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Agri-food distribution optimization using modified simulated annealing algorithm considering stochastic market demand

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ARTICLE INFO | ABSTRACT

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In recent years, the total loss of agricultural fresh product distribution has increased from 20% to 60% of the total amount of harvested products due to their fixed shelf-life time. Consequently, it is essential to select a logistics distribution path that is reasonable for the transportation of fresh agricultural products. To minimize the loss in the distribution of agricultural products in logistics, this study developed an optimization model for agri-food logistic distribution that takes into account the uncertainty of market demand. A novel algorithm called modified simulated annealing (mSA) is introduced to solve a problem with multiple objectives that involves randomness. As a result, the proposed mSA successfully optimizes the availability of the right quantity, quality, and supply chain net profit. The effectiveness of the proposed solution methods is assessed by comparing them with the current state-of-the-art techniques. The findings confirm the effectiveness of the proposed mSA algorithm in tackling the problem across various dimensions. The mSA algorithm led to a decrease in the overall cost of distribution, surpassing the results achieved by SA algorithms. Additionally, the data gathered from the avocado distribution network in the Ethiopian market was used to test the validity of the suggested model. The results showed that as transportation time increased, the quality deterioration rate also increased.

1. Introduction

Perishable goods, such as food items, fruits, and vegetables, often experience quality loss during transportation and degrade over time [1]. As these items are delivered, their quality and value tend to diminish steadily. In a highly competitive market, it is essential to continuously assess both product quality and the conditions of their transit. Supply chain networks inherently exhibit stochastic behavior. Understanding the dynamics of supply and demand involves recognizing the unpredictable nature of perishable product rates and supply chain systems [2-3]. Unique characteristics of materials in the perishable supply chain, including shelf life and seasonal variations, heighten the vulnerability of the supply chain. If manufacturers and consumers are aware of a product's condition prior to delivery, they may be able to make adjustments when demand is high. Stochastic demand further complicates the supply chain's operations [4]. The limited shelf life of perishable products leads to quality degradation and loss when stored in inventory, particularly under conditions of fluctuating demand. Therefore, an efficient network management model is essential in a market characterized by stochastic demand to enhance the availability and net profit of the perishable supply chain. Consequently, post-harvest supply strategies must carefully evaluate the distribution of perishable goods network.

Currently, there is significant public scrutiny regarding the supply chain practices related to perishable goods. Consumers who prioritize health are increasingly demanding high-quality, reasonably priced perishable items [5-6]. This competition among businesses necessitates strict management of costs, quality, and timeliness within the perishable goods supply chain. Unlike other supply chain models, perishable product supply chains are influenced by several unique factors, such as food quality and human safety. These elements contribute to the complexity of their structure, requiring the integration of various types of networks [7-8]. To meet these evolving demands, a holistic approach is essential for understanding, evaluating, and managing the supply chain of perishable products, ensuring that customers receive efficient and safe service [9-10].

The supply chain for perishable products consists of a network of companies that work together on various processes and tasks to create goods and services that fulfill consumer demands and bring them to market [11-12]. Products with a limited shelf life are referred to as perishable goods [13]. These items are distributed to consumers through a supply chain that spans from the producer to the end user. Nahmias provided an excellent overview of the management of inventories for perishable goods [14]. Belien and Force conducted an analysis of inventory and supply chain management specifically for blood products [15]. Additionally, Yu and Nagurney contributed to the understanding of food products within supply chains by integrating and synthesizing multiple food supply chain processes [16].

Recent research has produced numerous articles focusing on the optimal modeling of supply chain networks for perishable goods from a system-optimization viewpoint. Rong and Akkerman et al. [17] proposed a methodology for modeling food quality degradation, enabling its integration into a mixed-integer linear programming model designed for production and distribution planning. Additionally, they incorporated food quality considerations into decision-making processes regarding production and distribution within the food supply chain. A stochastic mathematical model was also created to accommodate an uncertain environment for constructing supply networks [18-21].

Wang and Li developed a pricing strategy that adjusted food shelf life dynamically, which helped reduce food spoilage and boost profits for food retailers [22]. Asgari, Farahani, and their colleagues employed a linear integer programming (LIP) model to identify the optimal monthly transportation volumes of wheat for each producing and consuming region over the course of the year [23]. Dabbene et al. introduced a method aimed at optimizing fresh food supply chains, balancing logistical costs with various metrics that assess meal quality from the customer's perspective [24]. To enhance profits within supply chain networks based on specific market demands, Yiliu proposed an equilibrium model for perishable goods grounded in discrete choice theory [25].

Yang and Wee enhanced their model by incorporating raw materials inventory and explored an external integration strategy within a single-vendor, multi-buyer production-inventory system that includes deteriorating items [26]. They employed an exponential function to illustrate the deterioration process, although they did not specifically highlight this characteristic. This approach is valid only if the rate of deterioration correlates with the quantity of available products and if the degradation process is not influenced by the products' history. While traditional agricultural products do not fit these criteria, radioactive materials exemplify items that do. A comprehensive analysis by Emana and Gebremedhin identified the primary participants in the market value chain in eastern Ethiopia as producers, middlemen/brokers, dealers, and consumers. Among these, brokers play the most dominant role in the horticultural product market channel [27].

