Simulation Analysis for CVS Health Supply Chain

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CVS Health

BACKGROUND

- CVS Health currently uses **barcodes** to track totes (containers used to move products from one location to another); however, this system has its **flaws**. **Tote shrinkage** (loss of totes) is serious issue that CVS is facing. However, it is difficult to diagnose and fix this issue under the current system because there is **no confirmation of receipt** - which means that it is impossible to track where the totes are in the system.
- To address this problem, CVS is planning to implement **RFID** (radio frequency identification). Placing RFID readers at the **distribution centers (DCs) and stores** can help track totes and calculate important metrics (e.g., **life cycle** of the totes and orders, **tote inventory** at the stores). RFID technology has potential to significantly improve the management of the tote inventory.

OBJECTIVES

We are working with representatives from CVS to build a simulation model that **simulates the life cycle of totes** in the supply chain. We aim to explore the **benefits and effectiveness** of implementing RFID by comparing CVS's current supply chain system **with and without RFID**. The simulation model will allow CVS to **confirm current assumptions** of tote loss rates and the associated costs.

CVS SUPPLY CHAIN SYSTEM

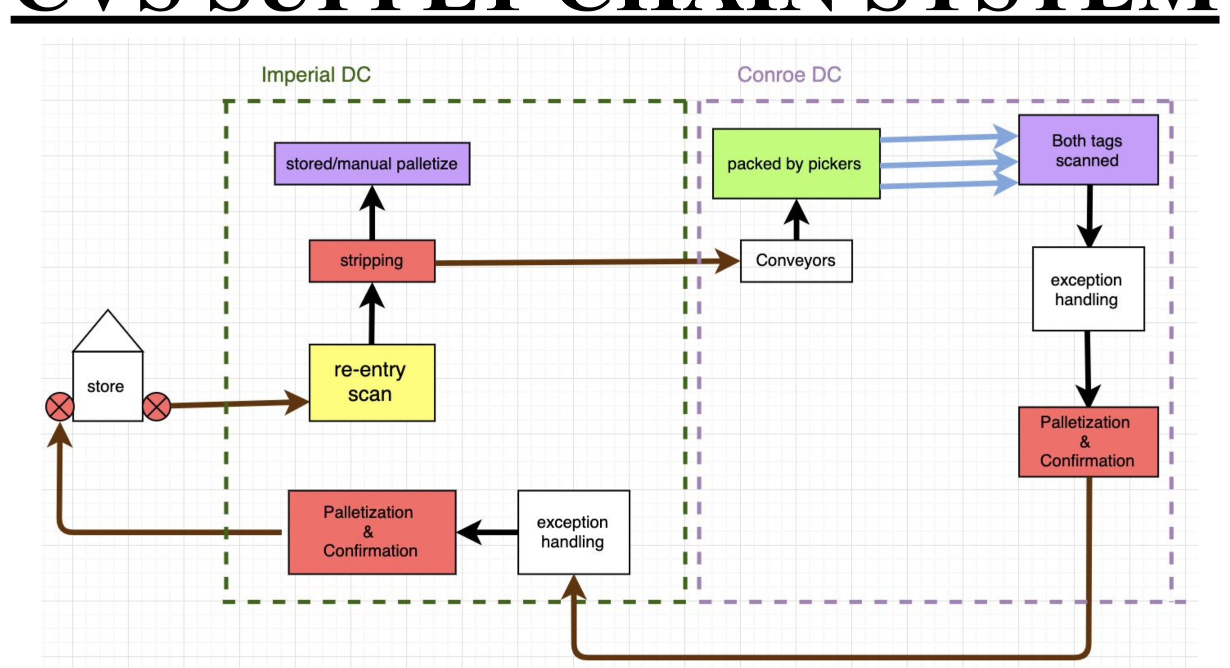

Fig.1. A simplified flow chart for the life cycle of the totes in a DC

Life Cycle of the Totes:

a. **Scan** the empty totes from the stores at Imperial DC.
b. The totes are **unloaded** into one container and the stripped totes are transported to Conroe DC.
c. The totes go through the **conveyors** for the **pickers** to put products in.
d. The filled totes are **palletized and validated** and sent to Imperial DC.
e. After another round of palletization and validation, the totes are **loaded onto the trucks** and sent to the stores.
f. The stores **unload** the filled totes and the empty ones will get picked up next time an order is sent.

SIMULATION MODEL

Model Assumptions:

➔ All the totes coming into the DC are **empty**.
➔ Totes are **unloaded immediately** when they reach the store.
➔ **No tote loss** will occur in the DC (tote loss only occur in the store).
➔ The value and demand for products in the same type of tote are considered the same.
➔ The trucks have **infinite capacity**.
➔ The systems with RFID and without RFID are **different** in:
- Values of totes.
- Inventory visibility.
- Probability of delivery the totes to the wrong store.
- Probability of losing an empty tote at the store per day.
- Whether the system immediately replenishes new empty totes when tote loss occurs.

