demand fulfilled ratios, inventory and lost sales (ratio of demand not fulfilled) are calculated, and are denoted as $\bar{\bar{X}}_{aijp}, \bar{\bar{W}}_{ajdp}, \bar{\bar{S}}_{ajp}$, and $\overline{\overline{LS}}_{dp}$, respectively.

First, the simulation model checks the available capacity for each DC that is to receive products. The available capacity from the optimization model decisions for 3PL or self-distribution facilities is calculated using the right-hand side of constraint (3). For the on-demand facilities, it is determined by the simulated random variable $\bar{\bar{K}}_{ajp}$. Further, depending on the factor value in the DOE (see Section 6), this available capacity may be further augmented to incorporate new 3PL extra capacity and new on-demand warehousing decisions. If there is enough in-bound capacity remaining, then $\bar{\bar{X}}_{ai'jp} = X_{ai'jp}$ where the closest supply location is denoted as i'. Otherwise, $\bar{\bar{X}}_{ai'jp} = Available\ Capacity - \bar{\bar{S}}_{ajp-1}$, with the excessive quantity shipped back to the closest supply location i' using a new variable, $\overline{\overline{returnC}}_{ajp} = X_{ai'jp} - \bar{\bar{X}}_{ai'jp}$.

For the outbound delivery, the simulation model initially tries to apply the W_{ajdp} ratios of the optimization model. If the simulated demand $\bar{\bar{\lambda}}_{dp}$ cannot be fulfilled completely due to insufficient available inventory levels at the facility, new $\bar{\bar{W}}_{ajdp}$ values are calculated as $\bar{\bar{W}}_{ajdp} = \frac{\bar{\bar{S}}_{ajp-1} + \bar{\bar{X}}_{ai'jp}}{\sum_{d \in D} W_{ajdp} \bar{\bar{\lambda}}_{dp}} W_{ajdp}$. The loss sales are updated based on constraint (8). This process results in the lost sales being equally divided across all demand locations served by an inadequately supplied DC. We then calculate the inventories ($\bar{\bar{S}}_{ajp}$) at the DC locations with the balance equation (12). If a DC reaches the end of its commitment period with any remaining inventory, the excess inventory is shipped back to the closest supply location using $\overline{\overline{returnOff}}_{ajp}$. The detailed sets, variables and calculations are presented in the supplemental materials simulation pseudocode section. The costs of the new $return$ decisions, as shown in S(27) and S(28), are added onto the objective function (1) and used to report total distribution costs from our simulation model.

$\overline{\overline{returnC}}_{ajp}$:Total units shipped back to the closest supply location (denoted as i') to location j due to insufficient capacity at an alternative a DC at location j at period p

$\overline{\overline{returnOff}}_{ajp}$: Total units shipped back to the closest supply location (denoted as i') to location j due to closing of an alternative a DC at location j at period p.

$$\sum_{a \in A} \sum_{j \in J} \sum_{p \in T} \overline{\overline{returnC}}_{ajp} \left(\theta_{i'j} C_{i'jp} + CF_{i'jp} + G_{ajp}\right) \quad \text{S(27)}$$

$$\sum_{a \in A} \sum_{j \in J} \sum_{p \in T} \overline{\overline{returnOff}}_{ajp} \left(\theta_{i'j} C_{i'jp} + CF_{i'jp} + G_{ajp}\right) \quad \text{S(28)}$$

3. Data Input Validation to Confirm Economies of Scale and Ownership Cost Advantages

The costs presented in Table 4 can change significantly based on various inputs. Therefore, we validate the cost relations between the alternatives and confirm that they incorporate the economies of scale and the ownership cost advantages. The cost input values are fed into equations S(29)-S(31) to estimate unit cost, UC_a, of distribution alternative a, given in $ per unit per period. These costs are a function of the time a unit spends in a facility, and thus depend on inventory turns. Let ψ denote the average number of turns per period. Assuming 100% capacity utilization for self and 3PL alternatives and ψ = 3 inventory turns per quarter in all DCs, then unit costs per period (quarter) and the relationship between alternatives' input costs are presented in **Supplemental Table 2**. For example, economies of scale are seen in the self-distribution alternatives, when the second largest capacity self-distribution alternative (*a=2*) has unit costs (UC_2) which are 3% to 8% more compared to the largest self-distribution alternative (*a=3,* UC_3). Further, economies of ownership (when fully utilized) are captured, for example, the 3PL alternative (*a=9*) has unit costs that are 30% to 35% more compared to the same sized self-distribution alternative (*a=3*).

