ANALYSIS OF A WAREHOUSE MANAGEMENT SYSTEM BY MEANS OF SIMULATION EXPERIMENTS

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ABSTRACT
The supply chains for perishable products are nowadays affected by significant wastes and losses. Their management hence requires optimized approaches in order to remove such inefficiencies. In particular optimized warehouse management policies is a well established research topic which has been recently enriched with specific formulations for deteriorating stocks and shelf life based picking rules. In such context the proposed research aims at investigating the optimal warehouse management policy, taking into account the effects of uncertainty by means of simulation and approaching the effect of optimal picking rules. In the proposed approach, on the basis of a Weibull deterioration process, the optimal order quantity is calculated taking into account the deterioration cost, and the performance of the system is analyzed taking into account the inherent variability in the quality of the products entering the cold chain. The numerical application developed confirms the effectiveness of the model proposed.

Keywords: supply chain, perishable inventory, simulation

1. INTRODUCTION

Perishable inventory systems are characterized by a reduction of the value of the products with time, which ultimately results in the discard of the products stored upon the loss of the minimal quality level required by the consumer. Due to the necessity of preserving the quality attributes of the products until they reach the final market, the management of the supply chain for perishable products is a challenging task. In particular the supply chain lead time is an extremely critical parameter influenced by the operational policies and logistics variables enforced throughout the entire chain. In order to maximize the performance of the supply chain such policies should be established taking into account exogenous parameters such as the deterioration rate and the demand rate of the products. Supply chain operations should hence be timely scheduled and properly managed in order to reach the best compromise between the cost of handling/transporting operations and the quality of the product delivered. In the practical context, significant losses of products are likely to occur due to inadequate management of the post harvest activities including warehousing, handling and transport operations. Such losses not only represent an industrial cost, but they also constitute an ethical and environmental concern which severely influences the sustainability of agro-industrial supply chains. Recent studies (Broekmeulen and Van Donselaar 2007), report that perishables stand for almost one third of the sales of the supermarket industry and approximately 15% of the perishables are lost due to spoilage.

Deterioration processes such as spoilage are the result of biochemical and biological phenomena such as respiration, lipid oxidation, microbiological proliferation, which ultimately determine the shelf life of the product. These phenomena are directly related to temperature, which in fact is the most significant environmental factor that influences the deterioration rate of harvested products. The relationship between product quality in terms of shelf life (SL) and temperature is studied extensively, e.g. by Doyle (1995) and Taoukis (1999). According to these studies, by knowing the time/temperature history of a product through the supply chain it is theoretically possible to predict its remaining shelf life (RSL) at any stage of the supply chain. The knowledge of the deterioration rate of a product is an information which should be considered when establishing an optimal inventory management system, as it influences for example the operative decisions about the replenishment policy, the optimal order quantity and the picking policy. Traditional warehouse management systems that are not based on such information are typically affected by the uncontrolled deterioration of products stored with time.

Optimal warehousing policies for perishable products is a well established research field which has lead to significant results concerning the efficiency of logistic throughout the supply chain. Ketzenberg and Bloemhof (2009) report that the knowledge of the deterioration state in real-time allows dynamic decision making through the supply chain, so that products that are soon to expire can be distributed locally while less deteriorated products can be distributed to more distant locations. Another important result achievable by the evaluation of the RSL is related to possibility of implementing SL based logistics policies as LSFO (Least Shelf life First Out) rather than traditional FIFO (Firs In First Out) and LIFO (Least In First Out) rules thus improving supply chain performance, by reducing the fraction of deteriorated products wasted before sale. Finally it must be pointed out that the performance of the supply chain is influenced by some uncertain and uncontrollable factors such as the inherent variability of the deterioration state of the products entering the cold chain. This is due to the harvest operations, which may take several hours and are generally performed outdoor where environmental conditions cannot be modified. Even when the temperature throughout the supply chain is perfectly controlled, the variability in the level of initial maturation of the products results in the presence of a fraction of perished products. In this paper such uncertainties, are taken into account by means of a simulation model. A Simulation method is in fact generally preferred when the existence of uncertainties makes the task of mathematical programming highly complicated. Simulation is the process of constructing a model of a real system and conducting experiments with such a model, with the purpose of analyzing the behavior of the system and evaluating different strategies of operation. Simulation-based optimization is an active research area in the field of the stochastic optimization. Reviews of the research on simulation-based optimization developments can be found in Andradottir (1998) and Fu and Hu (1997). The effects of uncertainties and the large number of control variables that may be present in a supply chain, is the main reason why simulation is widely employed in several supply chain analysis. For example, Sezen and Kitapçi (2007), developed a spreadsheet simulation model for a single distribution channel and simulated three different scenarios reflecting various levels of demand fluctuations. Similarly, Banerjee et al. (2003) developed a supply chain simulation model with the aim to compare two different trans-shipment approaches. Zhao et al. (2002) investigated the complex relationships between forecast errors and early order commitments by simulating a simple supply chain system under uncertain demand. Finally Young et al (2004) addressed the problem of determining the safety stock level to use in the supply chain in order to meet a desired level of customer satisfaction using a simulation based optimization approach.