Shumeta's study, which looked into the avocado market chain with a small number of farmers, was carried out in four regions in southwest Ethiopia. The author has agreed to sell a specific quantity of avocados and get paid prior to harvest in exchange for a 4.3% advance on sales of their items. The buyers established the price, and the remaining farmers accepted it. Quality was only taken into consideration by 3.3% of farmers when determining the selling price [28]. Tefera and Alemu

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conducted research on the fruit market value chain in northeastern Ethiopia and found that producers have a high marketing margin and a low profit share [29].

Both quality and quantity losses can be used to calculate post-harvest losses. Losses may occur during harvesting, shipping, packaging, and at the marketplace [30-33]. While knowing and understanding how to handle fruit to reduce losses is crucial, this knowledge is useless without the right tools. In underdeveloped nations, access to knowledge, information, and equipment is frequently limited. Using a cold chain is crucial to maintaining the freshness of fresh produce and reducing the rate at which fruit and vegetables deteriorate [34-37].

In recent years, the overall loss of fresh agricultural products has increased by 20% to 60% [34]. Perishable products, characterized by their limited shelf life, differ significantly from other supply chains due to their time-sensitive nature and the unpredictability of market demand. These factors often diminish the value and utility of fresh products. Consequently, an effective supply chain management model is essential for facilitating the distribution of perishable goods from producers to consumers, particularly in the context of fluctuating demand. This study addresses this critical need by developing a mathematical model that incorporates the rate of product deterioration as a function of transit time.

A review of the existing literature reveals several research gaps. First, while many studies have focused on minimizing quality loss and maximizing revenue in perishable goods supply chains, the majority of these efforts have been concentrated in developed countries. Emerging economies, which experience significant losses at various stages of the supply chain, remain underexplored. Second, there is a lack of studies that explicitly address loss minimization during distribution and transportation. Furthermore, quality loss has not been adequately integrated into transportation modeling or optimization, despite its direct impact on income, availability, and customer satisfaction. This study aims to fill these gaps by incorporating quality loss considerations into the supply chain model for perishable goods, specifically accounting for the impact of transit time on product quality from the end-user's perspective.

The objective of this research is to enhance net profit across the market channel while maximizing the availability of perishable goods under uncertain market demand. This is achieved by determining the rate of quality degradation during transportation as a function of transit time. This paper presents a supply chain model for perishable goods that considers the random nature of customer demand quantities. The originality of this study is highlighted in three key areas: (1) the development of a mathematical model for the supply chain network of perishable products under stochastic market demand; (2) the introduction of a novel modified simulated annealing algorithm (mSA) designed to address a stochastic multi-objective optimization problem. The mSA aims to optimize the availability of the correct quantity and quality of items while maximizing the net profit for all supply chain participants; (3) an evaluation of the mSA's effectiveness is conducted by comparing it with leading contemporary techniques

2. Methodology

2.1. Mathematical modeling

Let's examine a generic network, denoted as H = [G, L], where G refers to the set of nodes within the network and L indicates the set of directed links [38]. A uniform perishable product is generated by S producers. This type of perishable item is delivered to k merchants through d distributors. It's important to note that D_k denotes the demand for the perishable product at retailer k. Fig. 1 illustrates γ(t), representing the quality rate of the perishable product at time t.

2.2. Assumptions and notations

The agri-food distribution network development model considers a range of producers, local collectors, wholesalers, and retailers, and it assumes that supply and demand are unpredictable. The symbols and abbreviations used in this research are as indicated below:

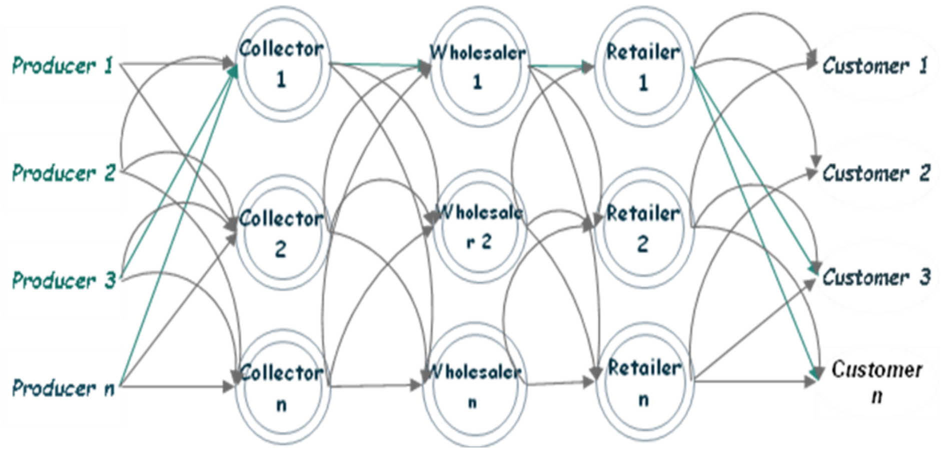

Fig. 1. Agri-food distribution network

Symbol	**Denotation**
s	Quantity of producers
l	Quantity of local collectors
i	A typical kind of transportation
j	Transportation methods model
γ(t)	Decline in quality at time t.
c	Cost of transportation per unit (USD)
p	Good price per unit (USD)
λ	Rate of deterioration
For producer	
Q_s	Amount of perishable good at producer
P_s	Producer selling price per unit (USD)
For local collector	
Q_{sl}	Amount of perishable goods between producer and collector
C_{sl}	Cost per unit for transporting product between producer and collector (USD)
TC_{sl}	Transaction costs between producers & collectors
P_l	Collector selling price per unit (USD)
T_{sl}	Transportation duration between the producer & the collector
For wholesaler	
Q_{ld}	Amount of perishable goods between collector & wholesaler
C_{ld}	Transportation cost per unit of product between the local collector and the wholesaler (USD)
TC_{ld}	Transaction costs between collector & wholesalers
P_d	Wholesale selling price per unit of product (USD)
T_{ld}	Transportation time between the collector and the wholesaler.
For retailer	
Q_{dr}	Amount of perishable goods between wholesaler and retailer.
C_{dr}	Cost per unit for transporting product between wholesaler and retailer (USD)
TC_{dr}	Transaction costs between wholesalers and retailers.
P_r	Retail selling price per unit (USD)
T_{dr}	Transportation duration between the wholesaler and the retailer.

Local Collector

At the village market, local collectors buy avocados from local growers, who subsequently sell them to distributors. The amount of perishable goods exchanged between local collector and

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producer is represented by Q_{sl}. Eq. (1) indicates that the total quantity of products handled by the local collector is equivalent to the overall amount transported to the collector, Q_l, utilizing a transportation method j.

$$Q_l = \sum_{s=1}^{n} \sum_{i=1}^{j} \mathrm{Q_{sl}} \tag{1}$$

The total cost incurred by producers and collectors in a transaction, denoted as TC_{sl}, includes transportation expenses and the expenses of disposing of perishable goods are illustrated in the Eq. (2).

$$TC_{sl} = C_{sl}{}^{i}(Q_{sl}.\gamma(t)) \tag{2}$$

The time it takes for transportation between the local collector and producer, T_{sl}, is directly proportional to the product amount being transported, as shown in the Eq. (3).

$$T_{sl} = \gamma(t).Q_{sl} \tag{3}$$

The overall volume of spoiled product, denoted as $Q_{sl}{}^{s}$, can be expressed as a function of time according to Eq. (4).

$$Q_{sl}{}^{s} = \gamma(t).Q_l \tag{4}$$

The profit earned by the local collector can be calculated by multiplying the product selling price by the total amount distributed to the wholesaler, and then subtracting the transaction costs and the disposal costs for the perishable product, as outlined in Eq. (5).

$$\mathrm{Max} \sum_{d}^{n} \sum_{i=1}^{j} P_l[1-\gamma(t)]Q_{ld} - \sum_{s}^{n} \sum_{i=1}^{j} (TC_{sl} + [Q_{sl}{}^{s}.P_s]) \tag{5}$$

Wholesaler

Wholesalers acquire products from markets where local collectors operate. Let Q_{ld} represent the amount of perishable goods between collector l and wholesaler d. The overall quantity of products available at the wholesaler is equivalent to the total of the products dispatched to the distributor, Q_d, as expressed in Eq. (6).

$$Q_d = \sum_{l}^{n} \sum_{i=1}^{j} \mathrm{Q_{ld}} \tag{6}$$

The overall transaction cost incurred between the collector and the wholesaler encompasses both transportation expenses and the disposal costs associated with perishable goods, TC_{ld} as outlined in Eq. (7).

$$TC_{ld} = C_{ld}{}^{i}(Q_{ld}.\gamma(t)) \tag{7}$$

The transportation time between the collector and the wholesaler depends on the volume of product flow, T_{ld} as indicated in Eq. (8).

$$T_{ld} = \gamma(t).Q_{ld} \tag{8}$$

The total volume of spoiled product between the collector and wholesaler, denoted as $Q_{ld}{}^{s}$, can be expressed as a function of time according to Eq. (9).

$$Q_{ld}{}^{s} = \gamma(t).Q_d \tag{9}$$

The profit earned by the wholesaler is calculated by multiplying the products selling price by the total amount of products distributed to the retailer, and then subtracting the transaction costs and the disposal costs associated with perishable products, as described in Eq. (10).

$$\text{Max} \sum_{r}^{n}\sum_{i=1}^{j} P_d\, x\,[(1-\gamma(t)]Q_{dr} - \sum_{l}^{n}\sum_{i=1}^{j} (\mathrm{TC}_{\mathrm{ld}} + [\mathrm{Q}_{ld}{}^{\mathrm{s}}.P_l\,]) \tag{10}$$

Retailer

The retailer's demand is influenced by factors that impact sales revenue, which in turn affect the consumption rate of perishable products. These factors include market scale (a), selling price (p), and quality rate at time (t). The interactions between these factors and retail demand are modeled accordingly. This model has been derived from existing literature [39-40]. The characterization of the demand is presented in the Eq. (11).

$$\mathrm{D}_1(\mathrm{t}) = \mathrm{a} - \mathrm{bp} + \mathrm{d}\gamma(\mathrm{t}) + \varepsilon \quad ,0 \le t \le t_o \tag{11}$$

