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Facoltà di Ingegneria

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PhD Thesis: Sviluppo di modelli decisionali per la supply chain di prodotti deperibili mediante l'applicazione di tecnologie innovative

PhD student:
ing. Cinzia Muriana

Coordinatore corso di dottorato:
ch.mo prof. Livan Fratini

Tutor:
ch.mo prof. Antonio Barcellona

Co-Tutor:
ch.mo prof. Mario Enea

Relatore:
ch.mo prof. Giuseppe Aiello

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Abstract

The supply chain of perishable products, as fruits and vegetables is affected by environmental abuses from harvest to the final destination which are responsible the uncontrolled deterioration of food. In order to reduce such phenomena the supply chain members should control and monitor the conditions of goods in order to ensure their quality for consumers and to comply with all legal requirements (Garcia Ruiz, 2008). The most important factor influencing the food quality is the temperature able to prolonging the shelf life of the products. Since the temperature can inhibit or promote the maturation and deterioration process, this parameter is involved both in the growing process of fruits and vegetables and in the transport and storage stages. Given this the aim of the present thesis is to show that the monitoring of such parameter during the pre and post harvest stages allows to improve the decision making process. In the context of temperature monitoring the introduction of emerging information technologies such as the Wireless Sensors Networks and the Radio Frequency Identification can now provide real-time status knowing of product managed. The real time monitoring can be of great help in the definition of the actual maturation level of products both in the field and during the cold chain. The suitability of such an approach is evaluated by means of case studies. The first case study concerns the monitoring of grapes growth directly in the vineyard. The suitability of Wireless Sensors Networks in the monitoring of the grapes growth process is evaluated in terms of the possibility to determine the date of starting or ending of phenological phases. This information allows to make faster decisions about the vineyard operations which must be performed during the grape growth and finally allows to predict the maturation date in order to optimize the harvest operations. In the next case study the possibility to apply the Radio Frequency Identification technology to the monitoring of the fresh fruits along the cold chain has been faced and the quality of the products at any stage of the supply chain has been determined through a mathematical model. The knowing of the current quality level allows to make decisions about the destination of products. In this case those products having a shorter shelf life can be distributed to a local market while those with longer shelf life can be distributed to more distant location. In the next case study the information about the current deterioration state of perishable products has been translated into a warehouse management system in order to determine the operational parameters able to optimize the quality of products stored. Even in this case the goal of the study was to provide a decision making tool for the proper management of the perishable products stored. However besides the advantages achievable by the real time evaluation of environmental conditions the costs involved with the implementation of innovative technologies must be determined in order to establish the suitability of the investment in such innovative technologies. The present thesis also faces this question by determining the optimal number of devices to apply to the stock keeping unit in order to minimize the total cost associated to the transferring batch from the producer to the distributor. In this case the methodology employed is that of a mathematical model including all costs associated to the product management. Finally the study conducted through the present thesis shows that in all of the cases treated the use of the innovative technologies allows to support the decision making process in the pre and post harvest phases thus improving the perishables management.

Acknowledgements

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INTRODUCTION

Problem Statement

Perishable goods such as fruits, fresh cut produce, meat, and dairy products represent an important percentage of the grocery turnover. In the US for example they account for over 50 percent of the $400 billion annual turnover of the US retail grocery industry. The management of such products is a crucial task for the entire supply chain. In fact improper storage, transport, and handling conditions often result in unsellable products and lead to out-of-stock situations. The impact of inefficient management of perishables also becomes apparent on a broader economic scale. For instance, Ilic and al. (2008) report that 10 million tons or 10 percent of the total industrial and commercial waste in the UK are caused by perishable food products. 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 percent of the perishables are lost due to spoilage. In this context the need is perceived to develop supply chain models able to optimize the management of perishables. Such task involves the important choice between supply chain efficiency and responsiveness. Generally speaking this decision must be taken on the basis of the product and market characteristics. In fact there are products whose quality with time can be considered fixed and others which lose quality with time. With regard to the latter category, a further distinction must be done between models that deal with degradation of product quality and value over time. Concerning this topic a number of frameworks have been proposed for supply chain design. Fisher (1997) proposed a taxonomy for supply chains based on the nature of the demand for the product. He distinguished between functional products (stable, predictable demand, long life cycle, slow “clockspeed”) and innovative products (volatile demand, short life cycle, fast “clockspeed”). The first require that the supply chain be designed for cost efficiency, while the latter that the supply chain be designed to be fast and responsive. Later on Blackburn et al. (2004) find that, for returned products that lose value rapidly over time, the supply chain should be responsive in the early stages and efficient in later stages. These studies suggest that supply chain strategies based on a simple choice between efficiency and responsiveness can be inappropriate when the product undergoes substantial differentiation or change in value as it moves through the chain. Furthermore research on the perishability of fresh produce indicates that the loss in product value and quality is at its highest rate immediately post-production (at harvest), and the rate of loss in value declines until the produce finally “spoils” (Hardenburg et al. (1986), Appleman and Arthur (1919)). Given this Blackburn and al. (2008) showed that this is the case for perishable produce: the value of the product changes significantly, and the appropriate supply chain structure should be responsive in the early stages and efficient in the later stages. This condition allows to reduce the loss of quality during the early stage of the supply chain (production) and to optimize the management costs (transportation, stock, disposal and deterioration costs) during the other stages. As results clear the limited lifetime and the deteriorating quality of perishable goods over time contribute greatly to the complexity of their management. The reaching of a tradeoff between responsiveness and efficiency in the supply chain mainly depends on the possibility to timely know the quality level of products both along the maturation stage and within the cold chain. This information allows to properly select the products on the basis on their remaining quality. The major challenge in this context, however, arises from the dependency of the remaining lifetime and quality on environmental factors such as temperature, relative humidity, and shock. In most supply chain operations, these factors are difficult to control. Even if the products are distributed being stored at proper environmental conditions some environmental abuses can occur that often lead to quality drops. In addition, two other conditions must be taken into account consisting in the variability of the maturation level of products due to decisions about harvest scheduling and the harvest phases which are performed outdoor under uncontrolled environmental conditions. These two conditions affect the product by giving an intrinsic variability in the initial quality of products entering the cold chain. Consequently, even products which have been harvested at the same time may arrive at the consumer with different quality levels. The quality decreasing are often difficult to assess by using the sensorial analysis. Perceptible changes in color and consistency mostly become apparent only during the later stages of a product's life (i.e. mostly on the sales floor), and therefore human-sense-based examinations are hardly able to aid decision making with respect to the future distribution of products (see Ilic and al. (2008)). Furthermore it must be considered that the temperature is the factor which most influencing the product quality since it can promote or inhibit intrinsic properties of products like the pH, the sugar content, etc., which are indicative of the deterioration state, and the traditional sensorial analysis are not able to detect these intrinsic properties. As a result, inherent supply chain problems are often not recognized when they occur, deficient shipments are further processed as planned even if the product will be spoilt before reaching the end customer, and products on the sales floor cannot be arranged in an optimal way with respect to their remaining shelf life. While the human senses have only a limited capability to assess the intrinsic product properties, modern sensor technologies such as the Wireless Sensor Networks and the Radio Frequency Identification can help to provide the required information. Tracking environmental parameters such as temperature for individual logistic units allows problems in the supply chain to be spotted and the actual quality levels of individual products to be more precisely predicted (Sahin and al. 2007), all of which aids the decision making with respect to the future distribution of products. Naturally the implementation of innovative technologies involve some infrastructural costs. The economic impact of these technologies must be taken into account when study their ability to improve the supply chain management.

Scope of the thesis

In this work the attention is focused on the study of the application of innovative technologies to the supply chain of perishable products in order to show the contribution of these technologies in realizing the dual aspect of responsiveness/efficiency of the supply chain. This goal is achieved by monitoring the environmental conditions of products both during the maturation process in the field (preharvest phases) and along the supply chain (postharvest phases). With regard the preharvest phases the monitoring allows to optimize the scheduling of operations which must be performed in the field as fertilization and pruning as well as the harvest operations. The precise scheduling of operations contributes to improve the responsiveness of the supply chain by allowing the fast response to market requirements. With regard to the postharvest phases the attention is focused firstly on the entire supply chain by showing that the monitoring of environmental conditions can be translated into the current quality level thus optimizing the efficiency of the supply chain by choosing the proper destination of products on the basis of their quality level. Afterwards the focus is paid on the warehouse management system by showing that the efficiency in terms of supply chain costs can be achieved by accurately choosing the operational parameters consisting in the optimal batch size and the picking policy for products outgoing the warehouse. Even in this case the monitoring of current quality level of products stored contributes to optimize the costs involved by allowing the use of picking policies based on the current quality level. Once showed the contribute that the innovative technologies can bring in the achievement of the responsiveness/efficiency of the supply chain the attention is focused on the affordability of the investment in innovative technologies. To this respect the focus is done on the determination of the optimal number of devices to apply to the stock keeping units in order to minimize the total cost function involved with the transfer of the products from the producer to the distributor. The scope of the present thesis is to develop models and methodologies to support the supply chain members and their decisions in order to properly manage the perishable goods along the stages of the supply chain thus improving the responsiveness of the chain in the early stages and its efficiency in the others. The models proposed will be implemented by mean of innovative technologies, in order to show their contribution in the supply chain decision making.

Structure of the thesis

The present thesis is organized as follows:

- Section 1 deals with the use of innovative technologies for the monitoring of ripening process of grapes. This section is divided in four chapters. At first a brief introduction about the expert systems has be made (Chapter 1), thus the monitoring of grape growth is faced on the basis of the traditional methodologies and of new methodologies based on the climatic detection (Chapter 2). Afterwards the Wireless Sensors Network technology is presented in order to explain the potential of such technology in the vineyard management (Chapter 3) and finally a case study is presented in which a model for an expert system capable to predict the start or the end of each phenological phase is proposed.
- Section 2 deals with the monitoring of environmental conditions of perishable products along the supply chain with the aim to determine the remaining quality of products at each stage of the chain. The section is divided in three chapters. At first an introduction about the relation between the product quality and the environmental conditions is done and a methodology for the assessment of the quality level of products by starting from the environmental conditions is taken into consideration (Chapter 1), thus the Radio Frequency Identification technology is presented in order to explain the tool employed to perform the monitoring (Chapter 2) and finally the case study is presented (Chapter 3).
- Section 3 deals with the decision making process in the inventory management. This section is divided in three chapters. The first argument treated is about the perishable inventory theory (Chapter 1), thus the design of simulation experiments is presented in order to illustrate the tool employed to perform the warehouse management system analysis and finally a warehouse management system is proposed through an experimental analysis (Chapter 3).
- Section 4 deals with the affordability of the investment in innovative technologies and it is divided in two chapters. The first argument treated is about the innovative techniques able to predict the remaining quality of products by starting from the conditions characterizing the environment around the product itself and a methodology using the Radio Frequency Identification technology is presented (Chapter 1). On the basis of this methodology a mathematical model is presented and the optimal batch size as well as the optimal number of devices to apply to the stock keeping units is determined (Chapter 2).

SECTION 1: INNOVATIVE TECHNOLOGIES FOR THE MONITORING OF RIPENING PROCESS

INTRODUCTION

The monitoring of ripening process is a topic extensively faced by viticulturist due to the importance of such process in determining the quality of wine. In fact the knowledge of the maturation level allows to optimize the scheduling of vineyard operations to be performed during the growth process (as the fertilization and other operations aiming at avoid pest and disease) and the harvest operations. However the assessment of the correct ripeness depends on the intended use for the grapes and it is influenced by the variety cultivated in the growing region. In such context even the common maturity parameters based on chemical composition of grapes as sugar, acid and pH depend from the variety considered. Generally speaking they are determined by genetic makeup of the variety and influenced by environmental conditions and growing practices. Since environmental parameters play a fundamental role on grape maturation, several researchers have faced the problem of determining the maturation level of grapes starting by the monitoring of pedoclimatic conditions. They have established a relation between the temperature perceived and the heat stored by plants which can be used to determine the maturation level as a function of temperature. This relation can be expressed through some indexes known as pedoclimatic indexes. Traditionally they are employed to determine the territorial vocation to the cultivation of a specific variety of wine. In this study the attention is focused on the application of pedoclimatic indexes to the determination of the maturation level of grapes. In this context the monitoring of environmental parameters is of fundamental importance. Until now this task has been accomplished by using weather stations aerial or satellite systems. However these systems are not able to monitor the microclimate in the vineyard where due to the disposition of grapes, the terrain slope, the light exposure of terrain and the humidity, the temperature perceived by grapes can be significantly different to respect the air temperature. Today the monitoring of the microclimate conditions in the vineyard is made possible by innovative technologies as Wireless Sensor Networks (WSN), composed by pervasive sensors able to detect environmental parameters around the plant during the ripening process. The present section aims at presenting an expert system based upon the monitoring of environmental parameters in the vineyard by means of a WSN. The core of the expert system proposed consists on the application of a growth model based on pedoclimatic indexes to the prediction of the start or the end of phenological phases of grapes by using a knowledge base which makes use of thresholds. By starting from the pedoclimatics index value the inference engine of the expert system proposed forecasts future value of such index by means of statistical models. The possibility of realizing a such system will allow to reduce the need of grape sampling and increase the precision of vineyard operations because of fact that the prediction of start or end of each phase allows to optimize those activities which must be performed at the transition from a phenological phase to another. The section is organized as follows: Chapter 1 deals with a brief abstract about expert systems. Chapter 2 is spent for the illustration of pedoclimatics indexes. Chapter 3 exposes a qualitative description of WSN and their main applications fields. Finally the model of the expert system is exposed through a case study presented in Chapter 4.

CHAPTER 1

1.1. Expert Systems

Expert Systems (ES) are interactive computer-based decision tools that use both facts and heuristics to solve difficult decision making problems, based on knowledge acquired from an expert. They are designed to simulate the problem-solving behavior of an expert in a narrow domain or discipline . ESs are used in several fields to perform many services which previously required human expertise. An ES reasons with judgmental knowledge as well as with formal knowledge of established theories, it is transparent i.e., it provides explanations of its line of reasoning and answers to queries about its knowledge, and flexible i.e., it integrates new knowledge incrementally into its existing store of knowledge. ESs have a number of major system components and interface with individuals who interact with the system in various roles. Such components are illustrated in Figure 1. As you can see from this figure an ES is composed by:

- Knowledge base
- Working storage
- Inference engine
- User interface
- Individuals who interact whit the system.

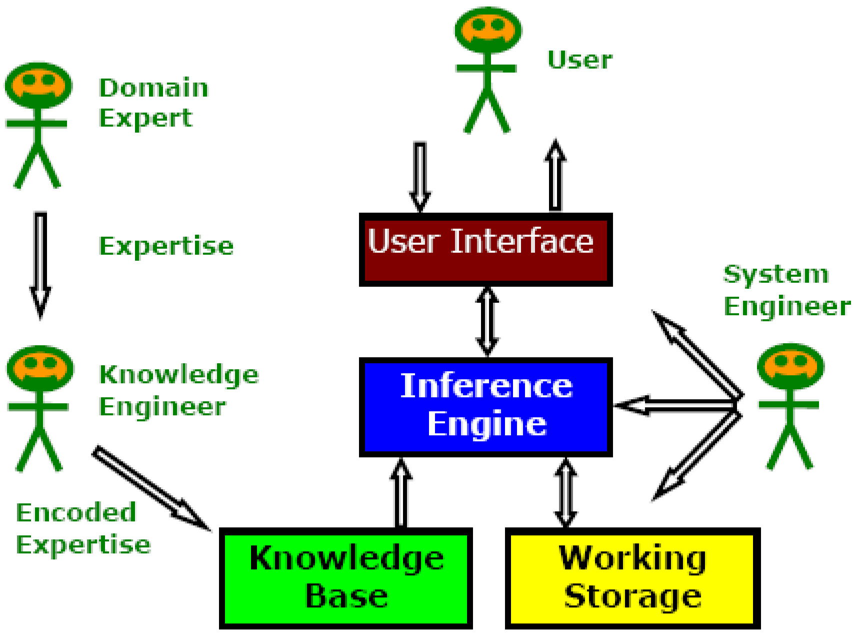


Figure 1. Components of an Expert System

The operating principle of an ES consists of a dialogue conducted by the user interface between the user and the system. The user provides information about the problem to be solved and the system then attempts to provide insights derived (or inferred) from the knowledge base. These insights are provided by the inference engine after examining the knowledge base.

The **knowledge base** consists of some encoding of the domain of expertise for the system. This can be in the form of semantic nets, frames, or production rules. Semantic nets represent the knowledge in terms of objects and relationships between objects. Objects are denoted as nodes of a graph. The relationship between objects are denoted as a link between the corresponding two nodes. The most common form of semantic nets uses links between nodes to represent IS-A and HAS relationships between objects. Frames represent the knowledge by decomposing it into modular pieces called frames, which are generalized record structures. Knowledge consists of concepts, relationships between concepts, and procedures to handle relationships as well as attribute values. In frame representation each concept may be represented as a separate frame. Attributes, relationships between objects and procedures are allotted to slots in a frame. The concept of a slot may be any data type – numbers, strings, functions or procedures and so on. Frames may be linked to other frames, providing the same kind of inheritance as that provided by a semantic network. A frame-base representation is ideally suited for object-oriented programming techniques. Production rules occur in sequences and are expressions of the form:

$$if\ < conditions >\ then\ < actions >$$

where if the conditions are true then actions are executed. Conditions are expressions involving attributes and the logical connective *and*. Several examples are:

temperature > 110
distance < velocity*(time1 - time2)
cost > budget and demand = low

Attributes are of course like programming language variables and have types which must be numerical or string. (A string type variable can possess a value from a set of strings, for example: {true, false} or {red, yellow, green}.). An action list consists of tasks which must be executed when the conditions are satisfied (e.g. a “print” command).

The **inference engine** is a generic control mechanism for navigating through and manipulating knowledge and deduce results in an organized manner. The inference engine’s control mechanism applies the knowledge present in the knowledge base to the task specific data to arrive at some conclusion. In the case of use of production rules the inference engine operates by examining rules and actions are executed if the information supplied by the user satisfies the conditions in the rules. The most common techniques for drawing inferences from the knowledge base are the Forward chaining , the Backward chaining and the Tree search. Forward chaining is a top-down method which takes facts as they become available and attempts to draw conclusions (from satisfied conditions in rules) which lead to actions being executed. Backward chaining is the reverse. It is a bottom-up procedure which starts with goals (or actions) and queries the user about information which may satisfy the conditions contained in the rules. It is a verification process rather than an exploration process. Tree search represents the knowledge as a branching network or tree. Many tree searching algorithms exists but two basic approaches are depth-first search and breadth-first search.

1.2. Expert Systems in agriculture

Agricultural production has evolved into a complex business requiring the accumulation and integration of knowledge and information from many diverse sources. In order to organize these information into the knowledge and facilitate the decision making, expert systems were identified as a powerful tool with extensive potential in agriculture. Expert systems have been in fact developed for many kinds of applications in agriculture (Carrascal and Pau, (1992)), and the importance of climatic conditions in scheduling harvesting (see for example Machado et al, (2004)) and soil management operations such as weed control, herbicide selection and pest control and irrigation is nowadays well recognized (e.g. Castro-Tendero and al. (1995), and Murali et al., (1999)).

Main application fields in agricultural are:

1. Diagnosis of disease
2. Assessment of the climate, water and soil properties
3. Scheduling of maintenance operations in the field
   - Fertilization
   - Irrigation
   - Pest control
   - Pruning
4. Control of environmental growth factors

ESs for each of these application are listed in literature. For more detail about e ESs in agricultural see for example Rafea and Prasad (2006). In all these application fields ESs help to make a decision about actions to be realized in order to optimize operations in the field.

The aim of the present study is to propose a model for an ES which allows to monitor the ripening process of grape berries in the vineyard by starting from the monitoring of environmental factors affecting grape growth. The ES will make use of a growth model based on pedoclimatic indexes which will be illustrated in the next Chapter 2. This will allow to predict the date of starting or ending of each phenological phase thus helping farmers to properly schedule interventions both during ripening process and at the harvest time. The model of the ES proposed will be illustrated in Chapter 4.

CHAPTER 2

2.1. Introduction

In the previous Chapter the main characteristics of ESs have been briefly illustrated. The main conclusion has been that ESs are useful tools in agricultural applications. Furthermore it has been underlined that climatic information can be comprised in the knowledge base of an ES in order to properly schedule agricultural operations. In this study the application of ES to the monitoring of grape ripeness is presented. In order to achieve this goal the ES proposed makes use of pedoclimatic indexes able to predict the start or the end of phenological phases. In this Chapter environmental factors affecting grape ripeness are illustrated and pedoclimatic indexes are presented to explain their potential in determining the start or the end of phenological phases.

2.2. Grape ripeness assessment

The production of high quality wines requires precise and accurate operations both in the vineyard and in the vinery. In order to achieve high quality production, it is crucial that viticulture operations and harvesting activities occur at the correct phenologic maturation level. In particular the scheduling of the harvesting operations has a fundamental role, as in fact grapes that are harvested before the optimal maturity level result in the production of green, acidic wines while late harvesting generally results in unbalanced fruit composition. The decision processes concerning vineyard operations are mostly subjective and involve the interaction between the enologist and the vineyard manager, which have different priorities and objectives. The enologist is mostly concerned about wine quality, while the vineyard manager considers more specific agricultural variables, including operational costs, thus originating the well known tradeoff between quality wine and grapes yield. The vineyard management decision processes hence involves different stakeholders with different objectives, multi criteria decision making methods (MDM) should therefore be applied to determine the best compromise decisions.

Generally speaking the vineyard operations can be branched into two main areas: viticulture maintenance and harvesting. Viticulture maintenance concerns all the operations related to fertilization irrigation pest and disease control, pruning level and soil management, while harvest operations involve sampling, monitoring, ripeness assessment and all other activities required to establish the harvesting time and to schedule the harvest operations. In both contexts, the assessment of grape maturity level is a primary information for winemakers and enologists. The date when optimal maturity is reached or when a new phenologic phase is entered, varies depending upon the quality of wine, the varietal typology of the vines, the site climatic conditions, the seasonal specific factors and the viticulture practices. A general classification of the elements which influence vineyard operations is represented in the following Table 1.

Soil Management	Climate	Cultural practice
Depth **Texture** **Phitosanization**	Radiation Temperature Humidity Windspeed Rainfall Evaporation	Vine density Section and rootstock variety Fertilization Irrigation Pest & Disease control Pruning Level

Table 1. Elements which influence viticultural maintenance decisions and operations

Due to the complexity of the decision processes involved in vineyard management, viticulturists have developed an assessment method based upon the establishment of a set of indicators to be evaluated experimentally by periodically sampling the vineyard. Since ripe wine grapes are very perishable, and are at their best for just a few days, the decision about the harvesting time is such an important decision that most winemakers and grape growers start sampling grapes several weeks before the harvest time and continue sampling with increasing frequency as harvest time approaches. The maturation process is then monitored on the basis of growth models and corresponding maturation curves reporting flavor aroma constituents, phenolics, color compounds, sugar content, pH and total acidity of the samples. The decision about vineyard management operations and harvesting time are hence undertaken when in the ripening process a correct balance among such indices is achieved, considering the typology of wine to be produced. The values generally considered for the harvesting decision (Amerine et al. (1980)), for example, are given in the following Table 2, while Figure 2 shows an example of maturation curves.

Kind of wine	Soluble solids (Brix)	Total Acidity (g/l)	pH
Sparkling wine	18.0 – 20.0	7.0 – 9.0	2.8 – 3.2
White wine	19.5 – 23.0	7.0 – 8.0	3.0 – 3.3
Red wine	20.5 – 23.5	6.5 – 7.5	3.2 – 3.4
Sweet Wine	22.0 – 25	6.5 – 8.0	3.2 – 3.4
Dessert Wine	23.0 – 26	5.0 – 7.5	3.3 – 3.7

Table 2. Parameters for harvesting decision for different wines

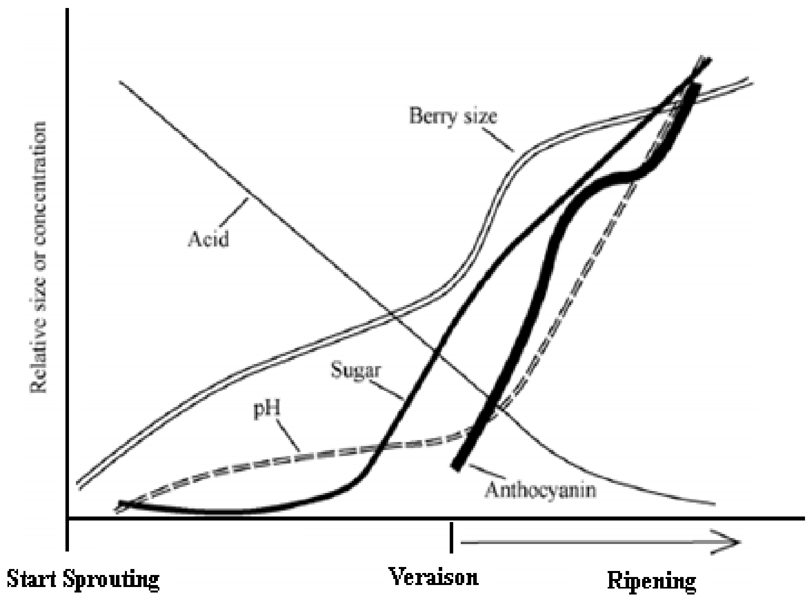


Figure 2. Maturation curves

Recent efforts for reducing the vineyard sampling costs and improving management strategies have lead to the establishment of precision farming techniques based on the correlation of the climatic condition to the growth of the vine grapes, thus relying on environmental data to support the vineyard operations. The effect of climatic conditions on the ripening process has been studied by several researches (Jones and Davis (2000), László et al. (2009)) although the resulting growth models are mainly employed to assess the compatibility of a certain area with a certain variety rather than supporting the vineyard decision processes. Environmental conditions that essentially affect grape ripeness are temperature, solar irradiation, relative humidity, and rainfall. Table 3 summarize the effect of such parameters on grapes development.

Parameter	Effect on ripeness	Period of action	Damage caused	Importance of detection
Temperature	can anticipate or delay each stage	From Flowering to ripening	Below 10 °C or above 35°C development of plant stops	Prediction of maturation of grapes
Solar Irradiation	affects sugar accumulation	Especially during ripening	grapes may have a sugar content not ideal	Possibility to establish optimal level of sugar
Relative Humidity	contributes to germination of some fungi	Especially during flowering and veraison	Development of infections and diseases that to kill the plant	Allows to establish risk of disease and realize actions of infections prevention
Rainfall	allows the development of molds	Especially during spring	Allows the development of molds	

Table 3. The parameters mainly influencing the grape ripeness

In particular the temperature plays a fundamental role for grape maturation, since it influences both the chemical composition of grapes by inhibiting or promoting sugar accumulation and sensorial aspects as the aroma and the coloration (Tonietto and Carbonneau (2004)). The importance of monitoring such parameter is due to the fact that it triggers the start of every phenological phase of ripening process. Sprouting for example generally starts when daily temperature reaches the minimum temperature that ensures the recovery of vegetation (between 8 to 13 °C). Flowering happens 6- 8 weeks after sprouting and generally starts when temperatures reach 16 – 20°C. Veraison happens when temperatures reach 22°C and involves the sugar accumulation and acidity reduction processes as well as accumulation and processing of many other phenolic substances (see Figure 3). As the berries approach full maturity, berry size reaches a maximum and sugar accumulation slows (see Hellman (2004)). This phase requires temperatures between 18 and 24°C.