The purpose of the present paper is to analyze the performance of a cold chain considering the effects of uncertainties and exogenous parameters such as the demand rate and the kinetics of the deterioration phenomena. The approach proposed allows to determine the best compromise between product availability and supply chain responsiveness by establishing the optimal set of supply chain operational parameters (stock levels) corresponding to the deterioration rate of the product and to the characteristics of the demand, taking into account holding/waste costs and product quality.

Finally a sensitivity analysis is conducted through an experimental plan in which the exogenous parameters as well as the RSL are varied in the two levels. A set of simulation runs is defined in which the warehouse replenishment cycle is modeled based on the optimal stock level in order to determine the operative variables.

2. SHELF LIFE MODELING AND DETERIORATION PROCESS

Shelf life is defined as the time until a perishable product becomes unacceptable to consumers under a given storage condition (Singh and Cadwallader 2004). The shelf life of a product can be measured directly by means of Accelerated laboratory tests, and subsequently evaluated by means of mathematical models. Mathematical Shelf Life models typically involve some input parameters that characterize the environmental conditions (as temperature, relative humidity, etc.) to determine the consequent decrease in the quality attributes. The modeling method based on the kinetic of reactions states that the quality decay of the product can be expressed through the Arrhenius law, by relating the reaction rate to the temperature based on the Activation Energy. In this case the following expression can be employed:

$$K = K_0 * exp\left(-\frac{E_a}{RT}\right) \tag{1}$$

where k_0 is the pre-exponential factor, E_a is the Activation Energy (temperature sensitivity) of the reaction that controls food quality loss, R is the universal gas constant and T is the absolute temperature (K), which may be constant or variable. Based on equation (1) the SL of a product exposed at variable temperature can be calculated on the basis of the following expression:

$$ln\, SL = ln\, SL_0 + \frac{E_a}{RT} \tag{2}$$

From (2) it is possible to determine the fraction of the SL consumed when a product is exposed to a constant temperature for a certain time interval (Giannakourou 2003). The formulation is:

$$f_c = \sum \frac{t_i}{SL_i} \tag{3}$$

where f_c represents the sum of the times at each constant temperature segment, t_i, divided by the SL_i at that temperature.

In order to preserve the quality of the product, all the logistics operations involved are carried out at preestablished temperature, and a temperature control system is enforced throughout the supply chain which is thus properly defined “cold chain”. There are however some operations which cannot be included in the cold chain, like for example the harvesting operations which must be carried out outdoor. The deterioration phenomena which take place during these operations are therefore responsible of a different deterioration level of the products entering the cold-chain even when the harvesting phase is scheduled at the same maturation level.

When the products enter the cold chain they are kept at proper temperature which is assumed to be perfectly controlled, the deterioration is thus function of time only. Several authors have faced the problem of modeling the dependence of the deterioration rate from time. The most common deterioration models are linear, quadratic and Weibull deterioration models. The Weibull deterioration model is expressed as:

$$\theta(t) = \alpha\beta t^{\beta-1} \quad (4)$$

where α is the scale parameter, $\alpha>0$; β is the shape parameter $\beta>0$; t is time of deterioration, $t>0$. It is seen from equation (4) that the two-parameter Weibull distribution is appropriate for an item with decreasing rate of deterioration ($\beta<1$) only if the initial rate of deterioration is extremely high. Similarly, this distribution can also be used for an item with increasing rate of deterioration ($1<\beta<2$) only if the initial rate is approximately zero. In the present paper the deterioration rate of products stored is determined by considering a Weibull distribution and RSL of products leaving the warehouse is calculated with the following equation:

$$RSL_{exit} = RSL * (1 - f_c) \quad (5)$$

The RSL at each stage of the supply chain is defined as the number of days a product is still available for consumption starting from the moment the product arrives at that stage of the supply chain. Van Donselaar and al. (2006), report that the RSL is a function of the SL, the distribution strategy (including e.g. decisions on direct delivery, cross-docking or delivery from stock at the retailer’s distribution channel and the shipping frequency) and the inventory replenishment logic (e.g. push or pull).

3. STOCK ROTATION SYSTEM AND EOQ FOR DETERIORATING ITEMS

A warehouse management system is characterized by the stock management policies enforced and the operative parameters such as the average stock level, the duration of the replenishment cycle, etc.

