ORANGE COLD CHAIN WITH MULTIPLE NUTRITIONAL COMPONENTS

by

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Abstract

Two echelon cold supply chain model is developed in which warehouse and retailer are the two main actors of supply chain. The model is based on energy consumption cost for chiller system and the stochastic lead time. To incorporate the quality degradation, global stability index (GSI) method is used. The objective is to analyze the effect of retailer's storage temperature and nutritional index weightage on the total cost of supply chain. A breakdown structure of all the associated costs is developed to formulate the total cost of cold chain. A numerical example is used for better understanding. To find the optimal solution, the model is numerically solved by using matlab genetic algorithm. The sensitivity analysis is being performed to study the model behavior against different parameters.

Keywords: Cold chain, echelon valuation, quality degradation, global stability index, stochastic lead time.

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1 Introduction

Prolonging the shelf life of fresh food is one of the major concern for perishable food items. For last couple of decades the cold chain has become an important subject in a supply chain management system. The “cold chain” is a logistical system use to manage the temperature sensitive products and is mostly implemented in food and pharmaceutical industry. The two considerable differences between cold chain and a traditional supply chain system are; an additional cost due to the energy consumed in refrigeration process and the shelf life of perishable items. In view of the fact 40% of all foods require refrigeration (Adekomaya et al., 2016). Since the life of wide range of products is temperature sensitive therefore; lot of studies have been carried out on the cold chain phenomenon and the need to develop improved cold chain technologies is ever increasing. In this context an optimal conditions are derived and maintained during the storage and transportation starting from the producer to the end user. It has been noticed that a slight change in storage or transportation temperature considerably effects the food life as there is a significant change in deterioration rate. However; the thermal sensitivity behavior differs from product to product. Orange fruit is one of the highly consumed product around the world. Its nutritional enrichment together with its taste makes it widely consumed fruit. According to the survey conducted by United State Agriculture Department (USAD), only in 2017, 49.282 million metric tons oranges were produced in different regions of the world which is approximately 12% of the total fruit production. The orange is used either in its raw form or is processed to make an orange juice. In either form, the nutritional and sensory quality of orange product is controlled by proper selection of temperature during its storage and transportation. Like other fruits and vegetables, the shelf life of oranges is variable as normally they do not have tags like ‘sell by date’, ‘use by date’ or ‘best before date’. Since there is no printed date and it is difficult to tell how long the fruit has been on the grocery shelf prior to purchase, the only date you can go by is the purchased date or date picked (if you are lucky enough to pick your own fresh fruit). It is therefore required to develop an efficient cold chain models for better quality and prolong shelf life of orange products. Among the all nutritional components, Ascorbic acid (Vitamin C), Anthocyanin and Dimethoate are the most important components in orange which are controlled and maintained during the storage time.

2 Literature review

In this section the relevant work by different researchers have been discussed. In the beginning of this section the focus is on general food supply chain (FSC) leading to an orange supply chain and then in the later part of this section, the theoretical background of *thermal degradation*, *global stability index*, *chiller system cost analysis* and the *lead time* has been explained. All the basic equations and their notational definitions are elaborated. Where necessary, some numerical examples are used for better understanding.

2.1 Food supply chain

The researchers have developed very useful cold chain models for food items that explicitly describe the degradation during their storage and transportation and the relevant cost effects. Achour (2006) developed a new method in which he considered multiple nutritional components of food with the weightage assigned to each component based on their relative importance. Working on fresh cut food items like watermelon, cantaloupe and honeydew, Ukuku and Sapers (2007) have explained the effect of waiting time before the refrigeration. Blackburn and Scudder (2009) presented their work on supply chain strategies for perishable products in which they defined the term marginal value of time (MVT) to be the change in value of a unit of product per unit time at a given point in the supply chain. MVT measures the cost of a unit time delay in the supply chain. Although it is simple to develop a two echelon model but generally there are multiple participants in a cold chain system. Working on multi echelon model of cold chain logistics Gui et al. (2010) explained that the cold storages can generally be divided into three levels i.e. the primary cold storage for fresh food processing and the initial pre-cooling is at farmer's end, which involve classification, segmentation, packing, and so on. The intermediate cold storage for fresh food is at delivery center which involve deep processing, quick-freezing and storage. The last level of cold storage for fresh food is at retailer's end that include distribution and sale. The three levels of storage show a strong confluency. Zarei et al. (2011) proposed a quality function deployment (QFD) model by linking Lean Attributes (LAs) and Lean Enablers (LEs). The QFD model improved the leanness of the food chain. Zanoni and Zavanella (2012) explained that energy should be appropriately used to prevent food product deterioration over the time avoiding the spoilage of perishable products and guarantying quality preservations. Kuo and Chen (2010) developed a model called MTJD (Multi-Temperature Joint Distribution system) which is a new development for continuously temperature controlled logistics. The cost effectiveness of this model can be explained based on coordinated inventory management system. MTJD system can satisfy the requirements of multi-temperature demand and one-stop logistics. Selection of best among the available alternates is also important for better performance of cold chain management system. Joshi et al. (2011) used Delphi method, AHP and TOPSIS techniques to compare the available alternates and then select the best one. Considering the kinetics, Arrhenius and Peleg equations are mainly used to describe the thermal degradation of food items with respect to time. Number of cold chain models are being developed by considering single nutritional component of food items. Nisha et al. (2005) conducted a study on degradation kinetics of riboflavin in spinach

(Spinacea oleracea L.). In a cold chain system the transportation plays a vital role. Transportation mode could affect the FSC system due to the delivery time, gas prices, capacity etc. Transportation plays important role in deterministic or stochastic behavior of shipment arrival time. Xiao et al. (2008) worked on the optimization and coordination of a fresh product supply chain under the CIF (Cost Insurance and Freight) business model by considering the long transportations with uncertainty in their distances. Similarly Jula and Leachman (2011) modeled the least-cost strategy for an importer, that explained the cost effectiveness of supply chain system by selecting an appropriate mode of transportation which accounts handling, storage and safety. Iannone and Thore (2010); Yang et al. (2011); Ma et al. (2018) worked on multimodal transportation schemes that helped researches to develop an efficient supply chain models. Tractability and tracking of food item is one of the major concern for every participant of the food chain system. Information (position, state, quality, etc.) about a logistics unit can be obtained by tracing and tracking along the supply chain. Sala et al. (2009); Zhang et al. (2011) have worked in the field of traceability and tracking. Food supply chain sustainability is another important area to be considered. A strict control by an external parties (e.g. NGOs, customers, regulators) forces the firms to maintain a sustainable supply chains. In this effort, the local firms need to play their role by forcing their supplier to maintain the sustainability. If the external bodies fail to differential between focal firms and the suppliers, then all the responsibilities come to the product manufacturer (Rao, 2002; Koplin et al., 2007). Furthermore (Soysal et al., 2014) modeled food logistics networks with emission considerations.

2.2 Orange supply chain

Discussing particularly orange fruit, there are number of publications. Kyriakidis et al. (2000) described the effect of storage temperature on the Degradation of Dimethoate in Fortified orange juice. Similarly some research has been done on Ascorbic Acid (AA or Vitamin C) as Hussain et al. (2017) presented their work on response of ascorbic acid content and its acidity to different storage temperatures and durations for oranges. Rapisarda et al. (2001); Carmona et al. (2017) worked on Anthocyanins in blood orange its composition and biological activity. Furthermore Bhardwaj and Sen (2003); Mditshwa et al. (2017) explained the environment effect on various components of citrus fruits. Klimczak et al. (2007); Aparicio et al. (2007) conducted their research by considering the sensory index as in important factor for orange.

The motivation for working on orange supply chain management system is due to an improvement potential in existing supply chain models. It has been noticed that till now, all the work has been done by considering a single nutritional component of an orange. But as a matter of fact when we look into the degradation phenomenon, all the nutritional components degrade simultaneously. However; the degradation rate varies for each nutritional component. Therefore a new model can be developed which encapsulate all the significant nutritional component simultaneously. Another missing element in pre-developed models for oranges is the effect of lead time. The lead time has considerable impact on the cost of cold chain system when the shipment arrival time is stochastic.