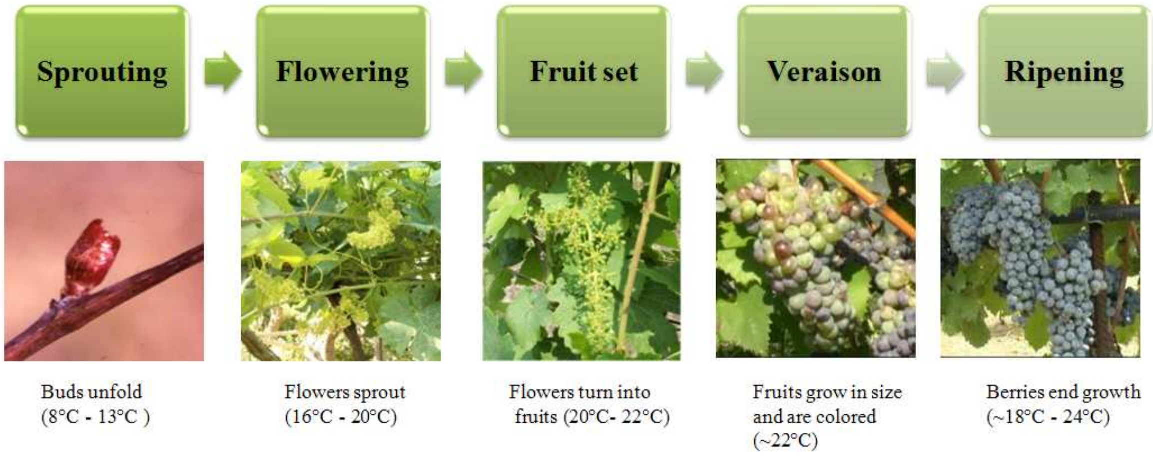


Figure 3. The phenological phases of the ripening process

2.3. Grape growth models: Pedoclimatic indexes

According to aforementioned considerations, growth models have been developed taking into account the relation between the temperature and the ripening process. In such context hence, grapes ripeness can be related to the heat that the plant has stored allowing it to move from one phenological phase to the next. Heat needed to reach one phenological phase is commonly expressed through the heat quantity that a plant can store depending on daily temperatures, which define the "Sum of Active Temperatures"(STA), expressed in "degree day"(DD). STA allows to express phenological cycle length or single phase length in terms of thermal units according to the following equation (Duchêne and al. (2005)):

$$STA = \sum_{i=1}^{n} \frac{(T_{Max}+T_{min})_i}{2} - cardinale\ min \quad (1)$$

where T_{Max} and T_{min} are the maximum and the minimum of daily temperatures; if T_{Max} is more than 35°C, T_{Max} is posed equal to this value. *Cardinale* min is the "zero vegetative", i.e. sprouting temperature. The *cardinale*min value must be determined each in turn because it depends on the climate of the area and by the type of cultivation considered. It has been verified that the "zero vegetative" can move from 6.9°C (Typically in Valle d'Aosta) to 16.5°C (Typically in Argentina). As an alternative the zero vegetative can be set equal to 10 °C (Branas and al. (1946)). On the basis of this growth model some researchers have proposed numerical index such as the Winkler Index (WI) (see Winkler and al. (1962) and Winkler (1948)), the Huglin Index (see Huglin (1986) and Huglin (1983)) and the Fregoni Index (see fregoni and al. (2002)). WI is known also as "thermal sum", because it is calculated as sum of all average daily temperatures (T_{med}) that there are from sprouting to ripeness and harvest, that is supposed to be on October. Because in the most of cases it is acceptable that the minimum temperature at which grape develops is 10°C, this value must be subtracted from the sum of daily temperatures. WI represents the concept that "more heat more ripeness", and it is calculated by means of the following equation (found in Orlandini et al. (2005)):

$$WI = \sum_{1/4}^{31/10} (T_{med} - 10) \quad (2)$$

where negative values of (T_{med}-10) should be set to zero.

Because WI does not consider days with average temperatures less than 10°C, the Huglin index has been proposed which also includes the maximum daily temperature (T_{Max}) and takes into account the different length of day between areas that are to different latitude by means of a coefficient K which increases with latitude (see Orlandini and al. (2005)).

$$HI = \sum_{1/4}^{30/9} \frac{(T_{Med}-10)+(T_{Max}-10)}{2} * K \tag{3}$$

Winkler and Huglin indexes applied to each phenologic phase allow to determine when a phase happens and then when grapes move from one phase to the next. Finally, Fregoni index allows to evaluate grape vine quality, when the following conditions are satisfied: the daily temperature range is high, in the months preceding the ripeness grapes have to reach STA values allowing the start of ripeness and in the month preceding the harvest temperatures are cool.

$$FI = \sum_{1}^{30}(T_{Max} - T_{min}) * Nh_{(T<10°)}, \tag{4}$$

where $Nh_{(T<10°)}$ is the number of daily hours with temperature less to 10° in the thirty days previous harvest.

Finally, since when temperature is more than 35°C grape development partially stops it is more realistic to consider this value as upper bound for the temperature. Accordingly to this it is possible to define a Standardized Winkler Index that reset to zero temperatures over 35°C. WI can be formulated as following:

$$NWI = \frac{3600}{553392} * \sum_{1}^{4392} T_i \tag{5}$$

where T_i are the average hourly temperatures in the 4392 hours between 1/4 and 30/9. For a more detailed discussion about pedoclimatic indexes see Eynard and Dalmasso (1990) . The establishment of referenced growth models based upon the aforementioned indices allows to determine the phenologic maturation process by means of suitable thresholds. In particular thresholds calculated with Winkler and Huglin indexes for the ripening process for different cultivar varieties and wine products are given in the following Tables 4 and 5.

Winkler Index at ripening stage	**Red**	**White**
1,200 – 1,400	Gamay, Pinot Nero	Chardonnay, Riesling, Traminer Aromatico
1,400 – 1,600	Cabernet Franc, Cabernet Sauvignon, Gamay, Grignolino, Malbech, Merlot, Pinot Nero,Ciliegiolo	Albana, Chardonnay, Riesling, Pinot Bianco, Sauvignon, Trebbiano Tosca
1,600 – 1,800	Cabernet Sauvignon, Grignolino, Lambrusco Grasparossa, Malbech, Refosco, Ruby Cabernet, Sangiovese	Albana, Montuni, Pignoletto, Pinot Bianco, Riesling Italico, Sauvignon,Trebbiano Toscano, Trebbiano Romagnolo
1,800 – 2,000	Aleatico, Barbera, Nebbiolo, Lambrusco di Sorbara, Lambrusco Salamino, Refosco, Ruby Cabernet, Sangiovese	Malvasia Bianca, Montuni, Moscato Bianco, Pignoletto Trebbiano Romagnolo

Table 4. The Winkler Index for different varieties

Huglin Index at ripening stage	Black	White
1,600 – 1,800	Cabernet franc, Gamay, Pinot Nero, Ciliegiolo	Chardonnay, Pinot bianco, Pinot Grigio, Riesling, Sauvignon, Sylvaner
1,900 – 2,100	Cabernet Sauvignon, Lambrusco Grasparossa, Merlot, Sangiovese, Ciliegiolo	Albana, Chenin Blanc, Pignoletto, Riesling, Semillon, Trebbiano Toscano
2,200 – 2,400	Carignano, Lambrusco Salamino, Lambrusco Sorbara, Sangiovese, Nebbiolo	Montuni, Pignoletto, Trebbiano Romagnolo

Table 5. The Huglin Index for different varieties

According to the above considerations, heat summation based growth models in conjunction with maturity thresholds allow to approximately forecast the optimal dates for viticulture operations. Such ripening assessment procedure however is uncertain and prone to errors, as in fact degree-day models involve significant approximations. In particular, a main source of error is that the degree-day model uses a linear equation to model a nonlinear phenomenon (temperature dependent growth and development).

Another source of error which compromises the ability of pedoclimatic indexes to precisely determine the start or the end of each phenological phase arises from the quality of data detected. In fact temperatures which characterize the microclimate in the vineyard can be very different from air temperatures; furthermore due to the slope of the terrain, the light exposure, the relative proximity of plants and the humidity, temperatures can vary a lot from a zone of the vineyard to another. Thus in order to optimize the quality of data detected it is required to precisely measure the environmental data in the vineyard. In such sense recent ubiquitous computing technologies may represent an effective solution which easily integrates with existing decision processes, providing extremely detailed and reliable information about environmental data. Pervasive computing technologies such as sensor network systems give new capabilities for sensing and gathering environmental data and offer new digital processing opportunities. Innovative infrastructures based on Wireless Sensor Networks (WSN) are a real-time, pervasive, non intrusive, low-cost, and highly flexible data analysis technologies that can ensure high accuracy in detecting micro climatic conditions on the ground. Recently, WSNs have been employed in the specific area of farming monitoring and precision agriculture (Wang et al. (2006)). Additionally, the capability of a WSN to collect a large amount of data can be effectively exploited in the context of expert systems and decision tools for farming and soil management (Zhang (2004)), and few prototypal applications are currently being developed in different sectors of agriculture including vinery management (Kim and Evans (2009), Matese et al (2009)). The WSN will be treated in the following Chapter 3 in which the main characteristics of such technology will be presented as well as its main application fields.

The aim of the present study is to show that a growth model based pedoclimatic indexes can be used to realize an expert system able to predict the start and/or the end of each phenological phase by starting from environmental factors detected by a WSN in order to optimize the vineyard management both in viticulture operations and harvesting activities. This model will be presented through a case study in Chapter 4.

CHAPTER 3

3.1. Introduction

Chapter 2 dealt with pedoclimatic indexes and aimed to explain their potential in determining the transaction of phenological phases. The conclusion of this chapter was that the ability of pedoclimatic indexes mainly depends on the quality of data detected. In fact several conditions related to terrain slope, proximity of plants, light exposure, etc., determine the fact that the microclimate in the vineyard can be very different from the air temperature and temperatures can vary a lot from a zone of the vineyard to another. In this context recent pervasive technologies as WSNs allow to precisely monitoring the microclimate on the ground level. In the present Chapter this innovative technology is presented in order to explain its main characteristics and application fields.

3.2. Wireless Sensor Networks

A Wireless Sensor Network (WSN) is composed of a large number of sensor nodes, which are densely deployed either inside the phenomenon or very close to it. The WSN can have either a predetermined or a dynamic topology, i.e. the position of sensor nodes need not be necessarily engineered. This allows the WSN actually reflects the shape of the site of interest. Figure 4 reports a typical WSN architecture in which it is possible to distinguish the fundamental components of a WSN:

- Several sensor nodes
- A gateway or access points which enables communication between the central remote system and field devices.
- A central remote system which is responsible for the generation, storage, and management of data detected by sensors.

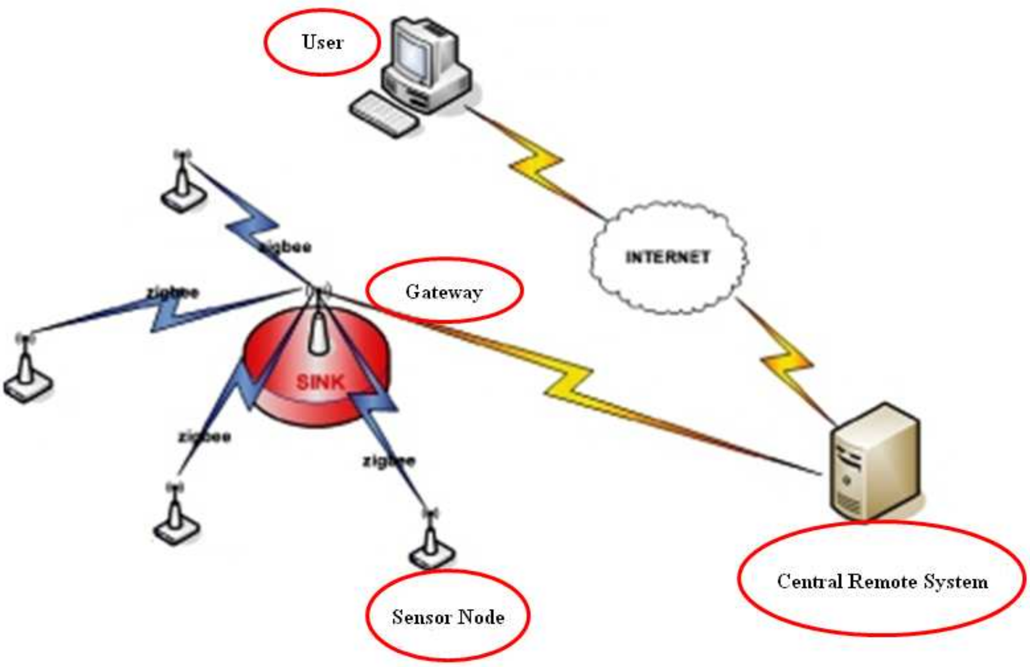


Figure 4. Wireless sensor network architecture

Sensors nodes are autonomous; they are battery powered and they can run unsupervised. This capability ensures that the measurements of interest can be automatically detected. Another unique feature of sensor networks is their cooperative effort. Sensor nodes communicate to each other by sharing information in order to accomplish various high level tasks. Sensor nodes are capable. They are fitted with an on-board processor which makes them able to memorizing, computing and sensing. Instead of sending the raw data to the nodes responsible for the fusion, sensor nodes use their processing abilities to locally carry out simple computations and transmit only the required and partially processed data. The data store function ensures that measurements of interest will be made available for future processing. Sensor nodes must be redundant in order to ensure the communication between them. In fact when a sensor node fails (because, for example, its battery is exhausted) the redundancy of the sensors ensures that exists an alternative route able to join the remaining nodes. Moreover the redundancy capability allows to carry out the interest measure diffusely in the environment. This is of fundamental importance when, for example, it must be detected environmental parameters which can change from a zone to another. Finally sensor nodes are programmable as they can programmed in order to detect the interest phenomenon with a desired frequency.

3.3. Characteristics of the WSN

In this paragraph the most important factors influencing the design of a WSN are presented on the basis of the publication of Akyildiz and al. (2002) . They are:

- 3.1.1 Sensor network topology
- 3.1.2 Fault tolerance
- 3.1.3 Scalability
- 3.1.4 Production costs
- 3.1.5 Operating environment
- 3.1.6 Hardware constraints
- 3.1.7 Power consumption

3.3.1 Sensor network topology

As we have just said in a WSN the position of sensor nodes need not be necessarily pre-determined. This ensures that the topology of the WSN actually reflects the shape of the site detected. However some topologies having a predetermined configuration have been designed in order to simplify the effort needed to built a WSN. The most common topologies are:

3.3.1.1 Star Network topology (Single Point-to-Multipoint)

A star network (Figure 5.1) is a communication topology where a single basestation can send and/or receive a message to a number of remote nodes. The remote nodes can only send or receive a message from the single basestation, they are not permitted to send messages to each other. The advantage of this type of network for wireless sensor networks is in its simplicity and the ability to keep the remote node's power consumption to a minimum. It also allows for low latency communications between the remote node and the basestation. The disadvantage of such a network is that the basestation must be within radio transmission range of all the individual nodes and is not as robust as other networks due to its dependency on a single node to manage the network. Furthermore if the basestation node fails the whole system is compromise.

3.3.1.2 Mesh Network topology

A mesh network (Figure 5.2) allows for any node in the network to transmit to any other node in the network that is within its radio transmission range. This allows for what is known as multihop communications; that is, if a node wants to send a message to another node that is out of radio communications range, it can use an intermediate node to forward the message to the desired node. This network topology has the advantage of redundancy and scalability. If an individual node fails, a remote node still can communicate to any other node in its range, which in turn, can forward the message to the desired location. In addition, the range of the network is not necessarily limited by the range between single nodes, it can simply be extended by adding more nodes to the system. The disadvantage of this type of network is that the power consumption for the nodes that implement the multihop communications are generally higher than for the nodes that don’t have this capability, often limiting the battery life. Additionally, as the number of communication hops to a destination increases, the time to deliver the message also increases, especially if low power operation of the nodes is a requirement.

3.3.1.3 Hybrid Star – Mesh Network topology

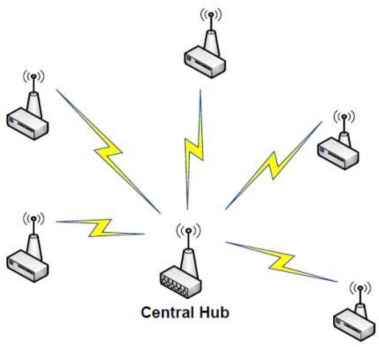
A hybrid between the star and mesh network provides for a robust and versatile communications network, while maintaining the ability to keep the wireless sensor nodes power consumption to a minimum. In this network topology, the lowest power sensor nodes are not enabled with the ability to forward messages. This allows for minimal power consumption to be maintained. However, other nodes on the network are enabled with multihop capability, allowing them to forward messages from the low power nodes to other nodes on the network. Generally, the nodes with the multihop capability are higher power, and if possible, are often plugged into the electrical mains line. This is the topology implemented by the up and coming mesh networking standard known as ZigBee.

3.3.1.4 Peer to peer Network topology

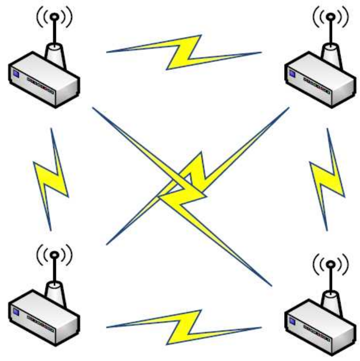
Peer-to-Peer networks (Figure 5.3) allows each node to communicate directly with another node without needing to go through a centralized communication hub. Each peer device is able to function as both a “client” and a “server” to the other nodes on the network.

3.3.1.5 Tree Network topology

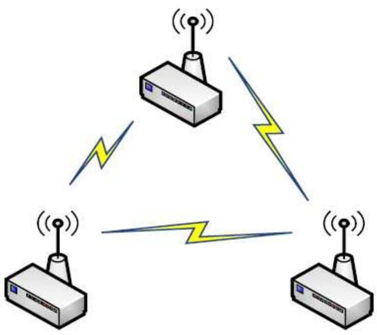
Tree networks (Figure 5.4) use a central hub called root node as the main communication router. One level down from the root node in the hierarchy is a central hub. This lower level then forms a Star network. The Tree network can be considered a hybrid of both the Star and Peer to Peer networking topologies.



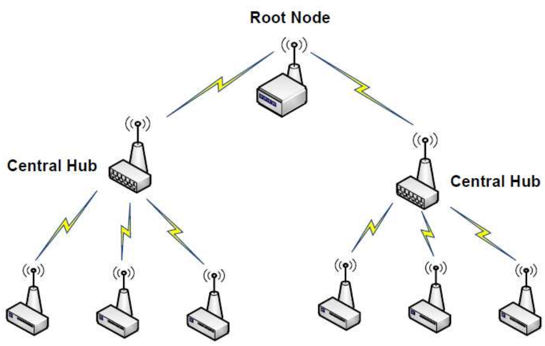
5.1. Star topology



5.2. Mesh topology



5.3. Peer to peer topology



5.4. Tree topology

Figure 5. WSN topologies

3.3.2 Fault tolerance

Some sensor nodes may fail or be blocked due to lack of power, have physical damage or environmental interference. The failure of sensor nodes should not affect the overall task of the sensor network. This is the reliability or fault tolerance issue. Fault tolerance is the ability to sustain sensor network functionalities without any interruption due to sensor node failures. The reliability $R_k(t)$ or fault tolerance of a sensor node is modeled using the Poisson distribution to capture the probability of not having a failure within the time interval (0 - t):

$$R_k(t) = \exp\,(-\boldsymbol{\lambda_k}(\boldsymbol{t})) \tag{6}$$

where $\boldsymbol{\lambda}_k$ and t are the failure rate of sensor node *k* and the time period, respectively.

3.3.3 Scalability

The number of sensor nodes deployed in studying a phenomenon may be in the order of hundreds or thousands. Depending on the application, the number may reach an extreme value of millions. The density of the sensor networks can be calculated as:

$$\mu(R) = (N\pi R^2)/A \tag{7}$$

where N is the number of scattered sensor nodes in region of area A; and R, the radio transmission range. Basically, $\mu(R)$gives the number of nodes within the transmission radius of each node in region A. By knowing the density $\mu(R)$ it is possible to determine the number of sensors must be employed to ensure the coverage of the region of interest.

3.3.4 Production costs

Since the sensor networks consist of a large number of sensor nodes, the cost of a single node is very important to justify the overall cost of the networks. If the cost of the network is more expensive than deploying traditional sensors, then the sensor network is not cost-justified. As a result, the cost of each sensor node has to be kept low. The state-of-the-art technology allows a Bluetooth radio system to be less than 10$. Also, the price of a PicoNode is targeted to be less than 1$. The cost of a sensor node should be much less than 1$ in order for the sensor network to be feasible. The cost of a Bluetooth radio, which is known to be a low-cost device, is even 10 times more expensive than the targeted price for a sensor node. Note that a sensor node also has some additional units such as sensing and processing units. In addition, it may be equipped with a location finding system, mobilizer, or power generator depending on the applications of the sensor networks. As a result, the cost of a sensor node is a very challenging issue given the amount of functionalities with a price of much less than a dollar.

3.3.5 Operating environment

Sensor nodes are densely deployed either very close or directly inside the phenomenon to be observed. As regards to the application WSNs can be classified into two main categories: monitoring and tracking (see Figure 6). Monitoring applications include indoor/outdoor environmental monitoring (biocomplexity mapping of the environment, flood detection, forest fire detection, precision agriculture), health and wellness monitoring (as telemonitoring of human physiological data and drug administration in hospitals), power monitoring, environmental control in office buildings, inventory location monitoring and managing inventory control, factory and process automation, and sismic and structural monitoring. Tracking applications include tracking objects, animals, humans, and vehicles. This list gives us an idea about under which conditions sensor nodes are expected to work. They work under high pressure in harsh environments, under extreme heat and cold and in an extremely noisy environment.

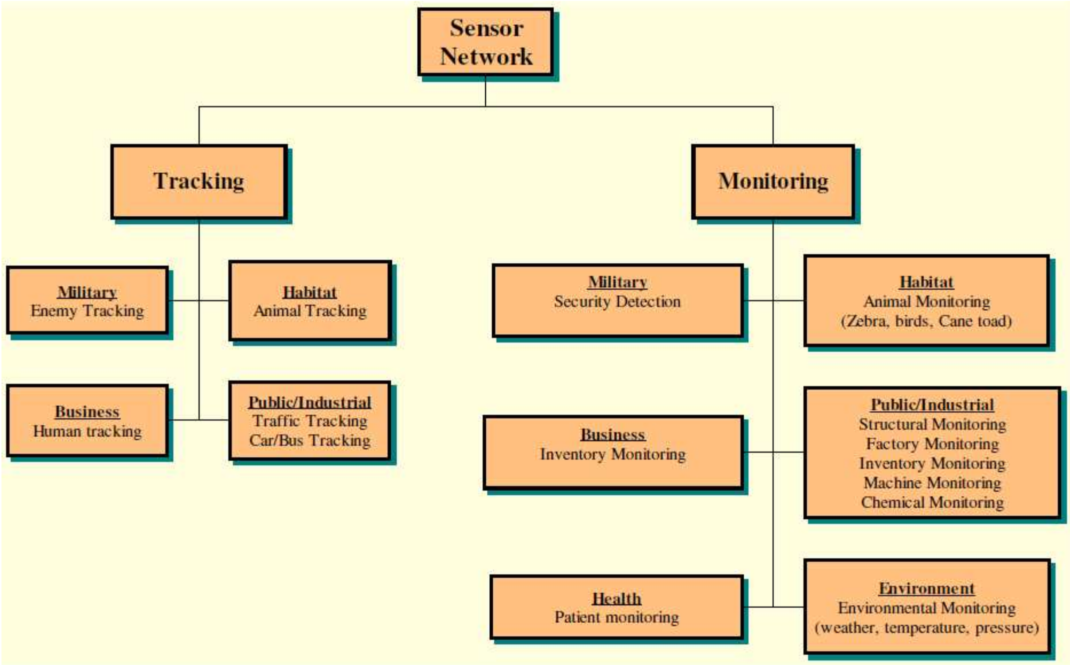


Figure 6. (taken in Yick and al. (2008))

3.3.6 Hardware constraints

A sensor node is made up of four basic components as shown in Figure 7.1: a sensing unit, a processing unit, a transceiver unit and a power unit. They may also have application dependent additional components such as a location finding system, a power generator and a mobilizer. The processing unit, which is generally associated with a small storage unit, manages the procedures that make the sensor node collaborate with the other nodes to carry out the assigned sensing tasks. A transceiver unit connects the node to the network. One of the most important components of a sensor node is the power unit. Most of the sensor network routing techniques and sensing tasks require the knowledge of location with high accuracy. Thus, it is common that a sensor node has a location finding system. A mobilize may sometimes be needed to move sensor nodes when it is required to carry out the assigned tasks. All these units must be fit into a unique module the size of which may be smaller than even a cubic centimeter. Apart from the size there are also some other stringent constraints for sensor nodes. Such nodes must:

- consume extremely low power
- operate in high volumetric densities
- have low production cost and be dispensable
- be autonomous and operate unattended
- be adaptive to the environment.

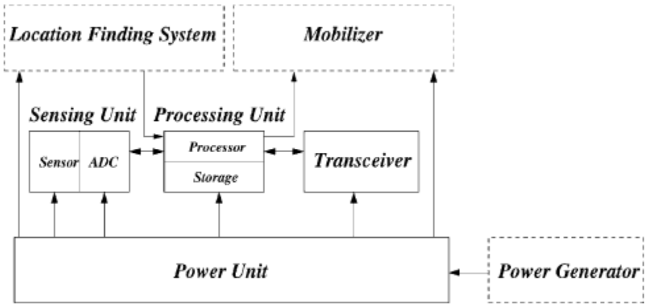


Figure 7.1. The components of a sensor node

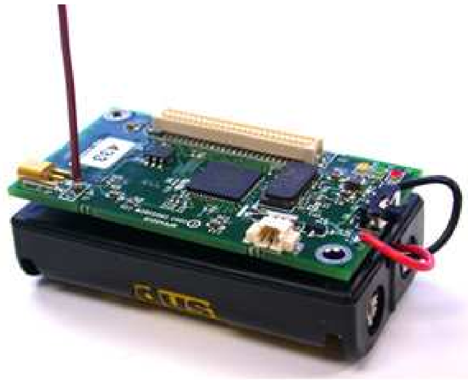


Figure 7.2. A wireless sensor node

Figure 7. Wireless sensor node

3.3.7 Power consumption

The wireless sensor node, being a micro-electronic device, can only be equipped with a limited power source (<0.5 Ah, 1.2 V). In some application scenarios, replenishment of power resources might be impossible. Sensor node lifetime, therefore, shows a strong dependence on battery lifetime. In a multihop ad hoc sensor network, each node plays the dual role of data originator and data router. The disfunctioning of few nodes can cause significant topological changes and might require re-routing of packets and re-organization of the network. Hence, power conservation and power management take on additional importance. In sensor networks though, power efficiency is an important performance metric, directly influencing the network lifetime. The main task of a sensor node in a sensor field is to detect events, perform quick local data processing, and then transmit the data. Power consumption can hence be divided into three domains: sensing, communication, and data processing. Sensing power varies with the nature of applications. Sporadic sensing might consume lesser power than constant event monitoring. The complexity of event detection also plays a crucial role in determining energy expenditure. Higher ambient noise levels might cause significant corruption and increase detection complexity. Of the three domains, a sensor node expends maximum energy in data communication involving both data transmission and reception while the data processing requires less energy expenditure.

3.4. Types of sensors networks

Current WSNs are deployed on land, underground, and underwater. Depending on the environment, a sensor network faces different challenges and constraints. Yick and al. (2008) classify the WSNs in: terrestrial WSN, underground WSN, underwater WSN, multi-media WSN, and mobile WSN (see Figure 8). **Terrestrial** WSNs typically consist of hundreds to thousands of inexpensive wireless sensor nodes deployed in a given area, either in an ad hoc or in a pre-planned manner. In ad hoc deployment, sensor nodes can be dropped from a plane and randomly placed into the target area. In a terrestrial WSN, reliable communication in a dense environment is very important. Terrestrial sensor nodes must be able to effectively communicate data back to the base station. While battery power is limited and may not be rechargeable, terrestrial sensor nodes however can be equipped with a secondary power source such as solar cells. In any case, it is important for sensor nodes to conserve energy. For a terrestrial WSN, energy can be conserved with multi-hop optimal routing, short transmission range, in-network data aggregation, eliminating data redundancy, minimizing delays, and using low duty-cycle operations. **Underground** WSNs consist of a number of sensor nodes buried underground or in a cave or mine used to monitor underground conditions. Additional sink nodes are located above ground to relay information from the sensor nodes to the base station. An underground WSN is more expensive than a terrestrial WSN in terms of equipment, deployment, and maintenance. Underground sensor nodes are expensive because appropriate equipment parts must be selected to ensure reliable communication through soil, rocks, water, and other mineral contents. The underground environment makes wireless communication a challenge due to signal losses and high levels of attenuation. Unlike terrestrial WSNs, the deployment of an underground WSN requires careful planning and energy and cost considerations. Energy is an important concern in underground WSNs. Like terrestrial WSN, underground sensor nodes are equipped with a limited battery power and once deployed into the ground, it is difficult to recharge or replace a sensor node's battery. As before, a key objective is to conserve energy in order to increase the lifetime of network which can be achieved by implementing efficient communication protocol. **Underwater** WSNs consist of a number of sensor nodes and vehicles deployed underwater. As opposite to terrestrial WSNs, underwater sensor nodes are more expensive and fewer sensor nodes are deployed. Autonomous underwater vehicles are used for exploration or gathering data from sensor nodes. Compared to a dense deployment of sensor nodes in a terrestrial WSN, a sparse deployment of sensor nodes is placed underwater. Typical underwater wireless communications are established through transmission of acoustic waves. A challenge in underwater acoustic communication is the limited bandwidth, long propagation delay, and signal fading issue. Another challenge is sensor node failure due to environmental conditions. Underwater sensor nodes must be able to self-configure and adapt to harsh ocean environment. Underwater sensor nodes are equipped with a limited battery which cannot be replaced or recharged. The issue of energy conservation for underwater WSNs involves developing efficient underwater communication and networking techniques. **Multi-media** WSNs have been proposed to enable monitoring and tracking of events in the form of multimedia such as video, audio, and imaging. Multi-media WSNs consist of a number of low cost sensor nodes equipped with cameras and microphones. These sensor nodes interconnect with each other over a wireless connection for data retrieval, process, correlation, and compression. Multi-media sensor nodes are deployed in a pre-planned manner into the environment to guarantee coverage. Challenges in multi-media WSN include high bandwidth demand, high energy consumption, quality of service (QoS) provisioning, data processing and compressing techniques, and cross-layer design. Multi-media content such as a video stream requires high bandwidth in order for the content to be delivered. As a result, high data rate leads to high energy consumption. Transmission techniques that support high bandwidth and low energy consumption have to be developed. **Mobile** WSNs consist of a collection of sensor nodes that can move on their own and interact with the physical environment. Mobile nodes have the ability to sense, compute, and communicate like static nodes. A key difference is mobile nodes have the ability to reposition and organize itself in the network. A mobile WSN can start off with some initial deployment and nodes can then spread out to gather information. Information gathered by a mobile node can be communicated to another mobile node when they are within range of each other. Another key difference is data distribution. In a static WSN, data can be distributed using fixed routing or flooding while dynamic routing is used in a mobile WSN. Challenges in mobile WSN include deployment, localization, self-organization, navigation and control, coverage, energy, maintenance, and data process. Mobile WSN applications include but are not limited to environment monitoring, target tracking, search and rescue, and real-time monitoring of hazardous material. For environmental monitoring in disaster areas, manual deployment might not be possible. With mobile sensor nodes, they can move to areas of events after deployment to provide the required coverage. In military surveillance and tracking, mobile sensor nodes can collaborate and make decisions based on the target. Mobile sensor nodes can achieve a higher degree of coverage and connectivity compared to static sensor nodes. In the presence of obstacles in the field, mobile sensor nodes can plan ahead and move appropriately to obstructed regions to increase target exposure.