Self-distribution $$UC_a = \frac{1}{K_a}\left(\frac{F_a}{N_a} + R_a\right) \quad \forall a \in A^s \qquad \text{S(29)}$$

3PL $$UC_a = \frac{1}{K_a}\left(\frac{F_a}{N_a} + R_a\right) + \psi\, G_a \quad \forall a \in A^l \qquad \text{S(30)}$$

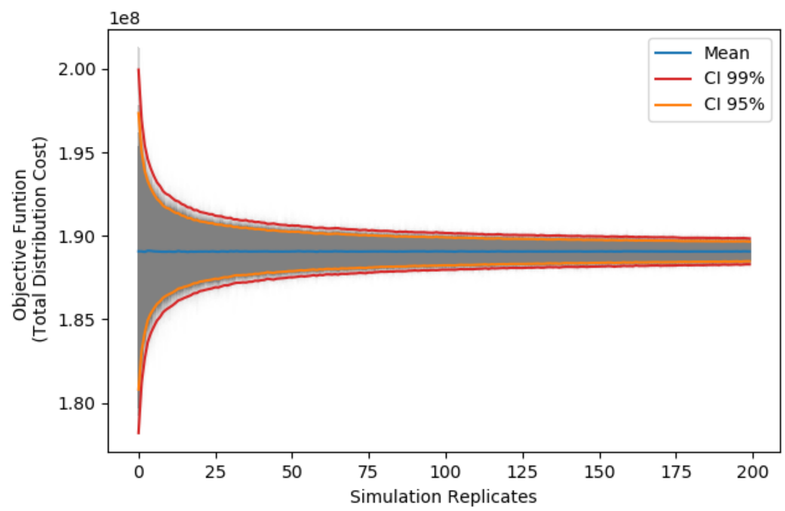
On-Demand $$UC_a = H_a + \psi\, G_a \quad \forall a \in A^o \qquad \text{S(31)}$$

Supplemental Table 2: Capacity and cost relationship input data validation of DC alternatives

a	Type	Cost per unit per period (UC_a)	Cost per unit per period (quarter) (UC_a)
1	Self Distribution 1	$(UC_2 * 1.03) \leq UC_1 \leq (UC_2 * 1.08)$	42.00
2	Self Distribution 2	$(UC_3 * 1.03) \leq UC_2 \leq (UC_3 * 1.08)$	40.68
3	Self Distribution 3	UC_3	38.52
4	3PL 1	$(UC_5 * 1.03) \leq UC_4 \leq (UC_5 * 1.08)$	65.70
5	3PL 2	$(UC_6 * 1.03) \leq UC_5 \leq (UC_6 * 1.08)$	62.25
6	3PL 3	$(UC_7 * 1.03) \leq UC_6 \leq (UC_7 * 1.08)$	59.46
7	3PL 4	$(UC_8 * 1.03) \leq UC_7 \leq (UC_8 * 1.08)$	56.82
8	3PL 5	$(UC_9 * 1.03) \leq UC_8 \leq (UC_9 * 1.08)$	54.24
9	3PL 6	$(UC_3 * 1.30) \leq UC_9 \leq (UC_3 * 1.35)$	51.24
10	On-demand	$(UC_4 * 1.15) \leq UC_{10} \leq (UC_4 * 1.20)$	78.00