In this paper, a new model has been developed for an orange cold chain in which multi nutritional components are considered and the lead time effect has included. This new model better optimizes the cost of cold chain as a new technique has been used to determine the life of perishable items. Also the relevant cost due to uncertainty of shipment arrival time is being included in this model.

2.3 Thermal degradation

In food science, Arrhenius equation is used to define the chemical kinetics. It helps to predict the expected change in food quality as a function of temperature.

$$K = A\left\{\exp\left(\frac{E_a}{RT}\right)\right\}. \tag{1}$$

Where E_a is Arrhenius activation energy, R is gas constant (8.31 J/mol-K) and A is a temperature independent constant. Even though all food items follow Arrhenius equation up to some extent but there are limitation of Arrhenius equation that it behaves differently at elevated temperatures as the plot between $ln(K)$ and $(1/T)$ is not linear at higher temperatures. Peleg et al. (2002) described the food quality degradation by following equation.

$$q(T,t) = q_0 e^{-b(T)t^{n(T)}}. \tag{2}$$

Where q is the quality of the product at time t (time passed since the fresh cut) and the storage temperature, T. $b(T)$ is the degradation rate parameter and $n(T)$ defines the power of degradation whereas q_o is the initial quality of the food item. Experiments have shown that the power $n(T)$ is either constant or a weak function of temperature hence $n(T) \approx n$. Normally first order degradation is involved i.e. $n(T)=1$. Peleg also defines the degradation rate by,

$$b(T) = \ln\left(1 + e^{m(T-T_c)}\right). \tag{3}$$

Where T_C defines the marker temperature at which the degradation phenomenon starts. Peleg explained that the degradation process of many compounds and enzymes starts only when certain temperature is reached. The constants T_C and m can be obtained from empirical data.

2.4 Global stability index

The new method to assess the quality degradation of food products during the storage is a very useful development in the food supply chain management system. In this technique GSI (Global Stability Index) is calculated that globally quantifies the quality degradation of food product during storage or commercialization (Achour, 2006). To form a single parameter GSI, crude experimental data is manipulated which takes into account simultaneous degradation of various nutritional components and their threshold values. The threshold values are the minimum acceptable limits of each index (nutritional component) defined by the end user or ministry of food. It is very important to define a proper weightage to each index (normally based on the importance of index). Following example will help us in better understanding of this method.

Let A_1, A_2, and A_3 are the three indices representing three important nutritional components of the food item whereas A_{TH1}, A_{TH2} and A_{TH3} are the predefined threshold limits for these indices. The storage time periods are t_0, t_1, t_2 and t_3 at a particular storage temperature T. The following matrix shows the measured value of each index A_i at storage time t_j. Also note that t_0 represent the fresh cut time. All the values in this example are imaginary because the idea is to explain the method. However; for orange case we used real data.

Table 1: Experimental data matrix.

Time	A_1	A_2	A_3
t_0	30	1.75	100
t_1	25	1.66	80
t_2	22	1.63	70
t_3	21	1.62	65
A_{TH}	15	1.5	50

Let X_{ij} represents experimental value of index A_i stored for time t_j, $A_{(TH)i}$ is the threshold value of nutritional index A_i and X_{i0} is the experimental value of index A_i at time t_0. Using previous data, the variability matrix can be generated by following formula.

$$V_{ij} = \frac{X_{ij} - X_{i0}}{A_{(TH)i} - X_{i0}}. \tag{4}$$

Table 2: Variability matrix.

Time	A_1	A_2	A_3
t_0	0	0	0
t_1	0.33333	0.36	0.4
t_2	0.53333	0.48	0.6
t_3	0.6	0.52	0.7

Now assuming the weightage α_i of each index be the 60%, 30% and 10%. Then the GSI value for each storage time j can be calculated by using following formula.

$$(GSI)_j = 1 - \sum_{i=1}^{3} \propto_i Y_{ij}. \tag{5}$$

Where Y_{ij} represents variation matrix value of index A_i stored for time t_j. Table 3 shows the global stability index values for given weightage of each nutritional index at particular temperature T.

Table 3: Global Stability Index.

Time	$(GSI)_j$
t_0	1
t_1	0.652
t_2	0.476
t_3	0.414

Figure 1 shows the trend of global stability index with respect to storage time for particular set of nutritional index weightage and at specific storage temperature.

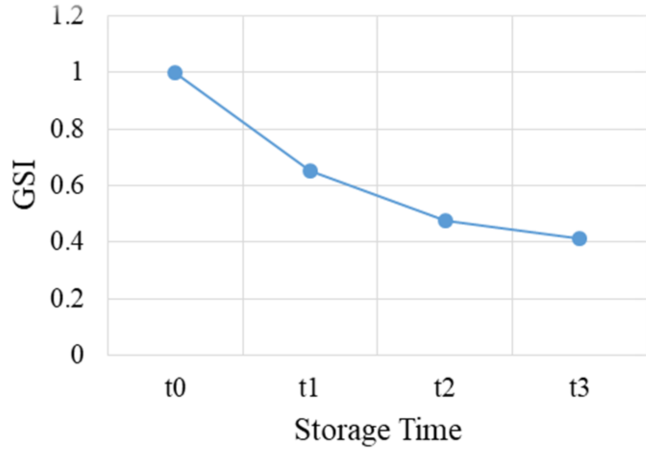

Figure 1: Global stability Index trend with respect to storage time.

Using same technique, the global stability index (GSI) can also be calculated for orange fruit. In this research we have discussed three main nutritional components of an orange fruit i.e. Ascorbic Acid, Anthocyanin and Dimethoate. Experimental data has been extracted from different research papers as Zanoni and Zavanella (2012) presented their work on ascorbic acid and Anthocyanin degradation during shelf life. Similarly, Kyriakidis et al. (2000) worked on effect of storage temperature on the degradation of Dimethoate orange juices. Combining all empirical data for 400 hours ≈ 16 days shelf life at 16.75^{o}C, we have following experimental matrix.

Table 4: Experimental data matrix for oranges at T=16.75^{o}C.

Time in days		Ascorbic Acid (mg/l)	Anthocyanin (mg/l)	Dimethoate (mg/kg)
t_1	0	580	84	1.525
t_2	5	550	77	1.51525
t_3	10	520	71	1.505
t_4	16	490	61	1.5
Threshold Value		400	40	1.3

For the given data in above experimental matrix, the following is the variability matrix.

Table 5: Variability matrix for oranges at T=16.75°C.

Time in days		Ascorbic Acid	Anthocyanin	Dimethoate
t_1	0	0	0	0
t_2	5	0.158	0.156	0.055
t_3	10	0.316	0.289	0.088
t_4	16	0.474	0.51	0.11

As discussed before the global stability index is based on the weightages assigned to the considered nutritional components, therefore; it is very crucial to assign an appropriate weight to each component. For example vitamin C is an important nutritional index in an orange fruit while sensory indices are relatively less important whereas for bananas, the blackening sensory index is more important and hence will have more weightage. For given weightage and storage length t_i the GSI values are calculated using Equation (5). Then using initial value of m=1.5 and T_c = 301K in Equation (3), we have calculated the theoretical values at T=16.75°C for the corresponding storage lengths. The data (observed and calculated) is then fitted by using excel solver tool and found the fitted constants values, m and T_c. Figure 2, shows the effect of different weightages whereas *A*, *B* & *C* show the GSI trend when purely one index is considered.

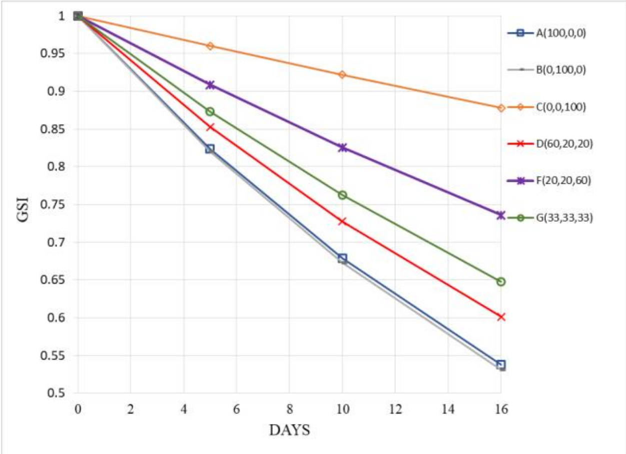

Figure 2: Global Stability Index for various set of weightages (Ascorbic Acid, Anthocyanin, Dimethoate).