The FIFO policy is the policy generally employed for managing perishable products and it is based on the assumption that the obsolescence of the products is related to their time of arrival. In this case the products that arrive first have the smaller RSL and then they must sell first. However in agroindustrial supply chains, due to the variability of the quality of harvested products, not always their obsolescence is perfectly correlated to the time of arrival. In this case a quality attribute such as the RSL, should be more effectively employed to decide which product must be picked first. This would ensure that products that have the smaller quality attribute leave the warehouse first. Therefore, if the information about the RSL is available it would be possible to release the products with shortest RSL first, thus enforcing a LSFO picking rule. Taoukis and Giannakourou (1998), demonstrate that compared with FIFO policy, the LSFO would reduce rejected products and eliminate consumer dissatisfaction since the fraction of product with unacceptable quality consumed can be minimized.

Another important decision that must be taken when establishing an inventory management policy concerns the replenishment policy. Traditional well-known optimizing strategies such as the economic order quantity (EOQ) cannot be directly applied to perishable inventories unless the costs of deterioration is additionally considered. The traditional EOQ model aims at optimizing the holding and ordering costs neglecting the influence of the deterioration costs as well as the salvage value of products perished. For this reason the extension of the EOQ model to perishable inventories is a topic intensively treated in recent years. Tarun Jeet Singh and al. (2009), have built an EOQ model when the deterioration rate has a linear trend in the two cases in which shortage are allowed or not. Shibsankar Sana and Chaudhuri (2004), refer to an EOQ model including a quadratic deterioration rate. Ghosh and al. (2005), Begum and al. (2010), have built a model including deterioration costs in the case in which the deterioration rate follows a Weibull distribution. Manna and al. (2006), Nita and al.(2008), have determined an EOQ model by considering the salvage value of products and a deterioration cost when deterioration rate follows a Weibull distribution and delay in payments are permissible.

In the present paper the EOQ model is proposed derived by the model proposed by Nita et al (2008). The model is developed using the following notations:

- C is the purchase cost per unit;
- γC is the salvage value, associated to deteriorated units during the cycle time, where $(0 \leq \gamma < 1)$;
- h is the inventory cost per unit per time;
- A is the ordering cost per order;
- T is the cycle time (a decision variable).

The following assumption are used:

- the demand rate of R units per time is assumed to be deterministic and constant;
- the system deals with a single item;
- the replenishment rate is infinite;

- the lead time is zero and shortages are not allowed;
- the deterioration rate of units follows the Weibull distribution function given by (4), where $0 \leq \alpha < 1$, $\beta \geq 1$, $0 \leq t \leq T$.
- the deteriorated units can neither be repaired nor be replaced during the cycle time.

Based on assumptions made and supposing that the decrease of inventory is only due to the demand rate and to the deterioration of products, the inventory level $Q(t)$ is governed by the differential equation:

$$\frac{dQ(t)}{dt} + \theta(t) * Q(t) - R, \quad 0 \leq t \leq T \qquad (6)$$

with the initial condition $Q(0) = Q_{opt} = EOQ$ and the boundary condition $Q(T) = 0$.

Taking series expansion and ignoring second and higher power of α (assuming α to be very small), the solution of the differential equation (6) using the boundary condition $Q(T) = 0$ is given by:

$$Q(t) = R\left[T - t + \frac{\alpha T}{\beta+1}\left(T^{\beta} - (1+\beta)t^{\beta}\right) + \frac{\alpha\beta t^{\beta+1}}{\beta+1}\right] \qquad (7)$$

that expresses the inventory level at each generic instant t The number of units that deteriorate during a cycle can be calculated as:

$$D = Q - RT = \frac{\alpha R T^{\beta+1}}{\beta+1} \qquad (8)$$

The cost of deterioration (CD) is:

$$CD = \frac{\alpha C R T^{\beta+1}}{\beta+1} \qquad (9)$$

The salvage value (SV) is:

$$SV = \frac{\alpha \gamma C R T^{\beta+1}}{\beta+1} \qquad (10)$$

The per cycle inventory holding cost (IHC) is:

$$IHC = h * \int_0^T Q(t)dt = hR\left[\frac{T^2}{2} + \frac{\alpha\beta T^{\beta+2}}{(\beta+1)(\beta+2)}\right] \qquad (11)$$

The ordering cost is: A (12)

The total cost per cycle is:

$$TC(T) = CD - SV + IHC + A \qquad (13)$$

and the Total Cost per Time Unit is:

$$TC_u(T) = \frac{[CD - SV + IHC + A\,]}{T} \qquad (14)$$

By deriving (14) with respect to T and solving it the optimal cycle time is determined and by equation (7) the corresponding optimal order quantity is calculated.

4. DESIGN OF SIMULATION EXPERIMENTS

In this paragraph the effect of the uncertainties on the warehouse management systems is addressed. According to Gong (2009) the uncertainty faced by warehouse systems can be classified in: sources outside the supply chain, sources in the supply chain but outside the warehouse, sources inside the warehouse, and sources within warehouse control systems. According to the variance structure of uncertainties, we classify uncertainty sources as unpredictable events like strikes, floods, and hurricanes, which usually are rare events, predictable events like demand seasonality, and internal variability like variance of order waiting time for batching. External uncertainty sources usually are more unpredictable, and will often bring higher variance to warehouse operations. On the other hand, inside uncertainty sources usually are more predictable and only bring low variance to warehouse operations.