	Terrestrial WSN	Underground WSN	Underwater WSN	Multi-media WSN	Mobile WSN
Definition	A network consists of hundreds to thousands of sensor nodes deployed on land	A network consists of wireless sensor nodes deployed in caves or mines or underground	A network consists of wireless sensor and vehicles deployed into the ocean environment	A network consists of wireless sensor devices that have the ability to store, process, and retrieve multi-media data such as video, audio, and images	A network consists of mobile sensor nodes that have the ability to move
Challenges	– In-network data aggregation to improve performance across communication, energy cost, and delay – Minimizing energy cost – Reduce the amount of data communication – Finding the optimal route – Distributing energy consumption – Maintaining network connectivity – Eliminating redundancy	– Expensive deployment maintenance, and equipment cost – Threats to device such as the environment and animals – Battery power cannot easily be replaced – Topology challenges with pre-planned deployment – High levels of attenuation and signal loss in communication	– Expensive underwater sensors – Hardware failure due to environment effects (e.g., corrosion) – Battery power cannot easily be replaced – Sparse deployment – Limited bandwidth – Long propagation delay, high latency, and fading problems	– In-network processing, filtering, and compressing of multi-media content – High energy consumption and bandwidth demand – Deployment based on multi-media equipment coverage – Flexible architecture to support different applications – Must integrate various wireless technologies – QoS provisioning is very difficult due to link capacity and delays – Effective cross-layer design	– Navigating and controlling mobile nodes – Must self-organized – Localization with mobility – Minimize energy cost – Maintaining network connectivity – In-network data processing – Data distribution – Mobility management – Minimize energy usage in locomotion – Maintain adequate sensing coverage
Applications	– Environmental sensing and monitoring – Industrial monitoring – Surface explorations	– Agriculture monitoring – Landscape management – Underground structural monitoring – Underground environment monitoring of soil, water or mineral – Military border monitoring	– Pollution monitoring – Undersea surveillance and exploration – Disaster prevention monitoring – Seismic monitoring – Equipment monitoring – Underwater robotics	– Enhancement to existing WSN applications such as tracking and monitoring	– Environmental monitoring – Habitat monitoring – Military surveillance – Target tracking – Underwater monitoring – Search and rescue

Figure 8. Types of sensor nodes

3.5. Communication protocols

The most common communication protocols for WSN are the Bluetooth and ZigBee. **Bluetooth** (IEEE 802.15.1) was developed as a wireless protocol for short-range communication in wireless personal area networks (PAN) as a cable replacement for mobile devices. It uses the 868 and 915 MHz and the 2.4 GHz radio bands to communicate at 1 Mb per second between up to seven devices. Bluetooth is mainly designed to maximize ad hoc networking functionality. Some of its common functions are passing and synchronizing data, e.g. between a PDA (personal digital assistant) and a computer, wireless access to LANs, and connection to the internet. It uses frequency-hopping spread-spectrum (FHSS) communication, which transmits data over different frequencies at different time intervals. Bluetooth uses a master-slave-based MAC (medium access control) protocol. The **ZigBee** standard is built on top of the IEEE 802.15.4 standard. The IEEE 802.15.4 standard defines the physical and MAC (Medium Access Control) layers for low-rate wireless personal area networks. The physical layer supports three frequency bands with different gross data rates: 2.4 GHz (250 kbs-1), 915 MHz (40 kbs-1) and 868 MHz (20 kbs-1). It also supports functionalities for channel selection, link quality estimation, energy measurement and clear channel assessment. ZigBee standardizes both the network and the application layer. The network layer is in charge of organizing and providing routing over a multi-hop network, specifying different network topologies: star, tree, peer-to-peer and mesh. The application layer provides a framework for distributed application development and communication. Aside from the agriculture and food industry, it is widely used in home building control, automation, security, consumer electronics, personal computer peripherals, medical monitoring and toys. These applications require a technology that offers long battery life, reliability, automatic or semiautomatic installation, the ability to easily add or remove network nodes, signals that can pass through walls and ceilings and a low system cost.

Table 6 provides a comparison between ZigBee and Bluetooth. For applications where higher data rates are important, Bluetooth clearly has the advantage since it can support a wider range of traffic types than ZigBee. However, the power consumption in a sensor network is of primary importance and it should be extremely low. Bluetooth is probably the closest peer to WSNs, but its power consumption has been of secondary importance in its design. Bluetooth is therefore not suitable for applications that require ultra-low power consumption; turning on and off consumes a great deal of energy. In contrast, the ZigBee protocol places primary importance on power management; it was developed for low power consumption and years of battery life. Bluetooth devices have lower battery life compared to ZigBee, as a result of the processing and protocol management overhead which is required for ad hoc networking. Also, ZigBee provides higher network flexibility than Bluetooth, allowing different topologies. ZigBee allows a larger number of nodes – more than 65,000. For more details about these two standard see Ruiz-Garcia and al. (2009).

	Bluetooth	**ZigBee**
Standard	IEEE 802.15.1	IEEE 802.15.4
Data Rate	1Mb s^{-1}	20-250 kb s^{-1}
Latency (time to establish a new link)	<10s	30 ms
Frequencies	2.4 GHz	2.4 GHz
No. of nodes	8	65,000
Range	8m (Class II, III) to 100 m (Class I)	1-100 m
Modulation	FHSS[2]	DSSS[1]
Network topology	*Ad hoc* piconets	*Ad hoc*, star, mesh
Data Type	Audio, graphics, pictures, files	Small data packet
Battery Life	1 week	>1 year
Extendibility	No	Yes

[1]DSSS: Direct Sequence Spread Spectrum. [2]FHSS: Frequency Hopped Spread Spectrum.

Table 6. Comparison between Bluetooth and Zigbee

CHAPTER 4

4.1. The case study: Introduction

In this Chapter a model for an Expert System able to automatically forecast the dates of each phenological phase of the ripening process on the basis of environmental data gathered by a WSN is presented. The ES proposed determines a pedoclimatics index by starting from temperature values detected in the vineyard and forecasts future values of such index. Thus the forecasted value of the index is compared with a fixed threshold and the forecast of the date of start or end of each phenological phase is determined. The model of the ES proposed will be illustrated in this Chapter by means of a case study conducted in a Sicilian vineyard.

4.2. The methodology proposed

The methodology proposed starts by gathering the temperature values in the vineyard by means of the WSN. Such data are transferred to the ES and the Winkler Index (WI) (discussed in Chapter 2 (eq. 2)) is determined. The ES assesses temperature data in order to determine whether they are suitable to forecast future values of WI. In this case a statistical model with level and trend is used in order to perform short-term forecasts of WI. The values forecasted are compared with a threshold depending on the variety cultivated and the optimal date for each phenological phase is determined. The forecast model employed aims at representing the linear growth model given by the WI, while the ripening process cannot be considered linear with time especially when the temperatures become hot in summer. Thus the ripening process is a non stationary process. This causes a risk that the forecasted value exceeds the threshold. In order to minimize this risk two features are included in the ES: the probability of the forecast violating the threshold is determined and the forecast value of the WI is continuously updated as the temperature values become available.

4.3. The case study proposed

4.3.1 The monitoring of temperature in the vineyard: the WSN deployed

The site chosen for the study is a vineyard located in Sicily which has been divided in 15 zones depending on terrain slope and solar irradiation. As stated before the ES is based on the measurement of local temperatures for the evaluation of the WI. The practical application of the proposed methodology therefore requires a reliable measurement system allowing fast and precise evaluation of local micro-climatic parameters such as air temperature, relative humidity, and solar irradiation. Sensor based ubiquitous computing techniques are spreading nowadays as a cheap and effective technology capable to deliver a higher accuracy compared to traditional weather stations aerial or satellite based monitoring. In this research a WSN has been designed and deployed in the vineyard in order to have extremely precise local estimates of the temperature. As discussed in Chapter 3 a WSN is a network of devices, denoted as nodes, which can sense the environment and communicate the information gathered from the monitored field through wireless links (Raghavendra et al (2004)). The data is forwarded, possibly via multiple hops, to a sink that can use it locally or is connected to other networks (e.g., the Internet) through a gateway.

Deploying such technology in a vineyard requires the definition of the density and number of sensors according to the vineyard topology. In the present study the determination of the optimal number of sensor nodes has been not dealt. In fact the monitoring of the microclimate in the vineyard makes necessary to place a high number of nodes. This high number ensures that the transmission range of nodes will cover the all area under study. Vineyards are typically organized into a hedgerow system, which is characterized by a supporting structure made of zinc-plated iron, wooden, or concrete poles, and some lines of steel wires to hold the vine canopy. The microclimate of the grapevine is affected by the environmental conditions of a limited area close to the rootstock. Battery powered temperature wireless sensors have been placed in each pole in the vineyard while sensor nodes have been placed along the rows of grapevines to form a connected multi-hop network which, once configured, runs unsupervised. Concerning the WSN topology, the distance between the hedgerows is 2.20 m, while iron poles are positioned at 80 cm from each other. A node was positioned on each pole at 90 cm, in order to obtain measurements about the micro-climate at the productive area of the grapevine, measurements about the micro-climate of the leaf-covered area, measurements from the top of the green canopy to be used as reference for the lower areas. For further details about the network topology refer to (Anastasi et al (2009)). A qualitative representation of the WSN deployed is depicted in Figure 9.

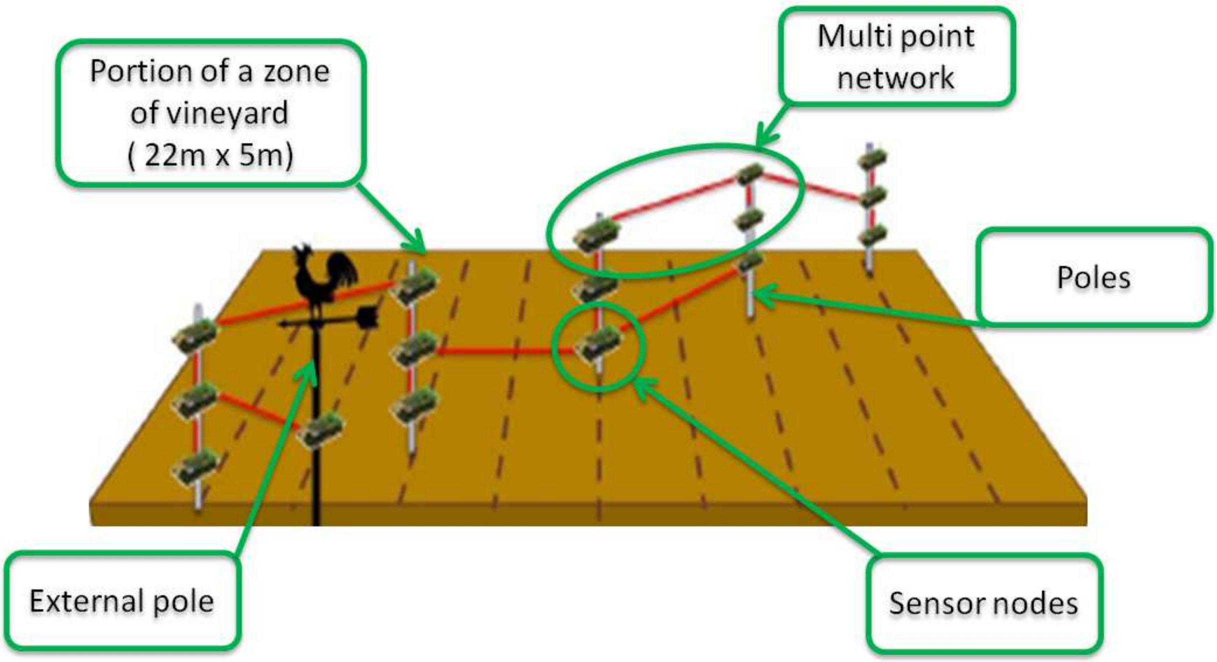


Figure 9. Topology of WSN in the vineyard

In the context of this research, the sensor nodes have been employed in order to measure temperature only, however different technologies allow the evaluation of additional parameters such as light exposure and humidity. Such elements, therefore, can be further integrated in the decision support system as soon as suitable ontology and corresponding decision models are developed. All the nodes are constituted by commercially available TelosB boards equipped with the Sensirion SHT11 combined temperature/relative humidity sensor. The TelosB (Polastre et al (2005)) mote, given in Table 7, is a 2.4 GHz, IEEE/ZigBee 802.15.4 (LAN/MAN Standards Committee of the IEEE Computer Society (1999)), device used for low-power, wireless, sensor networks. It has USB programming capability, Chipcon's CC2420 IEEE 802.15.4 standard-compliant radio transceiver for communication with integrated antenna, a low-power microcontroller (TI-MSP430) from with 128kB instruction memory, and 4KB RAM. Zigbee wireless technology is a short-range communication system intended to provide applications with relaxed throughput and latency requirements in WPAN, mainly devoted to the implementation of WSNs. The key features of 802.15.4 wireless technology are low complexity, low cost, low power consumption, low data rate transmissions, to be supported by cheap either fixed or moving devices (Chessa et al (2007)).

The Sensirion SHT11 temperature and humidity sensor is a single chip module providing calibrated digital output. Both instruments are coupled to a 14 bit AD converter and a serial interface for superior signal quality, low power consumption (tipically 30 µW), fast response time and insensitivity to external disturbances. The relative humidity (RH) sensor is accurate to <3% between 20-80% RH, <5% outside of that range as given in Figure 11.1. The temperature accuracy is within <2.5° C between -40° to 100° C, as given in Figure 11.2. Figure 10 gives the typical application range for such device.

	CPU			Memory	Radio		
TelosB 	**Description**	**Energy consumption**	**Sleep power**		**Description**	**Energy per bit**	**Idle Power**
	TIMSP430 16bit	Active power 3mW	15µW	4KB RAM 1MB Flash	CC2420 250kbps IEEE 802.154/Zigbee	430 nJ/b	7 mA

Table 7 Sensirion SHT11 Typical range of employment

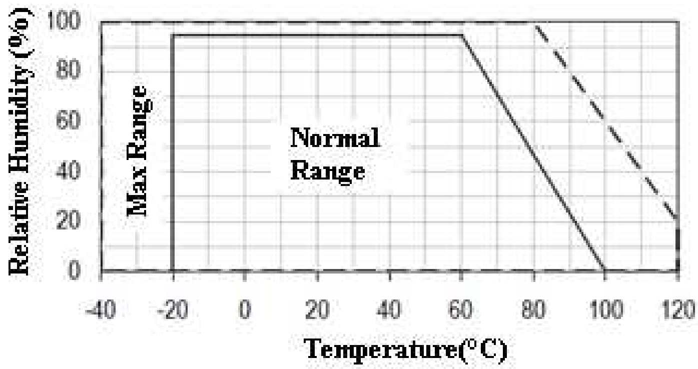
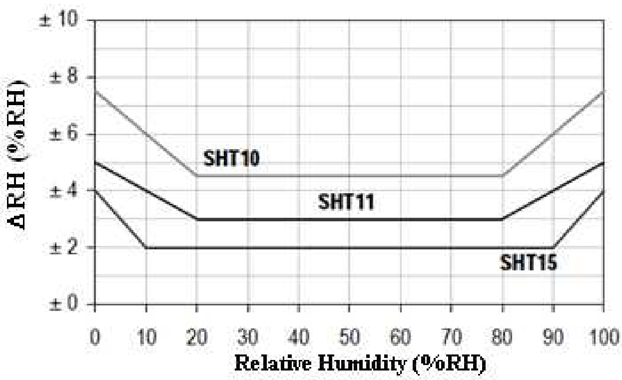


Figure 10. Sensirion SHT11 Typical range of employment



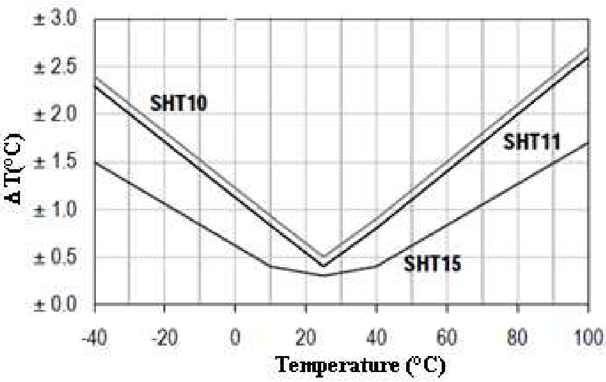


Figure 11.1 – Relative Humidity (RH) Accuracy

Figure 11.2 – Temperature Accuracy

Figure 11. Temperature-Humidity range

4.3.2 Quality control of data detected

An immediate advantage of the adoption of a WSN-based approach is that corrective actions on the cultivations may be timely and selectively chosen; furthermore, the system allows to collect a history of past events, and stored data may be analyzed in order to extract potential hidden correlations among the environmental variables and the obtained results. The availability of a considerable amount of precise data, superior to what is commonly attainable through traditional random sampling, allows for the construction of accurate models, and thus favors the proposals of improvements in the cultivation process. In addition to this parameters surveyed around the plants allow us to determine more accurately the microclimate in the vineyard and, consequently, to assess the ripening process. On the other hand, the large amount of data collected requires solid Quality Assurance (QA) and Quality Control (QC) procedures. This is a common feature of climatic monitoring systems, and standardized procedures are typically enforced including threshold, persistence, and spatial regression tests (see for example Hubbard et al. (2005)). In the system developed in the present research, spatial consistency tests consisting in comparing the values of the same parameter measured at the same time at nearby sensors are implemented. Potential erroneous data are automatically detected and purged by assuming maximally allowed variability in a certain area. In addition a time variability test is performed on a single station by checking a minimal required variability during a certain period.

4.3.3 The ES proposed

The proposed expert system aims at automatically forecasting the optimal ripeness dates on the basis of the environmental data gathered by the WSN deployed. The system developed hence involves a proper designed infrastructure for the transmission and storage of the environmental data. Depending upon the polling rate and the density of the sensors within the vinery, a large amount of data can be easily collected, a proper data warehouse has hence been designed in order to store such data for further elaboration. The data warehouse is periodically queried by a module for the evaluation of key-indices for decision process, which are evaluated by processing the data stored, according to WI based growth model.

The growth model and the environmental database constitute the main elements of the knowledge base the decision process is based upon. Such information is processed by means of a module for the evaluation of the maturity indices, which outputs the resulting values to the forecasting module. The forecasting module implements all required forecasting procedures to evaluate the ripeness indices at a specified time in the future. The forecasting technique employed is discussed in detail in the following paragraph. The decision making module (or inference engine), finally, compares the forecasted values with a maturity threshold, assessing the probability that the threshold is exceeded in the future time considered. The schematic structure of the expert system developed is given in the following Figure 12.

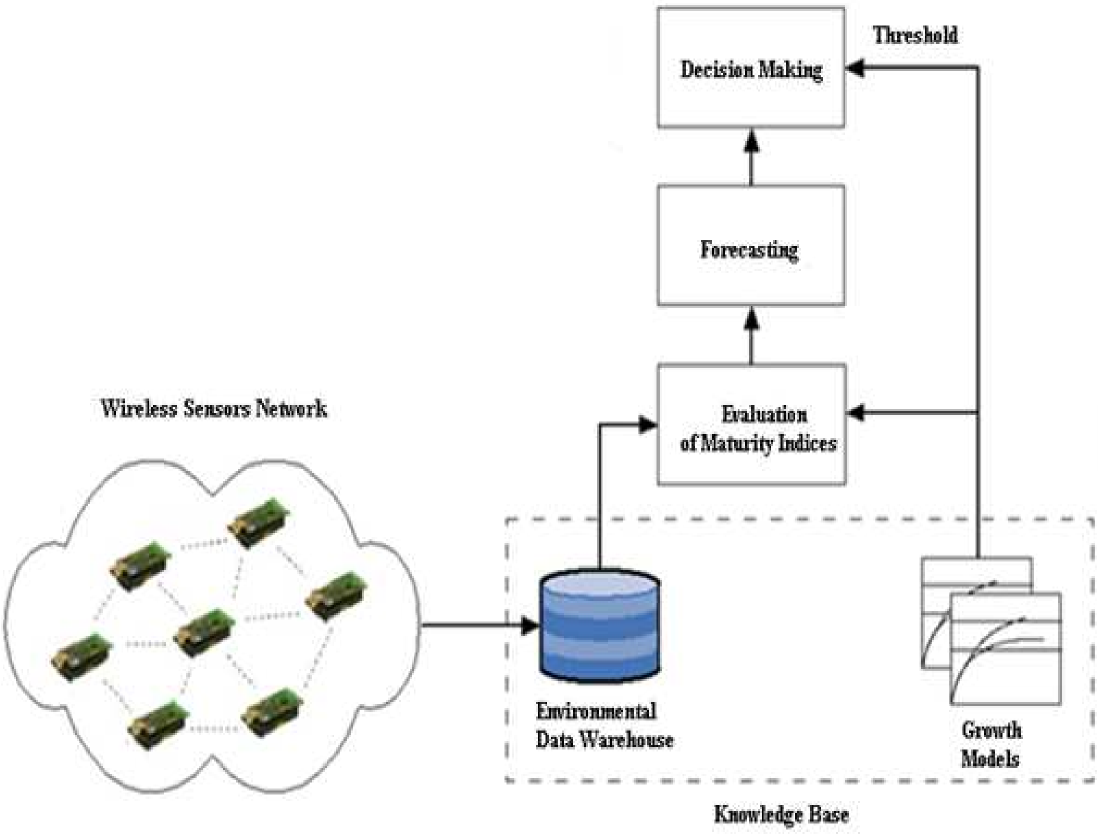


Figure 12. Schematic structure of the expert system developed.

This methodology will not allow to predict exact harvest dates at the beginning of the season due to the inherent approximations and to the many variables that influence the rate of fruit ripening. However, with experience and record keeping, it is possible to make reasonably accurate projections as the season progresses. It is also expected that the performance achievable with the initial setup of the system, based on referenced parameters and thresholds will increase as actual records of different seasons will be available. Finally, at the initial deployment of the system, the dates of major phenological stages, along with harvested yield and fruit quality parameters obtained by standard fruit sampling procedures should be recorded for each area of the vineyard together with local weather records and degree-day accumulations, in order to tune up growth models and the threshold values thus improving the quality of the assessments. This is a common feature in the deployment of expert systems.

The proposed methodology can ultimately allow to predict the harvest dates for each zone of the winery, taking into consideration the optimal maturity of the berries. Such information can be effectively employed to plan and schedule the harvesting operations, coping with constraints related to the limited stocking capacity of the winery and the availability of the harvesting machineries (Ferrer et al. (2008)). Finally, the degradation in quality caused by anticipating or delaying the harvesting operations with respect to the optimal ripening dates ultimately results in loss of production value as many hedonic pricing models for grapevines confirm (Ashenfelter (2008)).

4.3.4 Short-term forecasting for the prediction of phenologic maturity stages

4.3.4.1 Statistical analysis of data detected

In this paragraph the problem of predicting the occurrence of different phenologic maturation phases is considered. The ES in fact aims at determine the WI on the basis of temperature detected by the WSN and then forecasts future values of such index by means of statistical models. WI allows to represent the grape growth as a linear function of the heat a plant can store with time. From sprouting to maturation the slope of this linear function changes when the daily average temperatures increase. The grape growth, in fact, starts by an initial slow heat accumulation process, which dynamically increases as the weather gets hot in summer, thus resulting in a non-stationary process. Within the time in which temperatures can be considered nearly constant the future value of the WI can be determined through a linear model. In this sense the usefulness of pedoclimatic indexes to estimate the grape growth is dependent upon the quality of data used. Statistical quality control lends itself as a convenient means to screen these data. Shewhart is credited for being the first to apply statistical methods to quality control. In 1924, he proposed the concept of a control chart. A control chart shows the value of the quality characteristics of interest as a function of time or sample number. Generally, a control chart is made of a centerline which represents the mean value for the in-control process, and two horizontal lines, the upper control limit (UCL) and the lower control limit (LCL) (see Eching and Snyder). The applicability of the control chart is based upon the hypothesis of normal distribution of the characteristic under study. In this work the Shewhart control chart is used in order to test the quality of temperature values detected in the vineyard. The study is carried out by testing the normality of data detected and successively by building a control chart in order to investigate whether temperatures can be considered about constant in the period of observation. The methodology here presented consists in the determination of the WI by means of temperature values detected in the vineyard and a successive forecast of future value of such index by means of statistical models. Naturally the model proposed is able to carry out only short-term forecasts within the time where temperatures can be considered constant. The need for small term forecasts is often encountered in the design of decision support systems. In such context, the most common forecasting methods are adaptive and non-adaptive regression models, generalized exponential smoothing methods. The classical Bayesian linear regression models are unable to reproduce some of the features frequently observed in non-stationary processes, while, on the contrary, in such cases time series methods are extremely effective. In this research the growth of the berries is predicted on the basis of the heat summation measured by the WI. The heat summation value, consequently, is updated daily with field measurements, and it results in a non-decreasing series of values, originating trended time series. Future values of heat summation have been predicted by means of the well known Holt's model (Holt (1957)), which is an exponential adaptive forecasting method for trended data, based on the following equations:

$$\hat{X}_{t+k} = (L_t + kT_t) \tag{8}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta) * T_{t-1}) \tag{9}$$

$$L_t = \alpha X_t + (1-\alpha) * (L_{t-1} + T_{t-1}) \tag{10}$$

where *Lt* is the level at time *t*, T_t is the trend a time *t*, $\hat{X}_{t+k}$ is the forecast at time *t+k*, and α and β are the smoothing constants for the level and the trend, respectively (see Figure 13).

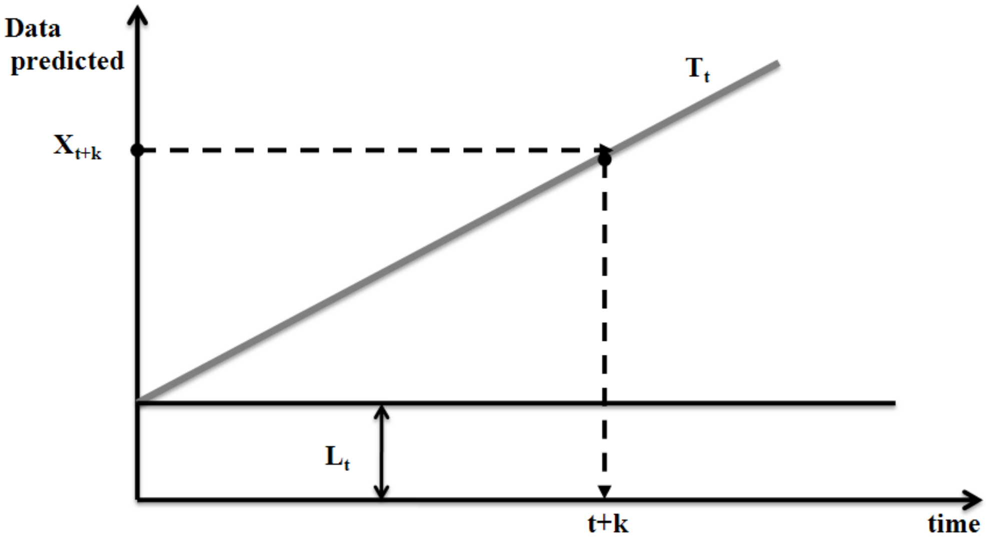


Figure 13. Level and trend of the forecasted measure

The three updating equations result in the evaluation of the heat summation at a future time $t+k$ as a weighted average of the (adjusted) previous estimate and the most recent information acquired at time t. Concerning to the establishment of the smoothing constants, α, and β, practical issues are discussed in detail in (Chatfield and Yar (1988)), however a common approach is to determine the values of α and β that minimize the mean or median absolute error, or a similar measure. Finally, as stated before, the decision about the harvesting time is based upon the comparison of the predicted value with a pre-established threshold (see Figure 14).