It is obvious from the Figure 2, that Ascorbic acid and Anthocyanin degrades at faster rate (shown by *A* and *B*) while Dimethoate degradation (shown by *C*) is very slow. It is therefore logical to assign high weightage to Ascorbic Acid and Anthocyanin and low weightage to Dimethoate.

2.5 Chiller system cost analysis

There are several ways for treating and preserving the food: however, the greatest part of them requires some contribution of energy (Zanoni and Zavanella, 2012). Cold storage design and build services are very specialized fields that require high level of expertise. Refrigerated warehouses, frozen food distribution centers and grocery freezers are the highest energy consuming sectors. The main consideration during the design of cooling facility are temperature stability, energy cost and maintenances cost. For the cold storage facilities, the two main costs are capital cost and operational cost. Both costs depend on the area of cold storage facility (walk-in freezers, display shelves or isolated areas) and the cooling capacity of the chiller system.

2.5.1 Capital cost

The capital cost includes designing, installation and commissioning whereas operational costs are maintenance cost and energy consumption cost. It is quite practical to include these costs while modeling the FSC (food supply chain). If we represent the capital cost of chiller system by Ω then we can convert this total value in unit time. Consider the chiller system is being financed for Z numbers of years with a payment of \$$b$ per month, then (with zero-interest financing scheme),

$$\Omega = \frac{(12)(b)(Z)}{T}. \tag{6}$$

Where T is the cycle time.

2.5.2 Maintenance cost

Based on the type of maintenance there are two main costs. *Preventive* maintenance cost which is fixed (as per schedule) and *corrective* maintenance cost which can be calculated by performing the reliability analysis (based on failure probability of components) (Schuerger et al., 2012; Calixto, 2016). Again it is possible to include a fixed overall annual maintenance costs in the model.

In order to analyze the second main operational cost i.e. energy consumption cost, it is important to discuss the effect of temperature on cold chain as the temperature strictly effects the degradation rate. Lower temperature leads to longer life and hence the replenishment size is bigger however; it costs more due to higher energy consumption. Rong et al. (2011) introduced ratio of coefficients of performance Ψ for cooling as follows,

$$COP_{cooling} = \frac{Q_{cold}}{Q_{hot} - Q_{cold}} = \frac{T_{cold}}{T_{hot} - T_{cold}}. \tag{7}$$

Since heat intake or given off Q is directly proportion to the reservoir temperatures, therefore; the heat ratio can simply be calculated by the ratio of absolute temperatures of the reservoirs. Where Q_{hot} is the heat taken by hot reservoir and Q_{cold} is the heat given off by the cold reservoir. We can consider T_{hot} as an environment temperature and T_{cold} is the desired temperature of cold storage area. Let us consider an example to discuss this concept in detail.

T_E =outside environment temperature = 25^{o}C = 298.15K.

T_1= -10^{o}C = 263.1K.

T_2 = -20^{o}C = 253.15K.

$$(COP)_1 = \frac{263.15}{298.15 - 263.15} = 7.5185.$$

$$(COP)_2 = \frac{253.15}{298.15 - 253.15} = 5.6255.$$

Ratio between two coefficients,

$$\Psi = \frac{(COP)_2}{(COP)_1}. \tag{8}$$

$$\Psi_{cooling} = 0.7482.$$

This ratio shows that the energy required to freeze at -10°C is 74.82 % of the energy required to freeze at -20°C.

2.6 Lead Time

Ideally the shipment should arrive at the finishing time of existing inventory. In practice it is not the case for every supply chain system due to number of reasons as for example in cross border trading it might take longer or shorter than usual that could be due to custom clearance or weather. The cost related to uncertainty in shipment arrival time cannot be ignored. Since the earlier delivery costs due to an additional energy consumed plus the holding cost while late delivery causes an opportunity loss. The stochastic lead time effect will be further explained in retailer's cost section.

3 Model

This model is being developed by considering two echelon supply chain system. The two actors of the cold chain are *warehouse* and the *retailer*. Let D be the the annual constant demand which is deterministic. The uncertainty of shipment arrival time could cause the shortage which costs δ per unit item. In this model the retailer places an order of quantity Q_R when the in-hand inventory level reaches to re-order point r having a mean lead time τ. The fixed set up cost for the retailer is K_R. The inventory at the warehouse does not follow the usual saw-tooth pattern, even though the end usage is deterministic and constant with time. The reason is that the withdrawals from the warehouse inventory are of size Q_R. For two echelon supply chain system, the warehouse deals with quantity $Q_W = NQ_R$ where N is an integer and represents the number of shipments. Also the setup cost for warehouse is K_W. We assume that there is no thermal quality degradation at warehouse. This assumption can be justified by maintaining a considerable low warehouse storage temperature along with shorter storage time period. To include the energy cost we use Ψ_W which is the ratio of coefficient of performance calculated for warehouse using a reference temperature as explained previously in Section 2.5.2. ϵ_W is the per unit average annual setup cost of the cooling equipment for warehouse that covers the capital cost whereas $\mathcal{B}_W$ is the energy cost per unit per year that includes the operational cost. Similarly Ψ_R, ϵ_R, and $\mathcal{B}_R$ are the notations for retailer. With these understandings and knowing the background knowledge, we can express the total cost for each actor of cold chain.

3.1 Warehouse cost

The warehouse cost is formulated by considering the associated setup cost, holding cost, operational cost and purchasing cost.

3.1.1 Setup cost.

As discussed earlier, compare to a traditional supply chain there is an additional cost due to the energy involve to maintain the desired storage temperature. Therefore; we will have two components of the setup cost as shown in Equation (9). The first component is the annual setup cost based on the annual demand D and order quantity Q_W. The second component is the annual setup cost for chiller system that accommodates the capital cost and is independent of order quantity but depends on annual demand. For predefined warehouse storage temperature $T_{W,}$ the value of Ψ_W can be calculated by using Equation (8).

$$SC_W(Q_W|T_W) = D\frac{K_W}{Q_W} + D\epsilon_W \Psi_W. \tag{9}$$

3.1.2 Holding cost

From conventional supply chain model we know that the inventory holding cost is a product of average inventory handled per year and the holding cost per year per item h. Also h=Ic. Where I is the annual interest rate and c is the cost per unit. Furthermore (Clark and Scarf, 2004) introduced echelon valuation c' at particular stage i is given by,

$$c_i' = c_i - \sum c_j. \tag{10}$$

Where c_j is sum of overall immediate predecessors, j. So we can express warehouse holding cost with following equation.

$$HC(Q_W) = \frac{Q_w}{2} I c_w'. \tag{11}$$

3.1.3 Operational cost

The operational cost is mainly due to energy consumption in cold chain system. The notation $\mathcal{B}$ includes the utility price plus the fixed maintenance cost in terms of per unit per year. The value of Ψ_W can be calculated for predefined storage temperatures T_W with respect to ambient conditions. This gives us the total energy cost for the warehouse as follow.

$$OC(Q_W|T_W) = \frac{Q_W}{2} \mathcal{B}_W \Psi_W. \tag{12}$$

3.1.4 Purchasing cost

The purchasing cost is constant for a constant annual demand. It can be simply define by the product of annual demand and the echelon cost per unit.

$$PC = Dc'_w. \tag{13}$$

Here it is assumed that there is no quality degradation of an orange fruit in warehouse. This assumption is based on either it is not stored for longer time period or the temperature of the warehouse is kept significantly low that the degradation does not occur. However; it is practical it include the quality loss cost. This cost is explained in detail in retailer's section and can be applied on warehouse cost analysis in similar fashion. Since all the associated warehouse costs are defined, hence we can formulate the total cost of warehouse as follow,

$$TC = SC + HC + OC + PC$$

$$TC_W(Q_W|T_W) = D\frac{K_W}{Q_W} + D\epsilon_W\Psi_W + \frac{Q_W}{2}Ic'_w + \frac{Q_W}{2}Ɓ_W\Psi_W + Dc'_w,$$

or

$$TC_W(Q_R, N|T_W) = D\left(\frac{K_W}{NQ_R} + \epsilon_W\Psi_W\right) + \frac{NQ_R}{2}(Ic'_w + Ɓ_W\Psi_W) + Dc'_w. \tag{14}$$

3.2 Retailer cost

The retailer will have setup cost similar to the warehouse setup cost. The holding and energy consumption costs will be effected by uncertainty in shipment arrival time. Also we consider the quality degradation of food at retailer's end.

