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IFAC PapersOnLine 55-10 (2022) 1822–1827

# Multi-objective Inventory Optimization Problem for a Sustainable Food Supply Network under Lateral Inventory Share Policy

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**Abstract**: This study dives deep into a lateral supply chain network for perishable food products and aims to determine optimal re-order and order up to levels for multiple e-groceries within a common network using a simulation-based optimization technique. The algorithm aims to minimize the average inventory carried within the network while accounting for parameters like reduced wastage, improved customer satisfaction level, and a limited number of replenishments.



*Keywords*:Lateral inventory share, *s*, *S* inventory, food supply chain, heuristic optimization.

## 1. INTRODUCTION

With the growing concerns around environmental degradation, increased wastage, and pollution, it becomes significant that the world migrates towards more sustainable supply chain designs across various sectors in a way that it becomes more environmentally and pocket friendly. The COVID-19 pandemic escalated that shift where many existing supply chain networks crumbled in different parts of the world, including the food supply chain networks. One of the major constraints that often comes into play while maintaining optimum inventory for food industry stores is to account for the wastage caused by the expiration of perishable food products (e.g., milk, bread etc.). Hence, it is significant to determine the optimum inventory levels to carry in stores for such perishable products, especially with the tight shelf lives. The two of the important benchmarks in inventory decisions are the re-order and order up-to ($s$, $S$) levels where $s$ represents the inventory level beyond which a fresh order is placed, and $S$ represents the maximum level of the inventory. Therefore, when the order is placed the order quantity ($OQ$) can be calculated by (1):

$$OQ = S - I, if\ I \leq s \tag{1}$$

where $I$ is the current inventory level at the store. This study revolves around optimizing the inventory levels for a food supply chain network considering lateral inventory share policies across multiple e-groceries. It is well known that with the recent COVID-19 pandemic, the e-commerce sector witnessed a substantial rise in its share of all retail sales which also includes food products (UNCTAD, 2021).

While stocking products beyond a consumable limit leads to significant wastage, increased carbon footprint and higher inventory cost, and insufficient stock can often lead to dissatisfied customers. Thus, the retailers search for a balanced solution for those multi-objectives in finding the appropriate $s$, $S$ levels.

While accounting for all these factors it is also essential for the retailers to achieve their goals within the minimal operational cost. Each fresh order placed often comes with additional charges for placing the order and transportation; which makes it ideal to limit the number of replenishments occurring in a time unit. With the growing concerns around climate change and increasing carbon footprints; limiting the number of replenishments also takes care of raging environmental concerns by cutting down the number of trips being made by the delivery trucks.

Most of the existing research papers focus on optimizing a supply chain network on finding the optimum inventory levels based on cost parameters (Ekren and Ornek, 2015; Ekren et al., 2018). For example, Ekren and Arslan (2019) and Ekren et al. (2018) optimize a single-echelon supply chain network by minimizing the total cost in a pre-defined fill rate. Amiri et al. (2020) study the network for perishable products with multiple vendors while accounting for factors like sales and delivery costs. Ekren et al. (2021) study an IoT enabled food network while trying to optimize business profitability. However, accounting for cost factors alone is not enough for the food supply network inventory problem since they make the solution vulnerable and sensitive to a lot of external factors like inflation, currency rate, availability of resources etc. In order to generalize the solution and widen the scope of implementation, we also take into account the performance


10.1016/j.ifacol.2022.09.663

metrics like, wastage, customer satisfaction level, number of replenishments within the network and distance travelled, which in turn can be directly related to the carbon footprint generated, based-on multiples of each other. To solve the problem, we also develop an efficient inventory share algorithm and show its application on the studied network by simulating the studied system. We compare the optimal performance results of sharing policy with its equivalent non-sharing policy results, where we also optimize that non-sharing system separately. We draw a comprehensive network diagram which is not restricted to the particular network system and can be extended to a large pool of network designs.