In the present study the attention is focused on sources outside the warehouse but that affect warehouse management. They include predictable events like demand fluctuations and variability of RSL of products entering the warehouse.

In traditional warehouse management systems, where the picking policies used are based on arrival time of SKUs (FIFO) and no information management system is adopted, such uncertainties have a strong impact in terms of quality of products leaving the warehouse.

The purpose of this paper is to study the effect of these uncertainties by evaluating the RSL distribution of the products leaving the warehouse when the two policies LSFO and FIFO are applied. The study of warehouse system is carried out with the methodology of design of simulation experiments.

The simulation model is used to take into account the effect of the fluctuation in demand and variability of RSL of products entering the warehouse on the performance. Finally a sensitivity analysis is carried out consisting on a three factors experimental plan in which the RSL of products entering the warehouse, the demand rate and the deterioration rate vary on two levels. The response of the experimental plan, consisting in the average RSL of products leaving the warehouse has been determined. The results obtained show how the information about the RSL of the product can improve the operational and tactical management decisions thus increasing the quality of the products delivered.

An experimental plan is generally designed to estimate how changes in the input factors affect the results, or responses, of the experiment. While these methods were developed with physical experiments in mind (like agricultural or industrial applications), they can fairly easily be used in computer-simulation experiments as well, as described in more detail in Law and Kelton (2000). In fact, using them in simulation presents several opportunities for improvement that are difficult or impossible to use in physical experiments. In such situation the most suitable tool to know the system behavior is the computer based-simulation experiment. The design of simulation experiments starts by building the experimental plan including all parameters that affect the system behavior, thus the model simulation is realized to represent the actual system, and finally each configuration of the experimental plan is executed through simulation model and average measures of interest are calculated.

An important result achievable from an experimental plan is related to the possibility of estimating the main effect of each factor in the plan, defined as the average difference in response when this factor moves from its low level to its high level. Furthermore the interaction between the factors if it seems to be present can be determined to know if the effect of one factor might depend in some way on the level of one or more other factors.

As mentioned above when an experimental plan must be executed the simulation can result very helpful to substitute the physical experiment thus resulting in a very inexpensive tool. Any computer based simulator aims to mirror the behavior of the real system that it represents. To achieve this goal, the different decision processes along the operational cycle, the replenishment cycle and the picking policy of a warehouse in this case, must be accurately reproduced. Keeping this in mind, the simulation model presented here is built through a discrete event simulator. Discrete event simulation concerns the modeling of a system as it evolves over time by a representation in which system variable changes instantaneously at separate points in time – the ones in which an event occurs.

A simulation model takes the form of a set of assumptions concerning the operations of the system. These assumptions are expressed in mathematical, logical, and symbolic relationships between the *entities*, or objects of interest, of the system. Some of these assumptions can comprise those situations in which one or more input in the model are random variable. In this case the outputs provided by the model can be considered only as an estimates of the true characteristic of the model. Once developed and validated a model can be used to investigate a wide variety of "what if" questions about the real-world system. Potential changes to the system, defined through the experimental plan, can be first simulated, in order to predict their impact on system performance.

Most experimental designs are based on an algebraic regression-model assumption about the way the input factors affect the outputs. It is assumed that the independent variables are continuous and controllable by experiments with negligible errors. Furthermore it is required to find a suitable approximation for the true functional relationship between independent variables and the response surface. If all variables are assumed to be measurable, the response surface can be expressed as follows:

$$y = f(x_1, x_2, \dots \dots . x_k) \tag{15}$$

The goal is to optimize the response variable *y*. Usually a second-order model is utilized in response surface methodology as explained in Raissi (2009).

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i g_i + \sum_{i=1}^{k} \beta_{ii} g_i^2 + \sum_{i=1}^{k} \beta_{ij} g_i g_j + \varepsilon \tag{16}$$

where the β_j coefficients are unknown and must be estimated somehow, and ε is a random error term representing whatever inaccuracy such a model might have in approximating the actual simulation-model response *y*. The parameters of the model are estimated by making simulation runs at various input values according, for example, with the experimental plan, recording the corresponding responses, and then using standard least-squares regression to estimate the coefficients. In simulation, an estimated response-surface model can serve several different purposes. You use them as a proxy for the simulation, and very quickly explore many different input-factor-level combinations without having to run the simulation. And you could try to optimize (maximize or minimize, as appropriate) the fitted model to give you a sense of where the best input-factor-combinations might be. For more details see Kelton (2003).

When an experimental design is executed the quality control of the measures obtained is of fundamental importance to ensure a desired precision about average measures of variables of interest. This means that the average measures determined by each configuration of the experimental plan actually represent the estimate of the expected value (EV) for this measure. For this reason, depending on the precision desired for the measure under analysis, a certain number of replication of the model must be executed.