3.2.1 Setup cost

For the constant demand D, order size Q_R and predefined retailer storage temperature T_R, the total setup cost is given by,

$$SC(Q_R|T_R) = D\frac{K_R}{Q_R} + D\epsilon_R\Psi_R. \tag{15}$$

Where Ψ_R can be calculated by using Equation (8) for retailer storage temperature T_R.

3.2.2 Holding, shortage and energy cost

As discussed earlier in Section 2.6, the stochastic nature of lead time effects the cost of cold chain. Considering three scenarios for stochastic lead time, the shipment may arrive before finishing the inventory, after finishing the inventory or after the cycle time. It is therefore important to introduce the mathematical expression that accounts all the three possible scenarios under stochastic lead time. Sajadieh et al. (2009) formulated and simplified these expectations which can be expressed for retailer as follow,

$$H(Q_R, r) = h\int_0^{\frac{r}{D}} \left(\frac{Q_R}{2} + r - D_y\right) f_Y(y)dy + \int_{\frac{r}{D}}^{\frac{(r+Q_R)}{D}} \left[\frac{\delta(Dy-r)^2}{2Q_R} + \frac{h(Q_R+r-Dy)^2}{2Q_R}\right] f_Y(y)dy + \delta\int_{\frac{(r+Q_R)}{D}}^{\infty} \left(-\frac{Q_R}{2} - r + D_y\right) f_Y(y)dy. \tag{16}$$

For an exponential distribution for arrival of shipment $f_Y(y)=\tau e^{-\tau y}$ the above equation can be simplified into following equation.

$$H(Q_R, r) = h\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2(\delta+h)}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right). \tag{17}$$

Using Equation (17), we can formulate the retailer holding, shortage and energy cost as follow.

$$HC(Q_R, r|T_R) = h\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2(\delta+h)}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right) + \text{Ɓ}_R\Psi_R\left[\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right)\right]. \tag{18}$$

In Equation (18), the first two terms define the holding cost and shortage cost while the last term defines additional energy cost which is effective only if the shipment arrives before time.

3.2.3 Quality degradation cost

In Section 2.3 we have discussed in detail the quality degradation of food items which depends on storage length and storage temperature. Ideally the food item should be deliver to retailer without any quality loss. But in reality, the supplier tries to accommodate multiple food items in single delivery as a result some of the food items can be delivered on time without any considerable degradation while some might be delivered after the time period Q_R/D of that particular item. Therefore the retailer is obliged to markdown policy (Zanoni and Zavanella, 2012). Considering first order degradation i.e. $n(T) \approx 1$, the Equation (2), can be written in following simplified form to express the quality degradation (Rong et al., 2011).

$$Q_R - \int_0^{Q_R} e^{-b(T_R)\frac{(Q_R - q)}{D}} dq = Q_R - \frac{D}{b(T_R)}\left(1 - e^{-b(T_R)\frac{(Q_R)}{D}}\right). \tag{19}$$

Let p be the selling price of an item at the retailers end, then using Equation (19), we can define the quality degradation cost per unit time as follow.

$$DC(Q_R|T_R) = p\left(\frac{D}{Q_R}\right)\left\{Q_R - \frac{D}{b(T_R)}\left(1 - e^{-b(T_R)\frac{(Q_R)}{D}}\right)\right\}. \tag{20}$$

Finally we can formulate the retailer total cost for storage temperature T_R as follow.

$$TC = SC + HC + DC$$

$$\begin{aligned} TC_R(Q_R, r|T_R) = {} & D\frac{K_R}{Q_R} + D\epsilon_R\Psi_R + h\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2(\delta + h)}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right) \\ & + \mathrm{B}_R\Psi_R\left[\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right)\right] \\ & + p\left(\frac{D}{Q_R}\right)\left\{Q_R - \frac{D}{b(T_R)}\left(1 - e^{-b(T_R)\frac{(Q_R)}{D}}\right)\right\}. \end{aligned} \tag{21}$$

Now the total cost of the cold chain can be obtain by adding Equations (16) and (21).

$$
\begin{aligned}
&TC(Q_R, N, r|T_W, T_R) \\
&\quad = D\left(\frac{K_W}{NQ_R} + \epsilon_W \Psi_R\right) + \frac{NQ_R}{2}(Ic'_w + \mathrm{B}_W \Psi_W) + Dc'_w + D\frac{K_R}{Q_R} \\
&\quad + D\epsilon_R \Psi_R + h\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2(\delta + h)}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right) \\
&\quad + \mathrm{B}_R \Psi_R\left[\left(r + \frac{Q_R}{2} - \frac{D}{\tau}\right) + \frac{D^2}{\tau^2 Q_R}\left(e^{-\frac{r\tau}{D}} - e^{-\frac{(r+Q_R)\tau}{D}}\right)\right] \\
&\quad + p\left(\frac{D}{Q_R}\right)\left\{Q_R - \frac{D}{b(T_R)}\left(1 - e^{-b(T_R)\frac{(Q_R)}{D}}\right)\right\}. \qquad (22)
\end{aligned}
$$

Equation (22) shows that the total cost of cold supply chain is a function of retailer order quantity Q_R, number of shipments N in unit time period, reorder point r at predefined warehouse storage temperature T_W and retailer storage temperature T_R. The corresponding values of Ψ_W, Ψ_R and $b(T)$ at predefined T_W and T_R can be calculated by using equations (3) and (8). The only unknown independent variables that need to be optimize are Q_R, N and r.

4 Case study of an orange supply chain

To analyze the model we have conducted a case study of an orange supply chain and collected some practical data. In Florida, during the orange harvesting season the average temperature is 20°C. The post harvesting temperature adopted by the producer is normally around 4°C. Since the storage period at producer end is very short. Therefore; this storage temperature is considered good enough to prevent any quality degradation. The retailer have storage shelves at 16.75°C whereas the ambient temperature is assumed 20°C. The oranges are packed and shipped in a box of 80 pieces therefore; one box represents one item. An average weight of Florida orange is approximately 141 gram with the diameter about 2-5/8″ (Hannaone, 2018). This results an average weight of one box is about 11.28 kilograms.

Using Equation (7).

$$COP_{(W|4^{o}C)} = \frac{273.15 + 4}{293.15 - 277.15} = 17.3218.$$

Assuming the reference temperature 2^{0} C.

$$COP_{(W|2^{o}C)} = \frac{273.15 + 2}{293.15 - 275.15} = 15.175.$$

The ratio of two COPs.

$$\Psi_{W} = \frac{15.175}{17.3218} = 0.876.$$

Similarly for the retailer,

$$COP_{(R|16.75^{o}C)} = \frac{273.15 + 16.75}{293.15 - 289.85} = 87.33.$$

Assuming the reference temperature 10^{o}C.

$$COP_{(R|10^{o}C)} = \frac{273.15 + 10}{293.15 - 283.15} = 28.315.$$

The ratio of two COPs.

$$\Psi_{W} = \frac{28.315}{87.33} = 0.3174.$$

As discussed earlier in Section 2.4, the curve fitting of GSI for three nutritional orange indices (Ascorbic acid (33%), Anthocyanin (33%) and Dimethoate (33%) gives the constant values T_c=290.27 and m=1.4647.Using Equation (3) for thermal degradation,

$$b(T) = \ln\left(1 + \mathrm{e}^{1.4647(\mathrm{T_R} - 290.27)}\right)$$

For retailer's storage temperature T_R=16.75^{o}C (289.85 K) we will have $b(T)$= 0.4584.

Let us consider the following data used in case study.