Model Specifications:

We use **discrete-event simulation** (DES) to model the CVS supply chain system as a **modified (s, S) inventory** problem.

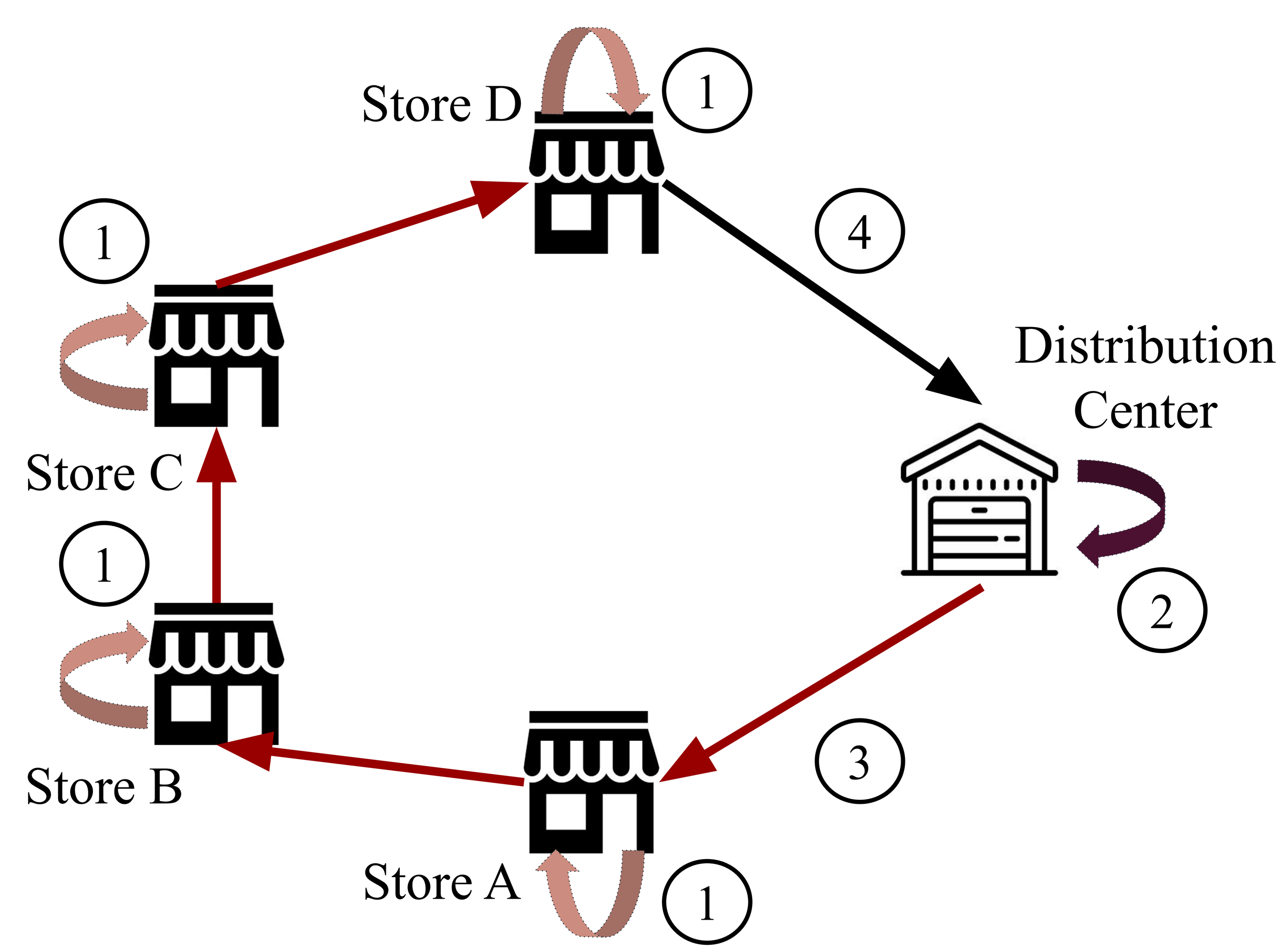

Fig.2. The four events in our CVS supply chain simulation model

1. **Demand & Loss Generate**: Generate **new daily demand** and **loss of empty totes** for a store.
2. **Route Generate**: For every store associated with a DC, put the stores that have **low inventory levels** on the **delivery route**. Totes are filled for delivery based on the **order quantity**.
3. **Order Delivery**: The filled totes arrive and are **unloaded** at the stores on the delivery route. The remaining empty totes are picked up.
4. **DC Arrival**: Delivery empty totes back to the DC from the stores.

PRELIMINARY RESULTS

We tested the model on a simple system with only 1 type of tote, 1 store, and 1 DC. Since we assume that the number of lost totes L during the time in-between deliveries W follows a binomial distribution, we know that with probability of losing a totes per day p and tote order quantity Q, the following holds: $L = Binomial(Q, 1-(1-p)^W)$.