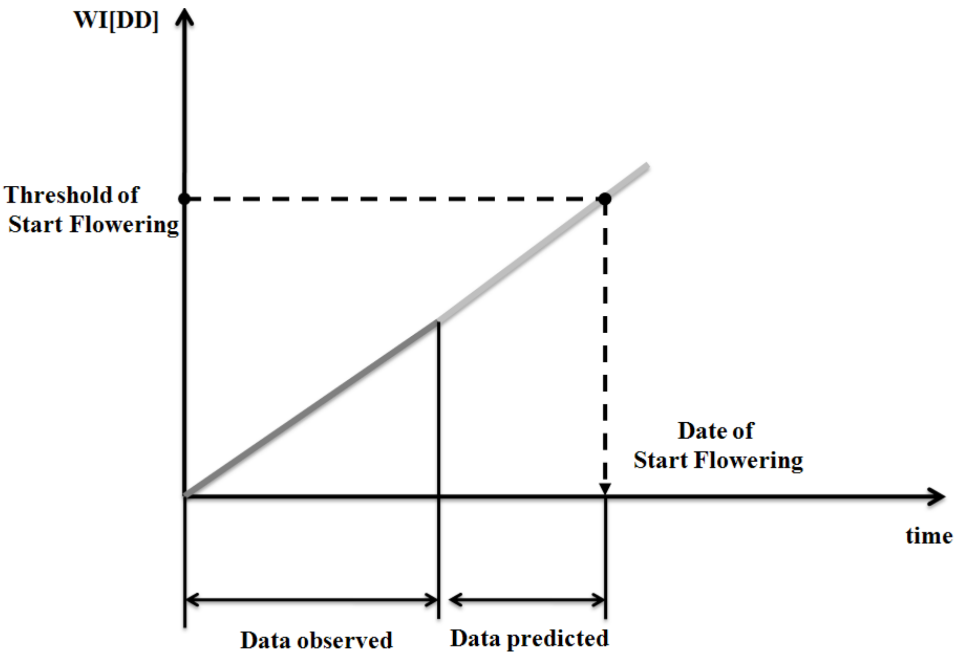


Figure 14. Comparison between the forecasted value and the threshold

The violation of this threshold means that a new phenologic phase has been entered. In order to support the decision process, hence the estimation of the probability of the forecast violating a threshold at a future time must be evaluated. This is generally accomplished by estimating the mean and variance of the future observations and relaying on the assumption of gaussian error terms to estimate the probability of violating the threshold. The standard deviation of the tracked data can be considered approximately equal to 1.25 times the mean absolute deviation, as usual referring to the Jensen's inequality. The probability of the forecast of exceeding the ripening threshold (θ) at the $(t+k)^{th}$ period can hence be evaluated as:

$$P_{t+k} = 1 - F(\frac{\theta - \hat{X}_{t+n}}{\sigma}) \tag{11}$$

For the decision model hence, the establishment of an acceptance probability ϕ is required, resulting in a risk of accepting the hypothesis of the achievement of the optimal ripening level at time $t+k$ when it is not ($1-\phi$) and rejecting this hypothesis when optimal ripening level is achieved with probability ϕ (see Figure 15).

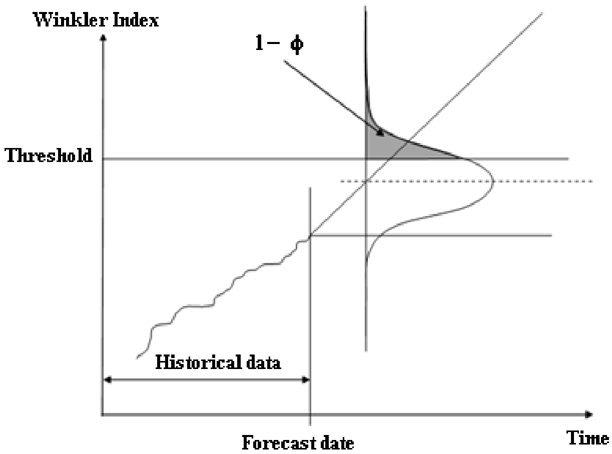


Figure 15. Probability of exceeding a fixed threshold

In conclusion, the methodology proposed for predicting the harvest date involves getting available information on the lower developmental threshold temperature, cumulative degree days, and the observed temperatures for the area considered. On the basis of such dataset it is possible to calculate the date when berries are expected to be in the desired stage of development, and ultimately establish the expected harvest date. As the number of observed temperature data increases, the accuracy of the forecast will eventually improve. Additionally the proposed system takes into account the possibility that the same variety may not achieve the same ripening stage in the same moment from one area to another of the vineyard.

4.3.5 Experimental analysis

In order to evaluate the effectiveness of the proposed methodology an experimental analysis has been performed involving the forecasting of the flowering date on the basis of the experimental values gathered by means of the previously described sensors network. The experiments were carried out in the area of Monreale (Sicily) where many varieties of DOC wines (Ansonica or Insolia, Cabernet Sauvignon, Chardonnay, Muller Thurgau etc.) are grown. Monreale has the typical Mediterranean climate, with mild and rainy winters and hot and dry summers; with an average annual rainfall of approx. 700 mm and average annual temperature of 18 °C. The experiments were carried on Chardonnay variety, which typically sprouts between the third decade of March and the first decade of April, blooms between the third decade of April and the second decade of May and ripens between the second and the third decade of August. The vineyard has been divided in 15 zones measuring approximatively 1 acre, each one with homogenous slope (maximum 3% variation) and solar exposure, consequently. This subdivision aims at highlighting by means of the experimental analysis the differences in the maturation process attributable to the microclimatic conditions in each zone. Sensors have been set to record temperature values each hour from April 2008 to May 2008. The experimental analysis here proposed involves the initial determination of the daily temperatures for each zone and the calculation of the WI. The sampling rate of the temperature sensor has been set at 15 minutes, the whole dataset thus obtained is given in Figure 16.

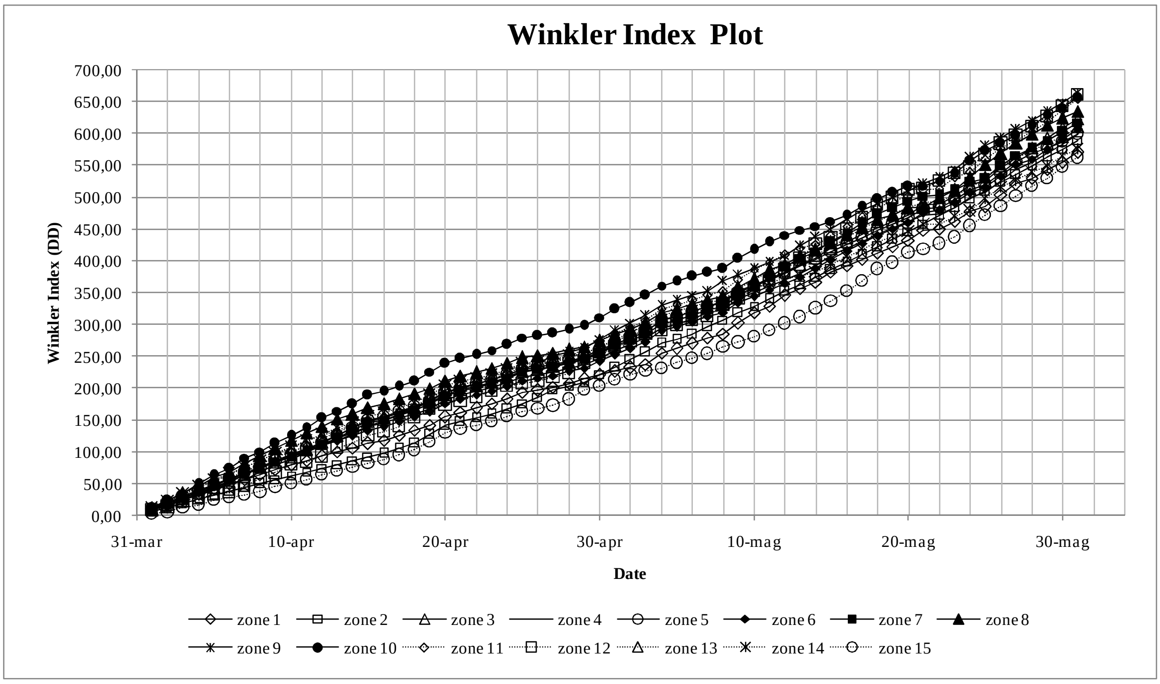
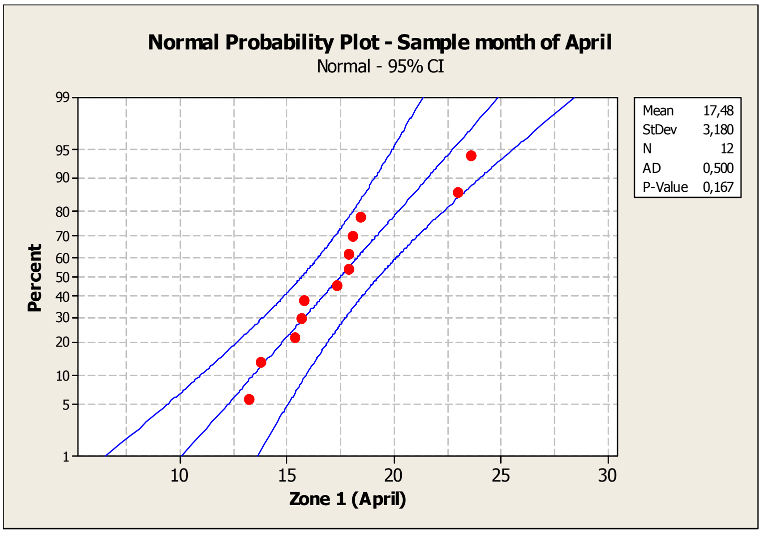
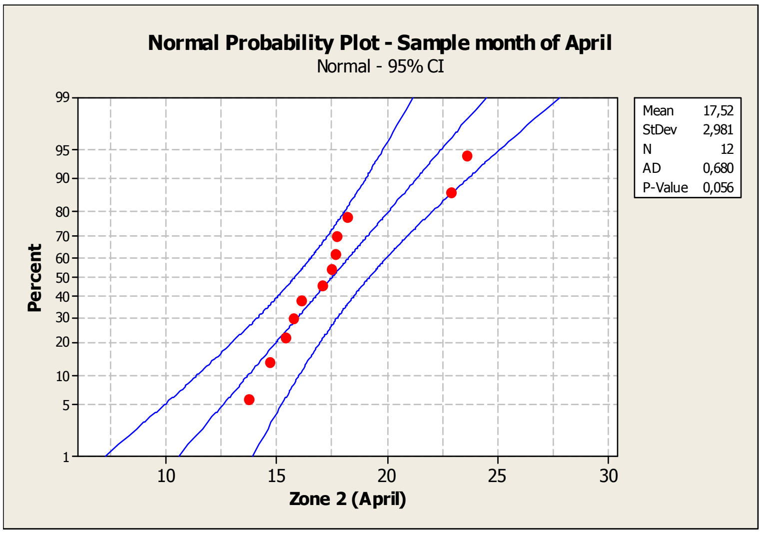
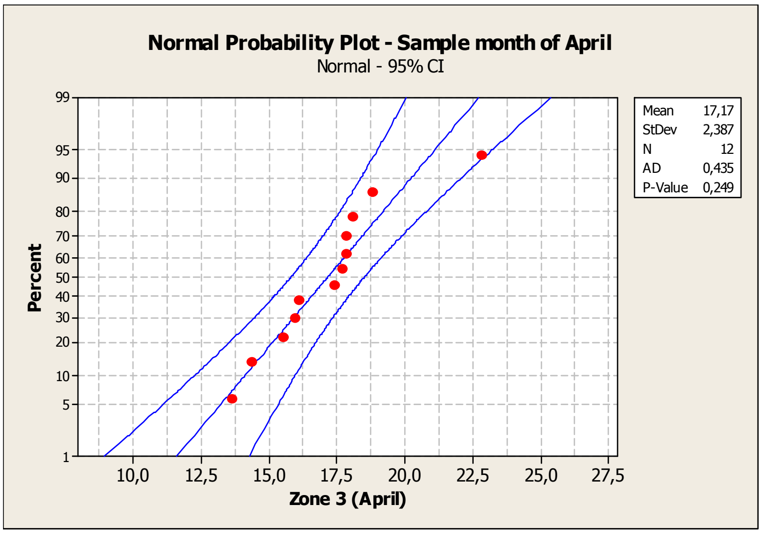


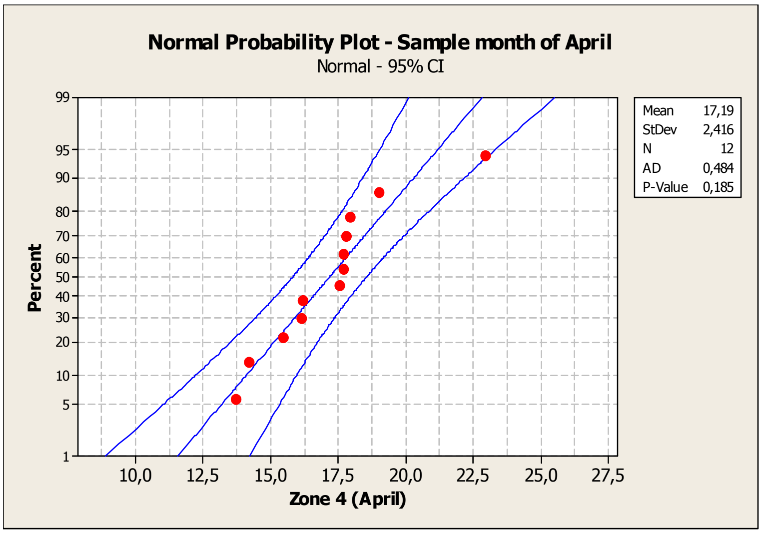
Figure 16.WI calcultion based on the measured temperatures

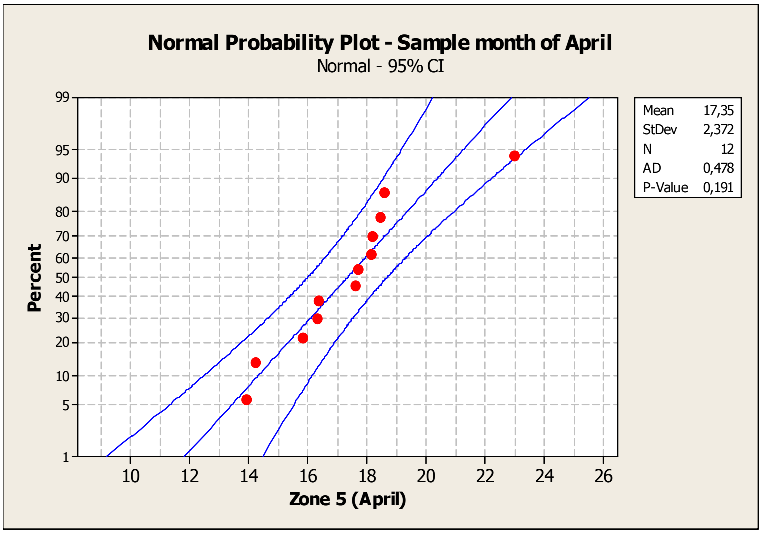
In order to investigate the possibility of applying a linear model to predict future values of WI it is required to test temperature data detected to establish if they are in control. To achieve this goal for each zone of the vineyard two samples consisting of daily average temperatures detected during 12 days of April and May have been considered. The analysis aims at showing that temperatures detected are constant in average. On the basis of considerations done in the previous paragraph at first a normality test was performed for the two sample. The results reported in each of the 15 zones are shown in Figures 17 e 18.

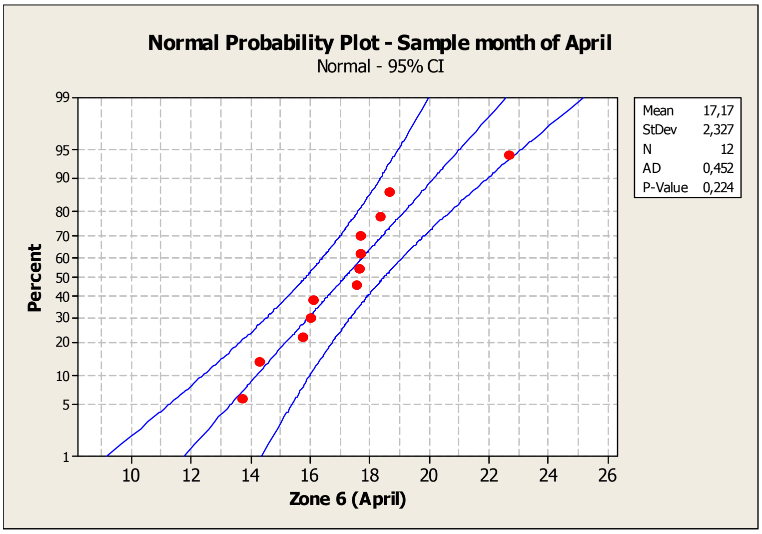

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 1 (April)
Mean 17,48
StDev 3,180
N 12
AD 0,500
P-Value 0,167

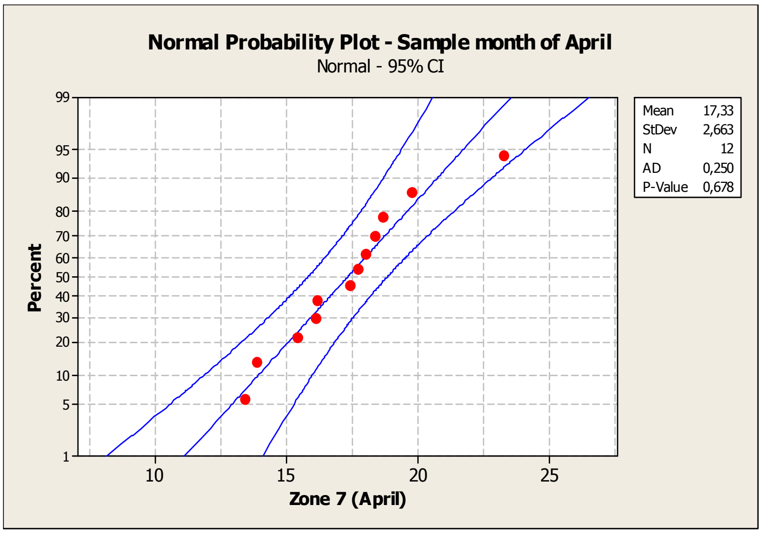

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 2 (April)
Mean 17,52
StDev 2,981
N 12
AD 0,680
P-Value 0,056

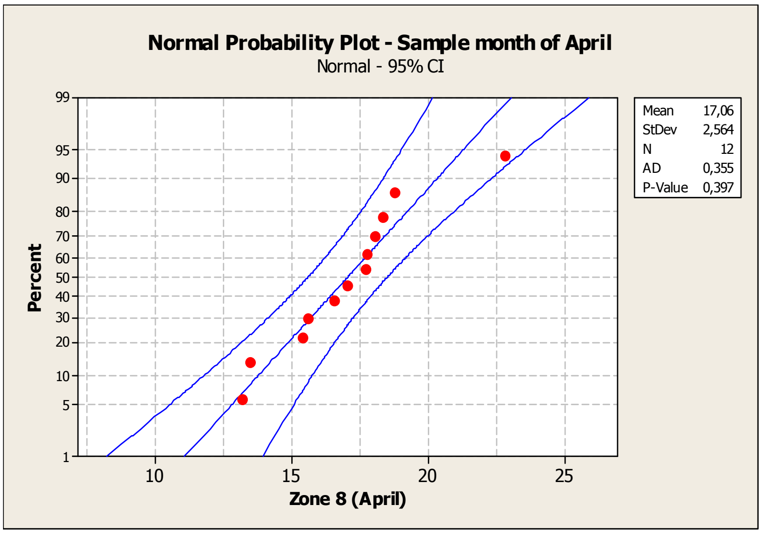

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 3 (April)
Mean 17,17
StDev 2,387
N 12
AD 0,435
P-Value 0,249

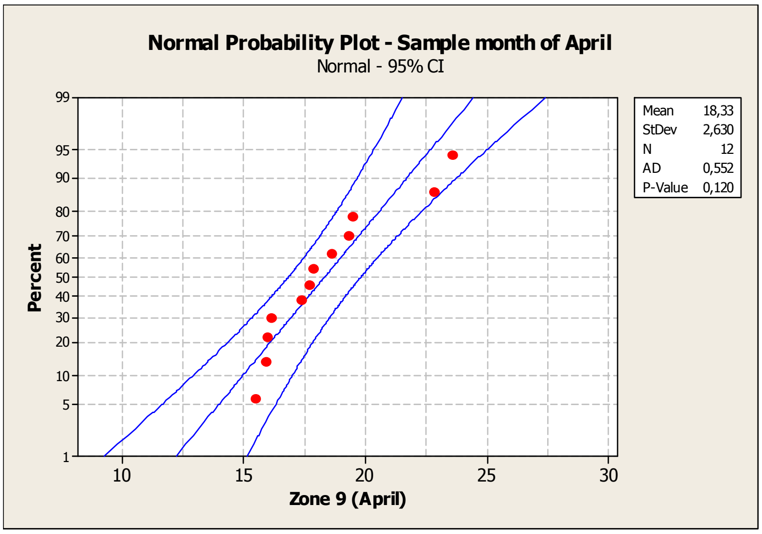

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
99
95
90
80
70
60
50
40
30
20
10
5
1
10,0
12,5
15,0
17,5
20,0
22,5
25,0
27,5
Zone 4 (April)
Mean 17,19
StDev 2,416
N 12
AD 0,484
P-Value 0,185

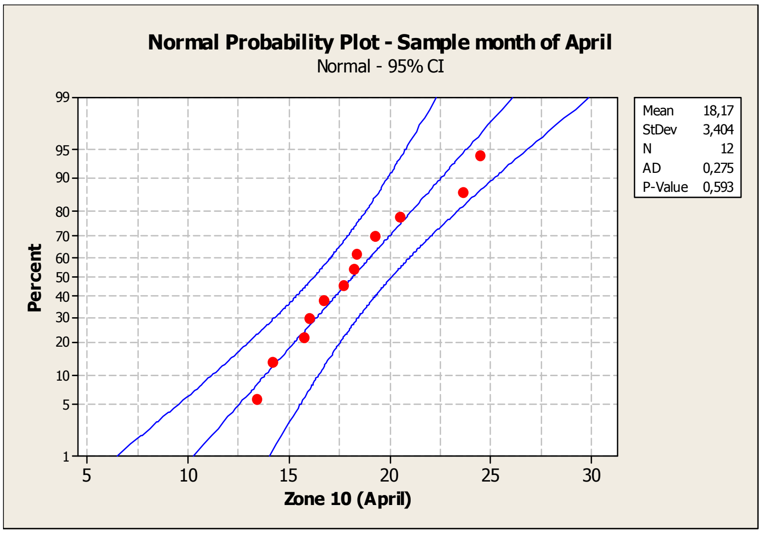

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
99
95
90
80
70
60
50
40
30
20
10
5
1
10
12
14
16
18
20
22
24
26
Zone 5 (April)
Mean 17,35
StDev 2,372
N 12
AD 0,478
P-Value 0,191

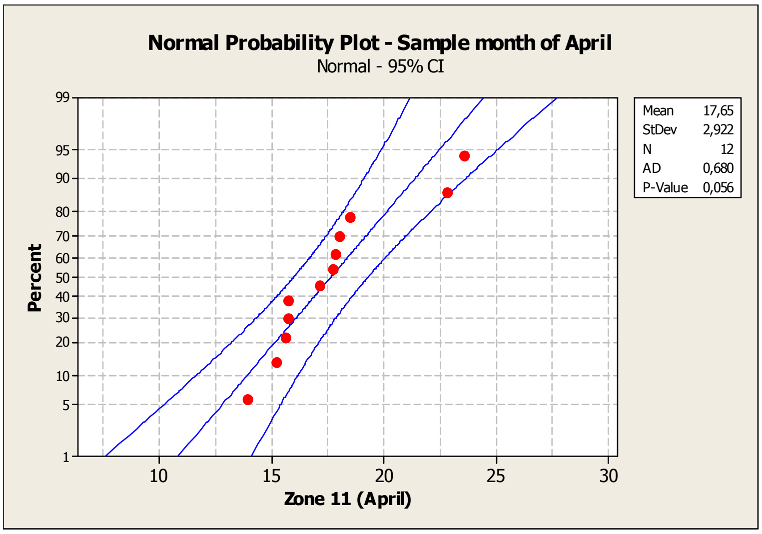

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
99
95
90
80
70
60
50
40
30
20
10
5
1
10
12
14
16
18
20
22
24
26
Zone 6 (April)
Mean 17,17
StDev 2,327
N 12
AD 0,452
P-Value 0,224

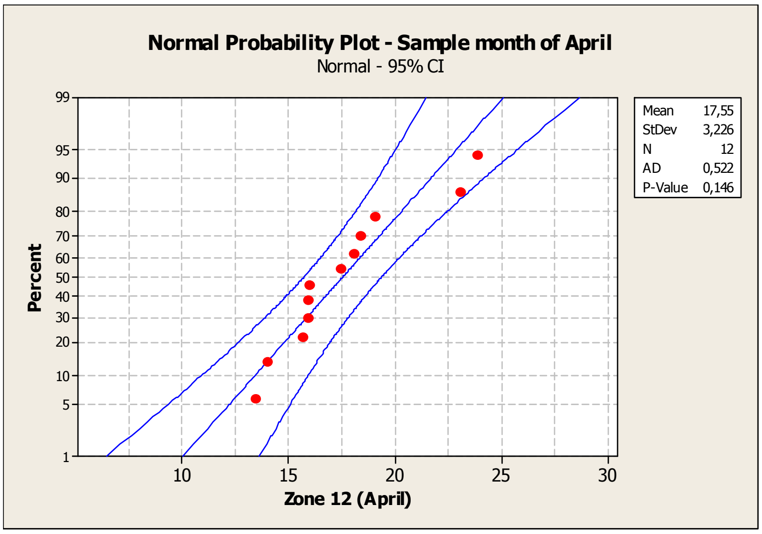

Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 7 (April)
Mean 17,33
StDev 2,663
N 12
AD 0,250
P-Value 0,678


Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 8 (April)
Mean 17,06
StDev 2,564
N 12
AD 0,355
P-Value 0,397


Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 9 (April)
Mean 18,33
StDev 2,630
N 12
AD 0,552
P-Value 0,120


Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 10 (April)
Mean 18,17
StDev 3,404
N 12
AD 0,275
P-Value 0,593


Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 11 (April)
Mean 17,65
StDev 2,922
N 12
AD 0,680
P-Value 0,056


Normal Probability Plot - Sample month of April
Normal - 95% CI
Percent
Zone 12 (April)
Mean 17,55
StDev 3,226
N 12
AD 0,522
P-Value 0,146