Fixed variables	Notations	Values
Annual Demand	D	10000
Warehouse setup cost	K_w	\$315
Retailer setup cost	K_R	\$75
Warehouse energy consumption cost/item/year	$\mathcal{B}_W$	\$20.00
Retailer energy consumption cost/item/year	$\mathcal{B}_R$	\$18.50
Warehouse chiller system setup cost/item/year	$\mathcal{E}_W$	\$1.00
Retailer chiller system setup cost/item/year	$\mathcal{E}_R$	\$1.50
Warehouse echelon valuation price per item	C'_W	\$7.00
Retailer echelon valuation price per item	C'_R	\$10.00
Selling price per item	p	\$53.00
Shortage price per item	δ	\$22.50
Lead time (10 days)	τ	\$36.50
Annual Interest	I	\$0.025
Decision variables.		
Retailer order quantity		Q_R
Reorder point		r
Number of shipments		N

After putting all the parameters in Equation (22), the numerical solution is found by using *Genetic Algorithm* technique in Matlab. The optimal values are Q_R=244.5563, r=293.228, N=4.34 and TC=92,393.27 Solving further for the integer values of N=4 and N=5. For $\lfloor N \rfloor = 4,$ we have $TC\lfloor N \rfloor = 92{,}403.$ For $\lceil N \rceil = 5,$ we have $TC\lceil N \rceil = 92424.$ Since the objective is to minimize the cost of cold chain therefore we will choose N=4. (*See appendix A for matlab code*)

4.1 Quality degradation

Again considering the case for nutritional indices Ascorbic acid (33%), Anthocyanin (33%) and Dimethoate (33%). Using Equation 2 and 3 for $n(T) = 1$, we have corresponding values of marker temperature T_c and slope m at different temperatures as shown in Table 6.

Table 6: The constant m and T_C values for set of retailer storage temperatures.

	T_R			
	15°C	16°C	17°C	17.5°C
m	1.47	0.845	1.45	1.5
Tc	290.5	292.15	291	291

Using Table 6 for constants T_C and m, the variations in quality degradation at T_R= 15°C, 16°C, 17°C and 17.5°C are plotted as shown in Figure 3. It is obvious from the figure that higher the temperature higher is the quality degradation which justifies the argument that the deterioration rate increase with the temperature.

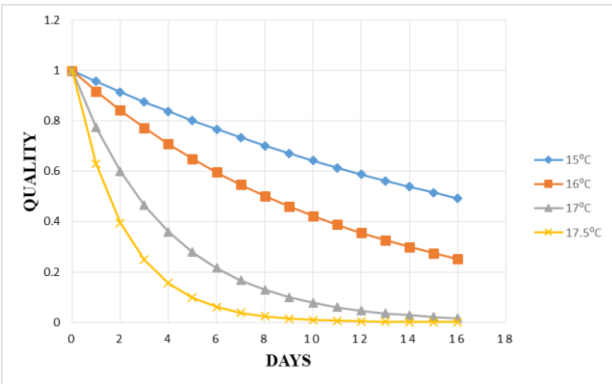

Figure 3: Quality degradation at T_R= 15°C, 16°C, 17°C and 17.5°C.

4.2 Effect of storage temperature

As the storage temperature has significant impact on the cost of cold chain system it is therefore important to conduct a sensitivity analysis of total cost with respect to storage temperature. The total cost and optimal values of decision variables are obtained for set of storage temperatures using corresponding values of constants m and T_C. As explained in Section 4, for each solution, the N is converted into ceil and floor values. The total cost is recalculated for both integer values of N and then the minimum cost between two, is an optimization criteria for other decision variables Q_R and r. Using scatter plot for numerical values, the temperature effect is being presented by an appropriate trend line. The outliers can be ignored as for limited experimental data, some of the global stability index values are interpolated or extrapolated that could cause an error in calculated values of constants T_C and m. Figure 4, shows the effect of storage temperature on total cost of cold chain. We can observe from the cost curve that the total cost increases with the rise in retailer storage temperature T_R mainly due to two reasons i.e. the quality degradation causes a food spoilage and the higher number of shipments which results higher cost due to uncertainty in shipment arrival.

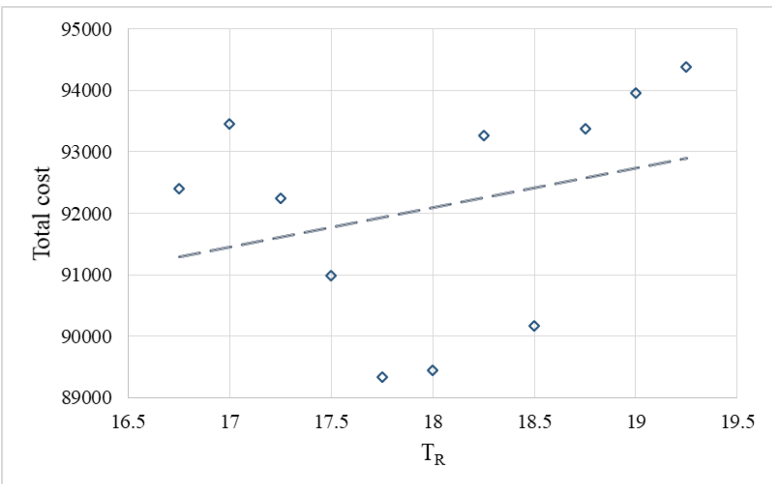

Figure 4: The total cost of cold chain versus retailer storage temperature.

Not only the cost of FSC varies with the storage temperature, also the three decision variables will gain their new optimal values. The optimal order quantity Q_R variation is shown in Figure 5. The optimal order quantity decreases for the given (constant) demand as the deterioration rate increases with the temperature which brings down the order quantity.

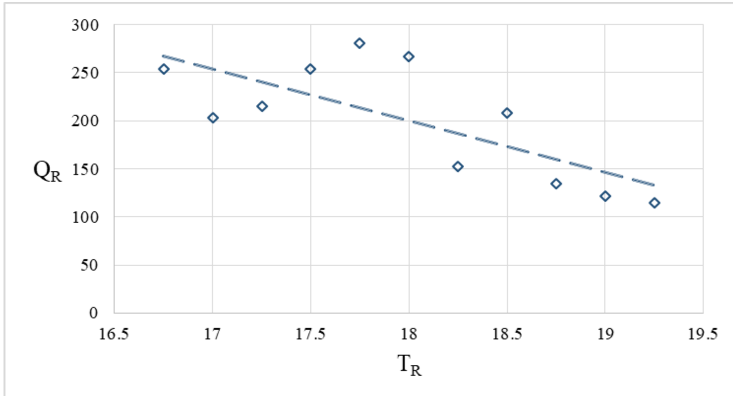

Figure 5: The retailer order quantity versus retailer storage temperature.

Figure 6 shows the change in reorder point *r* with respect to T_R. The reason for increasing reorder point is that the lead time is stochastic and due to the increase in temperature the degradation rate is higher therefore; to meet the constant demand under uncertainty of shipment arrival, the reorder point is raised.

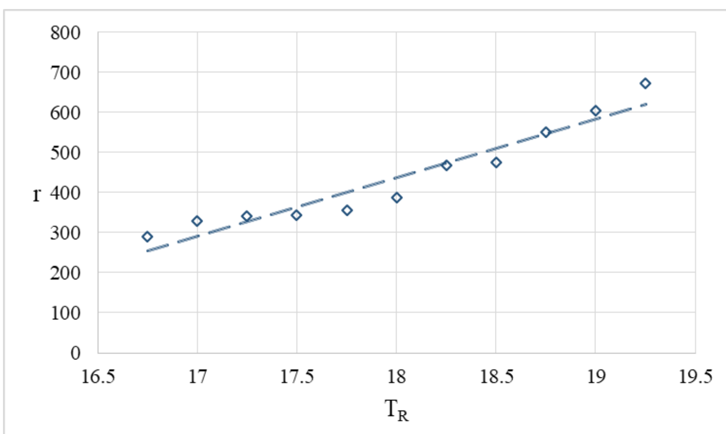

Figure 6: Reorder points versus retailer storage temperature.