4. Additional Simulation Results

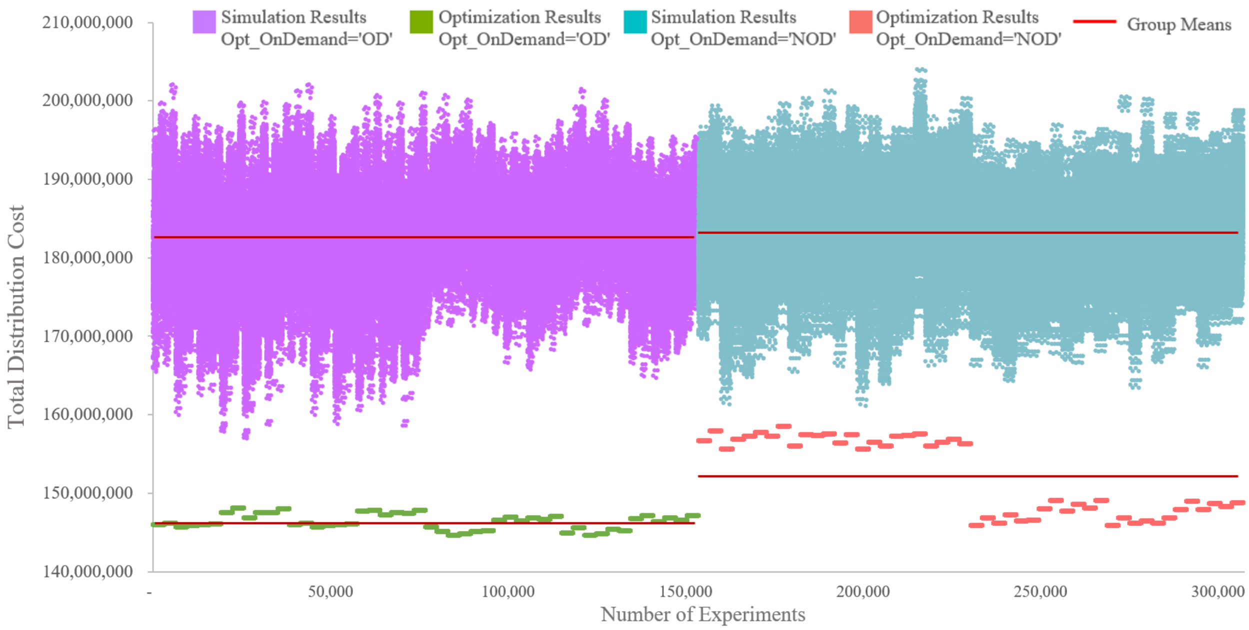
Supplemental Figure 2 presents the confidence intervals calculated based on the samples selected from the simulation replicates with bootstrapping method (5000 times random selection with replacement). This graph shows that the variability of simulation result decrease over the number of simulation replicates and we decided to use 100 replicates for our simulation models which appears to be adequate.



Supplemental Figure 2: Simulation Replicate Adequacy

Supplemental Figure 3 presents the total distribution costs from the 96 optimization and the 307,200 simulation outputs. As expected, the optimization values are smaller than the related replications from the simulation models.

doi = 10.1080/24725854.2021.2008066



Supplemental Figure 3: The total distribution costs for each of the optimization runs and simulation replications.

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5. Reproducibility Report

1. Metadata
Manuscript Title: Evaluating on-demand warehousing via dynamic facility location models
Manuscript ID (if available): UIIE-6397.R1
Authors: Kaan Unnu and Jennifer Pazour

2. Data availability

___________ A. Either no data are used in this study or all data used are included in the main text or supplemental materials.

___X_______ B. The data used in this study is publicly available at the following website

https://jenpazour.wordpress.com/research-2/

___________ C. The data used in this study is not yet publically available but will be made publically available at the time of paper acceptance** or will be made publically available subject to an embargo period of ____ years, counting from the time of paper acceptance. If an embargo period is invoked, please explain the reason for embargo.

___________ D. The data used in this study is not and will not be made publically available due to the following reason(s). Please present the reason(s).

3. Data use ethics

___________ My choice in Section 2 is (A).

___X_______ I certify that the authors have the legitimate access to the data and that nothing in the provisions governing the use of the data prohibits the authors from using the data in this research.

4. Computer code[#] availability

___________ A. Either no computer code is used in this study or the settings used in software are fully described in the main text or supplemental materials.

___X_______ B.The computer code used in this study is publically available at the following website.
https://jenpazour.wordpress.com/research-2/

___________ C. The computer used in this study is not publically yet available but will be made publically available at the time of paper acceptance or will be made publically available subject to an embargo period of ____ years, counting from the time of paper acceptance. Please describe where to make the data publically available. If an embargo period is invoked, please explain the reason for embargo.

___________ D. The computer code used in this study is not and will not be made publically available due to the following reason(s). Please present the reason(s).

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5. Reproducibility

5.1 Computer and software environment

Please describe the computer hardware conditions and software environment on which the authors produce the results reported in the paper.