In this context, b and d denote the price elasticity and product quality, respectively. The variable **ε** serves as a random variable to account for demand fluctuations, which are modeled by a uniform distribution **ε** ∈U[-L, L]). Over time, the rate of product quality declines, resulting in a corresponding decrease in retail demand. Typically, retailers will apply a discount rate (θ) to items with appealing prices (***f***), which is influenced by the quality degradation function illustrated in Fig. 3. The demand function, after applying the discount to the products, is represented by Eq. (12).

$$\mathrm{D}_2(\mathrm{t}) = \{\mathrm{a} - \mathrm{bp} + \mathrm{d}\gamma(\mathrm{t}) + f + \varepsilon \quad ,t_o \le t \le T \tag{12}$$

By utilizing the limits $\mathrm{D}_1(\mathrm{t})$ for the non-discount period and $\mathrm{D}_2(\mathrm{t})$ for the discount period, as specified in Eq. (13) and Eq. (14).

$$\int_0^{\mathrm{to}} \mathrm{D}_1(\mathrm{t})\, dt = (a - bp)t_o + dq_o\left(\frac{1 - e^{-}\lambda \mathrm{t_o}}{\lambda}\right) + \varepsilon \mathrm{t_o} \tag{13}$$

$$\int_{t0}^{T} D_2(t)dt = (a - b\theta p + f)(T - t_o) + dq_o\left(\frac{e^{-}\lambda \mathrm{t_o} - e^{-}\lambda \mathrm{T}}{\lambda}\right) + \varepsilon(\mathrm{T} - \mathrm{t_o}) \tag{14}$$

Consequently, the revenue generated by the retailer from product sales at $\mathrm{D}_1(\mathrm{t})$ and $\mathrm{D}_2(\mathrm{t})$ is expressed in Eq. (15) and Eq. (16).

$$\mathrm{E}\,[p\int_0^{\mathrm{to}} \mathrm{D}_1(\mathrm{t})\, dt] = p\,(a - bp)t_o + pdq_o(\frac{1 - e^{-}\lambda \mathrm{t_o}}{\lambda}) \tag{15}$$

$$\mathrm{E}\,[\theta p\int_{t0}^{T} D_2(t)dt] = \theta p\,(a - b\theta p + f)(T - t_o) + \theta p d q_o(\frac{e^{-}\lambda \mathrm{t_o} - e^{-}\lambda \mathrm{T}}{\lambda}) \tag{16}$$

2.3. Modified simulated annealing (mSA) algorithm

Steps in mSA algorithm

STEP 1: Randomly choose an initial feasible solution, $\mathrm{X_o}$, and designate $\mathrm{t_o}$ as the initial temperature. Set the current solution to $\mathrm{X_i} = \mathrm{X_o}$, initialize the current iteration step to k = 0, and assign the current temperature to $\mathrm{t_k} = \mathrm{t_o}$.

STEP 2: Determine whether the temperature meets the loop's termination condition. If it does, proceed to step 3. If not, randomly select a neighboring solution, $\mathrm{X_j}$, from the neighborhood and compute ($\Delta\mathrm{E_{ji}} = \mathrm{E}(\mathrm{X_j}) - \mathrm{E}(\mathrm{X_i})$. If $\Delta\mathrm{E_{ji}} \le 0$), set$(\mathrm{X_i}) = (\mathrm{X_j})$. Otherwise, if (exp$(-\frac{\Delta\mathrm{E_{ji}}}{\mathrm{t}} > rand(0,1)$), return to step 2.

STEP 3: Implement the temperature control function by updating (k) with (k = k + 1) and calculating ($\mathrm{t_{k+1}} = \mathrm{y}(\mathrm{t_k})$. If the termination criteria are satisfied, proceed to Step 4; if not, return to Step 2.

STEP 4: Present the results and conclude the simulated annealing (SA) algorithm.

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To solve this problem, the traditional simulated annealing technique was optimized based on the features of VRP, and a new simulated annealing algorithm was built. These are the enhancements that have occurred:

Representation and evaluation

In real life, a distribution program may consist of several different distribution paths, as represented by the solution. The customer point nodes are located in the midst of a loop that begins at the central distribution center (0) and terminates 0. For example, if the solution is 0-1-2-0-3-4-0, it indicates that the delivery program covers both of the 0-1-2-0 and 0-3-4-0 distribution channels. Three fundamental phases are used to develop the first workable solution for the optimization process: grouping, routing, and optimization (refer to Fig. 2).

Clustering → Routing → Optimization

Fig. 2. mSA grouping

Grouping: At this point, a consumer is paired with one of the n linkages. Eq. (17) is the distance computation are used to grouping.

$$D_{(c,\ I)} = \sqrt{(X_c - X_0)^2 + (Y_c - Y_0)^2} \tag{17}$$

Where,$D_{(c,\ 0)}$, represents the distance between customer (c) and depot (0).