Figure 7 shows the increase in number of shipments *N* with increase in T_R. The decrease in order quantity Q_R with increase in T_R justifies this argument. Since for an efficient supply chain system, the customer demand should be fulfilled therefore; for a constant demand the decrease in order quantity will increase the number of shipments.

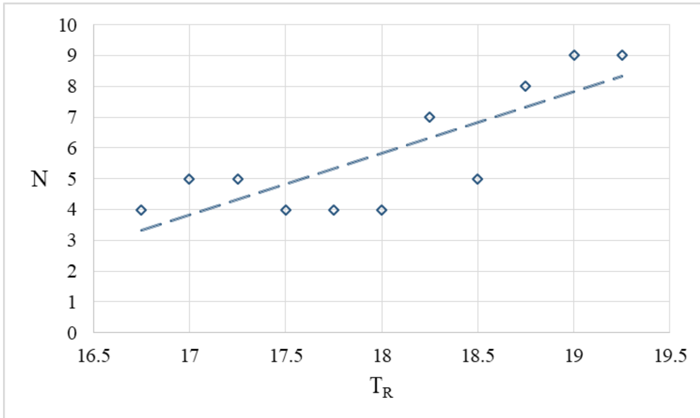

Figure 7: The number of shipments versus retailer storage temperature.

4.3 Effect of nutritional index weightage

As explained in Section 2.4, the weightage assigned to various nutritional components is one of the important decision factor. For each set of weightage we have a new corresponding value of constants *m* and T_c which effects the total cost of cold chain. The sensitivity analysis is conducted using different set of weightages for three main nutritional indices of orange i.e. Ascorbic Acid, Anthocyanin and Dimethoate at storage temperature T_R=16.75^{o}C. To capture a broader perspective of weightage effect, the analysis is conducted over a range Q_R. Figure 8 shows the effect of weightage on total cost of cold chain. It can be observed that considering pure Ascorbic Acid results highest cost while the lowest cost is for single nutritional component Dimethoate. This is because, as in Figure 2, among the under consideration set of weightages, we can see pure Ascorbic Acid shows the fastest degradation rate while pure Dimethoate degrades at slowest rate.

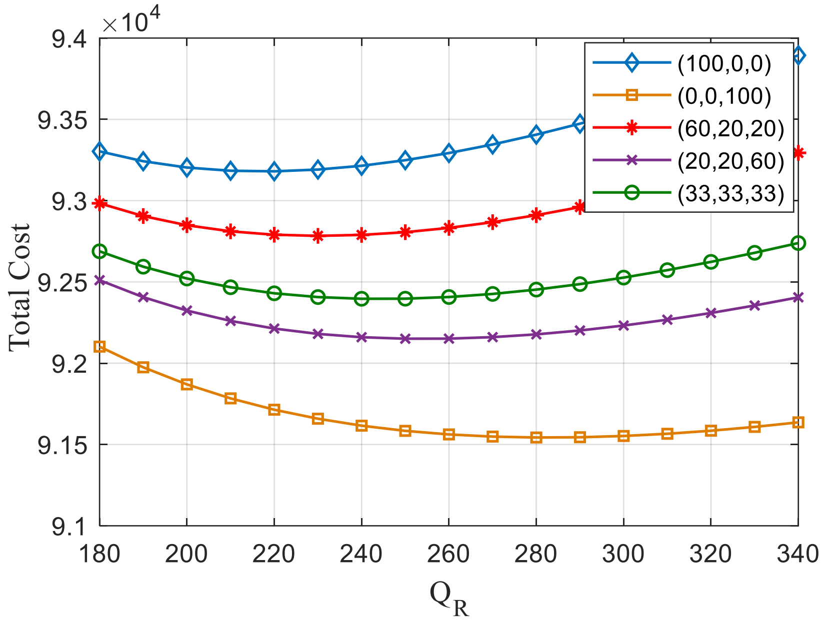

Figure 8: The total cost for various sets of nutritional index weightage.

In order to analyze the behavior of reorder point for various index weightages, the number of shipments N for each order quantity Q_R, are converted into an optimal integer values and then the corresponding reorder point r is calculated. Figure 9 shows the results for this sensitivity analysis.

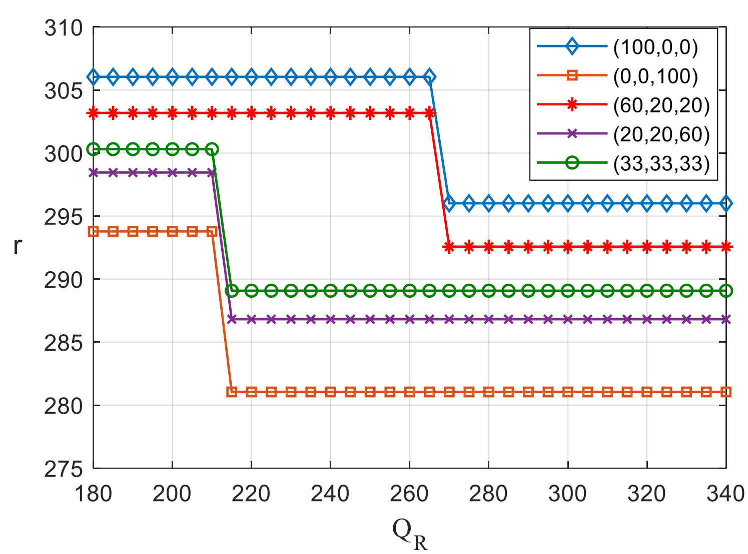

Figure 9: The reorder point for various sets of nutritional index weightage.

As discussed, the number of shipments is always an integer value therefore, all the numerical values of N are converted into integers as shown in Figure 10. Since most of the optimal N values for all set of weightages are 4 and 5 therefore; the curves are overlapped. To avoid the over saturation, only two legend markers are used.

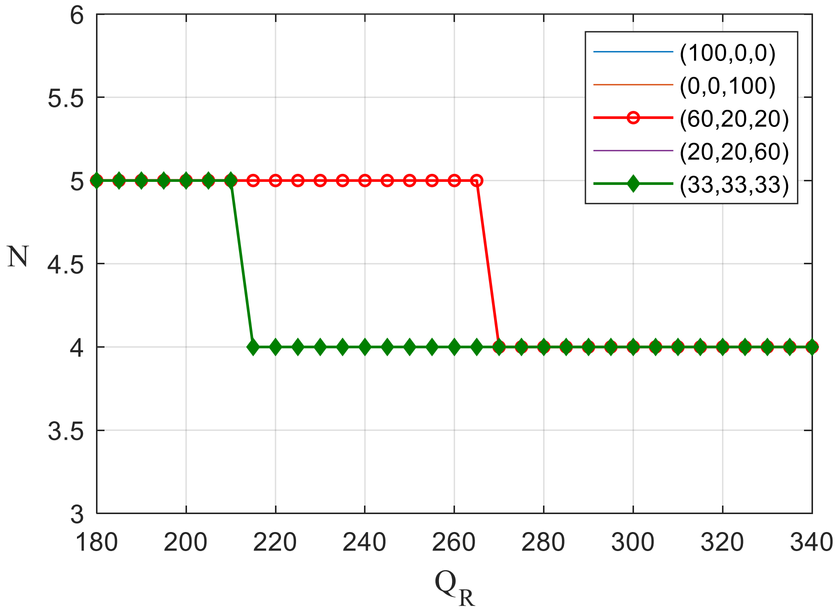

Figure 10: The number of shipments for various sets of nutritional index weightage.

4.4 Effect of lead time

The stochastic nature of lead time effects the cost of supply chain. When the lead time is large, the order size increases and the cost associated with the uncertainty of shipment arrival is also increases. Furthermore; for larger order quantity the holding and energy cost is higher. Figure 11 represents the total cost for various mean lead times.