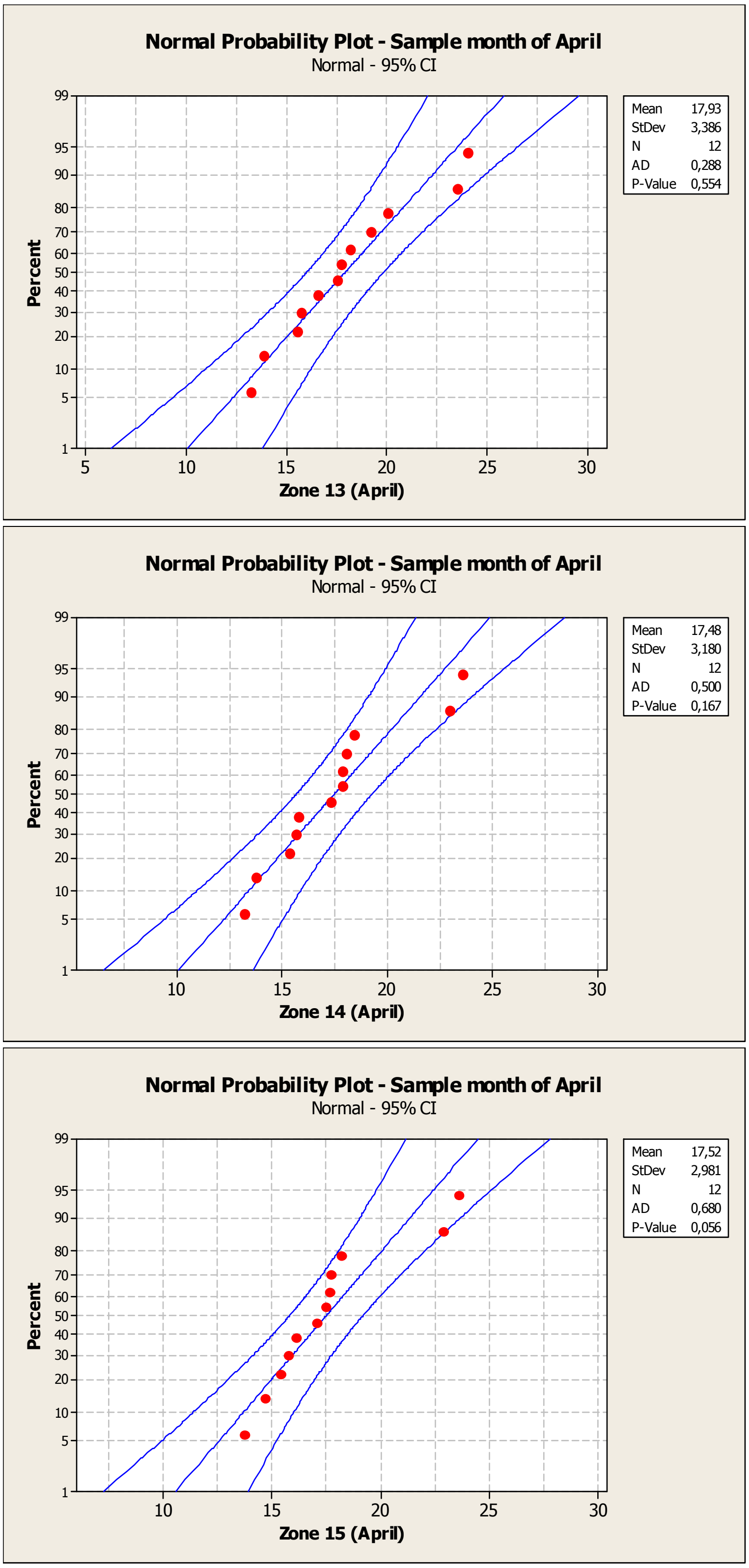
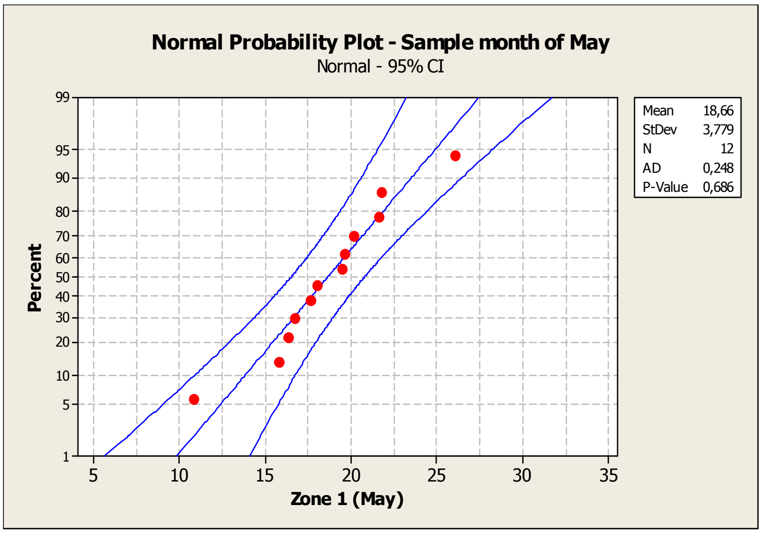
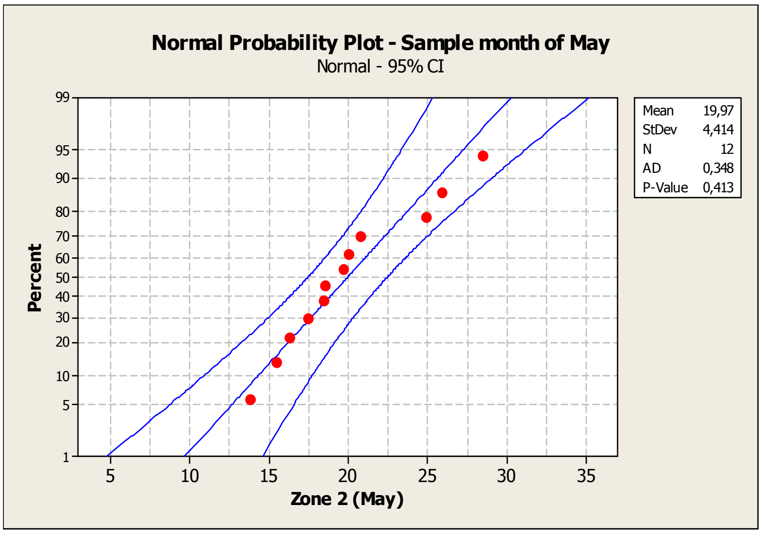
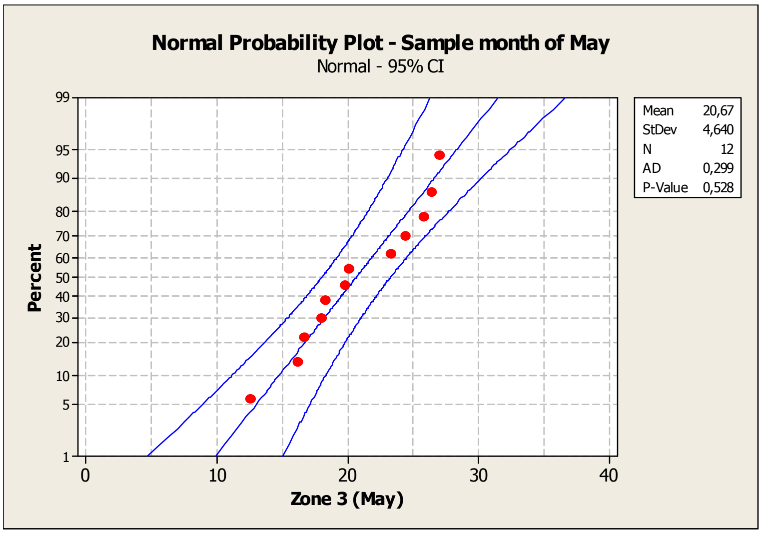


Figure 17. Normality test of sample of April


Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 1 (May)
Mean 18,66
StDev 3,779
N 12
AD 0,248
P-Value 0,686
99
95
90
80
70
60
50
40
30
20
10
5
1
5
10
15
20
25
30
35


Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 2 (May)
Mean 19,97
StDev 4,414
N 12
AD 0,348
P-Value 0,413
99
95
90
80
70
60
50
40
30
20
10
5
1
5
10
15
20
25
30
35


Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 3 (May)
Mean 20,67
StDev 4,640
N 12
AD 0,299
P-Value 0,528
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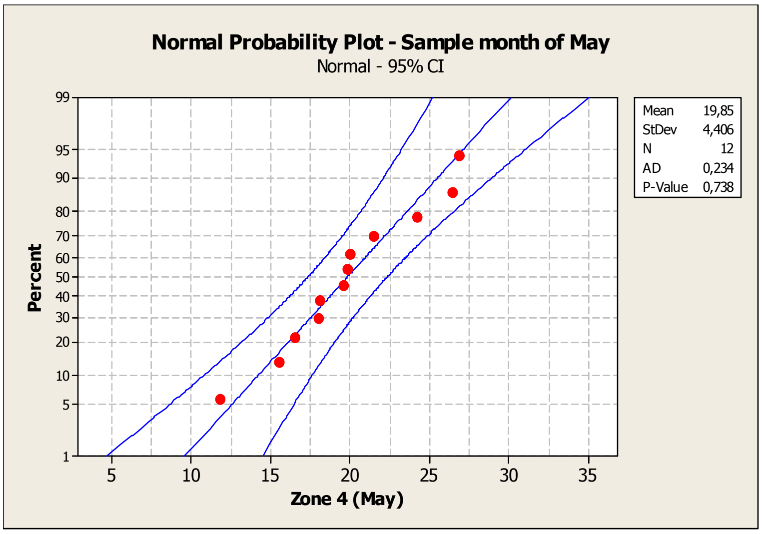
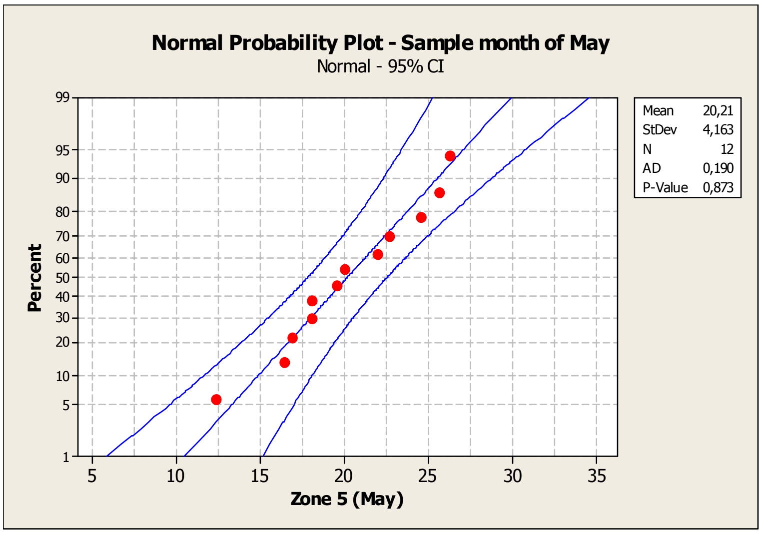
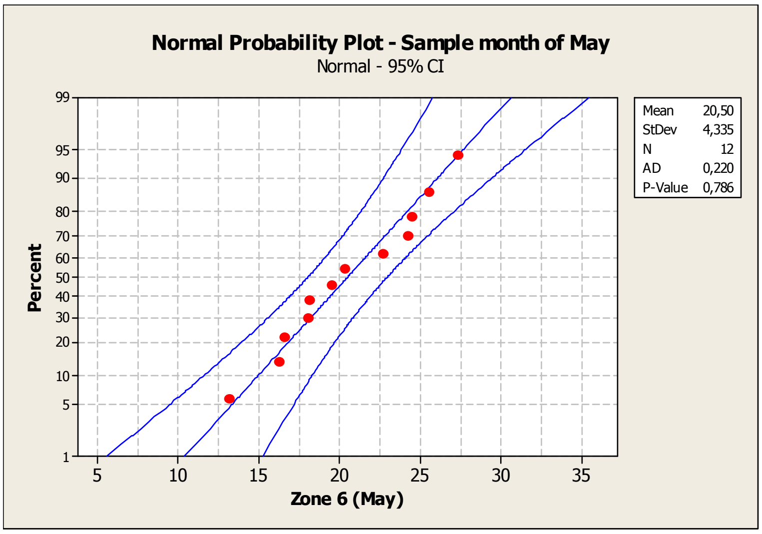
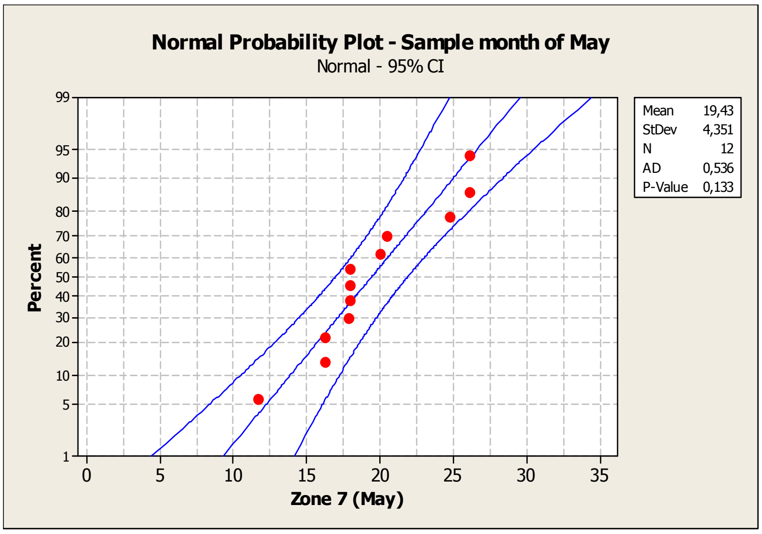
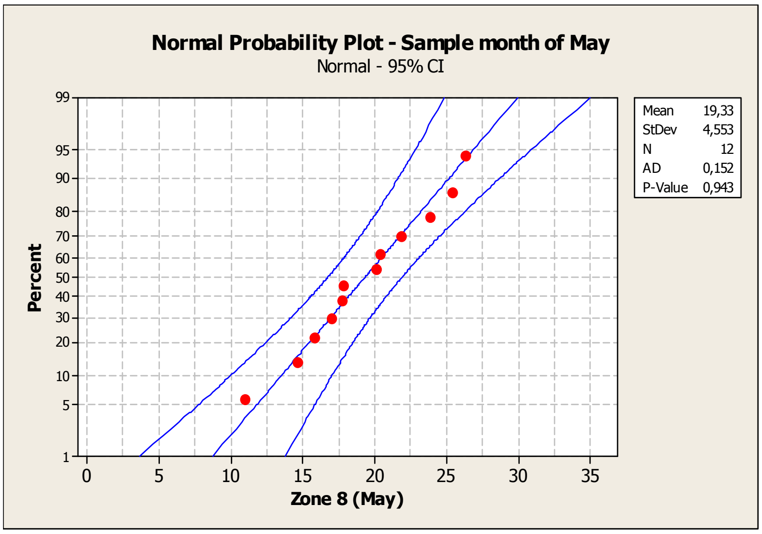
95
90
80
70
60
50
40
30
20
10
5
1
0
10
20
30
40

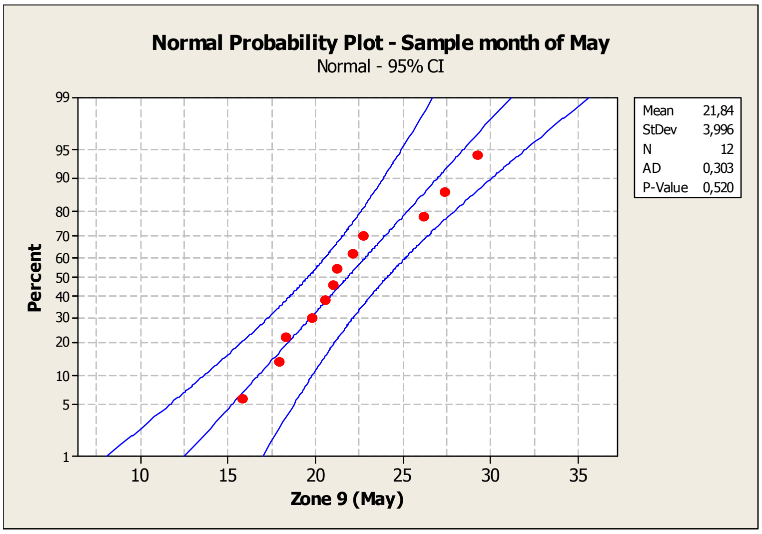

Normal Probability Plot - Sample month of May
Normal - 95% CI
Mean 19,85
StDev 4,406
N 12
AD 0,234
P-Value 0,738
Percent
Zone 4 (May)

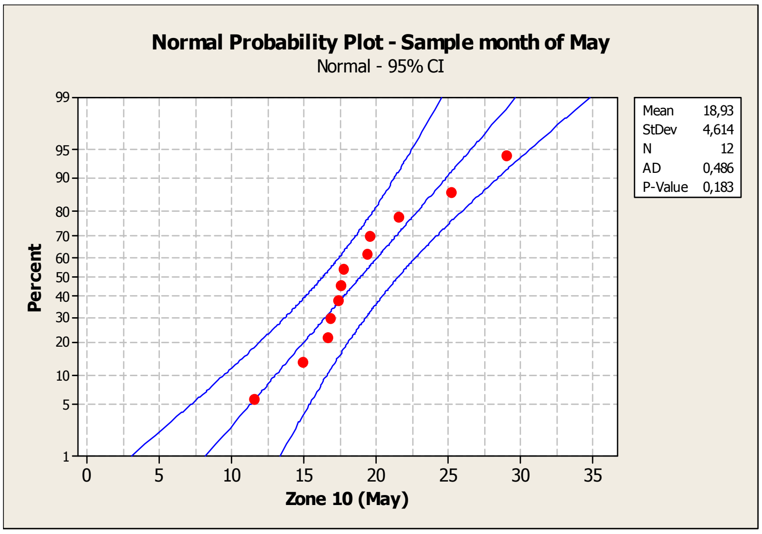

Normal Probability Plot - Sample month of May
Normal - 95% CI
Mean 20,21
StDev 4,163
N 12
AD 0,190
P-Value 0,873
Percent
Zone 5 (May)


Normal Probability Plot - Sample month of May
Normal - 95% CI
Mean 20,50
StDev 4,335
N 12
AD 0,220
P-Value 0,786
Percent
Zone 6 (May)

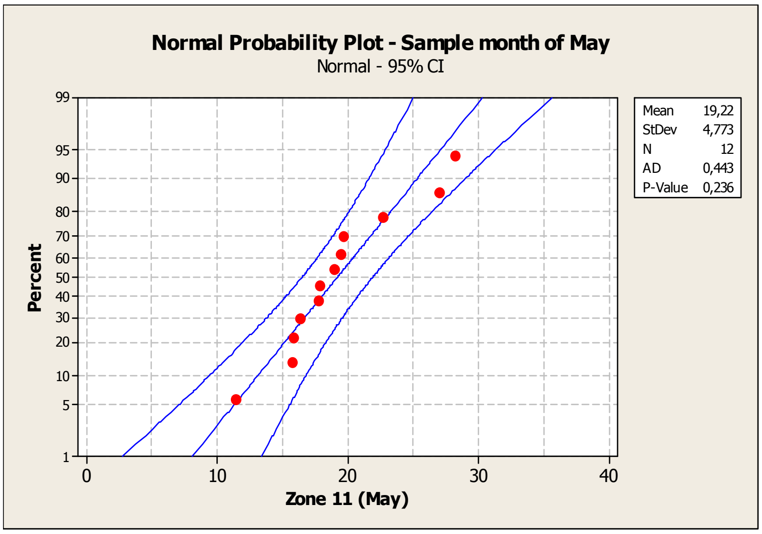

Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 7 (May)
Mean 19,43
StDev 4,351
N 12
AD 0,536
P-Value 0,133


Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 8 (May)
Mean 19,33
StDev 4,553
N 12
AD 0,152
P-Value 0,943

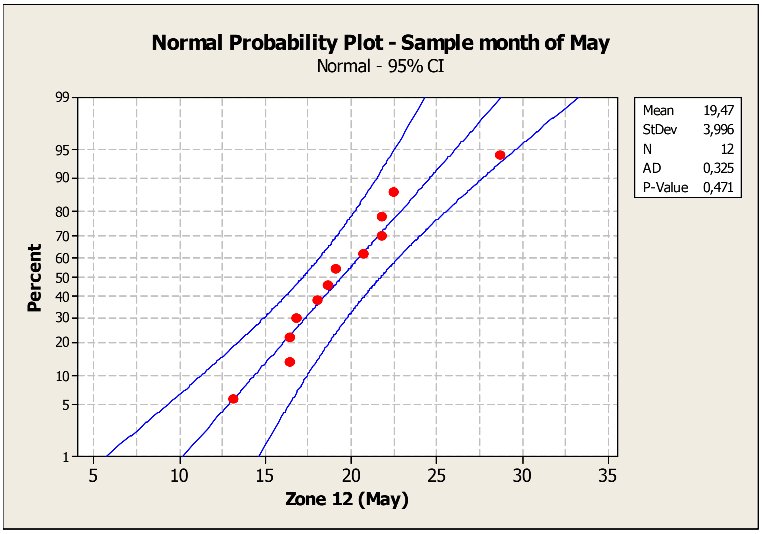

Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 9 (May)
Mean 21,84
StDev 3,996
N 12
AD 0,303
P-Value 0,520



Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 10 (May)
Mean 18,93
StDev 4,614
N 12
AD 0,486
P-Value 0,183



Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 11 (May)
Mean 19,22
StDev 4,773
N 12
AD 0,443
P-Value 0,236



Normal Probability Plot - Sample month of May
Normal - 95% CI
Percent
Zone 12 (May)
Mean 19,47
StDev 3,996
N 12
AD 0,325
P-Value 0,471

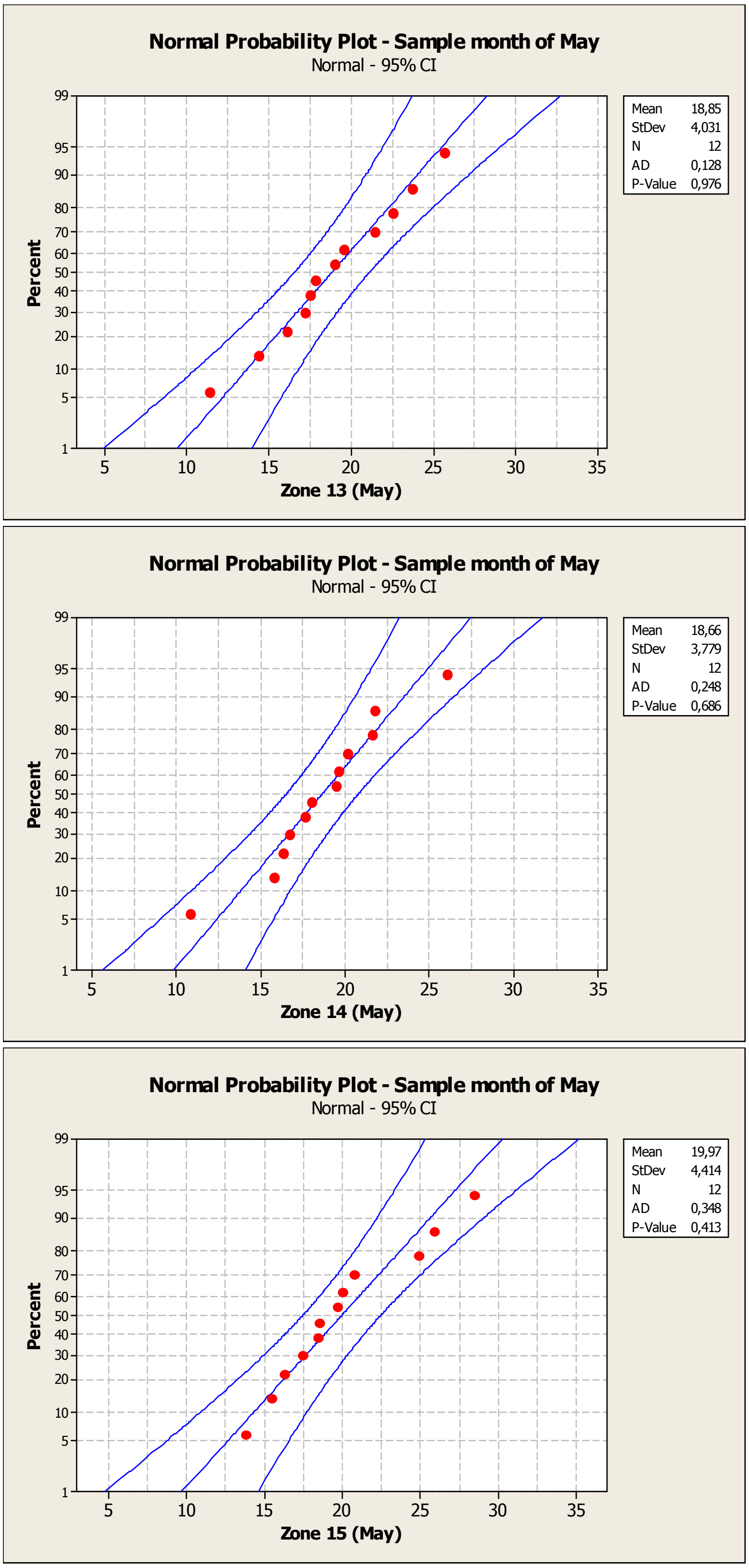


Figure 18.Normality test of sample of May

The Figures 17 and 18 show that the normality test confirms the hypothesis of the normal distribution of the two samples (pvalue >0.05 everywhere). Thus the control charts for each sample and for each of the 15 zones have been realized in order to show if temperatures detected are in control. For this purpose the Shewhart control chart has been built. The UCL and the LCL have been calculated as follows:

$UCL = \bar{x} + k * s$

$LCL = \bar{x} - k * s$

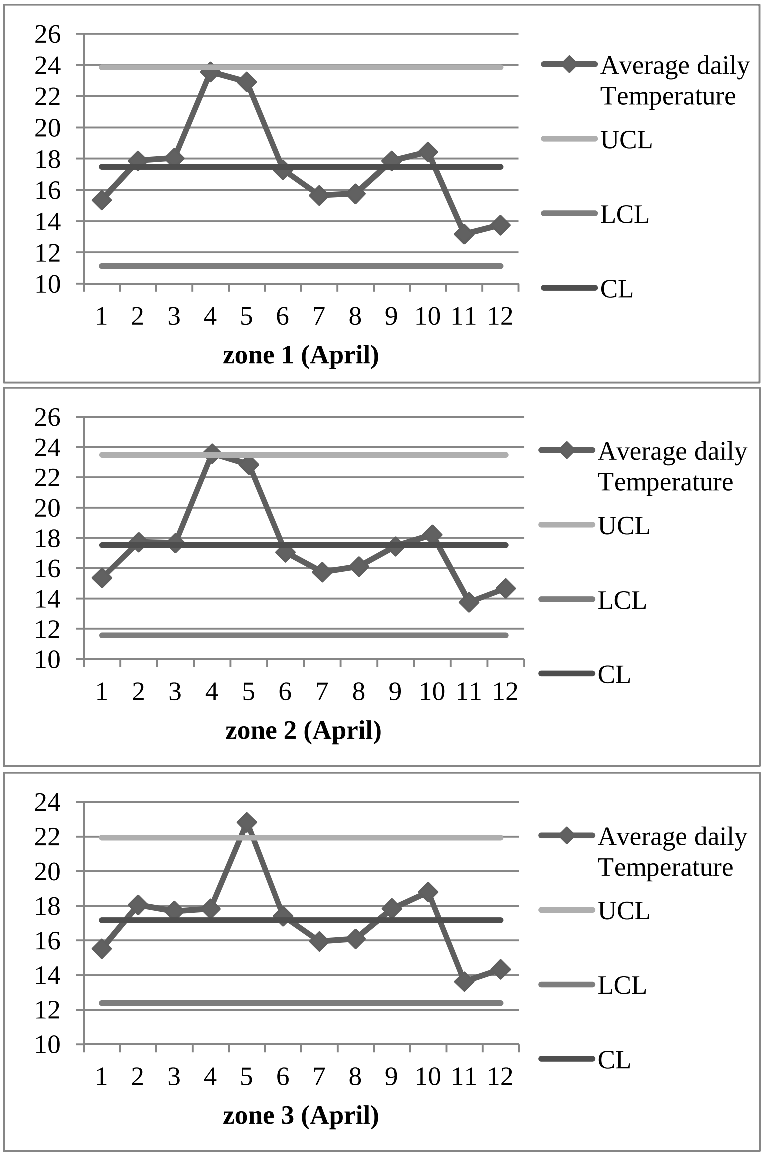
where:

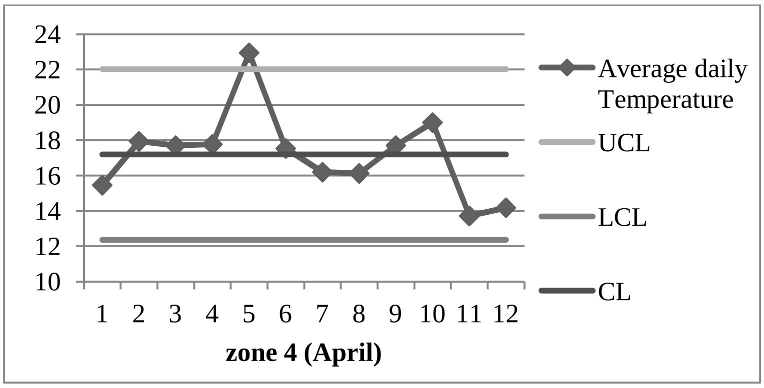
$\bar{x}$= sample mean

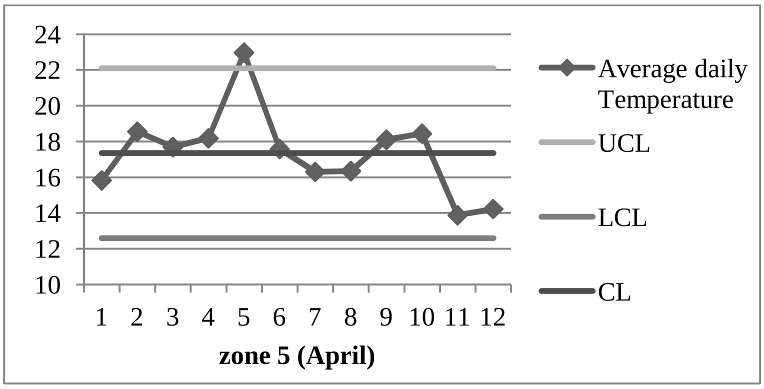
k = an integer multiplier equal to 2

s = sample standard deviation

The results for the two sample of April and May are reported respectively in Figures 19 and 20.