Routing: The Clarke and Wright Saving method is used to assign consumers in the same connection to many routes. For each pair of customers, ci and cj, in the same connection, a saving matrix ($S_{ci,cj}$) is created. Furthermore, without going above capacity limits, the consumers with significant savings value are placed together on the same route. The saving matrix is built in Eq. (18).

$$S_{ci,cj} = D_{(0,\ ci)} + D_{(0,\ cj)} - D_{(ci,\ cj)} \tag{18}$$

Optimizing: Choosing a delivery order so that the following customer is as near as possible to the preceding one begins with the first customer. Until every consumer who was not chosen is sorted, this process is repeated as shown in Fig. 3.

Neighborhood: 2 − opt exchange (exchanging two nodes at a time) is the convectional neighborhood operation method of the SA algorithm. It takes a while to explore the solution space at each temperature to find the best solution. In this study, the neighborhood switching in-circuit is carried out at random using the 2-opt and 3-opt approaches in order to produce a new feasible solution.

Modified metropolis acceptance criterion

Metropolis acceptance criteria determine the acceptance of the worse solution generated by the neighborhood search (see Fig.3). A metropolis acceptance criterion is derived from the Boltzmann function which is given in Eq. (19).

$$exp(-\Delta T) \tag{19}$$

The standard metropolis acceptance criterion is given in Eq. (20).

$$exp - \left(\frac{new\ soultion - current\ solution}{T}\right) > rand\ [0,1] \tag{20}$$

Therefore, in the present study, the standard metropolis acceptance function has been modified as shown in Eq. (21) [41].

$$exp - \left(\frac{new\ soultion - current\ solution}{\log (T)}\right) > rand\ [0,1] \tag{21}$$

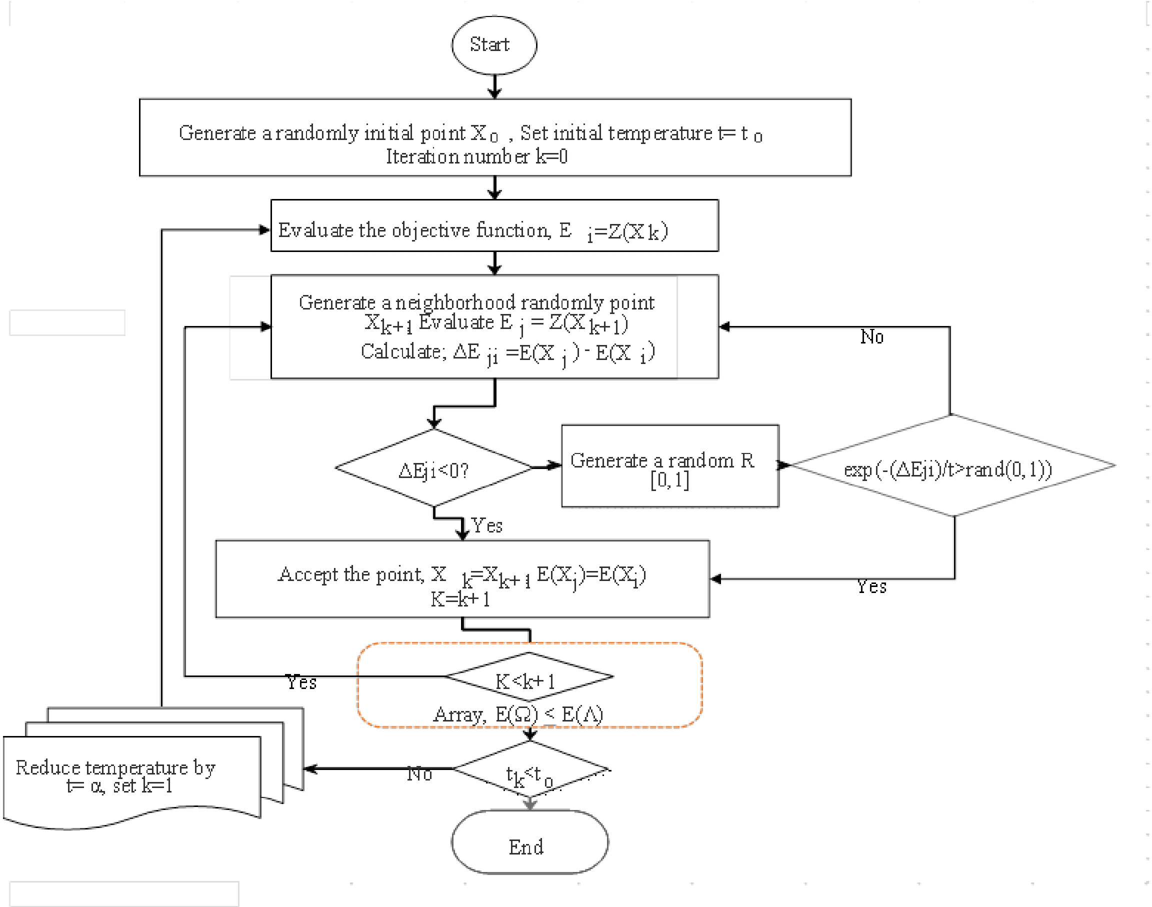

Fig. 3. Proposed mSA algorithm

The logarithm of temperature makes the denominator lower and therefore, the value of Boltzmann function becomes a larger negative value. Therefore, the probability of accepting the worse solution goes down. This modified metropolis acceptance criterion has been used in high temperature range whereas at low temperature range the standard metropolis acceptance function is applied [42].