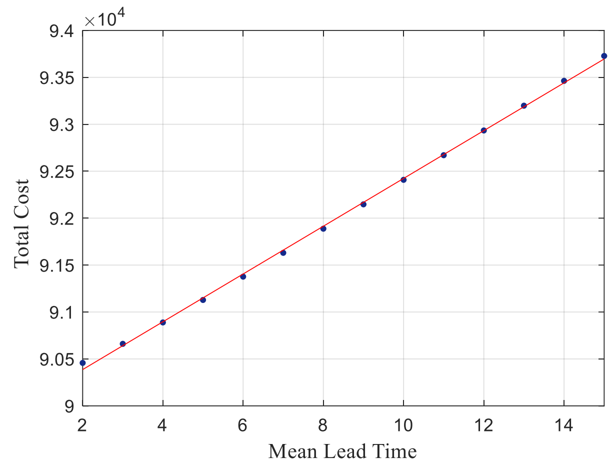

Figure 11: Effect of lead time on total cost of cold chain.

As explained before, the order quantity Q_R increases with the lead time. This trend can be seen in Figure 12. We can observe that there is a jump in order quantity from day 3 to day 4, this is because the number of shipments are reduced from 5 to 4.

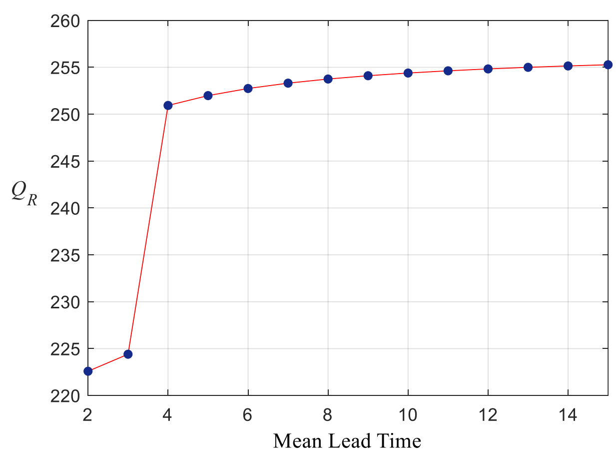

Figure 12: Effect of lead time on order quantity.

Increase in reorder point with increase in lead time is very logical as it represents the in hand inventory which will be fulfilling the demand during the lead time. Figure 13 represents the variation in reorder points with respect to mean values of lead time.

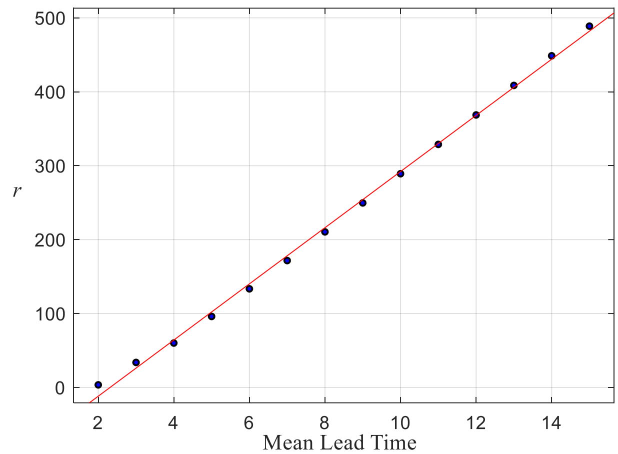

Figure 13: Effect of lead time on reorder point.

Figure 14 represents an optimal integer values for N for various mean values of lead times. The number of shipments decreases as we have previously seen the order quantity Q_R increases.

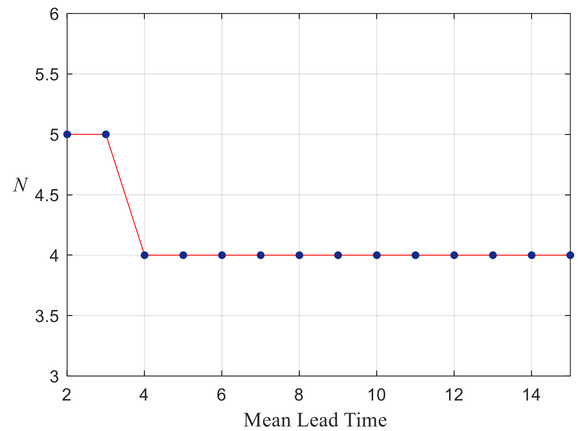

Figure 14: Effect of lead time on number of shipments.

5 Conclusion

The two echelon cold chain model for oranges has been developed where the main actors are *warehouse* and *retailer*. This model is an exemplary picture of cold chain which encapsulates the cost effective attributes. The model is being developed on the basis of energy cost, quality cost, stochastic lead time cost together with the traditional supply chain costs. It has been assumed that the quality loss occurs only at the retailer’s end. The model has been solved numerically and sensitivity analysis of total cost of cold chain, retailer order quantity, reorder point and number of shipments have been conducted with respect to retailer storage temperature. Furthermore; the quality degradation of three main nutritional components of orange i.e. Ascorbic Acid, Anthocyanin and Dimethoate is discussed and the technique called *global stability index* is used to consider multiple nutritional components simultaneously. It is observed that the weightage of nutritional components directly effects the cost of FSC and hence, considered another important decision criteria. A realistic approach of stochastic lead time makes the model more reliable which has a significant impact when the lead time is large or when the number of shipments are high.

This model can be very helpful in further developments of food chain management system as there is still a potential for improvement like one can consider coordinated inventory management system where multiple food items can be considered. Another extension of this model could be for multi echelon systems. Furthermore efficient transportation methods can also be included in this model.

Appendix A

```
1.  %This code will numerically solve the total cost function and can be used for a set of retailer
    % of retailers temperatures. Make sure the number of constant m(T) (line-8) and TC (line-10)
    %values should be % equal to the range of temperature (line-6).
2.  clc;clear
3.  global Y
4.  global Ror
5.  % Retailer's storage temperatures.
6.  Temps=16.75;
7.  % using constant m(T)=1.46474
8.  a1=1.46;
9.  % using constant marker temperature Tc=290.27
10. TM1=290.27;
11. % Calculating thermal degradation b(T) and ΨR.
12. h=zeros(1,length(Temps));
13. g=zeros(1,length(Temps));
14. COP1=zeros(1,length(Temps));
15. for k=1:length(Temps)
16. TR=Temps;
17. a=a1;
18. TM=TM1;
19. h(k)=log(1+exp(a*((TR+273.15)-TM)));
20. COP1(k)=(273.15+TR)/(293.15-(273.15+TR));
```

```
COP2=28.315;
g(k)=COP2/COP1(k);
end
% Solution
Q1=zeros(1,length(Temps));
R1=zeros(1,length(Temps));
N1=zeros(1,length(Temps));
TC4=zeros(1,length(Temps));
for i=1:length(Temps)
Y=h(i);
Ror=g(i);
[X,TC] = s2(3,[0 0 0],[1000 1000 15]);
Q1(i)=X(1);
R1(i)=X(2);
N1(i)=X(3);
TC4(i)=TC;
end
% Following function defines how genetic algorithm is used for function name f2.
function [X,TC,exitflag,output,population,score] = s2(nvars,lb,ub)
options = optimoptions('ga');
options = optimoptions(options,'MaxGenerations', 100000);
options = optimoptions(options,'FunctionTolerance', 1e-10);
options = optimoptions(options,'Display', 'off');
```

```
[X,TC,exitflag,output,population,score] = ...
ga(@f2,nvars,[],[],[],[],lb,ub,[],[],options);
end
% This is the actual model function
function tc = f2(z)
global D; % constant annual demand.
global Kw; % warehouse setup cost
global Kr; % retailer setup cost
global Ew; % warehouse chiller system setup cost/item/year
global Er; % retailer chiller system setup cost/item/year
global Cr;
global NETCr; echelon valuation for retailer.
global Cw;
global NETCw; echelon valuation for warehouse.
global Br; % retailer energy cost per item/year
global Bw; % warehouse energy cost per item/year
global I; % annual interest
global Y; % thermal degradation b(T)
global Ror; % Ψ_R (ratio of COPs for retailer)
global Row; % Ψ_W(ratio of COPs for warehouse)
global p; % selling price per item
global LT; % lead time
global DELTA; % Shortage cost.
```

```
% VALUES OF THE GOBAL PARAMETERS.
D=10000;
Kw=315;
Kr=75;
Er=1.5;
Ew=1;
Cr=17;
NETCr=10;
Cw=7;
NETCw=7;
Br=20;
Bw=18.5;
I=0.025;
Row=0.2928;
p=53;
LT=36.5;
DELTA=22.5;
Q=z(1);
R=z(2);
N=z(3);
tc=D*((Kw/(N*Q))+Ew*Row)+((N*Q)/2)*(I*NETCw+Bw*Row)+D*NETCw+((D*Kr)/Q)+(D
*Er*Ror)+(I*NETCr)*(R+(Q/2)-D/LT)+(D^2/((LT^2)*Q))*(DELTA+I*NETCr)*(exp(-
```

(R*LT)/D)-exp(-((R+Q)*LT)/D))+(Br*Ror)*(R+(Q/2)-D/LT+(D^2/((LT^2)*Q))*(exp(-

(R*LT)/D)-exp(-((R+Q)*LT)/D)))+p*(D/Q)*(Q-(D/Y)*(1-exp(-(Y*Q)/D)));

87. End

% To find the optimal integer number of shipments replace the line 32 by .