The *optimization models* are solved with IBM ILOG CPLEX 12.9 with a maximum time limit based on the model characteristics. The optimization solution times varied between 30 seconds up to of 22 hours and returned optimality gaps between 0% and 1.15%. All 96 optimization runs were solved using 154 hours of solve time. The *simulation models* are coded with Python 3.7.3 and results are based on 100 replications per simulation run. 516 hours of computational time were required to solve the 3072 simulation runs explained in Table 4.

5.2 Workflow

Which results to reproduce	**Data File**	**Code File**	**Expected output**
CPLEX Optimization Runs	1_TUp_SNone_VNone.dat 2_TUp_SMajor_VNone.dat 3_TNone_SNone_VNone.dat 4_TNone_SMajor_VNone.dat 5_TDown_SNone_VNone.dat 6_TDown_SMajor_VNone.dat ScenarioSet.xlsx	1_OD_100_NOC_NSS.mod 2_OD_100_NOC_SS.mod 3_OD_100_OC_NSS.mod 4_OD_100_OC_SS.mod 5_OD_250_NOC_NSS.mod 6_OD_250_NOC_SS.mod 7_OD_250_OC_NSS.mod 8_OD_250_OC_SS.mod 9_NOD_100_NOC_NSS.mod 10_NOD_100_NOC_SS.mod 11_NOD_100_OC_NSS.mod 12_NOD_100_OC_SS.mod 13_NOD_250_NOC_NSS.mod 14_NOD_250_NOC_SS.mod 15_NOD_250_OC_NSS.mod 16_NOD_250_OC_SS.mod	Optimization, and decision variables (see example folder)
Simulation runs based on optimization results	Optimization outputs and ScenarioSet.xlsx	Simulation.py (simulation model) SimulationRunner.py (automates simulation runs and automatically changes the factor levels)	Simulation results, and plots (see example folder)

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Simulation Model Pseudocode

Input: Sets, parameters and decision variable results of the optimization model

$\bar{\bar{Z}}_{ajp} \leftarrow Z_{ajp}$

$\boldsymbol{for}\ \langle a, j, p\rangle\ in\ (Z_{ajp} = 1 \quad \forall a \in A, \forall j \in J, \forall p \in T)$

  $\boldsymbol{for}\ t\ in\ [p, (p + N_a)]$: $Z'_{ajt} \leftarrow 1$

$\boldsymbol{for}$ rep = 1 to Number of Replicates:

  $\bar{\bar{X}}_{iajp}, \bar{\bar{W}}_{ajdp}, \bar{\bar{S}}_{aj0}, \bar{\bar{S}}_{ajp}, \overline{\overline{LS}}_{dp}, \overline{\overline{OC}}_{ajp} \leftarrow 0 \quad \forall i \in I;\ \forall d \in D;\ \forall p \in T;\ \forall j \in J;\ \forall a \in A$

  $\bar{\bar{K}}_{ajp} = K_{ajp} \quad \forall a \in A;\ \forall j \in J;\ \forall p \in T$

  $returnC_{ajp}, returnOff_{ajp} \leftarrow 0 \quad \forall a \in A;\ \forall j \in J;\ \forall p \in T$

  $\boldsymbol{for}\ t$ = 1 to |T|:

    $\boldsymbol{if}$ demand variability = low $\boldsymbol{then}$

      $\bar{\bar{\lambda}}_{dt} = \lambda_{dt}(1 + (Uni[-0.1, 0.1]) \quad \forall d \in D$

    $\boldsymbol{endif}$

    $\boldsymbol{if}$ demand variability = high $\boldsymbol{then}$

      $\bar{\bar{\lambda}}_{dt} = \lambda_{dt}(1 + (Uni[-0.3, 0.3]) \quad \forall d \in D$

    $\boldsymbol{endif}$

    $\boldsymbol{if}$ forecast variability = yes $\boldsymbol{then}$

      $\bar{\bar{\lambda}}_{dt} = \bar{\bar{\lambda}}_{dt}\ (1 + \left(Uni[-0.1, 0.1] * \frac{t}{|T|}\right)) \quad \forall d \in D$

    $\boldsymbol{endif}$

    $\boldsymbol{if}$ on-demand capacity = yes $\boldsymbol{then}$

      $\bar{\bar{K}}_{10jt} = K_{4jt}.\ Uni[0,1] \quad \forall j \in J$

    $\boldsymbol{endif}$

    $\bar{\bar{X}}_{iajt} \leftarrow X_{iajt} \quad \forall d \in D;\ \forall j \in J;\ \forall a \in A$