## 2. LITERATURE REVIEW

There are a few studies focusing on lateral inventory share problems. A recent study by Ekren et al. (2021) focuses on lateral inventory share policies in food supply networks minimizing food waste as well as backorders resulting in more sustainable networks. Ekren and Heragu (2008) study shares policies in supply chains where physical lateral trans-shipments take place. The studied products are not food products.

Recent works on lateral-inventory share policies are also completed by Izmirli et al. (2020, 2021, 2022) and by Ekren et al. (2020) for food products. They study omni-channel networks where online and offline stores are connected so that they can share their inventories among stores to provide better service for the customer (Izmirli et al, 2020). Later, they added a circular economy concept in the inventory sharing policy (Izmirli et al., 2021).

Ekren et al. (2018) study different lateral-inventory share policies under a physical-internet concept. They seek a better policy optimizing total cost in the network.

Yang et. al. (2015) study lateral inventory share policy under physical transshipments between stocking locations under a physical internet concept.

Yan et al. (2019) study two-echelon and multi-location optimal inventory models making a match between supply and demand balance by lateral trans-shipments and emergency shipments.

Rohmer et al. (2019) focus on a two-echelon inventory routing problem for perishable products minimizing the total transportation and holding cost in the network. They solve the problem by a mixed-integer linear program by applying a two-stage metaheuristic with a combination of adaptive large neighbourhood search.

Alkaabneh et al. (2020) present an inventory routing problem in perishable products providing near-optimal replenishment scheduling and vehicle routes. The objective is to maximize the profit of the supplier and minimize fuel consumption, inventory holding costs and greenhouse emissions.

Different from the existing works, in this study, we focus on multi-objectives in an e-grocery supply network inventory problem under lateral share policies where there is no physical transshipments between stores and also by taking into consideration generic cost values by developing multiples of each other. The multi-objectives consider, minimization of average inventory carried, wastage of food products, distance travelled by stores, and maximization of customer satisfaction in terms of customer service level. The problem is modelled and solved by simulation optimization by using the Python programming language. In Section 3, we define the problem by providing our research questions and giving the modelling and solution procedure as well as findings from the work. In Section 4, we provide a conclusion part summarizing the problem and findings.

## 3. SYSTEM DESIGN

In this section, we define the studied problem and provide the solution procedure.

### *3.1 The studied e-grocery network design*

We study the e-grocery network whose design is given in Figure 1. The network comprises three e-groceries with three respective demand points focusing on a single food product with limited shelf lives. This network is motivated by e-groceries where typically each zone (i.e., demand point) is serviced by a specific e-grocery fulfilment store assigned based-on the proximity to those demand points. We assume that each demand point follows a normal distribution for its demand amount with different mean and standard deviation values. The e-grocery products are replenished from the main depot with an infinite capacity supplier (i.e., main depot). The distance units between the e-groceries and different demand points have been clearly depicted in Figure1.

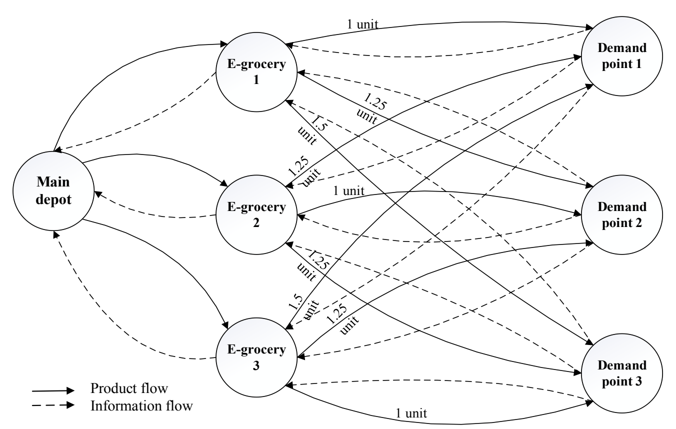


Figure 1. E-grocery food supply network.