% [X,TC] = s2(3,[0 0 *upper integer value*],[1000 1000 *upper integer value*]); find the total cost,

%then replace with

%[X,TC] = s2(3,[0 0 *lower integer value*],[1000 1000 *lower integer value*]);

%And then compare the two costs. However; we can directly program the optimal *N* values (as

%done for all the sensitivity analysis), here the idea is to see the difference in two cost values.

References

Achour, M. (2006). A new method to assess the quality degradation of food products during storage. *Journal of Food Engineering*, 75(4):560-564.

Adekomaya, O., Jamiru, T., Sadiku, R., & Huan, Z. (2016). Sustaining the shelf life of fresh food in cold chain - A burden on the environment. *Alexandria Engineering Journal*, 55(2):1359-1365.

Bhardwaj, R. L., & Sen, N. L. (2003). Zero energy cool-chamber storage of Mandarin (citrus reticulata blanco).“Nagpur Santra.” *Journal of Food Science and Technology*, 50(2):325-331.

Blackburn, J., & Scudder, G. (2009). Supply chain strategies for perishable products: The case of fresh produce. *Production and Operations Management*, 18(2):129-137.

Calixto, E. (2016). Reliability, Availability, and Maintainability (RAM Analysis). In *Gas and Oil Reliability Engineering*, 11(1):87-90.

Carmona, L., Alquézar, B., Marques, V. V., & Peña, L. (2017). Anthocyanin biosynthesis and accumulation in blood oranges during postharvest storage at different low temperatures. *Food Chemistry*, 237:7-14.

Clark, A. J., & Scarf, H. (2004). Optimal Policies for a Multi-Echelon Inventory Problem. *Management Science*, 50(12_supplement):1782–1790.

Gui, S., Feng, W., & Zhang, Z. (2010). Research on multi-echelon inventory model of cold-chain logistics on random demand. *International Conference on Logistics Systems and Intelligent Management*, 3:1454-1457.

Hussain, I., Rab, A., Khan, N. U., Sajid, M., Ali, N., Khan, S. M., & Ali, S. (2017). Effect of chilling exposure and vapor heat treatment duration on the quality of sweet orange during simulated marketing. *Acta Scientiarum Polonorum, Hortorum Cultus*, 16(5):39-47.

Iannone, F., & Thore, S. (2010). An economic logistics model for the multimodal inland distribution of maritime containers. *International Journal of Transport Economics*, 37(3):281-326.

Joshi, R., Banwet, D. K., & Shankar, R. (2011). A Delphi-AHP-TOPSIS based benchmarking framework for performance improvement of a cold chain. *Expert Systems with Applications*, 38(8):10170-10182.

Jula, P., & Leachman, R. C. (2011). Long- and Short-Run supply-chain optimization models for the allocation and congestion management of containerized imports from Asia to the United States. *Transportation Research Part E: Logistics and Transportation Review*, 47(5):593-608.

Klimczak, I., Małecka, M., Szlachta, M., & Gliszczyńska-Świgło, A. (2007). Effect of storage on the content of polyphenols, vitamin C and the antioxidant activity of orange juices. *Journal of Food Composition and Analysis*, 20(3):313-322.

Koplin, J., Seuring, S., & Mesterharm, M. (2007). Incorporating sustainability into supply management in the automotive industry - the case of the Volkswagen AG. *Journal of Cleaner Production*, 15(11):1053-1062.

Kuo, J. C., & Chen, M. C. (2010). Developing an advanced Multi-Temperature Joint Distribution System for the food cold chain. *Food Control*, 21(4):559-566.

Kyriakidis, N. B., Athanasopoulos, P., & Georgitsanakou, I. (2000). Effect of storage temperature on degradation of methidathion in fortified orange and peach juices. *Journal of AOAC International*, 83(4):967-970.

Ma, Q., Wang, W., Peng, Y., & Song, X. (2018). An optimization approach to the intermodal transportation network in fruit cold chain, considering cost, quality degradation and carbon dioxide footprint. *Polish Maritime Research*, 25(1):61-69.

Martínez-Sala, A. S., Egea-López, E., García-Sánchez, F., & García-Haro, J. (2009). Tracking of Returnable Packaging and Transport Units with active RFID in the grocery supply chain. *Computers in Industry*, 60(3):161-171.

Mditshwa, A., Magwaza, L. S., Tesfay, S. Z., & Opara, U. L. (2017). Postharvest factors affecting vitamin C content of citrus fruits: A review. *Scientia Horticulturae*, 218:95-104.

Nisha, P., Singhal, R. S., & Pandit, A. B. (2005). A study on degradation kinetics of riboflavin in spinach (Spinacea oleracea L.). *Journal of Food Engineering*, 67(4):407-412.

Pérez Aparicio, J., Ángeles Toledano Medina, M., & Lafuente Rosales, V. (2007). Descriptive sensory analysis in different classes of orange juice by a robust free-choice profile method. *Analytica Chimica Acta*, 595(1):238-247.

Rao, P. (2002). Greening the supply chain: a new initiative in South East Asia. *International Journal of Operations & Production Management*, 22(6):632-655.

Rapisarda, P., Bellomo, S. E., & Intelisano, S. (2001). Storage temperature effects on blood orange fruit quality. *Journal of Agricultural and Food Chemistry*. https://doi.org/jf010032l [pii]

Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics*, 131(1):421-429.

Sajadieh, M. S., Jokar, M. R. A., & Modarres, M. (2009). Developing a coordinated vendor-buyer model in two-stage supply chains with stochastic lead-times. *Computers and Operations Research*, 36(8):2484-2489

Schuerger, B., Githu, G., & Kurkjian, C. (2012). Reliability Modeling for Data Center Cooling Systems. *ASHRAE Transactions*, 118(2):427–436.

Soysal, M., Bloemhof-Ruwaard, J. M., & Van Der Vorst, J. G. A. J. (2014). Modelling food logistics networks with emission considerations: The case of an international beef supply chain. *International Journal of Production Economics*, 152:57-70.

Ukuku, D. O., & Sapers, G. M. (2007). Effect of time before storage and storage temperature on survival of Salmonella inoculated on fresh-cut melons. *Food Microbiology*, 24(3):288-295.

Xiao, Y., Chen, J., & Xu, X. (2008). Fresh Product Supply Chain Coordination under CIF Business Model with Long Distance Transportation. *Systems Engineering - Theory & Practice*, 28(2):19-34.

Yang, X., Low, J. M. W., & Tang, L. C. (2011). Analysis of intermodal freight from China to Indian Ocean: A goal programming approach. *Journal of Transport Geography*, 19(4):515-527.

Zanoni, S., & Zavanella, L. (2012). Chilled or frozen? Decision strategies for sustainable food supply chains. *International Journal of Production Economics*, 140(2):731-736.

Zarei, M., Fakhrzad, M. B., & Jamali Paghaleh, M. (2011). Food supply chain leanness using a developed QFD model. *Journal of Food Engineering*, 102(1):25-33.

Zhang, K., Chai, Y., Yang, S. X., & Weng, D. (2011). Pre-warning analysis and application in traceability systems for food production supply chains. *Expert Systems with Applications*, 38(3):2500-2507.