    $\overline{\overline{OC}}_{ajt} \leftarrow OC_{ajt} \quad \forall d \in D;\ \forall j \in J;\ \forall a \in A$

    $\boldsymbol{if}\ t \neq |T|\ \boldsymbol{then}$

      $\boldsymbol{for}\ a\ in\ A$

        $\boldsymbol{for}\ j\ in\ J$

          $previnv \leftarrow \bar{\bar{S}}_{ajt-1}$

          $availcap \leftarrow (\bar{\bar{K}}_{ajt}\left(1 + \overline{\overline{OC}}_{ajt}\beta\right) - previnv),$

          $tmprec \leftarrow \sum_{i \in I} X_{iajt}$

          $tmpdel \leftarrow \sum_{d \in D} W_{ajdt}\bar{\bar{\lambda}}_{dt}$

          $\boldsymbol{if}\ (tmpdel + tmprec \geq 0)\ \boldsymbol{then}$

            $\boldsymbol{if}\ (availcap \geq tmprec)\ \boldsymbol{then}$

              $\boldsymbol{if}\ tmpdel \leq\ (tmprec + previnv)\ \boldsymbol{then}$

                $\boldsymbol{for}\ d\ in\ D$: $\bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

                $\boldsymbol{if}\ Z'_{ajt+1} = 1\ \boldsymbol{then}$

                  $\boldsymbol{if}\ \left(tmprec\ -\ tmpdel\ +\ previnv > \bar{\bar{K}}_{ajt+1}\right)\boldsymbol{then}$

                    $\bar{\bar{S}}_{ajt} \leftarrow \bar{\bar{K}}_{ajt+1}$

                    $returnC_{ajp} \leftarrow mprec\ -\ tmpdel\ +\ previnv - \bar{\bar{K}}_{ajt+1}$

                  $\boldsymbol{else}$

                    $\bar{\bar{S}}_{ajt} \leftarrow (tmprec\ -\ tmpdel\ +\ previnv)$

                  $\boldsymbol{endif}$

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$\boldsymbol{else}$
$\bar{\bar{S}}_{ajt} \leftarrow 0$
$returnOff_{ajt} \leftarrow (tmprec\ -\ tmpdel\ +\ previnv)$
$\boldsymbol{endif}$
$\boldsymbol{else}$
$\boldsymbol{for}\ d\ in\ D{:}\ \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt}\ * \frac{tmprec + previnv}{tmpdel})$
$\bar{\bar{S}}_{ajt} \leftarrow 0$
$\boldsymbol{endif}$
$\boldsymbol{else}$
$\boldsymbol{if}\ (a \in A^l)\ \&\ (\overline{\overline{OC}}_{ajt} = 0)\ \&\ ($overcapacity open = yes$)\ \boldsymbol{then}$
$\overline{\overline{OC}}_{ajt} \leftarrow 1$
$availcap \leftarrow (\bar{\bar{K}}_{ajt}\left(1 + \overline{\overline{OC}}_{ajt}\beta\right) - previnv)$
$\boldsymbol{if}\ (availcap < tmprec)\ \boldsymbol{then}$
$\boldsymbol{for}\ i\ in\ I{:}\ \bar{\bar{X}}_{iajt} \leftarrow \left(X_{iajt} * \frac{availcap}{tmprec}\right)$
$tmprec_2 \leftarrow \sum_{i \in I} \bar{\bar{X}}_{iajt}$
$\boldsymbol{if}\ tmpdel \leq\ (tmprec_2 + previnv)\ \boldsymbol{then}$
$\boldsymbol{for}\ d\ in\ D{:}\ \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$
$\boldsymbol{if}\ Z'_{ajt+1} = 1\ \boldsymbol{then}$
$\bar{\bar{S}}_{ajt} \leftarrow (tmprec_2\ -\ tmpdel\ +\ previnv)$
$\boldsymbol{else}$
$\bar{\bar{S}}_{ajt} \leftarrow 0$
$returnOff_{ajt} \leftarrow (tmprec_2\ -\ tmpdel\ +\ previnv)$
$\boldsymbol{endif}$
$\boldsymbol{else}$
$\boldsymbol{for}\ d\ in\ D{:}\ \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt}\ * \frac{tmprec_2 + previnv}{tmpdel})$
$\bar{\bar{S}}_{ajt} \leftarrow 0$
$\boldsymbol{endif}$
$returnC_{ajt} \leftarrow tmprec - tmprec_2$
$\boldsymbol{endif}$
$\boldsymbol{if}\ (availcap \geq tmprec)\ \boldsymbol{then}$
$\boldsymbol{if}\ tmpdel \leq\ (tmprec + previnv)\ \boldsymbol{then}$
$\boldsymbol{for}\ d\ in\ D{:}\ \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$
$\boldsymbol{if}\ Z'_{ajt+1} = 1\ \boldsymbol{then}$
$\boldsymbol{if}\ \left(tmprec\ -\ tmpdel\ +\ previnv > \bar{\bar{K}}_{ajt+1}\right)\boldsymbol{then}$
$\bar{\bar{S}}_{ajt} \leftarrow \bar{\bar{K}}_{ajt+1}$
$returnC_{ajp} \leftarrow mprec\ -\ tmpdel\ +\ previnv$
$-\ \bar{\bar{K}}_{ajt+1}$
$\boldsymbol{else}$
$\bar{\bar{S}}_{ajt} \leftarrow (tmprec\ -\ tmpdel\ +\ previnv)$
$\boldsymbol{endif}$
$\boldsymbol{else}$