If the variables X_n of interest can be considered mutually independent and identically distributed (IID) with mean μ and finite variance σ^2, we can use the simple mean $\overline{X_n}$ to estimate the mean. Clearly, the classical case arises whenever we use independent replications to do estimation. In the classical case, the sample mean $\overline{X_n}$ is a consistent estimator of the mean μ by the law of large numbers (LLN). Then there is no bias and the MSE coincides with the variance of the sample mean, $\overline{\sigma_n^2}$, which is a simple function of the variance of a single observation X_n:

$$\overline{\sigma_n^2} = MSE\ (\overline{X_n}) = \frac{\sigma^2}{n} \tag{17}$$

Moreover, by the central limit theorem (CLT), X_n is asymptotically normally distributed as the sample size *n* increases, i.e.,

$$n^{1/2}[\overline{X_n} - \mu] \rightarrow N(0, \sigma^2) \text{ as } n \rightarrow \infty, \tag{18}$$

where *N(a,b)* is a normal random variable with mean *a* and variance *b*, and → denotes convergence in distribution. We thus use this large-sample theory to justify the approximation:

$$P(\bar{X}_n \leq x) \approx P\left(N\left(\mu, \frac{\sigma^2}{n}\right) \leq x\right) = P\left(N(0,1) \leq \frac{x-\mu}{\sqrt{\frac{\sigma^2}{n}}}\right)$$

(19)

Based on this normal approximation, a (1-α)100% confidence interval for μ based on the sample mean $\overline{X_n}$ is:

$$\left[\bar{X}_n - z_{\frac{\alpha}{2}}\left(\frac{\sigma}{\sqrt{n}}\right), \bar{X}_n + z_{\frac{\alpha}{2}}\left(\frac{\sigma}{\sqrt{n}}\right)\right] \quad (20)$$

where

$$P\left(-z_{\frac{\alpha}{2}} \leq N(0,1) \leq +z_{\frac{\alpha}{2}}\right) = 1 - \alpha \quad (21)$$

and α denotes the error (width of confidence interval divided by the estimated mean) admitted in the measure. The statistical precision is typically described by either the absolute width or the relative width of the confidence interval, denoted by $w_a(\alpha)$ and $w_r(\alpha)$, respectively, which are:

$$w_a(\alpha) = \frac{2z_{\frac{\alpha}{2}}\sigma}{\sqrt{n}} \quad (22)$$

$$w_r(\alpha) = \frac{2z_{\frac{\alpha}{2}}\sigma}{\mu\sqrt{n}} \quad (23)$$

For specified absolute width or relative width of the confidence interval, ε, and for specified level of precision α, the required sample size $n_a(\varepsilon,\alpha)$ or $n_r(\varepsilon,\alpha)$ is then

$$n_\alpha(\epsilon, \alpha) = \frac{4\sigma^2 z_{\frac{\alpha}{2}}^2}{\varepsilon^2} \quad (24)$$

$$n_r(\epsilon, \alpha) = \frac{4\sigma^2 z_{\frac{\alpha}{2}}^2}{\mu^2\varepsilon^2} \quad (25)$$

For detailed discussion about statistic aspect refer to Whitt (2005). Generally to calculate how many replications are needed for the precision required at first a certain number of replication of each configuration are run, the confidence interval and initial level of precision are determined. Thus the number of replication is calculated through equation (24) by fixing the desired precision.

The goal of this study is to show that applying an EOQ model for perishable product (taking into account the deterioration rate of its) and moving from the FIFO policy to the LSFO policy it is possible to improving warehouse performance. To achieve this goal the optimal order quantity (EOQ) is determined depending on some uncertainty sources that are internal the supply chain but sometimes uncontrollable as demand rate and deterioration rate. Thus a sensitivity analysis consisting in a three factorial experimental plan is presented in which each factor varies on two quantitative levels.

Experimental plan has been replicated to ensure a desired precision in the measures. To execute the experimental plan the simulation tool has been chosen as enabling the modeling of a real-life system. The simulation tool allows to model the system behavior when some stochastic input as RSL of products entering the warehouse are present, to determine RSL of products leaving the warehouse that represent the response of the experimental plan proposed.

5. PROPOSED METHODOLOGY

The study here presented focuses on the postharvest operations of perishable products that are transferred from the field to the refrigerated warehouse where they are before being shipped to the final retailer.

The first step carried out concerns the determination of the optimal warehouse management policy.

Initially the problem of determining the optimal batch size is considered, taking into account the deterioration cost of the product. It is in fact well known that traditional optimal policies such as the Economic Order Quantity (Wilson 1934) model which do not take into account deterioration costs, result in batch sizes which are generally unfeasible for perishable goods. According to the methodology here proposed the optimal order size is determined by equation (7) on the basis of the model reported in Section 3, and the TC_u is determined by equation (14).