The expected total number of lost totes M over time R can therefore be calculated as the total number of deliveries R/W multiplied by the expected number of lost totes (E[L]) during the time in-between deliveries W. M can be expressed solely using W, which is a parameter we would like to vary across different scenarios. Given daily demand D, we can derive the following:

$$
\begin{aligned}
M(W) &= \frac{R}{W} \cdot \mathbb{E}[L] \\
&= \frac{R \cdot Q}{W}(1-(1-p)^W) \\
&= \frac{(\mathbb{E}[D] \cdot W) \cdot R}{W}(1-(1-p)^W) \\
&= \mathbb{E}[D] \cdot R \cdot (1-(1-p)^W)
\end{aligned}
$$

M(W) increases with W when W is relatively small.

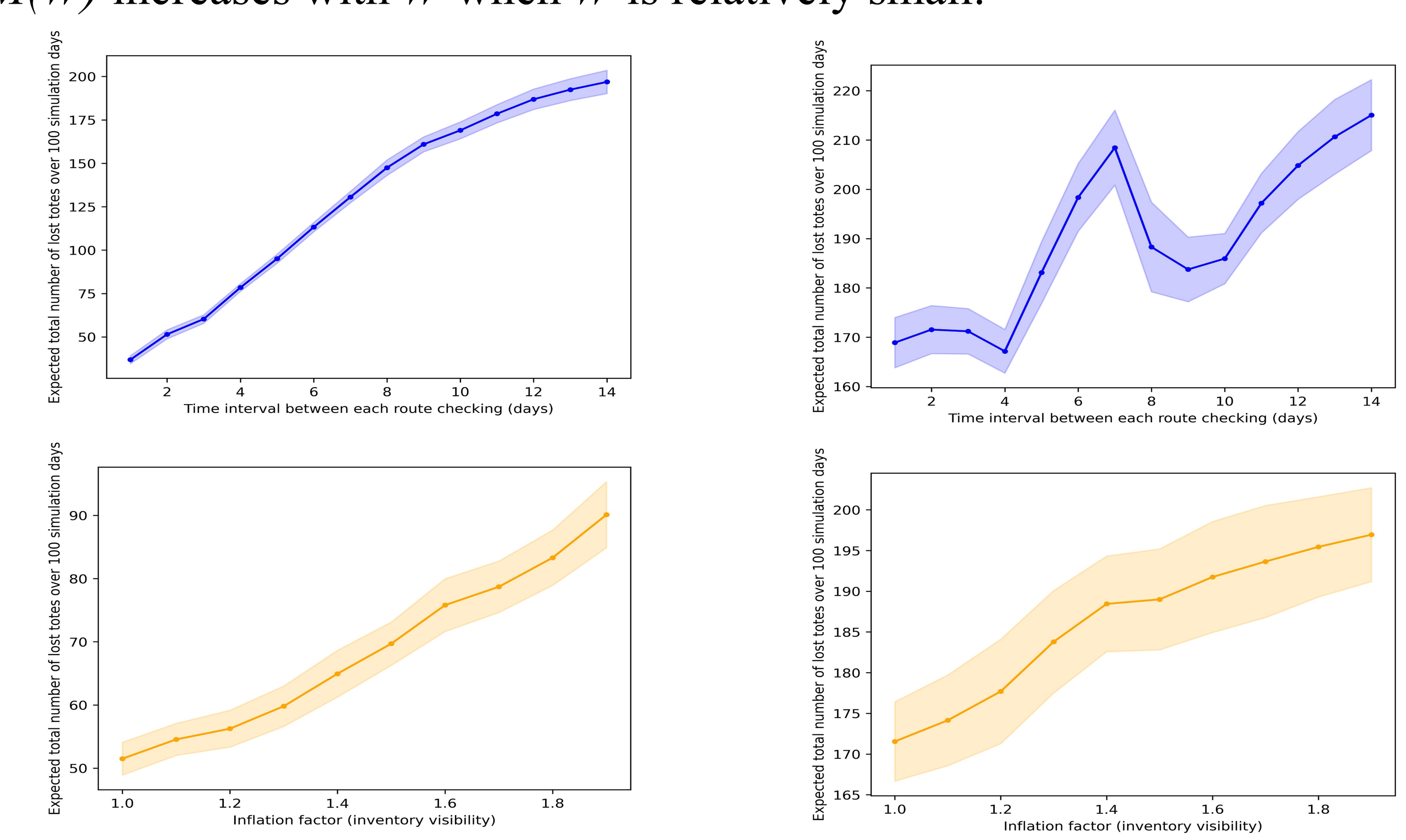

Fig.3. Time between route checking and inflation factor vs. expected total number of lost totes w/o (left plots) and w/ (right plots)) inventory threshold.

- Inventory visibility influences the tote loss **similarly** to delivery (route checking) frequencies, which is consistent with our expectation (an approximately **positive** relationship).
- Adding **inventory threshold** adds another layer of complexity but is more close to real-world scenario.

Next Steps

Test on **more complicated systems**, such as one with 1 DC serving 400 stores. Incorporate **real parameters** into the model and conduct **sensitivity analysis** on parameters that cannot be obtained.