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$\bar{\bar{S}}_{ajt} \leftarrow 0,$

$returnOff_{ajt} \leftarrow (tmprec - tmpdel + previnv)$

$\boldsymbol{endif}$

$\boldsymbol{else}$

$\boldsymbol{for}\ d\ in\ D\colon \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} * \frac{tmprec + previnv}{tmpdel})$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$\boldsymbol{endif}$

$\boldsymbol{endif}$

$\boldsymbol{endif}$

$\boldsymbol{if}\ (a \in A^l)\ \&\ (\overline{\overline{OC}}_{ajt} = 0)\ \&$ (overcapacity open = no) $\boldsymbol{then}$

$\boldsymbol{for}\ i\ in\ I\colon \bar{\bar{X}}_{iajt} \leftarrow \left(X_{iajt} * \frac{availcap}{tmprec}\right)$

$tmprec_2 \leftarrow \sum_{i \in I} \bar{\bar{X}}_{iajt}$

$\boldsymbol{if}\ tmpdel \leq (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D\colon \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

$\boldsymbol{if}\ Z'_{ajt+1} = 1\ \boldsymbol{then}$

$\bar{\bar{S}}_{ajt} \leftarrow (tmprec_2 - tmpdel + previnv)$

$\boldsymbol{else}$

$\bar{\bar{S}}_{ajt} \leftarrow 0, \quad returnOff_{ajt} \leftarrow (tmprec_2 - tmpdel + previnv)$

$\boldsymbol{endif}$

$\boldsymbol{else}$

$\boldsymbol{for}\ d\ in\ D\colon \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} * \frac{tmprec_2 + previnv}{tmpdel})$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$\boldsymbol{endif}$

$returnC_{ajt} \leftarrow tmprec - tmprec_2$

$\boldsymbol{endif}$

$\boldsymbol{endif}$

$\boldsymbol{endif}$

$\boldsymbol{if}\ t = |T|\ \boldsymbol{then}$

$\boldsymbol{for}\ a\ in\ A$

$\boldsymbol{for}\ j\ in\ J$

$previnv \leftarrow \bar{\bar{S}}_{ajt-1}, availcap \leftarrow (\bar{\bar{K}}_{ajt}(1 + \overline{\overline{OC}}_{ajt}\beta) - previnv),$

$tmprec \leftarrow \sum_{i \in I} X_{iajt}, tmpdel \leftarrow \sum_{d \in D} W_{ajdt}\bar{\bar{\lambda}}_{dt}$

$\boldsymbol{if}\ (tmpdel + tmprec \geq 0)\ \boldsymbol{then}$

$\boldsymbol{if}\ (availcap \geq tmprec)\ \boldsymbol{then}$

$\boldsymbol{if}\ tmpdel \leq (tmprec + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D\colon \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

$\bar{\bar{S}}_{ajt} \leftarrow 0, \quad returnOff_{ajt} \leftarrow (tmprec - tmpdel + previnv)$