Once the optimal batch size is determined, the proposed analysis focuses on the evaluation of the expected RSL of the products as they leave the warehouse after storage. This is carried out by considering an initial RSL value attributed to the products harvested as they enter the warehouse. Due to the inherent variability to the maturation level, the uncontrollable environmental conditions, and the variable duration of the harvesting operations, the RSL of the products entering the warehouse presents an intrinsic variability, it has therefore been modeled by means of a stochastic random variable. Such uncertainty has been taken into account in the analysis of the storage system by means of a simulation approach, considering the RSL of the products entering the warehouse, the demand rate, the deterioration rate as input parameters and evaluating the RSL of the products leaving the warehouse as the output parameter. Such output value is calculated in each run on the basis of the initial RSL and considering the deterioration of the products during the storage time, which is assumed to follow a Weibull function.

Thus the effect of the system parameters on the output variable has been explored by means of a simulation experiments plan specifically designed. The experimental plan has been replicated to ensure a desired precision of the measures obtained. Finally the effect of a shelf-life based picking rule has been compared to the traditional FIFO rule generally employed for perishable goods and a sensitivity analysis has been performed.

6. EXPERIMENTAL APPLICATION

In this paragraph a numerical application is proposed, based on experimental data. In particular a warehouse is considered for the allocation of a perishable product characterized by a Weibull deterioration model having α=0.2, β=1.5. The optimal batch size is determined considering A=50€, R=16 SKUs/day and h=0.1€/SKU/period. The product cost *(C)* has been considered equal to 0.5 €/SKU and the salvage value of the perished product is γC=0.01€/SKU.

Products that remain unsold at the end of the generic warehouse cycle are considered perished and thus sold at their salvage value.

In such conditions the TC_u is of 22.51€ which corresponds to a cycle time of 3.7 days. The optimal order quantity has been determined by equation (7) and is equal to 93 SKUs. The EOQ and the related optimal TC_u for different values of α is reported in Figure 1, and the corresponding Inventory level *I(t)* is reported in Figure 2. Such figures confirm that the optimal order size warehouse decreases when α increases.

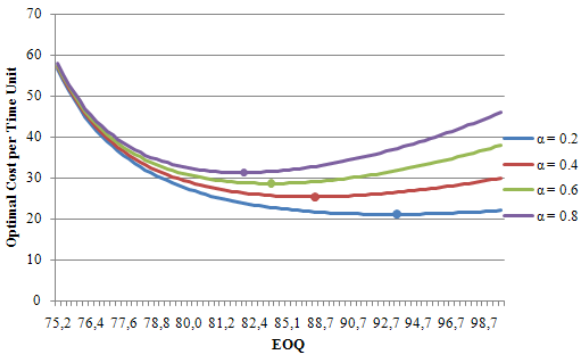

Figure 1: Optimal Order Quantity and Optimal Total Cost per Time Unit for several value of α

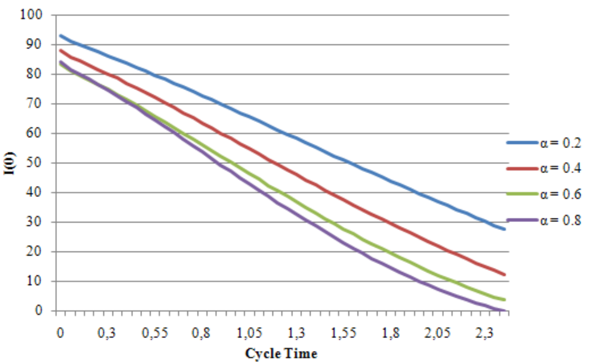

Figure 2: Trend of Inventory level for several value of α

For the same values of α and β the TC_u is reported in Figure 3 which shows that the cycle time related to the minimum total cost per unit time decreases when the α increases.

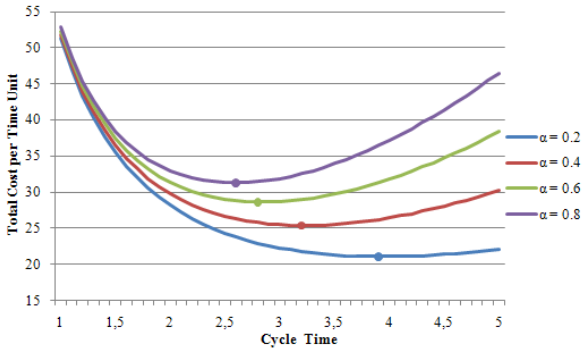

Figure 3: Cycle Time for different value of α

Once the optimal order size has been determined the effect of the inherent variability in the RSL of the products entering the warehouse has been addressed. In this study the RSL of the batches entering the warehouse has been assumed to be a stochastic random variable distributed according to a Normal density probability function with the following parameters: N(μ_{SL}=24 days, σ_{SL}=3.5). A simulation model has hence been generated in order to determine the distribution function of the RSL values of the products leaving the warehouse after the storage period, taking into account the deterioration process.