### *3.2 The addressed research questions*

While a lot of inventory optimization problems have focused on cost factors, there is an emerging need to focus on environmental factors in the food supply network as well. Building on this idea, we have tackled two primary research questions:

*RQ1:* How an *s*, *S* inventory model can be developed by ignoring specific cost parameters but focusing on unit-cost parameters based-on multiples of each other?

*RQ2:* Is lateral sharing in a food supply chain network a more sustainable option compared to a non-sharing supply chain network?

In order to tackle the first research question, we illustrate a simulation-based optimization solution procedure by applying a metaheuristic optimization technique named Basin-hopping algorithm. Note that by considering unit-cost parameters based-on multiples of each other, we create a solution approach on insensitive approach to cost values. For *RQ2*, we compare two policies: the developed sharing and non-sharing models. We apply an experimental design study also to observe how sensitive the results on parameter changes are.

### *3.3 Food supply chain network system and simulation assumptions*

The supply chain network in consideration aims to develop a model of operation that ensures profitability, increased customer satisfaction level (*CSL*), reduced food wastage, reduced-order frequency from the main depot as well as for lateral replenishments, minimal distance traversed during lateral replenishments. To solve that multi-objective optimization problem, the main performance metric to be optimized is defined to be the minimization of average inventory carried in the network. Namely, we seek the optimum $s$, $S$ levels in e-groceries minimizing the average inventory carried in the whole network. To design the model close to real life, we consider stochastic shelf life, demand amounts following normal distributions, and the lead times. The studied sharing policy works as follows:

1. Demands arrive at groceries on a daily basis.
2. Demand arriving at each e-grocery is dispatched at the end of each day.
3. Each e-grocery prioritizes the demand arriving at its nearest demand point first.
4. However, in the case that the nearest e-grocery fails to meet the complete demand at a particular point, it is checked if the other e-groceries in the network can fulfil the remaining demand after they meet the demands of their respective demand points. This would help to improve the customer satisfaction level of the network.
5. The remaining two e-groceries are always in positions to meet the remaining demand based on the closest one to the demand point. However, if both are equidistant from the demand point, then either of the two is picked. That would provide decreased travel distance and hence, decreased emission amount in the network.
6. In case both e-groceries fail to meet the remaining demand then the leftover demand is accounted as lost sales leading to dissatisfied customers.
7. At the end of each day, the inventory is reduced and deterioration due dates are updated by decreasing one day from their current remaining dates. Also, the spoiled products (i.e., products passing their deterioration due dates) is cleared from the inventory and they are counted as wastage.
8. A continuous $s$, $S$ policy is implemented to review the inventory, that is, a fresh order is placed at the main depot when the inventory level goes below $s$ and the order quantity is given as in (1).

The other simulation model assumptions are given below:

1. The lead time for an order arrival from the main depot follows a uniform distribution with parameters (1, 3) days.
2. The shelf life of the product follows a uniform distribution with parameters (3, 7) days from the time of arrival to the e-grocery.
3. The wastage within the network should not be more than 10%.

### *3.4 Algorithm and pseudo code of the shared inventory model*

The sharing algorithm's details are already given in Section 3.3. Figure 2 shows the pseudo-code integrated with the simulation model, specifically illustrating how demand is fulfilled in the lateral sharing policy while prioritizing customer satisfaction and optimizing the extra distance travelled. The lateral sharing policy follows the nuances as captured in points 1 to 8 in Section 3.3. However, in order to understand the pseudo-codes and equations better, it is important to understand some important notations which have been used in the model. The notations used in the models are explained below:

- $D_{it}$: Demand amount arriving at demand point $i$ on day $t$
- $I_{i1t}$: Inventory of e-grocery that is closest to demand point $i$ on day $t$
- $I_{i2t}$: Inventory of e-grocery that is second closest to demand point $i$ on day $t$
- $I_{i3t}$: Inventory of e-grocery that is farthest to demand point $i$ on day $t$
- $UD_{it}$: Unfulfilled demand at point $i$ during the simulation run on day $t$
- *Dist*: Total extra distance travelled due to lateral sharing during the simulation run
- $d_{i2}$: The distance between the demand point $i$ and the second closest e-grocery
- $d_{i3}$: The distance between the demand point $i$ and the farthest e-grocery
- $was_{it}$: Waste generated by e-grocery $i$ at the end of day $t$
- $was_{tot}$: Total number of units wasted in the system during the simulation run
- *wastage*: % age of waste generated in a year
- $I_t$: Total inventory across all e-groceries in the network on the day $t$
- $I_{avg}$ : Average inventory carried in the system
- $C$: the number of replenishments completed in a year

In order to understand the inventory notations better, we provide a specific case: E-grocery 1 is closest to demand point 1 where it is relatively distant from demand point 2, and farthest from demand point 3. Therefore, on a given day $t$, $I_{11t}$, $I_{22t}$, and $I_{33t}$ point towards the same variable which stores the inventory of e-grocery 1.

```
Start                //continuous check
I =1                 //chosen demand point
While i <= 3
    If (D_it <= I_i1t)    //check if demand at point I can be met by closest e-grocery
        I_i1t = I_i1 - D_it
        UD_it = 0
    Else
        UD_it = D_it - I_i1t
        I_i1t = 0
    End If
    i++
End While
i =1
While i <= 3
    If (UD_it <= I_i2t)    //check if unfulfilled demand at point i can be entirely
                             met by the second closest e-grocery
        Dist = Dist + d_i2  //calculate extra distance travelled due to lateral
                              sharing
        I_i2t = I_i2t - UD_it
        UD_it = 0
    Elseif (UD_it <= I_i3t)    //check if unfulfilled demand at point i can be entirely m
                                 by the second closest e-grocery
        Dist = Dist + d_i3  //calculate extra distance travelled due to lateral
                              sharing
        I_i3t = I_i3t - UD_it
        UD_it = 0
    Elseif (UD_i <= I_i3 + I_i2)   //check if unfulfilled demand at point i can be
                                     met by the e-groceries collectively
        Dist = Dist + d_i3 + d_i2 //calculate extra distance travelled due to
                                    lateral sharing
        I_i3t = I_i3t – (UD_it - I_i2t)
        I_i2t = 0
        UD_it = 0
    Else
        Dist = Dist + d_i3 + d_i2
        UD_it = UD_it – (I_i2 + I_i3)
        I_i2t = 0
        I_i3t = 0
    End If
    i++
End While
End
```

Figure 2. The pseudo-code to show how demands are met in the lateral sharing network

At the end of the simulation for a period of 365 days, the model further calculates metrics like extra distance travelled, wastage, and customer satisfaction level to evaluate the performance of the model. The average inventory carried is in the network is minimized to obtain the optimized *s*, *S* levels. The metrics are measured collectively for a period of $T$ (365) days. Equations (2) – (6) capture the expressions used to calculate these metrics.

$$I_{avg} = \frac{\sum_{t=1}^{T} I_t}{T} \quad (2)$$

where, $$I_t = I_{11t} + I_{21t} + I_{31t} \quad (3)$$

The inventory for e-grocery 1, 2, 3 on day $t$ as symbolized by $I_{11t}$ , $I_{21t}$ , $I_{31t}$ respectively, and is equal to the average of the inventory in the e-grocery at the start and end of the day.

$$CSL = 1 - \frac{\sum_{t=1}^{T}\sum_{i=1}^{3} UD_{it}}{\sum_{t=1}^{T}\sum_{i=1}^{3} D_{it}} \quad (4)$$