$\boldsymbol{else}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} \ * \dfrac{tmprec + previnv}{tmpdel})$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$\boldsymbol{endif}$

$\boldsymbol{if}\ (availcap < tmprec)\ \boldsymbol{then}$

$\boldsymbol{if}\ (a \in A^l)\ \&\ (\overline{\overline{OC}}_{ajt} = 0)\ \&\ ($overcapacity open = yes$)\ \boldsymbol{then}$

$\overline{\overline{OC}}_{ajt} \leftarrow 1$

$availcap \leftarrow (\bar{\bar{K}}_{ajt}(1 + \overline{\overline{OC}}_{ajt}\beta) - previnv)$

$\boldsymbol{if}\ (availcap < tmprec)\ \boldsymbol{then}$

$\boldsymbol{for}\ i\ in\ I: \bar{\bar{X}}_{iajt} \leftarrow \left(X_{iajt} * \dfrac{availcap}{tmprec}\right)$

$tmprec_2 \leftarrow \sum_{i \in I} \bar{\bar{X}}_{iajt}$

$\boldsymbol{if}\ tmpdel \leq\ (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$returnOff_{ajt} \leftarrow (tmprec_2\ -\ tmpdel\ +\ previnv)$

$\boldsymbol{if}\ tmpdel >\ (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} \ * \dfrac{tmprec_2 + previnv}{tmpdel})$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$returnC_{ajt} \leftarrow tmprec - tmprec_2$

$\boldsymbol{if}\ (availcap \geq tmprec)\ \boldsymbol{then}$

$\boldsymbol{if}\ tmpdel \leq\ (tmprec + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$returnOff_{ajt} \leftarrow (tmprec\ -\ tmpdel\ +\ previnv)$

$\boldsymbol{if}\ tmpdel >\ (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} \ * \dfrac{tmprec + previnv}{tmpdel})$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$\boldsymbol{endif}$

$\boldsymbol{if}\ (a \in A^l)\ \&\ (\overline{\overline{OC}}_{ajt} = 0)\ \&\ ($overcapacity open = no$)\ \boldsymbol{then}$

$\boldsymbol{for}\ i\ in\ I: \bar{\bar{X}}_{iajt} \leftarrow \left(X_{iajt} * \dfrac{availcap}{tmprec}\right)$

$tmprec_2 \leftarrow \sum_{i \in I} \bar{\bar{X}}_{iajt}$

$\boldsymbol{if}\ tmpdel \leq\ (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow W_{ajdt}$

$\bar{\bar{S}}_{ajt} \leftarrow 0$

$returnOff_{ajt} \leftarrow (tmprec_2\ -\ tmpdel\ +\ previnv)$

$\boldsymbol{endif}$

$\boldsymbol{if}\ tmpdel >\ (tmprec_2 + previnv)\ \boldsymbol{then}$

$\boldsymbol{for}\ d\ in\ D: \bar{\bar{W}}_{ajdt} \leftarrow (W_{ajdt} \ * \dfrac{tmprec_2 + previnv}{tmpdel})$

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$\bar{\bar{S}}_{ajt} \leftarrow 0$
$returnC_{ajt} \leftarrow tmprec - tmprec_2$
endif
endif
endif
endif
if new ondemand = yes ***then***
for $\langle a, j, p\rangle$ *in* $(returnC_{ajp} > 0 \quad \forall a \in A, \forall j \in J, \forall p \in T)$
if $\left(a \notin A^o \textbf{ and } \left(\sum_{d\in D} W_{ajdt} - \sum_{d\in D} \bar{\bar{W}}_{ajdt}\right) > 0\right)$ ***then***
$\bar{\bar{Z}}_{a'jp} \leftarrow 1\ (a' \in A^o),\ availcap \leftarrow \bar{\bar{K}}_{a'jt}\ \ (a' \in A^o)$
for d *in* D
$returnC^{(-)}_{ajp} \leftarrow (W_{ajdp} - \bar{\bar{W}}_{ajdp})\,\bar{\bar{\lambda}}_{dp}$
if $\left(availcap \geq returnC^{(-)}_{ajp}\right)$ ***then***
$\bar{\bar{W}}_{a'jdp} \leftarrow (W_{ajdp} - \bar{\bar{W}}_{ajdp}) + \bar{\bar{W}}_{a'jdp} \quad (a' \in A^o)$
$returnC_{ajp} \leftarrow \left(returnC_{ajp} - returnC^{(-)}_{ajp}\right)$
$availcap \leftarrow availcap - returnC^{(-)}_{ajp}$
endif
if $\left(availcap < returnC^{(-)}_{ajp} \textbf{ and } availcap > 0\right)$ ***then***
$\bar{\bar{W}}_{a'jdp} \leftarrow \left(\frac{availcap}{\bar{\bar{\lambda}}_{dp}}\right) + \bar{\bar{W}}_{a'jdp} \quad (a' \in A^o)$
$returnC_{ajp} \leftarrow \left(returnC_{ajp} - availcap\right)$
$availcap \leftarrow 0$
endif
endif
endif
for d *in* D
for p *in* T
$\overline{\overline{LS}}_{dp} \leftarrow (1 - \sum_{a\in A}\sum_{j\in J} W_{ajdp})$