The simulation model thus generated has been employed to determine the performance of the system and to analyze the effect of different storage policies and picking rules. In particular, in the warehouse system considered three fundamental factors have been selected which affect warehouse performance. Such parameters are RSL of the incoming products, the demand rate and the deterioration rate. Based on the assumptions made in section 4 a three factors experimental full plan has been generated in which each factor varies on two levels, thus resulting in 2^3=8 configurations, as shown in Table 1.

Table 1: Experimental Plan

Scenario	RSL (Days at 10°C)	θ (Unit/unit time)	R (Batch/Day)
1	20	0.3	16
2	24	0.3	16
3	20	0.6	16
4	24	0.6	16
5	20	0.3	24
6	24	0.3	24
7	20	0.6	24
8	24	0.6	24

This experimental plan reports the input parameters used in the simulation model to get the response in terms of the warehouse performance.

The influence of two different policies FIFO and LSFO has also been investigated. This aspect has been modeled by ranking the products according to their RSL, once they are stored in the warehouse, and by using such rank in the picking list, when the LSFO policy is adopted. On the contrary, when the traditional FIFO policy is adopted, the products leave the warehouse based on their arrival order, products entering the warehouse the same day are therefore undistinguishable: they are thus inserted in the picking list randomly. In other words, when the LSFO policy is adopted, products inside the warehouse can be ranked even when they enter the warehouse in the same time. This ranking is clearly determined by the stochastic variation in the RSL of the incoming products.

The simulation model hence aims to determine the average RSL of products when they leave the warehouse, when the FIFO and LSFO policies are applied. To build the two simulation models the following assumptions and notation has been used: the interarrival time of the batches is deterministic and equal to (EOQ-Total perished)/Demand rate. For each configuration the EOQ quantity arriving at the warehouse is determined by equation (7) based on the demand rate and the deterioration rate reported in Table 1. The EOQ corresponds to one batch. For each SKU in the batch is assigned a RSL value within the normal distribution; the RSL of the products entering the warehouse decreases with time each day the stocks are held in the warehouse. The RSL at the shipping time is then determined based on equation (5), by fixing E_a equal to 59.7 Kj mol^{-1} (which is the activation energy of CO_2 production for the avocado fruit, Fonseca 2001) and by considering that the storage temperature is equal to 10°C.

To ensure that the values determined by the simulation satisfy the principles of quality control, a required precision has been fixed equal to 95%. Thus 10 warehouse replenishments cycles corresponding to 10 replications of the simulation have been carried out in the two cases in which LSFO and FIFO are applied and the confidence interval for each measure of interest has been determined. Then the equation (24) has been employed to calculate the number of replications needed in the two cases. The number of replications necessary to ensure the desired precision for each of the measures of interest for the experimental plan is 23 equivalent to 8*23=184 tests for each of the two scenarios (FIFO and LSFO). The performances of the warehouse system for the two policies under study are illustrated in Table 2 and Figure 4.

Table 2: Results of the Experimental Plan

Scenario	Average RSL (Days)		σ_{RSL} (Days)		Average Number of products with a RSL_{exit} equal to Average RLS_{exit} ±1	
	LSFO	FIFO	LSFO	FIFO	LSFO	FIFO
1	16.835	16.862	1.442	3.596	75	30
2	20.835	20.862	1.442	3.596	75	30
3	17.424	17.429	1.416	3.391	46	29
4	21.424	21.429	1.416	3.391	45	29
5	18.008	18.034	1.996	3.273	57	32
6	22.008	22.034	1.996	3.273	57	32
7	18.420	18.426	1.936	3.144	56	30
8	22.420	22.426	1.936	3.144	56	30
Average value	19.672	19.6875	1.697	3.35	58.375	30.25

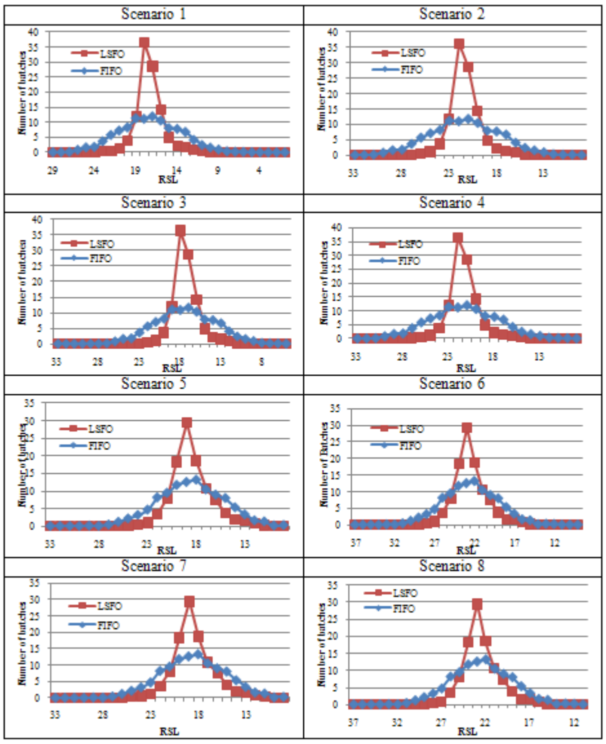

Figure 4: Average Number of products leaving the warehouse and their RSL for the two picking policies in each scenario of the Experimental Plan