The various wastages are calculated as follows:

$$was_{tot} = \sum_{t=1}^{T}\sum_{i=1}^{3} was_{it} \quad (5)$$

$$wastage = \frac{was_{tot}}{I_{avg}} \times T \quad (6)$$

### *3.5 Optimization of the simulation model*

Once again, our objective is to optimize the *s*, *S* levels for each e-grocery while accounting for different constraints. However, this is a complex real-time control problem, and it is often too challenging to provide an exact mathematical representation for the objective function. Therefore, we have utilized a meta-heuristic optimization algorithm known as the Basin-Hopping Algorithm (Wales et al., 1997). It is a global optimization technique that starts with an initial point that is fed into the system and performs multiple local optimizations by random perturbation of points. A point is accepted if the value of the objective function is lower than the previously achieved value. The optimizer is stopped once the results stop showing further improvement after a certain number of runs or a given time frame. The optimal result for the various *s*, *S* values thus obtained is again utilized as the initial point for the next run. To avoid errors or biased results we have conducted five independent runs which are found to be appropriate by relatively small half-width values.

Python language, which is an open-source platform and one of the popular programming languages as of today, has been used to model the system as well as the optimization algorithm. The optimization problem can be summarized by equations (7) – (11), where (7) represents the objective function and (8) – (11) represent the constraints. The limits for (9) and (10) are varied based on the experiment as discussed in 3.3.

Minimize $$I_{avg} \quad (7)$$

Subject to: $$wastage \leq 10\% \quad (8)$$

$$CSL \geq 95\% \text{ or } 90\%, \qquad CSL \in R^{+} \quad (9)$$

$$C \leq 250 \text{ or } 400, \qquad C \in Z^{+} \quad (10)$$

$$s < S \qquad s, S \in Z^{+} \quad (11)$$

Note that, one of the objectives in the problem is to minimize the total number of transportations completed from the main depot. Here, $C$ represents that objective value. We set that value as a constraint, either 250 or 400 number of replenishments completed in a year. A low level of $C$ might cause to increase in the average inventory level, while a high level of $C$ might cause to decrease in the average inventory level but increase food wastage. Those experimental values are defined by trial and error by finding trade-off points between inventory and wastage.

## 4. EXPERIMENTAL STUDY AND RESULTS

We conduct an experimental design work to understand how sensitive the performance metrics (i.e., wastage amount, distance travelled, *s S* levels, average inventory carried, etc) are on various predefined parameter values. We conduct Table 1 experiments developed for two sets of values (levels) for considered input variables. Specifically, we change the *CSL*, *C* and demand values while carrying out the optimization problem. This helps to conduct different sets of experiments.

While the *CSL* and *C* are used as limiting values in the system, the daily demands are directly assigned to generate dynamic demand arrivals following normal distribution at each point. As the demand for food items can't be negative or fractional in the model, we consider the rounded absolute values of the dynamic demand being generated. Note that, the demand values have experimented with for higher variance cases to observe, how the results are affected by high variability. Totally, eight experiments ($2^3$) are completed.

**Table1. Design parameters and their levels**

| Parameters | Level 1 | Level 2 |
|---|---|---|
| *CSL* (% age) | ≥ 95 | ≥ 90 |
| Number of replenishments per year (*C*) | ≤ 400 | ≤ 250 |
| Daily Demand at Point1($D_{1t}$) | normal(35,50) | normal(35,100) |
| Daily Demand at Point2 ($D_{2t}$) | normal(70,75) | normal(70,150) |
| Daily Demand at Point3 ($D_{3t}$) | normal(100,100) | normal(100,200) |

The optimum *s, S* values for the following experiments are obtained and the respective metrics like *CSL*, *C*, $I_{avg}$, $was_{tot}$, are captured. While the *s*, *S* values obtained from the metaheuristic optimization might not be the global optimum, it is expected to be a good solution close to the global optimization. The results for the lateral sharing-based simulation models are given in Table 2 for the averages of runs. It is worth noting here that $s_i$, and $S_i$ represent the re-order and order-up-to values for the $i^{th}$ grocery.