3. Results and Discussion

3.1. Results

A revised SA algorithm was executed using MATLAB R2016a on a PC equipped with an Intel Core 5 Duo processor (1.73GHz) and 3GB of RAM. To assess its performance, the modified SA (mSA) was tested against a selection of four benchmark instances known as Cordeaux's instances, specifically P03, P05, P06, and P07 as illustrated in Table 1, where:

Table 1. Instances parameter of Cordeaux instances

Benchmark Instance (I)	Customer Number (N)	Number of Depots (M)	Maximum Distance Traveled (D)
P03	75	3	∞
P05	100	2	∞
P06	100	3	∞
P07	100	4	∞

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Clustering: In the clustering process customers are allocated to nearby depots to reduce the distance traveled. The Clark and Wright saving method is utilized for customer clustering [43]. This involves grouping customers for local warehouses based on their proximity to adjacent depots (refer to Fig. 4). In the illustration, blue signifies the geographical positions of customers, while red denotes the locations of the depots.

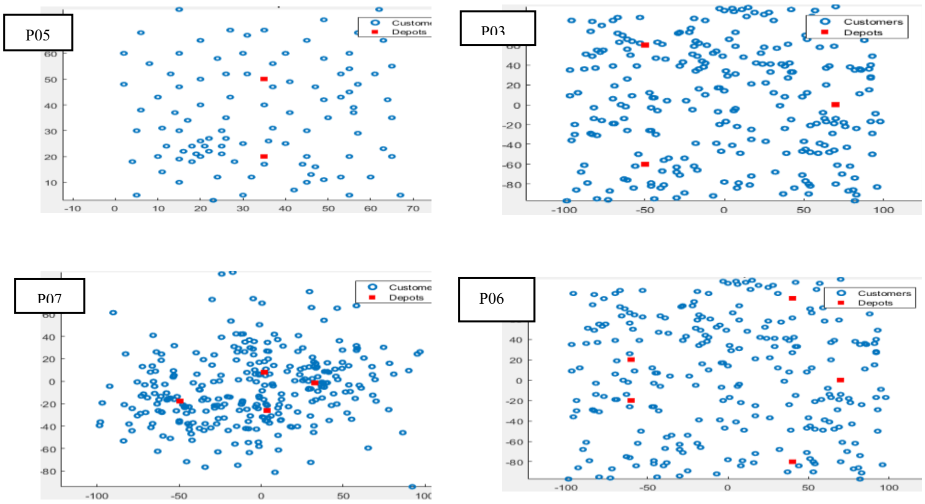


Fig. 4. Illustration of initial customer location with respect to depot

Routing and Optimization: In the routing process, customers are grouped into various routes at each depot, as shown in Table 2 - Table 5. The primary objective of routing is to reduce the total number of routes or vehicles utilized while adhering to the vehicle capacity limitations. A neighborhood search algorithm is employed to expedite the computation of these routes.

Table 2. P03 optimal route assignment

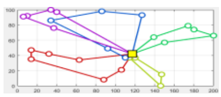
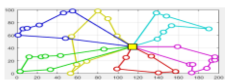
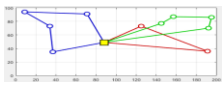
Depot	Optimal route path	Best optimal distance	Served customer	No. of vehicles
B (30,40)		330.48	25	5
D (10,20)		**232.2926**	**40**	**6**
C (20,10)		101.9574	10	3

Table 3. P05 optimal route assignment

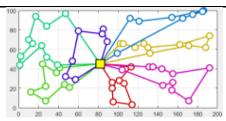
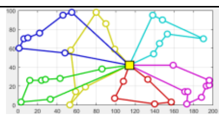
Depot	Optimal route path	Best optimal distance	Served customer	No. of vehicles
A (20,20)		381.2767	60	7
B (30,40)		370.2926	40	6

Table 4. P06 optimal route assignment

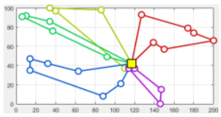
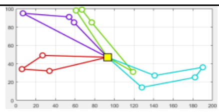
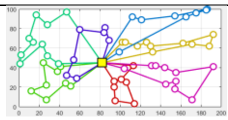
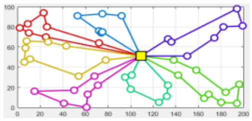
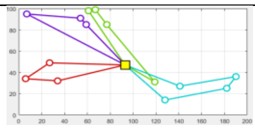
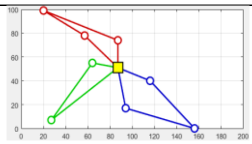
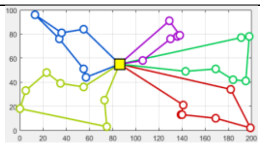
Depot	Optimal route path	Best optimal distance	Served customer	No. of vehicles
A (20,30)		324.601	25	5
B (30,20)		275.4021	14	4
C (30,40)		381.2767	60	7