24
22
20
18
16
14
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 4 (April)
Average daily Temperature
UCL
LCL
CL


24
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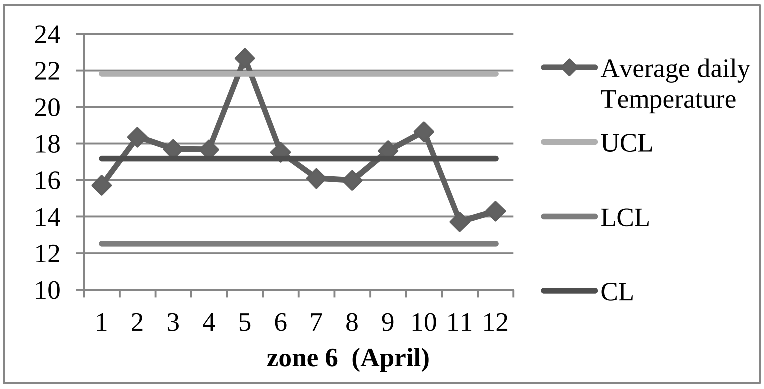
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 5 (April)
Average daily Temperature
UCL
LCL
CL


24
22
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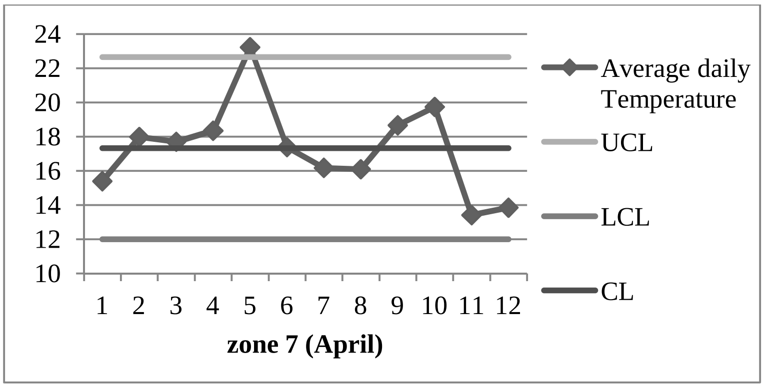
16
14
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 6 (April)
Average daily Temperature
UCL
LCL
CL


24
22
20
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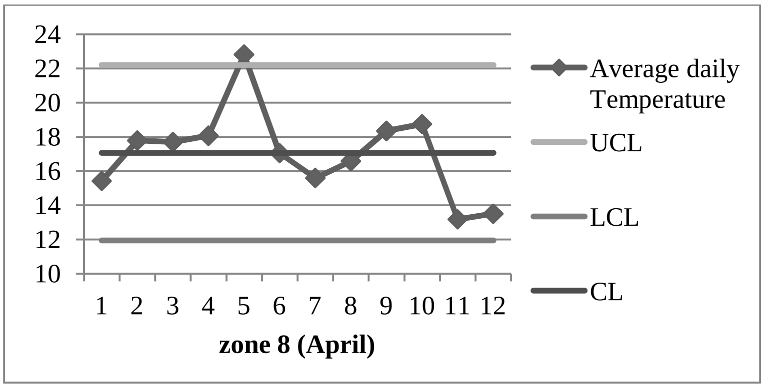
16
14
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 7 (April)
Average daily Temperature
UCL
LCL
CL


24
22
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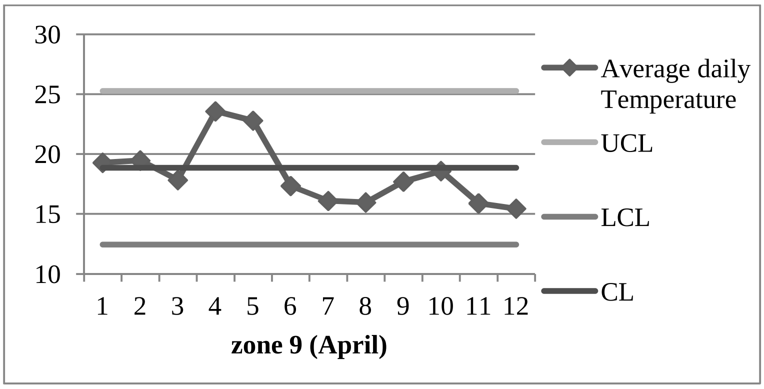
16
14
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 8 (April)
Average daily Temperature
UCL
LCL
CL


30
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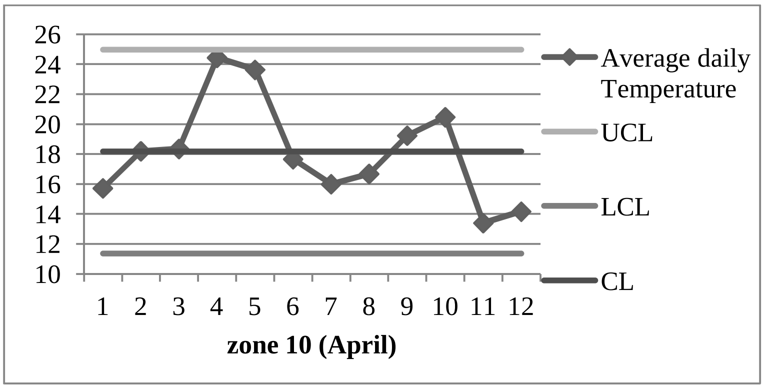
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 9 (April)
Average daily Temperature
UCL
LCL
CL


26
24
22
20
18
16
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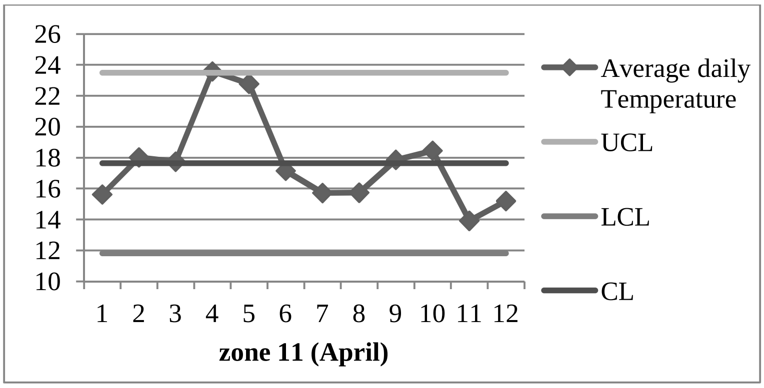
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 10 (April)
Average daily Temperature
UCL
LCL
CL


26
24
22
20
18
16
14
12
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 11 (April)
Average daily Temperature
UCL
LCL
CL

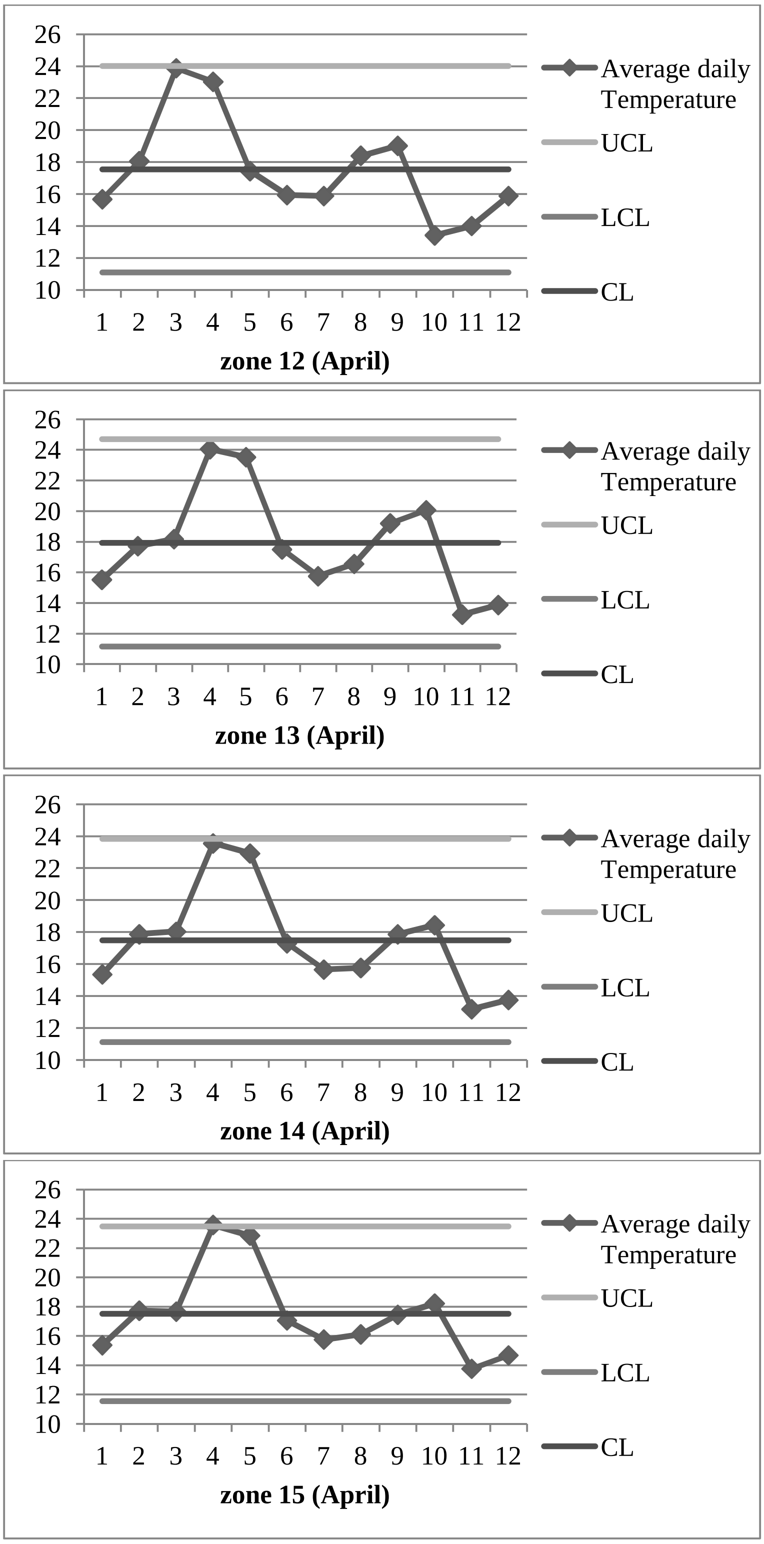
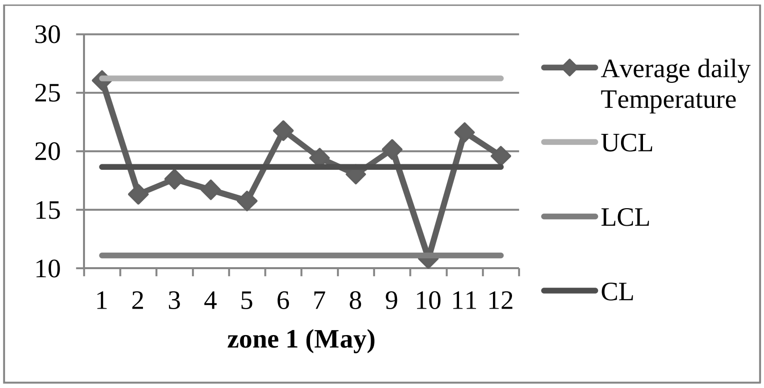
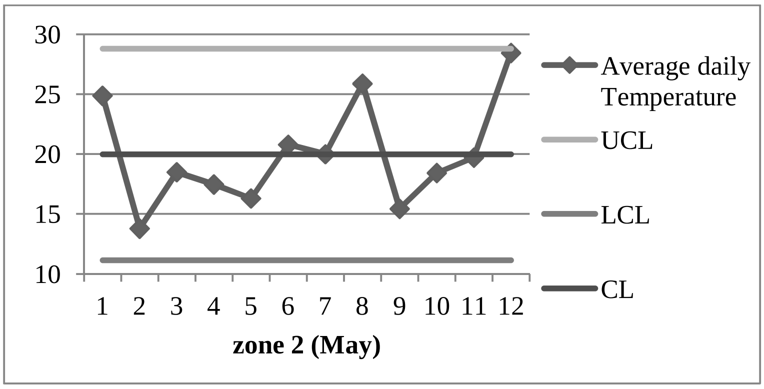
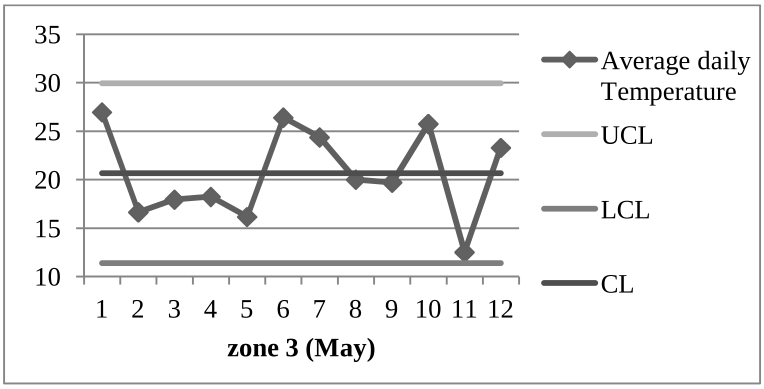
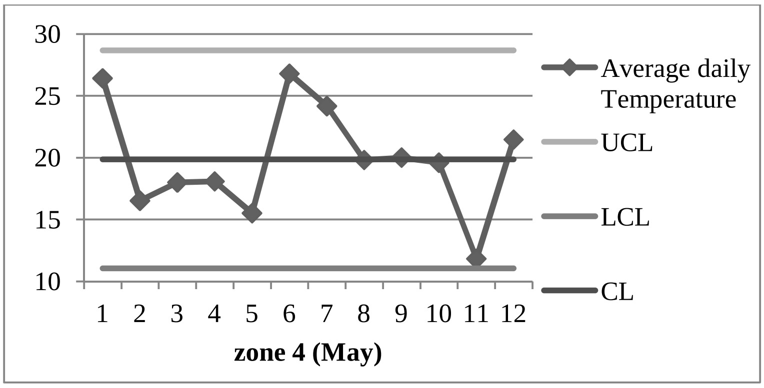


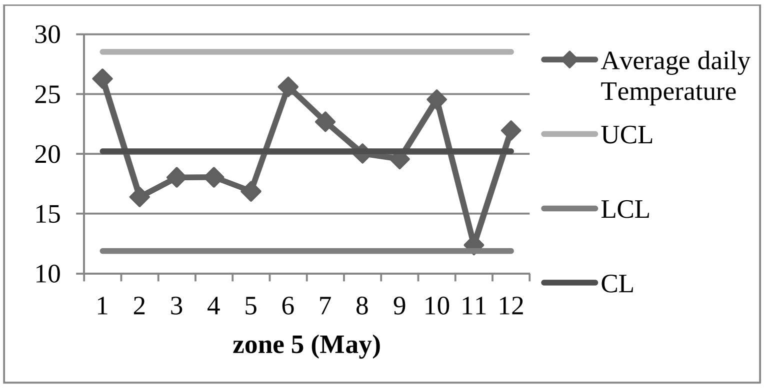
Figure 19. Schewhart control chart for the sample of April

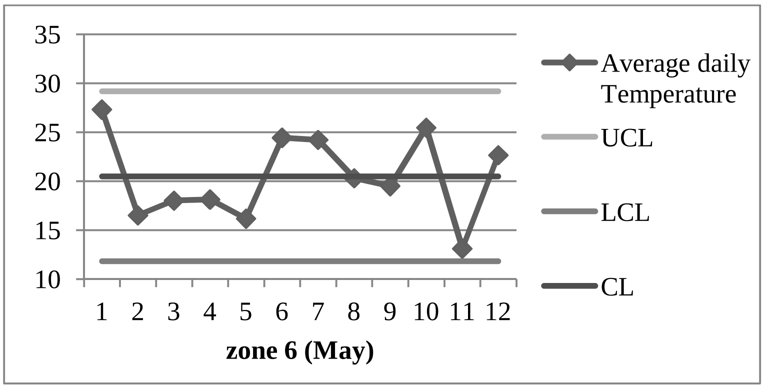

30
25
20
15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 1 (May)
Average daily Temperature
UCL
LCL
CL


30
25
20
15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 2 (May)
Average daily Temperature
UCL
LCL
CL


35
30
25
20
15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 3 (May)
Average daily Temperature
UCL
LCL
CL


30
25
20
15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 4 (May)
Average daily Temperature
UCL
LCL
CL


30
25
20
15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 5 (May)
Average daily Temperature
UCL
LCL
CL


35
30
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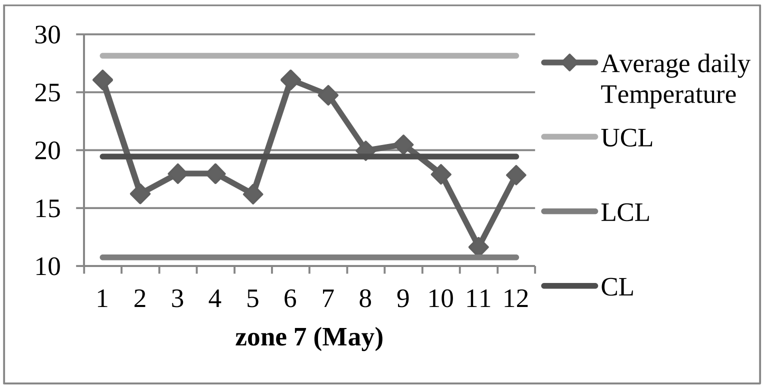
1 2 3 4 5 6 7 8 9 10 11 12
zone 6 (May)
Average daily Temperature
UCL
LCL
CL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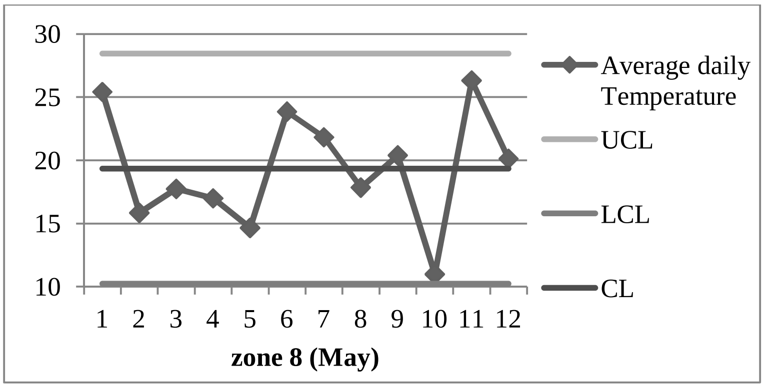
1 2 3 4 5 6 7 8 9 10 11 12
zone 7 (May)
Average daily Temperature
UCL
LCL
CL


30
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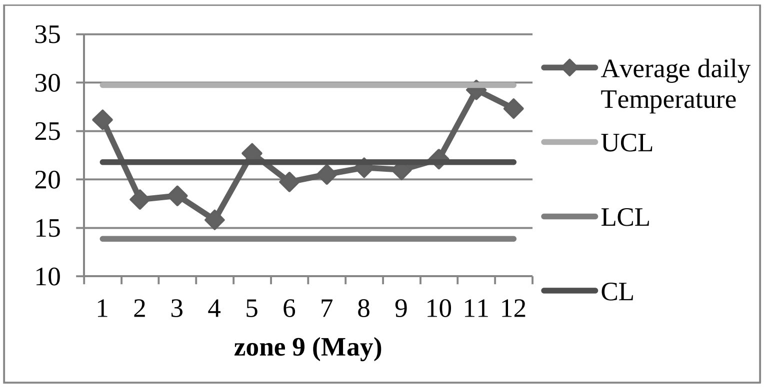
1 2 3 4 5 6 7 8 9 10 11 12
zone 8 (May)
Average daily Temperature
UCL
LCL
CL


35
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15
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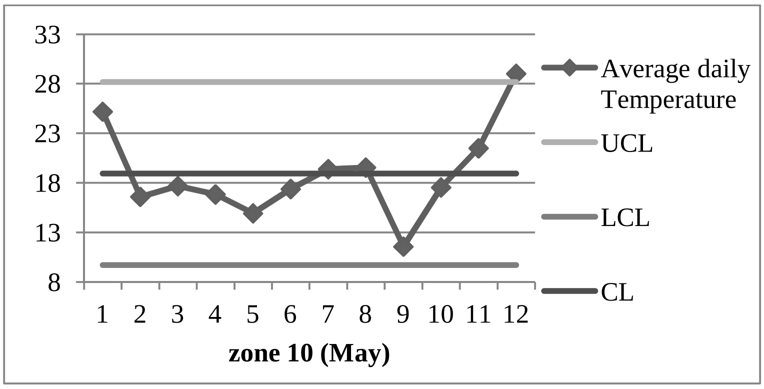
1 2 3 4 5 6 7 8 9 10 11 12
zone 9 (May)
Average daily Temperature
UCL
LCL
CL


33
28
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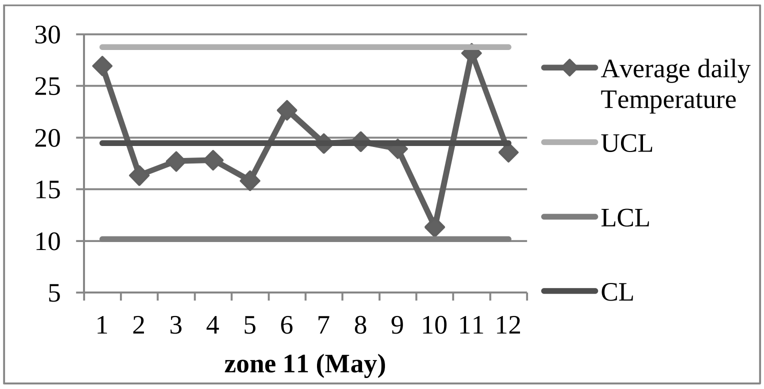
13
8
1 2 3 4 5 6 7 8 9 10 11 12
zone 10 (May)
Average daily Temperature
UCL
LCL
CL


30
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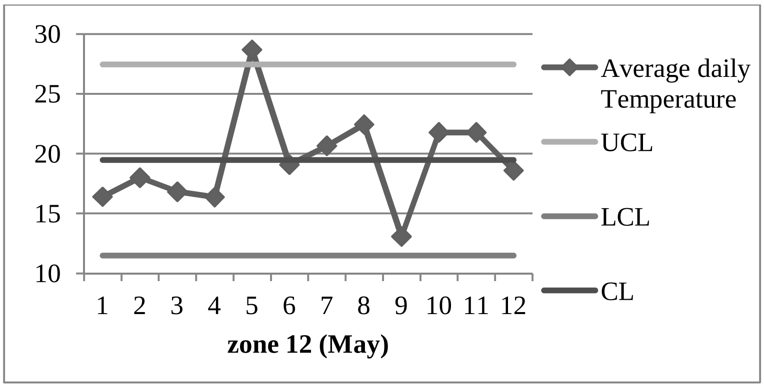
1 2 3 4 5 6 7 8 9 10 11 12
zone 11 (May)
Average daily Temperature
UCL
LCL
CL


30
25
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15
10
1 2 3 4 5 6 7 8 9 10 11 12
zone 12 (May)
Average daily Temperature
UCL
LCL
CL

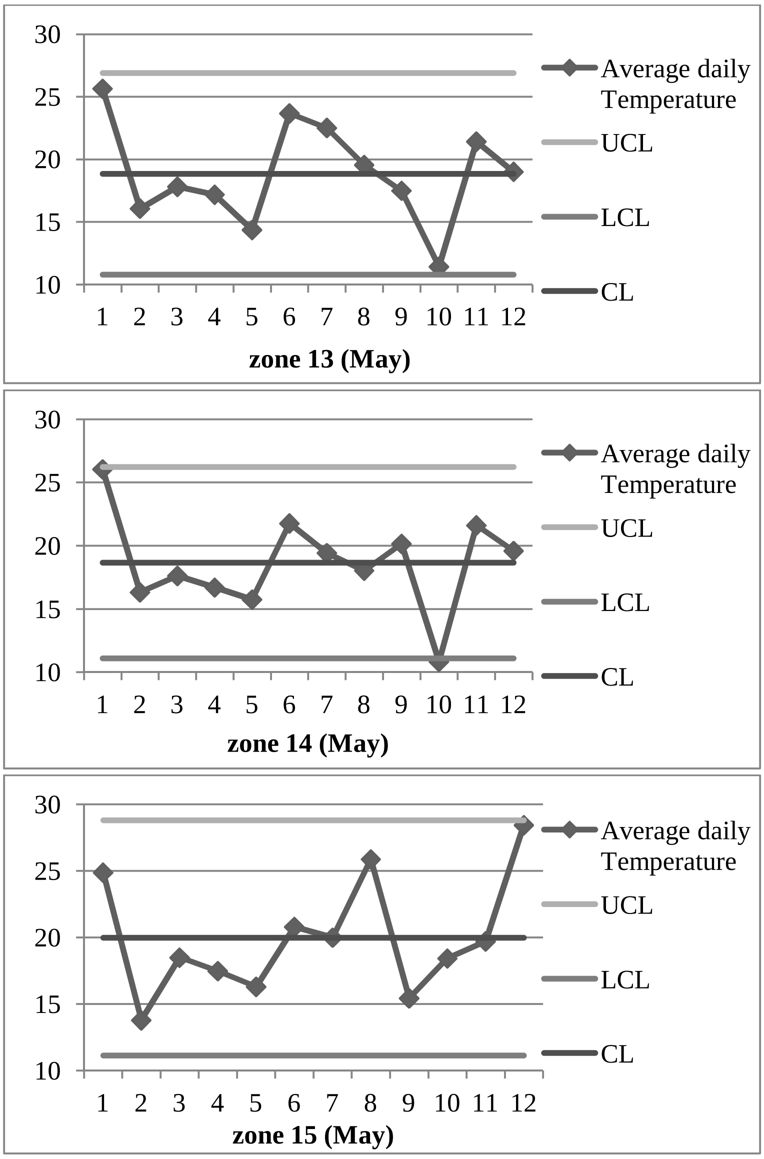


Figure 20. Schewhart control chart for the sample of May

Results show that temperatures detected in each of 15 zones of the vineyard are substantially in control. In fact only one point of zones 3-4-5-6-7-8 of sample of April and one point of zone 12 of sample of May exceed the UCL. Each of them represent the 8.3% of the sample considered. This means that the temperatures referred to time under examination can be considered constant. Accordingly to this it is possible to represent the WI as a linear function having a constant slope. In Figures 21 and 22 the WI for the two samples are shown. For each of 15 zones and for each of two samples the regression analysis has been conducted and the R^2 coefficients have been determined. Results are reported in Tables 8 and 9.

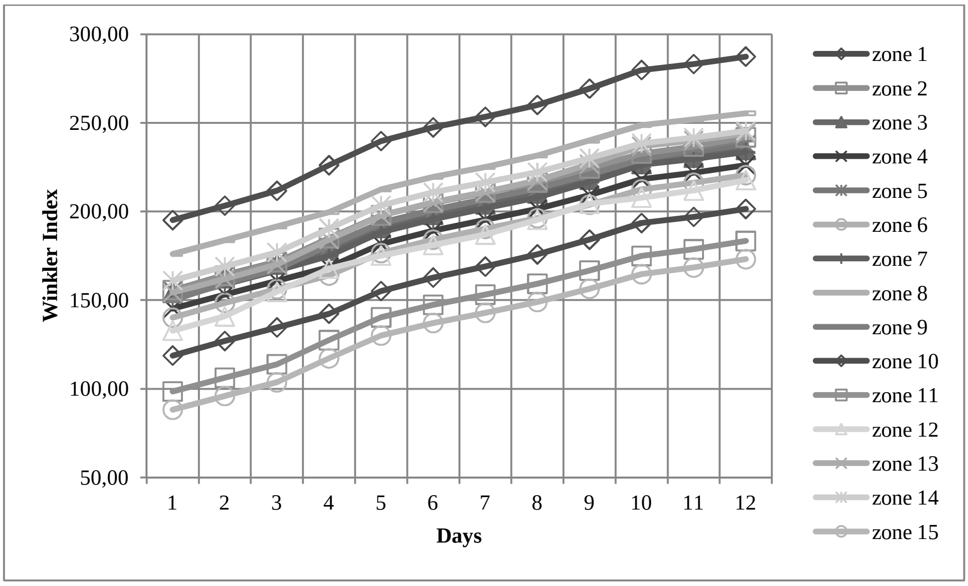


Figure 21. WI for the 15 zones- Sample of April.