**Table 2. Optimum *s*, *S* levels for lateral sharing policy**

| Ex. | D. | *C* | *CSL* | $s_1$ | $S_1$ | $s_2$ | $S_2$ | $s_3$ | $S_3$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 250 | 0.90 | 2 | 258 | 2 | 375 | 7 | 402 |
| 2 | 1 | 250 | 0.95 | 2 | 250 | 20 | 351 | 15 | 430 |
| 3 | 1 | 400 | 0.90 | 3 | 137 | 8 | 249 | 117 | 270 |
| 4 | 1 | 400 | 0.95 | 15 | 161 | 38 | 229 | 146 | 308 |
| 5 | 2 | 250 | 0.90 | 2 | 420 | 5 | 598 | 10 | 620 |
| 6 | 2 | 250 | 0.95 | 10 | 417 | 33 | 589 | 54 | 649 |
| 7 | 2 | 400 | 0.90 | 27 | 254 | 35 | 379 | 109 | 398 |
| 8 | 2 | 400 | 0.95 | 49 | 268 | 163 | 353 | 106 | 595 |

Table 3 summarizes the $I_{avg}$ and $was_{tot}$ results under optimal solutions for two policies, sharing and non-sharing. Remember that, in the non-sharing policy demands are fulfilled only by the closest e-grocery to that demand point. No other e-grocery in the network will provide supply to meet that demand.

**Table 3. Other performance metric results for lateral sharing policy**

| Exp. | Sharing | | Non-sharing | |
|---|---|---|---|---|
| | $I_{avg}$ | $was_{tot}$ | $I_{avg}$ | $was_{tot}$ |
| 1 | 315 | 791 | 394 | 2,740 |
| 2 | 334 | 888 | 388 | 2,526 |
| 3 | 164 | 49 | 210 | 346 |
| 4 | 206 | 111 | 242 | 508 |
| 5 | 498 | 796 | 623 | 4,713 |
| 6 | 544 | 1,443 | 645 | 4,730 |
| 7 | 250 | 33 | 333 | 668 |
| 8 | 377 | 345 | 456 | 1,493 |

From Tables 2-3, the observed findings are summarized as below:

1. The average inventory carried in the network, and the wastage amounts within the network are always higher in the non-sharing policy than the sharing policy.
2. When *CSL* is at a high level, the network tends to carry more inventory and hence, the wastage amount increases.
3. When *C* is high, $I_{avg}$ tends to decrease as expected. It also contributes to the decrease of wastage amount in the network. Note that, a high level of *C* means more transportation and hence, more $CO_2$ emissions. There is a trade-off between those two variables, *C* and $I_{avg}$.
4. When demand variability increases, the average inventory carried increases in the network. Besides, the performance gap between the two policies increases dramatically, under high variance conditions. Namely, lateral inventory share works much better under a highly variable demand environment.
5. In any condition, it is observed that lateral inventory share policy contributes to all performance metrics positively in the supply chain network.

## 5. CONCLUSION

This paper studies comparison of two inventory management policies in an e-grocery supply chain network providing food products. Our aim is to compare a lateral-inventory share policy with a non-sharing policy under optimized *s*, *S* inventory control management. By a lateral-share policy, we aim to decrease the average inventory carried in the network helping to result in a more sustainable network design providing decreased food wastage as well as transportation frequency from the upper supplier depot. The results show that under the proposed lateral inventory share policy, the average inventory carried in the network decreases contributing to all other performance metrics, wastage, replenishment frequency, and hence carbon emission, positively. It is also observed that when demand variability is high, considering a lateral inventory share policy in a food network would be much more beneficial.

The limitation of this paper is that the demand distribution is the normal distribution. However, trial of different demand distribution scenarios would help to enhance the work to receive more generic findings.

This work can be extended in many directions for instance, by considering different novel sharing policies in the network as well as different demand and parameter values (e.g. lead time, number of e-groceries), etc.

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