Table 5. P07 optimal route assignment

Depot	Optimal route path	Best optimal distance	Served customer	No. of vehicles
A (10,10)		257.5058	50	7
B (10,30)		245.4021	14	4
C (20,10)		124.1634	8	3
D (15,25)		294.1318	30	5

6.2. Comparison with other studies

The optimal distances achieved for the benchmark instances using the modified SA algorithm are compared with established methods in the literature, including Genetic Clustering (GC) [44] and Genetic Algorithm (GA) [45]. Table 5 shows the modified SA computational results for the four benchmark instances. Table 6 illustrates the customer number, the depot number, the best-known distance, and the optimal distance relative to the best distances reported in the literature. The best-known distance's percentage difference from the optimal distance attained with the modified SA is determined by,

$$\%\ \text{Deviation} = \frac{C_{bod} - C_{bkd}}{C_{bkd}} \text{x}100 \tag{22}$$

In this context, C_{bod} represents the optimal distance achieved through the modified SA method, while C_{bkd} denotes the best-known distance based on the Cordeaux benchmark instances. The tabulated results indicate that the total delivery distances are close to those of the best-known solutions.

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Table 6. Comparison of mSA with other studies

I	N	M	Best known distance (km)	Distance stated in other studies (km)		Optimal distance (km) mSA	Optimal distance (km) SA	% Deviation
				GC [43]	GA [44]			
P03	75	3	641.19	694.49	706.88	664.73	732	3.67
P05	100	2	750.03	-	-	751.5693	794	0.205
P06	100	3	876.5	976.02	908.88	957.1493	1137	9.2
P07	100	4	885.8	-	-	921.2031	1248	3.99

6.3. Avocado supply chain

This paper focuses on the analysis of the avocado supply chain, as illustrated in Fig. 5. An exponential distribution is used to forecast the avocado quality rate, γ(t). Based on the literature [46-47], the quality rate has been determined as presented in Eq. (23).

$$\gamma(t) = q_o e^{-\lambda t} \tag{23}$$

Where qo and λ denotes the initial quality and deterioration rate respectively.

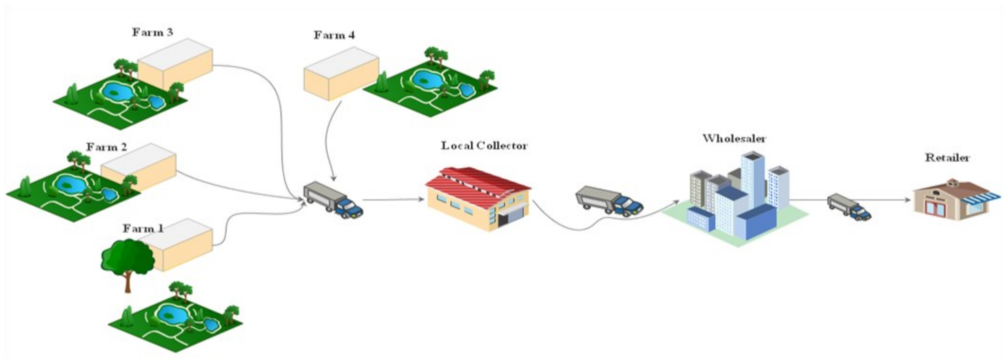

Fig. 5. Network of avocado supply chains

6.3.1. Total net profit of avocado distribution

The net profit of avocado distribution network is depicted in Eq. (24).

$$\textbf{Max P} = ((\mathbf{A} + \mathbf{B} + \mathbf{C}) - (\mathbf{D} + \mathbf{E})) \tag{24}$$

$$\boldsymbol{A} = \sum_{s}^{n} \sum_{i=1}^{j} P_l x \, [(1 - \gamma(t)] Q_{sl} \tag{25}$$

$$\boldsymbol{B} = \sum_{d}^{n} \sum_{i=1}^{j} P_d x \, [(1 - \gamma(t)] Q_{ld} \tag{26}$$

$$\boldsymbol{C} = [\theta p(a - b\theta p + f)(T - t_o)] + \theta p d q_o \frac{(e^{-}\lambda t_o - e^{-}\lambda T)}{\lambda} \tag{27}$$

$$\boldsymbol{D} = \sum_{l}^{n} \sum_{i=1}^{j} (TC_{sl} + [Q_{sl}{}^{s} . P_s] \tag{28}$$

$$\boldsymbol{E} = \sum_{l}^{n} \sum_{i=1}^{j} (\mathrm{TC_{ld}} + [\mathrm{Q}_{ld}{}^{s} . P_l]) \tag{29}$$

Eq. (25), Eq. (26), and Eq. (27), respectively, represent the sales revenue for the collector, wholesaler, and retailer, which are represented by the letters A, B, and C in the objective function Eq. (24). Eq. (28) describes the cost of transaction between the producer and the collector, while Eq. (29) outlines the cost of transaction between the collector and the wholesaler. Table 7 illustrates the input parameters to stochastic multi-objective programming model.

Table 7. Input parameters

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
a	7	T	30	P_s	1.6	$C_{sl}{}^{i}$, $C_{ld}{}^{i}$	4
b	4.42	ϴ	0.65	P_l	3.125	Q	100
d	4.42	F	2	P_d	5.125	P_r	6

In this study, sensitivity analysis was conducted by varying key parameters, including rate of deterioration and transportation time, to evaluate the avocado supply chain quality rate. Fig. 6 illustrates the trend of the quality rate.