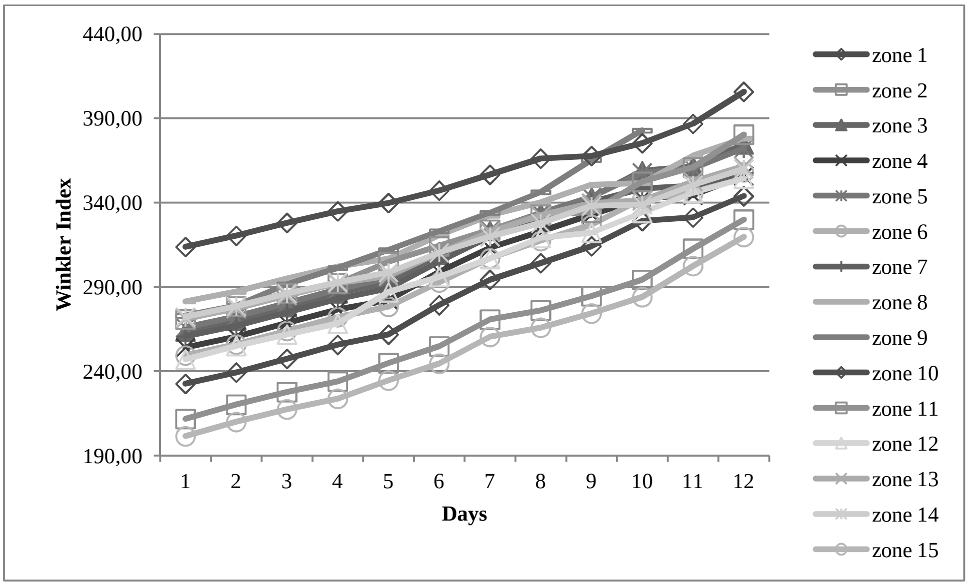


Figure 22. WI for the 15 zones- Sample of May

Sample of April			
Zone	Linear regression (Slope)	Linear regression (Level)	R^2
1	7.794	112.8	0.9902
2	7.9421	94.198	0.9803
3	7.553	149.1	0.9902
4	7.6104	139.79	0.9903
5	7.8124	145.16	0.9902
6	7.524	135.19	0.9901
7	7.73	150.35	0.9898
8	7.52	170.7	0.989
9	8.3	145.84	0.9854
10	8.72	189.71	0.983
11	8	151.39	0.9818
12	7.673	131.54	0.974
13	8.5097	148.82	0.9825
14	7.9481	157.2	0.977
15	7.942	83.946	0.9803
Mean	**7.905**	**140.38**	**0.98494**

Table 8. Regression of the WI - Sample of April

Sample of May			
Zone	Linear regression (Slope)	Linear regression (Level)	R^2
1	10.689	216.66	0.9896
2	10.352	196.26	0.9848
3	10.584	247.5	0.9906
4	9.824	240.63	0.9881
5	10.145	251.18	0.9921
6	10.329	233.72	0.9924
7	9.6283	247.95	0.9838
8	8.8792	268.5	0.99
9	11.98	255.03	0.9851
10	7.666	303.76	0.9794
11	9.489	257.69	0.9857
12	10.061	234.4	0.9936
13	8.4817	260.14	0.9902
14	8.0591	262.12	0.994
15	10.352	186	0.9848
Mean	**9.767**	**244.10**	**0.98828**

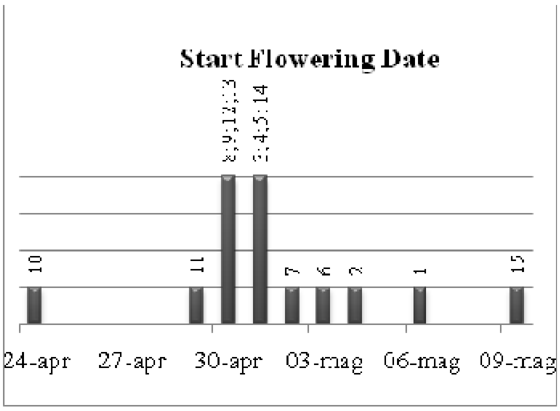
Table 9. Regression of the WI - Sample of May

Results show that the average value of R^2 is about equal to 0.98 for all zones of two samples. This suggests that in each of 15 zones of the vineyard about the 98% of variation of the WI is due to the linear relation between the WI and the time of detection. This means that a statistical model including level and trend can be used to forecast the future value of the WI. For this reason short-term forecasts of WI have been determined by means of Holt’s model discussed in the previous paragraph. In order to apply the Holt’s model the initial values of the level and the trend have been determined by a linear regression, while α and β have been chosen in order to minimize the Mean Absolute Deviation (MAD), on the basis of the data acquired in the first 20 days of monitoring, namely, from April the 1st to April 20th. This way, α and β values have been determined for each zone of the vineyard. Finally, the reference values (Policarpo et al. (2008)) given in Table 10 have been considered as the thresholds corresponding to the most significant phenological phases of the grapes ripening process for some varieties including the one considered (Chardonnay).

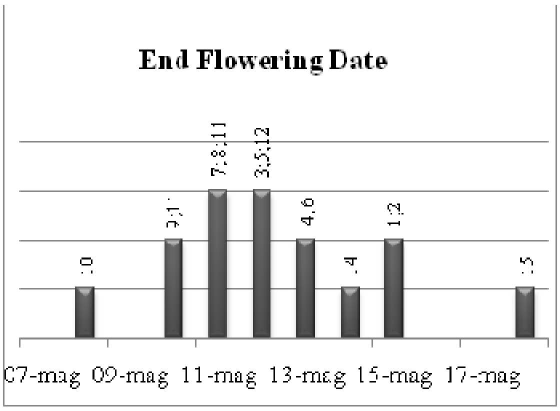
Cultivar	Start Flowering	End Flowering	Start Veraison	End Veraison	Maturation
Ansonica	345,6±13,6	441± 11	1335,8 ± 57,1	1462,6 ± 147,9	1510,5 ± 165,5
Cabernet franc	292,8 ±22,6	424,8 ± 21	1032 ± 11,54	1335 ± 116,2	1461,7 ± 83,6
Cabernet sauvignon	314,1 ± 21,7	452,7 ± 23	1109 ± 73,1	1324,6 ± 138,2	1453,7 ± 94,4
Chardonnay	270,9 ± 30,2	386,9 ± 32,2	1010,3 ± 82,7	1256 ± 96,3	1319,6 ± 130,5
Muller Thurgau	297,2 ± 26,2	372,3 ± 21,9	843,4 ± 11,63	1085,9 ± 52,7	1205,7 ± 46,2
Nero d'Avola	340,7 ± 22,3	437,1 ± 37,4	1128,5 ± 61	1437,8 ± 31,1	1544,4 ± 19,9
Pinot Noir	268,1 ± 30,7	366,3 ± 28,1	1019,5 ± 84,2	1250,1 ± 78,8	1283,8 ± 99
Viognier	363,7 ± 25	457,8 ± 31,6	1186,3 ± 76,7	1397,1 ± 38	1474,7 ± 95,9

Table 10. Triennal average (2005-2007) of WI (average ± standard deviation).

According to the thresholds given in Table 10, and to the WI values calculated by means of the temperature monitoring system, the forecasts for the start flowering date and the end flowering date have been calculated for each zone of the winery. Also the standard deviation was calculated assuming a random error and considering an acceptance probability of 0.5. The results obtained, in terms of forecast dates are given in the following Figures 23.a and 23.b. The proposed methodology allowed to cluster the 15 zones of the vineyard in 9 different forecasted start flowering dates and 8 forecasted end flowering dates. The average number of days required to start and end the flowering phase for all the zones of the vineyard is 30 and 41 respectively, with a corresponding average duration of the flowering phase of 11 days, as given in Table 11.



23.a



23.b

Figure 23. Forecasted start flowering (a) and end flowering dates (b) for the sampled areas of the vineyard

	Days from 1 April to Start flowering	Days from 1 April to End flowering	Distance between Start and End flowering
Average	30± 3,288	41,33± 2,748	11,00

Table 11. Average number of days required to start and end the flowering phase for all the zones of the vineyard and corresponding average duration.

Finally, in order to evaluate the forecast error, the forecasted values of the WI are compared with the values of WI calculated by means of the actual temperature datasets acquired by the sensor network in the days subsequent to the forecast date. In other words, the forecasted dates are compared with the dates when the reference thresholds are achieved by the WI values calculated by means of the temperatures acquired. The values thus obtained have been employed to benchmark both the forecasted values obtained by the proposed methodology based on the Holt's model and the values obtained by means of a simple linear regression. Common error measures have been employed to benchmark the forecasts. Table 12 gives the average values of the Mean Squared Error (MSE), Mean Absolute Deviation (MAD) and Total Error (ET) calculated for each zone of the vineyard. The forecast errors show that the Holt's outperforms the Regression model in forecasting the values of the WI.

Average	Holt's model	Linear Regression
MSE (DD)	657,98	1610,57
MAD (DD)	20,53	29,91
ET (DD)	194,47	-302,95

Table 12. Average forecasts errors

	Start Flowering					End Flowering				
Zone	**Actual**	**Linear Regression**	**Holt's model**	**Linear Reg. error (days)**	**Holt's model error (days)**	**Actual**	**Linear Regression**	**Holt's model**	**Linear Reg. error (days)**	**Holt's model error (days)**
1	6-May	6-May	6-May	0	0	15-May	21-May	15-May	6	0
2	4-May	8-May	3-May	4	-1	15-May	25-May	14-May	10	-1
3	1-May	29-Apr	29-Apr	-2	-2	12-May	12-May	11-May	0	-1
4	1-May	1-May	30-Apr	0	-1	13-May	13-May	10-May	0	-3
5	1-May	29-Apr	29-Apr	-2	-2	12-May	11-May	12-May	-1	0
6	3-May	2-May	3-May	-1	0	13-May	15-May	12-May	2	-1
7	2-May	30-Apr	2-May	-2	0	11-May	12-May	10-May	1	-1
8	30-Apr	26-Apr	29-Apr	-4	-1	11-May	8-May	10-May	-3	-1
9	30-Apr	29-Apr	30-Apr	-1	0	10-May	11-May	8-May	1	-2
10	24-Apr	24-Apr	26-Apr	0	2	8-May	4-May	7-May	-4	-1
11	29-Apr	29-Apr	29-Apr	0	0	10-May	10-May	9-May	0	-1
12	29-Apr	29-Apr	29-Apr	0	0	12-May	12-May	9-May	0	-3
13	30-Apr	29-Apr	29-Apr	-1	-1	11-May	11-May	10-May	0	-1
14	1-May	28-Apr	30-Apr	-3	-1	14-May	10-May	10-May	-4	-4
15	9-May	8-May	9-May	-1	0	18-May	24-May	19-May	6	1

Table 13. Comparison among the forecasts dates

Finally, Table 13 gives the comparison among the start flowering date and end flowering date for each zone of the vineyard compared with the forecasts obtained by the Linear Regression and Holt's model methods, and the difference between the actual dates and the forecasts in terms of days before or days after. The final benchmarks among the actual start and end flowering dates and the forecasted values obtained by means of the proposed methodology and a standard linear regression are given in Figures 24 and 25.

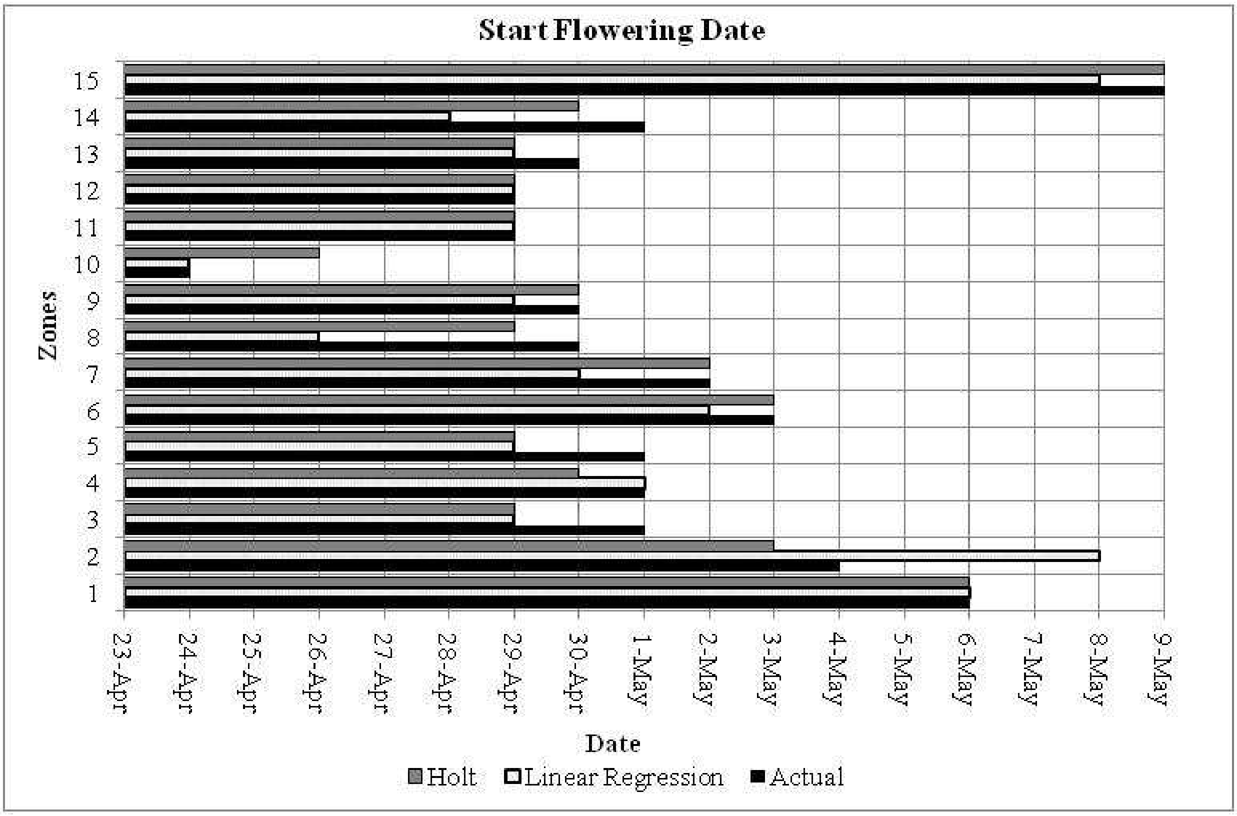


Figure 24. Start flowering dates Comparison between forecast, regression and actual values

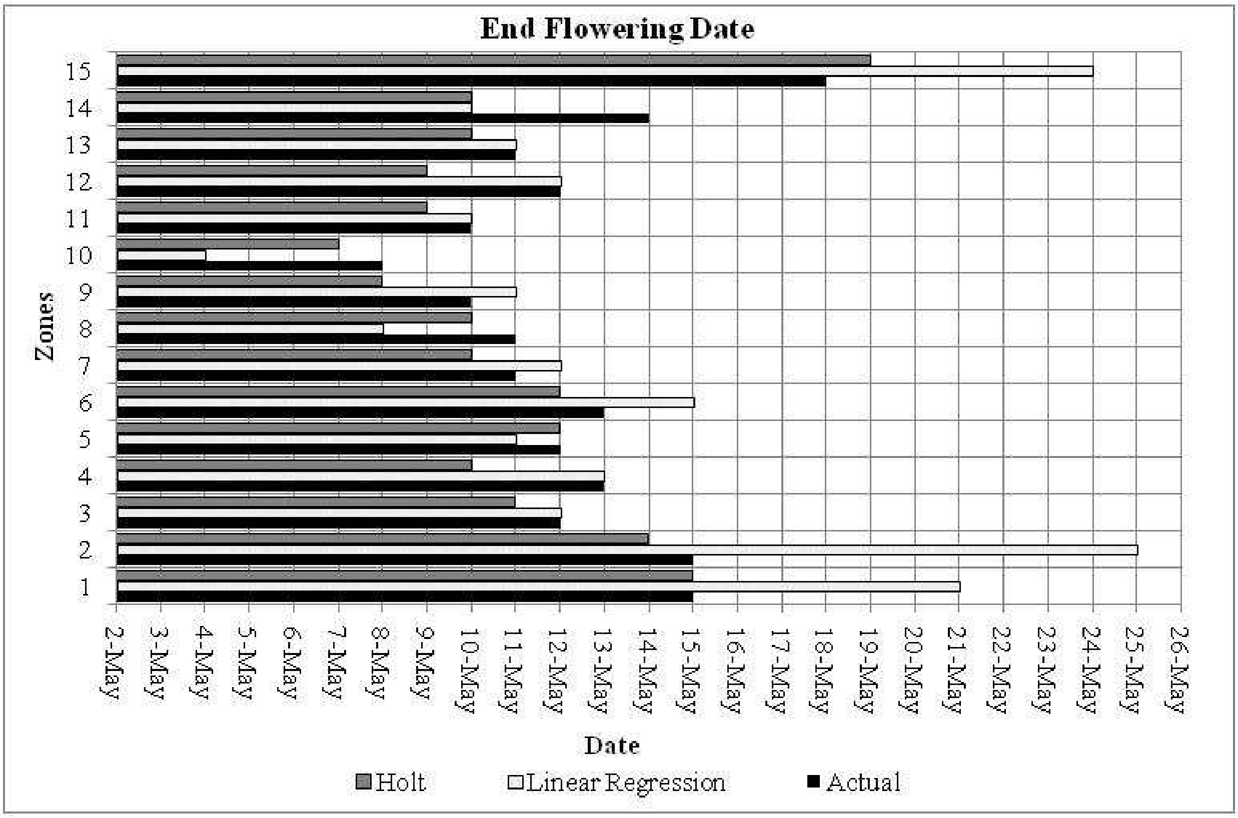


Figure 25. End flowering dates Comparison between forecast, regression and actual values

4.3.6 Conclusions

In this section a methodology to predict the occurrence of the most significant phenological maturation phases of the grape vines has been proposed. Such information is crucial for effectively planning vineyard operations, as in fact monitoring activities based on manual sampling of the berries are currently common practice in vineyard management. The methodology essentially consists in the calculation of referenced heat summation indicators of the ripening level of the berries, to be employed in order to forecast the achievement of pre-established threshold values. In particular in the case here proposed, the WI has been evaluated by means on a micro-climatic monitoring system based on a WSN deployed within the vineyard, thus obtaining an extremely precise and detailed temperature mapping within the vineyard. The experiments show that 9 different start flowering dates spanning an interval of 15 days and 8 end flowering dates distributed in an interval of 11 days could be discriminated. Also the intrinsic uncertainty measured by the standard deviation of the forecasts has been taken into account and the forecast errors have been estimated showing the accuracy of the results obtained. Clearly the accuracy of the results is drastically influenced by the establishment of reliable thresholds for the particular variety considered and the growing zone, as well as, the distance in time when the forecasts are performed. Such issues are well known in expert systems involving uncertain elements in the decision processes. The proposed research, hence, aims at demonstrating how traditional vineyard management practices can be integrated by innovative support tools, based on non expensive technologies as ubiquitous computing and sensors networks. Therefore the proposed methodology can be effectively considered as a useful decision making tool able to help in the optimization of vineyard operations during the ripening process and finally at the harvesting time. The methodology in fact can be extended to the entire ripening process at the same manner in order to predict the harvest date. The methodology also allows to discriminate between different zones of the vineyard which are subjected to different microclimate conditions. This allows to optimize the harvest date and to make the supply chain of the wine industry more responsive with regard to the market requirements. The methodology here proposed, however, is quite preliminary and further developments should be focused on the employment of multi criteria decision making (MCDM) methods as well as approximate reasoning formulations in order to take into account the objectives of different decision makers, as well as imprecise and subjective judgments. Also additional information should be taken into account for example resulting from monitoring humidity or solar irradiation, taking advantage of the capabilities offered by the sensor technology. These capabilities, however, pose several questions in the application space regarding for example what data should be gathered and how often, how information must be processed, how should the result be presented to the user and how can the knowledge based be employed to support the decision processes. Therefore, in order to fully exploit the potential of such technologies and systems such issues must properly investigated.

SECTION 2: INNOVATIVE TECHNOLOGIES ENABLING THE DECISION MAKING IN THE SHELF LIFE MONITORING

INTRODUCTION

the management of perishable supply chains is a difficult task because of the limited life of such products. Monitoring and keeping of proper environmental parameters at every stage of the cold chain is a critical issue in order to preserve perishable products from uncontrolled deteriorative processes responsible for quality loss. Food quality can be defined by a set of product attributes that influence a product's value to the consumer. This includes negative attributes such as spoilage, contamination, discoloration, off-odors and positive attributes such as the origin, color, flavor, texture and processing method of the food (FAO and WHO, (2003)). A quantitative measure of product quality is the Shelf Life (SL), defined as the time until a product becomes unacceptable to consumers under a given storage condition. The knowledge of the SL of fruits and vegetables is a key issue in order to optimize the supply chain management since it allows to improve both inventory and distribution strategies. Traditionally the determination of such parameter relies on qualitative analysis based on the evaluation of intrinsic factors related to the product. However these are disruptive methods which can be applied only to a product sample. Furthermore they are time consuming and expensive due to the human intervention and laboratory instruments required. A recent approach studied, e.g. by Doyle (1995) and Taoukis and al. (1999) aims at establish a relation between the time–temperature history to which a product is subjected and the remaining quality of the product in terms of its SL. This approach relies on the kinetic theory of reactions and on Arrhenius equation. In this case the precision of the SL value determined with respect to the actual value depends on the proper evaluation of reaction order, the validity of the Arrhenius law for the process under consideration and the possibility to detect the temperature conditions of the product at any stage of the supply chain. Today the possibility of contemporary identification and monitoring of environmental parameters is made possible by an innovative and pervasive technology, such as the Radio Frequency Identification (RFID). The monitoring of the current quality of products allows to realize important issues in the optimization of the supply chain management. In fact the knowing of the remaining quality level at any stage of the supply chain allows to appropriately directing products themselves since those products having a shorter SL can be send in a closer market thus avoiding further quality loss. Furthermore those products which are considered perished and not marketable in the target market can be delivered in an alternative market where they are still suitable for consumption. This ensure to achieve a profit also for these products which otherwise should be discarded by implementing pricing policies SL based by means of the application of differentiated prices representing the actual remaining quality level of products. Finally the possibility of monitoring the quality level allows to move from traditional picking policies, such as First In First Out (FIFO) to SL based picking policies as Least Shelf Life First Out (LSFO). In this section a study on the monitoring of the SL on supply chain performance is proposed. The study concerns the monitoring of time-temperature history of peaches fruit along the supply chain by means of a RFID system. The study aims at determine the fraction of SL consumed from the production site to the final destination by considering the kinetic of the reaction triggering the deterioration process and by applying the Arrhenius law. Furthermore the performance of the chain is evaluated in terms of quality of products delivered in the case in which a SL based picking policy is applied as an alternative to the FIFO policy. The section is organized as follows: at first a brief introduction about the kinetic theory and the Arrhenius law is done in order to illustrate the relation between the kinetic model of deterioration reactions and the SL (Chapter 1); thus the RFID technology is depicted as well as its main application fields (Chapter 2); finally an application of the methodology here discussed is presented through a case study (Chapter 3).

CHAPTER 1

1.1. The Shelf Life of perishable products

Consumers are increasingly demanding consistently high food quality, and have corresponding expectations that such quality will be maintained at a high level during the period between purchase and consumption. These expectations are a consequence not only of the primary requirement that the food should remain safe, but also of the need to minimize unwanted changes in sensory quality. Acceptable sensory characteristics are consequently often defined by company policy, but nonetheless it is important to understand how they change during storage. According to IFST Guidelines (1993) the SL is defined as the time during which the food product will:

- remain safe;
- be certain to retain desired sensory, chemical, physical and microbiological characteristics;
- comply with any label declaration of nutritional data, when stored under the recommended conditions.

The IFST definition raises the important issue of storage conditions on product SL. Measurement of storage characteristics takes place under carefully controlled environmental conditions that are rarely met in practice. In fact thermal abuse in the distribution chain is common. Furthermore it is important for the food manufacturer to have an understanding of the storage characteristics of the perishable product under a wide range of storage conditions, and even under the fluctuating or cyclical conditions that are commonly encountered in practice in the supply chain. If the behavior of the product on storage is to be understood, it is equally important for the manufacturer to have a thorough understanding of the mechanism of the deterioration process, which can be complex in many perishable foods, especially those with composite structures (Kilcast and Subramaniam (2000)).

Another definition of the SL can be found in Steele (2004) where the SL is defined as the time until a perishable product becomes unacceptable to consumers under a given storage condition. This definition allows to quantify the measure of SL and underlines that the SL is a measure which depends on consumer preference and rather than the actual end of product life. Factors influencing the SL of perishable products can be categorized between intrinsic (referred to the properties of the final product) as for example water activity, pH value and total acidity, redox potential, available oxygen, nutrients, natural microflora and surviving microbiological counts, natural biochemistry of the product formulation, use of preservatives in product formulation, and extrinsic (the factors that a final product encounters as it moves through the food chain) as for example time–temperature profile during processing, pressure in the headspace, temperature control during storage and distribution, relative humidity, exposure to light and environmental microbial counts encountered during processing, storage and distribution, composition of atmosphere within packaging, subsequent heat treatment (e.g. reheating or cooking before consumption), consumer handling. The interaction of such intrinsic and extrinsic factors either inhibits or stimulates a number of processes which limit the SL. These processes can be defined as microbial (due to microbial growth during storage), chemical (due to reactions that occur between within the food or from reactions of food components with external species) physical (due to moisture migration) or temperature related (due both to elevated or depressed temperature). The effect of one of more of these processes in limiting the SL of perishable product must be put in relation with the type of product considered as for example, fish, meat or fruits and vegetables.

1.2. The Shelf life prediction of fruits and vegetables

Fruits and vegetables, unlike other fresh products, remain as living tissues until the moment they are consumed, cooked or otherwise processed. In these products intrinsic and extrinsic factors change rapidly during storage, thus accelerating unwanted quality changes that limit the SL. Another factor, which differentiates fruit and vegetable from many other food products, is the fact that their behavior is determined by either the genetic make-up (species, cultivar, clone, etc.), its stage of development (maturation, stage of ripening, etc.) and the pre and post harvest conditions they have experienced (as already discussed in the case study of Section 1). So, for example, the position of a fruit on the tree will determine its nutrient and water status and its exposure to environmental factors such as sunlight or pests and diseases. All these factors may ultimately influence post-harvest SL implying that products harvested at the same time have different SL. Table 14 summarizes the range of storage periods for selected fruits and vegetables under typical storage conditions of temperature and relative humidity.

Commodity	**Temperature (°C)**	**Humidity(%)**	**Storage period**
Apples	-1 - 4	90-95	1-8 months
Aubergines	8-12	90-95	1-2 weeks
Avocadoes (unripe)	4,5-13	85-90	2-5 weeks
(ripe)	2-5	85-90	1-2 weeks
Bananas (green)	13-15	85-90	10-30 days
(ripe)	13-16	85-90	5-10 days
Beans (French)	7-8	95-100	1-2 weeks
Broccoli	0-1	95-100	1-2 weeks
Cabbage (green)	0-1	95-100	3 months
(white)	0-1	95-100	6-7 months
Carrots (immature)	0-1	95-100	4-6 weeks
(mature)	0-1	95-100	4-8 months
Cauliflower	0-1	95-100	2-4 weeks
Celery	0-1	95-100	1-3 months
Citrus	4-8	90	3-8 weeks
Courgettes	8-10	90-95	1-2 weeks
Cucumbers	8-11	90-95	1-2 weeks
Garlic	0	70	6-8 months
Grapefruit	10-15	90	4-16 weeks
Grapes	-1 - 0	90-95	1-6 months
Kiwifruit	-0,5 - 0	90-95	2-3 months

Leeks	0-1	95-100	1-3 months
Lemons	10-14	90	2-6 months
Lettuce	0-1	95-100	1-4 weeks
Mangoes	5,5-14	90	2-7 weeks
Melons	4-15	85-90	1-3 weeks
Mushrooms	0	90-95	5-7 days
Onoins	-1 - 0	70-90	6-8 months
Oranges	2-7	90	1-4 months
Pears	-1 - 0	90-95	1-6 months
Peas	0-1	95-100	1-3 weeks
Potatoes (immature)	4-5	90-95	3-8 weeks
(mature)	4-5	90-95	4-9 months
Soft fruits	-1 - 0	90-95	2 days- 3 weeks
Spinach	0-1	95-100	1-2 weeks
Stone fruit	-1 - 1	90-95	1-7 weeks
Sweet peppers	7-10	90-95	1-3 weeks
Tomatoes (green)	12-15	90	1-2 weeks
(ripe)	8-10	90	1 week

Table 14. Shelf life of most common fruits and vegetables

The SL of fruits and vegetables is usually determined by fixing the quality criteria and the standard limit for each of them. Naturally this evaluation do not take into account the inherent variability in all quality factors of fruits and vegetables. Even if the measurement of certain qualities were able to predict shelf-life accurately, individual differences in produce means that, ideally, each individual item would need to be assessed. Currently, many of the tests in use for the measuring of the SL cause damage to the produce and therefore can only be used on a small sample of the produce. The most common methods based on intrinsic factors for SL evaluation are: measurement of visual qualities (color, external and internal defects), measurement of textural properties (firmness), measurement of flavor factors (taste and aroma components) and sensory evaluation which applies the principles of experimental design and statistical analysis to the use of human senses (sight, smell, taste, touch and hearing). Other methods for the SL evaluation are based on the detection of extrinsic and intrinsic factors contemporary. Between them the predictive models based on kinetic of chemical reactions and Arrhenius theory are increasingly used to predict the SL of a product. In particular the theory of kinetic of reactions consists in determining the SL of a product by assessing how the deterioration process behaves as a function of time. In chemical reactions such information is provided by the order of reaction. The Arrhenius theory says that about all decay reactions are influenced by the temperature and uses this parameter to determine the SL of a product. Finally by combining these two theories it is possible to perform accelerated SL tests able to predict the SL of a product subjected to stressed conditions. These models will be illustrates in the following paragraph.