For both the FIFO and the LSFO policy, in each test configuration and for each run, the number of products leaving the warehouse with the same RSL_{exit} has been calculated. The average of such values in the 23 runs has finally been determined and reported in Table 2. The results show that the average RSL_{exit} of products leaving the warehouse is the same for both LSFO and FIFO policies, while the average standard deviation differs substantially (in the FIFO policy is more than two times higher than LSFO). In any case, as expected, the best value of the response is obtained when the RSL of the incoming products is at its high level, the deterioration rate is at its low level and the demand rate is at its high level (Scenario 6 of the experimental plan). Table 2 also shows that when the LSFO policy is applied a greater number of products have a RSL about equal than the average RSL value ±1 compared to the case in which the FIFO policy is applied allowing an improving in quality of 46.64%.

Based on the experimental plan realized an analysis of the factors has been conducted to determine their impact on the response in the two cases in which LSFO and FIFO policies are applied. Results are shown in Table 3 and 4.

Table 3: Factorial Analysis for LSFO and FIFO policy

LSFO	Effect	Coefficient	T	P
Constant		19.6718	893.41	0.00
RSL	4.0	2.0	90.83	0.000
θ	0.5008	0.2504	11.37	0.000
R	1.0847	0.5424	24.63	0.000
FIFO				
Constant		19.6875	895.64	0.00
RSL	4.0	2.0	90.99	0.000
θ	0.4794	0.239	10.90	0.000
R	1.0846	0.5423	24.67	0.000

Table 4 ANOVA for LSFO and FIFO policy

ANOVA		
LSFO	DF	SS
Main Effects	3	34.8548
Residual Error	4	0.0155
Total	7	34.8703
FIFO		
Main Effects	3	34.8121
Residual Error	4	0.0155
Total	7	34.8275

Results show that in both cases the initial RSL ,the demand rate and the deterioration rate has positively influence on the response. In both cases the effect which contributes mostly to improving the performance is initial RSL. The ANOVA analysis shows that the three main factors are responsible for the 99.9% of the total variance.

Based on coefficients shown in Tables 3 the response surface are determined for the experimental plan with equation (16) by considering only the first order terms. The two response surfaces referred respectively to LSFO and FIFO responses are:

$$y = 19.67 + 2RSL + 0.250\vartheta + 0.542R + \epsilon \qquad (26)$$

and

$$y = 19.68 + 2RSL + 0.239\vartheta + 0.542R + \epsilon \qquad (27)$$

The high value of R-Sq equal to 99.9% for LSFO and FIFO shows that the linear model obtained with the two response surfaces actually represents the relation between the predictors (initial RSL, deterioration rate and demand rate) and the response (RSL_{exit}). This result can be employed to investigate the behavior of the response without the need of to run further simulations thus allowing to gain fast information about the warehouse system behavior when the input parameters vary.

7. CONCLUSIONS

The optimal management of supply chain for perishable products is a relevant research topic which has recently gained attention due to the poor sustainability of such systems. Agri-Food supply chains are in fact affected by several inefficiencies which typically result in a high industrial cost and in an ethical and social concern. Since deterioration phenomena are generally influenced by the temperature, the logistic operations are carried out in refrigerated conditions, in the so-called cold chain. Ensuring a specified temperature through the supply chain, however, does not ensure the avoidance of deteriorated products through the supply chain, since other important supply chain parameters such as the order quantity or the lead times have a strong effect on the performance of the chain. Finally, some uncertain parameters are involved in the process, which must be taken into account. Optimizing the performance of such systems is hence a complex task, which involves a good knowledge of the deterioration processes in order to properly assess the deterioration costs. In this paper a simulation model is proposed to evaluate the performance of a warehouse system for perishable products taking into account the effect of the uncertainties which typically affect the supply chain. In particular, a mathematical model is employed to determine the optimal stock level and the effect of shelf-life based picking policy on the performance of the supply chain. The results of the experimental plan proposed show that in the case considered the average RSL_{exit} of products leaving the warehouse is about the same for both LSFO and FIFO policies, while the average standard deviation differs substantially (in the FIFO policy is about two times higher than LSFO). When the LSFO policy is applied, thus, a greater number of products have a RSL_{exit} about equal than the average RSL_{exit} value ±1 to compared to the case in which the FIFO policy is applied allowing an improvement in the quality of 46.64%. The effect of input parameters has been studied emphasizing the role of the deterioration rate as the factor which the most influences the response. Finally the response surface has been built representing a tool able to predict the warehouse behavior for any variation of the input factors considered allowing the optimization of perishable warehouse management policies.

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