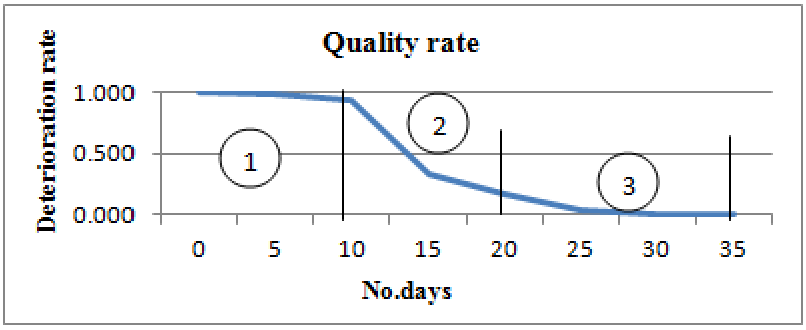

Fig. 6. Quality loss

The quality rate of avocados was examined over different time intervals: 1) stable, 2) visible change, and 3) unacceptable [26]. The quality rate probability ranges from 1 (fresh) to 0 (spoiled), while the deterioration rate probability (λ) spans from 0.0005 to 0.08. As seen in Table 8, the quality rate falls in proportion to the rate of deterioration. The rate of degradation and transportation time have an inverse relationship with the quality rate of perishable goods.

Table 8. Computational analysis of γ(t) with different values of λ

λ	0.0005	0.003	0.005	0.04	0.06	0.07	0.076	0.08
t	0	5	10	15	20	25	30	35
γ(t)	1.000	0.98117	0.9436196	0.334226	0.16295	0.03493	0.0136	0.0

Table 9 displays the supply chain's overall quality loss as a function of transportation time, while Table 10 illustrates the net profit margin. The variable (t) represents the time taken in days. The quality rate and net profit fluctuate over different time periods. The total amount lost across the supply chain network, from producer to retailer, steadily rises as transportation times increase. As seen Table 10, a longer transportation time results in a greater quantity loss, which lowers the supply chain network's net profit.

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Table 9. Computational analysis of quantity reduction over various time periods (t) in days.

t	0	5	10	15	20	25	30	35
$Q_{sl}{}^s$	0	2	6	67	84	97	99	100
$Q_{ld}{}^s$	0	2	5	22	14	3	1	0
$Q_r{}^s$	0	2	5	52	72	93	97	100

Table 10. Computational results of the model's net profit.

t	0	5	10	15	20	25	30	35
A	313	307	295	104	51	11	4	0
B	513	503	484	171	84	18	7	0
C	1124	1124	803	932	484	322	162	0
D	400	395	386	240	199	168	163	0
E	400	402	405	248	135	31	12	0
Max P	1149	1137	791	720	284	152	0	0

The seller may make money or lose money depending on the market margin, contingent upon marketing costs and the selling price. Conversely, a retailer's profit margin is influenced by the market selling price, which is directly related to the quality rating of the avocados. Table 11 illustrates how variables θ and f impact the retailer's net profit. The retailer's profit margin is determined by both the quality rating of the avocados and consumer demand. When there are significant fluctuations in quality ratings, the retailer may introduce appealing pricing strategies by offering different discounts to reduce customer dissatisfaction.

Table 11. Sales revenue for retailers at various discount rates (θ)

t	*f*	*0.5*	*0.55*	*0.6*	*0.65*	*0.7*	*0.75*
10	1	237	326	427	540	666	803
15		300	413	541	685	843	1017
20		79	109	143	180	222	268
10	2	192	277	373	482	603	735
15		243	350	473	610	763	931
20		64	92	125	161	201	245
10	3	147	227	319	423	540	668
15		186	288	404	536	683	846
20		49	76	107	141	180	223

7. Conclusion

This study presents a mathematical model for supply chain networks specifically designed for perishable products, addressing stochastic market demand, and introduces an innovative modified simulated annealing algorithm (mSA) to tackle a multi-objective optimization problem under uncertainty. The model quantifies the quality loss of perishable goods as a function of the quality deterioration rate in relation to transportation time. It takes into account the total quantity loss resulting from product deterioration at different stages within the supply chain network. This research offers significant opportunities for enhancing the availability of fresh produce in appropriate quantities and quality, while also improving net profits for perishable supply chain management. The findings from the developed mathematical model indicate that the quality rate inversely correlates with critical factors such as rate of deterioration and transportation time, and optimal outcomes can be determined based on numerical analysis. Additionally, the rate of deterioration and transportation time have a positive correlation with the overall quantity loss. The retailer's net profit tends to fluctuate over time due to stochastic market demand and variations in the quality rate. Consequently, to mitigate regret loss, it is advisable for retailers to implement discount rates with appealing prices. The findings showed that applying larger discount rates to specific transportation delays enhanced the retailer's sales income. Conversely, with minimal delays in transportation time and standard discount rates, the retailer's sales revenue declined. Future research may explore how different modes of transportation affect quality control.

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