$TransportCost1_{rep} \leftarrow \sum_{i\in I}\sum_{j\in I}\sum_{p\in T}\sum_{a\in A} \bar{\bar{X}}_{aijp}\,(\theta_{ij}C_{ijp} + CF_{ijp})$
$StartupCost_{rep} \leftarrow \sum_{j\in J}\sum_{p\in T}\sum_{a\in A} \bar{\bar{Z}}_{ajp}F_{ajp}$
$HandlingCost_{rep} \leftarrow \sum_{i\in I}\sum_{j\in J}\sum_{p\in T}\sum_{a\in A} \bar{\bar{X}}_{iajp}G_{ajp}$
$HoldingCost1_{rep} \leftarrow \sum_{j\in J}\sum_{p\in T}\sum_{a\in A^o} \bar{\bar{S}}_{ajp}\,H_{ajp}$
$HoldingCost2_{rep} \leftarrow \sum_{j\in J}\sum_{d\in D}\sum_{p\in T}\sum_{a\in A^o} \bar{\bar{W}}_{ajdp}\bar{\bar{\lambda}}_{dp}H_{ajp}$

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$$Fixedcost1_{rep} \leftarrow \sum_{j\in J} \sum_{\substack{p\in T:\\ p\leq(|T|-N_a)}} \sum_{a\in A} \bar{\bar{Z}}_{ajp}\, N_a R_{ajp}$$

$$FixedCost2_{rep} \leftarrow \sum_{j\in J} \sum_{\substack{p\in T:\\ p>(|T|-N_a)}} \sum_{a\in A} \bar{\bar{Z}}_{ajp}\, (|T|-p)\, R_{ajp}$$

$$OverCapacity_{rep} \leftarrow \sum_{j\in J} \sum_{p\in T} \sum_{a\in A^l} \left(\overline{\overline{OC}}_{ajp}\, R_{ajp}\right) \beta\, \rho +$$

$$TransportCost2_{rep} \leftarrow \sum_{j\in J} \sum_{d\in D} \sum_{p\in T} \sum_{a\in A} \bar{\bar{W}}_{ajdp} \bar{\bar{\lambda}}_{dp} (\theta_{jd} E_{jdp} + EF_{jdp})$$

$$LossSalesCost_{rep} \leftarrow \sum_{d\in D} \sum_{p\in T} \overline{\overline{LS}}_{dp} \bar{\bar{\lambda}}_{dp} \gamma \varphi$$

$$ReturnCostClose_{rep} \leftarrow \sum_{j\in J} \sum_{p\in T} \sum_{a\in A} returnOff_{ajp} \left(\theta_{ij} C_{ijp} + CF_{ijp} + G_{ajp}\right) : i \; in \; \min(\theta_{ij})$$

$$ReturnCostCap_{rep} \leftarrow \sum_{j\in J} \sum_{p\in T} \sum_{a\in A} returnC_{ajp} \left(\theta_{ij} C_{ijp} + CF_{ijp} + G_{ajp}\right) : i \; in \; \min(\theta_{ij})$$

$$SimObjFunct_{rep} \leftarrow (TransportCost1_{rep} + StartupCost_{rep} + HandlingCost_{rep} + HoldingCost1_{rep} + Fixedcost1_{rep} + Fixedcost2_{rep} + OverCapacity_{rep} + TransportCost2_{rep} + LossSalesCost_{rep} + ReturnCostClose_{rep} + ReturnCostCap_{rep})$$

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