1.3. The Kinetic Theory of deterioration reactions

The kinetic of chemical reactions models says that the loss of quality with time can be express, at constant temperature, through the expression (see Tijskens and Polderdijk (1996)):

$$\pm\frac{dQ}{dt} = KQ^n \tag{12}$$

where Q is a measurable characteristic which expresses the product quality;

t is the time;

K is the reaction rate constant;

n is the order of reaction.

Equation (12) can take different forms depending on the value o *n*; in most cases *n* is equal to 0,1,2 in order to define kinetic of zero, first or second order.

1.3.1 Zero order kinetics (or linear kinetics) (Piergiovanni and Limbo (2010))

In the case of zero order reaction the equation (12) takes the following form (valid for product having a decreasing quality with time):

$$\frac{dQ}{dt} = -K \tag{13}$$

i.e.:

$$dQ = -Kdt \tag{14}$$

which can be formulated as:

$$\int_{Q_i}^{Q_{lim}} dQ = -k\int_{t_i}^{t_{sl}} dt \tag{15}$$

Where Q_i is the initial quality, Q_{lim} the quality limit, t_i the initial time, corresponding to Q_i, t_{sl} the time at which the quality limit is achieved, i.e. the SL of the product. Generally Q_i must be measured immediately after the production, while Q_{lim} is the quality level under which the product is not still marketable.

thus:

$$Q_{lim} - Q_i = -Kt_{sl} \tag{16}$$

and

$$Q_{lim} = Q_i - Kt_{sl} \tag{17}$$

$$t_{sl} = \frac{Q_i - Q_{lim}}{K} \qquad (18)$$

Equation (18) underlines that the keeping quality is the inverse of the rate K of quality decrease. In order to determine the $-K$ value it is sufficient to know some value of Q with time, at constant temperature, and apply equation (17). The $-K$ value is the slope of the linear function expressed by this equation (Figure 26.a).

1.3.2 First order kinetics (or Exponential kinetics) (Piergiovanni and Limbo (2010))

For first order reaction equation (12) takes the following form (valid for product having a decreasing quality with time):

$$\frac{dQ}{dt} = -KQ \qquad (19)$$

Assuming constant temperature, integration gives:

$$Q_{lim} = Q_i e^{-Kt} \qquad (20)$$

$$lnQ_{lim} = lnQ_i - Kt_{sl} \qquad (21)$$

From this relation, the keeping quality can be derived as:

$$t_{sl} = \frac{ln\left(\frac{Q_i}{Q_{lim}}\right)}{K} \qquad (22)$$

The exponential relation can be represented by considering $ln\,(Q)$ vs t. This allows to determine $-K$ (the slope of equation (21)) obtained by knowing some values of Q with time at constant temperature (Figure 26.b). As for linear decay, the keeping quality for exponential decay is proportional to the inverse of the rate K of quality decrease.

1.3.3 Second order reaction (see Piergiovanni and Limbo (2010))

In this case the relation between the variation of quality attribute and the time (eq. (12)) is exponential:

$$\frac{dq}{dt} = -KQ^2 \qquad (23)$$

$$\frac{1}{Q_{lim}} = \frac{1}{Q_i} + Kt_{sl} \qquad (24)$$

$$t_{sl} = \frac{\left(\frac{1}{Q_{lim}} - \frac{1}{Q_i}\right)}{K} \qquad (25)$$

The value of $-K$ can be obtained by knowing some values of Q with time and by plotting $1/Q$ vs t (Figure 26.c).

1.3.4 Logistic kinetics (Tijskens and Polderdijk (1996))

Logistic behavior is also frequent in natural processes. The formulation of these types of reactions can be written in different form. One is shown in equation (26):

$$\frac{dQ}{dt} = -KQ\left(1 - \frac{Q}{Q_{inf}}\right) \tag{26}$$

where Q_{inf} represents the quality maximally possible at infinite time.

By integration, assuming constant temperature, the following equation (27) can be obtained:

$$Q = \frac{Q_{inf}}{1+C_{ba}e^{Kt}} \tag{27}$$

with

$$C_{ba} = \frac{Q_{inf} - Q_i}{Q_i} \tag{28}$$

where C_{ba} is a constant representing information about the biological age of the product. From this relation the keeping quality can be derived as:

$$t_{sl} = \frac{ln\left(\frac{Q_{inf}-Q_{lim}}{Q_{lim}C_{ba}}\right)}{K} \tag{29}$$

Again the keeping quality is proportional to the inverse of the rate *K* of quality decrease. Figures 27 and 28 summarize the kinetics discussed.

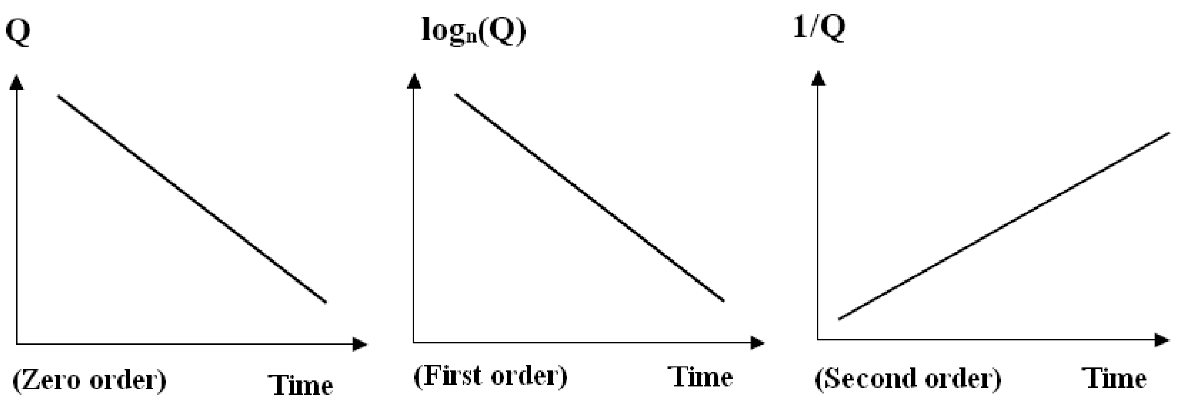


Figure 26.a Figure 26.b Figure 26.c

Figure 26

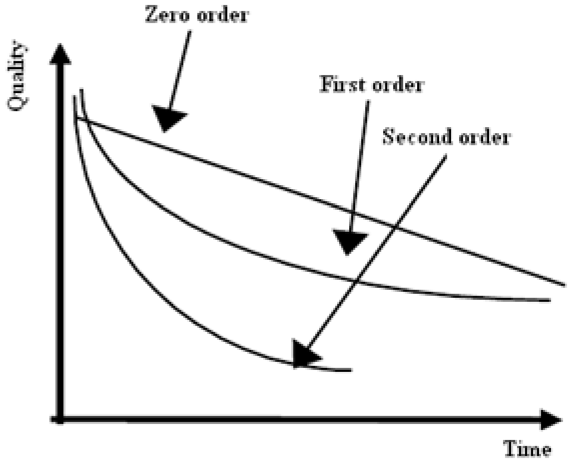


Figure 27

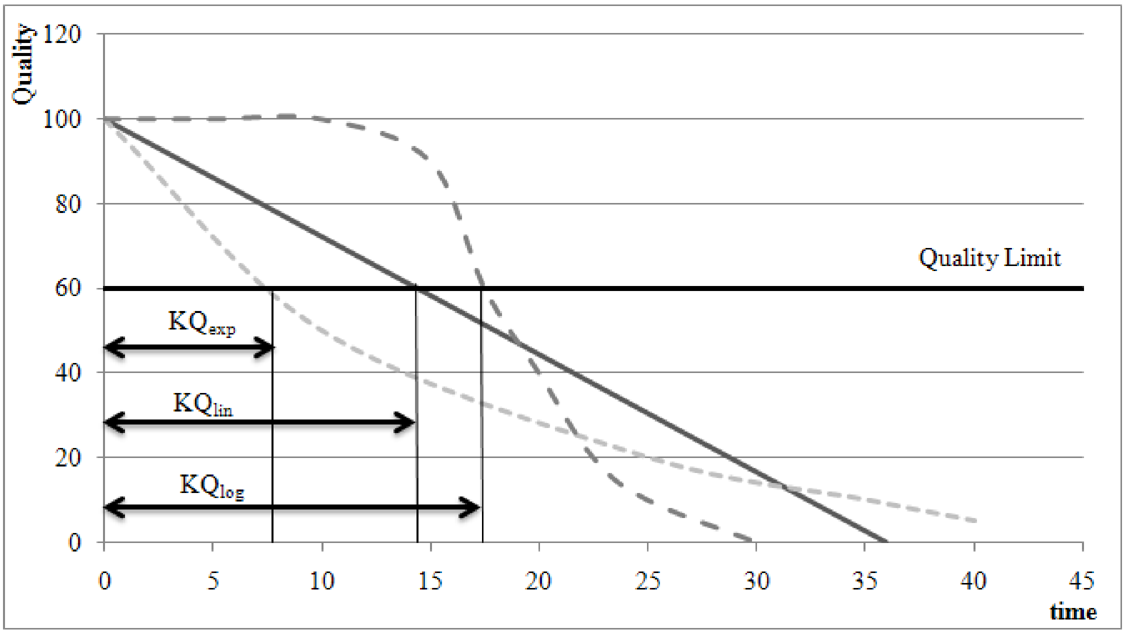


Figure 28

As just mentioned, zero, first and second order kinetics can be represented by first degree polynomial which describe a straight line. Thus the order of reaction of a unknown phenomenon (if it is of the zero, first or second order) can be determined by checking the linearity of Q vs t, $ln(Q)$ vs t, and $1/Q$ vs t of the experimental data. The better the equations (17), (21) and (24) interpolate the experimental data, i.e. as much the determination coefficient R^2 is close to one, the higher the probability to estimate the order of reaction. The first order kinetic is able to represent a large variety of reactions, while zero order and second order reactions are less common but also very numerous. However the differences between different order reactions can be appreciated only for high variation of quality with time. On the contrary if you are interested to a small variation of the quality index all phenomena can be approximated with a zero order reaction assuming the phenomenon having a constant speed of reaction. This is explained in Figure 29, from which it is clear that the zero order reaction approximation tends to overestimate the speed of phenomenon thus underestimating the SL of the product; in fact in high order kinetics the speed of reaction will tend to decrease with time as the phenomenon evolves. In other words the hypothesis of constant speed of decay will lead to consider exhausted the marketability of a product when the product itself is still suitable for consumption thus avoiding to sell expired products.

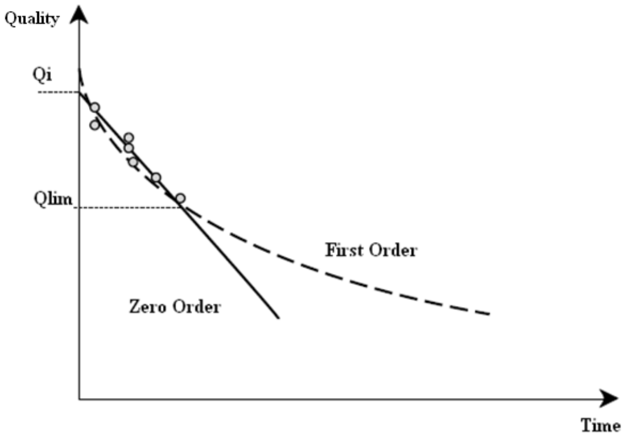


Figure 29

As you can see the kinetic theory aims at estimating the SL of a product by knowing the order of reaction, the initial quality level and the quality limit referred to a measurable intrinsic factor and the speed of reaction responsible for the deterioration process. In other cases it can be of great help to determine the SL by starting from the knowing of environmental parameters to which the product is subjected during its life. In this case it is need to know the relation between the decreasing in quality and the environmental parameter responsible for the decay process. This argument will be discussed in the following paragraph.

1.4. Temperature dependence of deterioration rate

Since almost all reactions of quality loss are influenced by temperature, their dependency from the temperature can be effectively expressed by the Arrhenius law (30):

$$K = K_0 e^{-\left(\frac{E_a}{RT}\right)} \tag{30}$$

Where:

K is a constant representing the speed of reaction

K_0 is a constant corresponding to the speed of reaction at infinite temperature;

E_a is the activation Energy (J mol^{-1}), independent from temperature;

R is the gas constant (8.314 J $K^{-1}mol^{-1}$)

T is the absolute temperature (K)

The Arrhenius law expresses the concept that the speed of reaction increases exponentially when the temperature increases as well, based on the E_a of reaction. On the other hand as greater the K is, the higher will be the deterioration rate. Equation (30) can be rewritten in logarithmic form as follows:

$$logK = logK_0 - \left(\frac{E_a}{2.3R}\right)\frac{1}{T} \tag{31}$$

Equation (31) allows to determine the E_a as the slope of this equation by knowing some values of K. The higher is the E_a, the higher will be the speed of reaction when the temperature increases and vice versa. Since the SL is the inverse of speed of reaction (see equations (18), (22), (25) and (29)), it is possible to write:

$$t_{sl} \propto \frac{1}{K} \tag{32}$$

This means that effects of temperature on the SL can be expressed by an exponential relation as the following:

$$logt_{sl} = logt_0 + \left(\frac{E_a}{2.3R}\right)\frac{1}{T} \tag{33}$$

This equation allows to determine the SL of a product subjected at constant temperature.

Finally in order to underline the strong correlation between the Arrhenius law and the kinetic of reaction it is possible to rewrite the Arrhenius equation on the basis of equations (18), (22), (25), (29) by reminding the relation (32). For the zero and first order reaction, for example, the expression takes the following forms:

$$ln_{t_{sl}} = \ln(q_i - q_{lim}) - \ln(k_0) + \frac{E_a}{RT} \tag{34}$$

$$ln_{t_{sl}} = \ln\left(ln\left(\frac{q_i}{q_{lim}}\right)\right) - \ln(k_0) + \frac{E_a}{RT} \tag{35}$$

Another method used to evaluate the SL is to calculate the Q_{10}, a dimensionless number, defined as the factor of acceleration of speed constant when the temperature increases of 10°C or 10°K. Q_{10} is equal to the ratio between two temperatures which differ for 10 degrees:

$$Q_{10} = \frac{K_{(T+10)}}{K_{(T)}} \tag{36}$$

and for eq. (32),

$$Q_{10} = \frac{SL_{(T)}}{SL_{(T+10)}} \tag{37}$$

The Q_{10} exponentially depends on temperature as can be underlined by following equations derived by eq.(36):

$$Q_{10} = e^{\frac{10E_a}{RT(T+10)}} \tag{38}$$

$$lnQ_{10} = \frac{10E_a}{RT(T+10)} \tag{39}$$

It is clear by equations (36) and (37) that the Q_{10} can be calculated very simply by knowing the constant speed of reaction of a phenomenon or the corresponding SL for two temperatures which differ for 10 degrees. Furthermore it represents a simple way to calculate the E_a (eq.(38) and (39)). When the Q_{10} is known the dependency of K or SL from temperature can be expressed by following expressions:

$$K_T = K_{T_{ref}} Q_{10}^{[(T-T_{ref})/10]} \tag{40}$$

and

$$SL_T = SL_{T_{ref}} Q_{10}^{[(T_{ref}-T)/10]} \tag{41}$$

It must be pointed out that the Q_{10} depends on temperature and falls when the temperature increases. Typical values for Q_{10} are reported in Table 15 (Saltveit 2004).

Temperature range (°C)	**Q_{10}**
0 – 10	2.5 to 4
10 – 20	2.0 to 2.5
20 – 30	1.5 to 2.0
30 – 40	1.0 to 1.5

Table 15

These typical Q_{10}values allow us to construct a table showing the effect of different temperatures on the rates of respiration or deterioration and relative SL of a typical perishable commodity as you can see from Table 16. The values reported have been determined with eq. (41) by knowing the SL at 0°C and the Q_{10} at different temperatures. This table shows that if a commodity has a mean SL of 13 days at 20 °C it can be stored for as long as 100 days at 0 °C, but will last no more than 4 days at 40 °C.

Temperature (°C)	**Q_{10}**	**Shelf Life (Days)**
0	-	100
10	3.0	33
20	2.5	13
30	2.0	7
40	1.5	4

Table 16. The effect of temperature on deterioration rate (Saltveit 2004)

1.5. ASTL tests

The knowledge of the kinetic of reaction (zero, first, second order or logistic) in conjunction with the relation between the speed of reaction and the factor responsible for the deterioration process (defined for example by the Arrhenius law) allows to perform accelerated SL tests (ASLT). The basic premise of an accelerated test is that by changing a storage condition, the chemical or physical process that leads to deterioration is accelerated, and that a predictive SL relationship related to environmental conditions can be defined. The key to this premise is the assumption that the deteriorative process limiting the SL remains the same under the two conditions (accelerated and actual storage conditions). If this is not the case, and another deteriorative process dominates at the abuse condition, then a valid relationship is not attainable (see Kilcast and Subramaniam, 2000). The ASTL tests are carried out by sampling experimental data concerning the speed of reaction or the SL of a product; by knowing their relation with the factor responsible for the acceleration of deteriorative process it is possible to determine the speed of decay or the SL at the interest conditions. Generally speaking the conditions which accelerate the deterioration process are related to the temperature abuse. In this case the Arrhenius law can be used to estimate the SL. By considering a zero order kinetic, for example, the SL can be determined by substituting eq. (30) in eq. (18):

$$t_{sl} = \frac{Q_i - Q_{lim}}{K_0 e^{-\left(\frac{E_a}{RT}\right)}} \quad (42)$$

Instead of determining the k_0 it is possible to calculate the SL by knowing the E_a and K at certain temperature to estimate the value of K at the interest temperature. In fact by the equation

$$lnK = lnK_0 - \left(\frac{E_a}{RT}\right) \quad (43)$$

it is possible to write:

$$lnK_1 + \frac{E_a}{RT_1} = lnK_0 = lnK_2 + \frac{E_a}{RT_2} \quad (44)$$

thus:

$$lnK_1 - lnK_2 = \frac{E_a}{R}\left(\frac{1}{T_1} - \frac{1}{T_2}\right) \quad (45)$$

and for eq. (21)

$$lnt_1 - lnt_2 = \frac{E_a}{R}\left(\frac{1}{T_1} - \frac{1}{T_2}\right) \quad (46)$$

By knowing the Ea and the K_1 or the SL of a product at certain temperature T_1 it is possible to determine the K_2 or the SL at a different temperature T_2. The Ea can be determined by knowing the Q_{10} by equation (38).

1.6. The Shelf Life for products subject to variable temperatures

The model developed up to now can be exclusively applied under the hypothesis of constant temperatures. However when a product flows through the supply chain the thermal conditions to which it is subjected are such that the temperature cannot be considered constant. In this case we are interested in knowing the quality of the product subjected to variable temperature with respect to time. This goal can be achieved by knowing the time-temperature history of the product and the kinetic of the reaction involved in the quality loss. In this way it is possible to predict the SL of the product at any stage of the supply chain. Under the hypothesis of zero order reaction, for example, a simple approximation which represents the solution to this problem can be expressed as follows (see Piergiovanni and Limbo (2010)):

$$Q_{lim} = Q_i \sum_{n=1}^{SL} K_n t_n \quad (47)$$

where $\sum_{n=1}^{SL} K_n t_n$ is the summation of products of speed constants K_n at the average temperature T_m multiplied by the interval time t_n corresponding to this average temperature. In other words, since the time temperature history is known, it is divided in time intervals and the T_m of each interval is determined. By Arrhenius diagram it is possible to calculate the constant K_n corresponding to each T_m; thus they are multiplied by the t_n. $K_n t_n$ are summed until they achieve the Q_{lim} which corresponds to end of the SL. Alternatively, instead of calculating actual rate constants, the time for the product to become unacceptable can be measured, and eq. (47) can be modified by considering (32) to give:

$$Q_{lim} = Q_i \sum_{n=1}^{SL} \frac{t_n}{SL_n} \quad (48)$$

and

$$f_c = \sum \left[\frac{t_i}{SL_i}\right] \quad (49)$$

(as can be found in Giannakourou and Taoukis, (2003-a)).

The SL can also be expressed in terms of the fraction of SL remaining, f_r:

$$f_r = 1 - f_c \quad (50)$$

Equation (49) shows that the f_c is calculated by combining the kinetic theory and the knowing of the SL calculated through the Arrhenius law. This underlines the strong relationship between the quality loss (expressed by the order reaction) and the speed of reaction (expressed by the speed constant).

1.7. The Shelf Life in presence of more non interfering processes

As discussed in paragraph 1.3 the product quality in a constant environment can be represented as:

$$KQ = \frac{f(Q)}{K} \quad (51)$$

Where $f(Q)$ is an expression comprising the initial quality Q_i, and the limiting quality Q_{lim}. The exact formulation of $f(Q)$ depends on the reaction kinetics governing the decrease of the limiting quality attribute. In many horticultural products, the quality attribute that limits the acceptance by the consumer shifts from one attribute at a certain temperature to another attribute at another temperature. This can for example be observed in chilling sensitive products. For the description of this situation, let us assume that the storage temperature remains constant during the whole storage period, but the quality attribute that limits the keeping quality of the product changes from one attribute to another, depending on the level of the constant temperature. In tomatoes, for example, kept at constant temperatures below 8°C the limiting factor is usually the color, above 13°C it is firmness. The extension to be made to the previous model by determining which quality attribute is limiting at which temperature. Each separate quality attribute has to be described by its own kinetic mechanism. For this goal a distinction must be made between interfering and non interfering quality processes. Non-interfering processes can be considered as additive at the level of differential equations, interfering ones as multiplicative. In non-interfering processes, the change of each quality attribute can be described by its own process without interference of other quality attributes. So, part of the overall quality decrease is connected to that specific process. The combination of each of these processes for each of the quality attributes then describes the decrease of overall quality. Assuming the same type of kinetics for each process (e.g. first order), this situation for three separate processes, acting on the same overall quality, is depicted in equation (52).

$$\frac{dq}{dt} = -(K_1 + K_2 + K_3)Q \qquad (52)$$

Assuming the kinetics of reaction following a first order kinetics the solution of this differential equation takes the form of the following eq. (53):

$$KQ = \frac{log\left(\frac{Q_i}{Q_{lim}}\right)}{K_1+K_2+K_3} \qquad (53)$$

Each of the individual reaction rates, however, will exhibit its own Arrhenius type dependency on temperature. Consequently, the keeping quality will be inversely proportional to the sum of the three rate constants, each with its own temperature relation. When the processes or quality attributes do interfere with one another, the situation becomes very complex. Logical assumptions for obtaining a common or generic model can no longer be made. In that case, the different processes, including the interferences, have to be modeled separately (for more details about the paragraph 1.7 see Tijskens and Polderdijk (1996)).

1.8. Keeping quality for dynamic conditions

With a dynamically changing temperature acting on a decreasing quality, the remaining keeping quality at some standard temperature has to be calculated to compare different time-temperature combinations. The quality function $f(Q)$ for each type of kinetics is exactly the inverse function of the quality behavior at constant temperature. Consequently, the keeping quality will change linearly during the (very small) time period during which the temperature can be considered constant. For each day of storage a certain fraction of keeping quality will vanish. The slope of the linear change will depend on the storage temperature as described by the complex rate constant. Provided the quality limit remains the same throughout the storage period and provided the initial quality is the same as or comparable to the measuring situation, in the case of non interfering processes, the dynamic model can be formulated as:

$$KQ = KQ_{ref} - \frac{\int_0^t \sum_{i=1}^N K_{ref_{(i)}} * e^{\frac{E_a}{RT}\left(\frac{1}{T_{ref}} - \frac{1}{T_{(t)}}\right)}}{\sum_{i=1}^N K_{(i)}(T_{st})} \qquad (54)$$

Where KQ_{ref} is the keeping quality at the reference temperatureT_{ref}, $K_{ref}$is the constant at the reference temperature, T_{st} is the constant temperature of a specific application or commodity, N is the number of such applications or processes (for more details about the paragraph 1.8 see Jedermann and al. (2006)).

1.9. Arrhenius deviations

In this paragraph some consideration are done about Arrhenius equation in order to establish when it is possible to properly use it. In fact although it is the most important relation for the study of dependency of chemical reactions occurring in foods from temperature there are several reactions whose behavior cannot be understand with Arrhenius equation. Some factors which result in deviations from Arrhenius law and give a non linear trend of Q vs t, $ln(Q)$ vs t, and $1/Q$ vs t are:

- The phase transition in the product;
- The contemporary presence of various chemical reactions having different activation energy;
- The increase of water activity whit temperature;

- The solubility of reagents with the temperature;
- The decreasing of the solubility of gas with the increasing of temperatures;
- The loss of water at high temperatures.

A simple method to screen experimental data and define if the Arrhenius equation can be used consists in plotting $ln(SL)$ vs $1/\mathrm{T}$, and determining the correlation coefficient of the linear and polynomial regression of experimental data as explained in Petrou and al. (2002). Generally speaking in the absence of product-specific kinetic data, the assumption of a linear model for the reaction rate versus temperature may be justified by considering the range of temperatures. As studied by Labuza (1984) there is an upper limit of temperature that can be used for accelerating reactions; this temperature is about 40°C for canned foods, 35-45°C for dry foods, 7-10°C for refrigerated products and -5°C for frozen foods. Typical range temperatures for food supply chain are reported in Table 17.

Food	Temperature Range (°C)
Frozen food	(-24 to -18)
Fresh meat and mincemeat	(0 to 2)
Chilled delicatessen	(2 to 4)
Fresh goods (dairy products, fruit, vegetables)	(4 to 8)
Sensitive to cold fruits and vegetables	(8 to 15)

Table 17

From Table 17 appears clear that the Arrhenius law cannot be applied to frozen foods. For more detail see Petrou and al. (2002) in which the relation of $ln(SL)$ vs $1/\mathrm{T}$ is studied for such products.

The application of deterioration models requires the possibility to gathering information of intrinsic and extrinsic factors. Today this condition is satisfied by using the Radio Frequency Identification (RFID) technology, enabling the automatic identification data gathering. In the next Chapter an ex cursus is done about this technology in order to illustrate the main characteristics of the RFID devices and their main application fields.

The possibility offered by this innovative technology allowing the monitoring of the deterioration process of a product can be of great help in the optimization of supply chain management. This argument will be dealt in the Chapter 3.

CHAPTER 2: RFID TECHNOLOGY

2.1. Introduction

The Radio Frequency Identification (RFID) is an automatic identification and data capture technology composed by three main elements: a tag formed by a chip connected with an antenna, a reader with an antenna that emits radio signals and receives in return answers from tags, and finally a middleware that bridges RFID hardware and enterprise applications. Devices of a RFID system communicate each other providing a real-time communication with numerous objects at the same time at a distance, without contact or direct line of sight. The tag is placed on the object that has to be identified. The tag contains suitable information of the object. The reader has a number of different responsibilities like powering the tag, identify the tag, read and sometimes write data to the tag. The reader also communicates with the database in which information from tags will be processed. When the object that is tagged comes in a reader's interrogation zone (reading zone), where the tags are being read, the reader sends out a radio wave to the tag. The tag powers up and sends back its information to the reader, in some cases new information is sent from the reader to the tag. The reader sends information to a database that processes the data from the tag in a suitable way. The distance between the transponder and reader depends on which coupling and frequency are used. It is possible to achieve distances from a few centimeters up to hundreds of meters. The speed with which the data can be transferred between tag and reader is also depending on which frequency is used; lower frequencies cannot transfer data as fast as the higher frequencies, due to the higher clock frequency allowed in the higher frequencies. This means that if it is necessary to read many tags at the same time a higher frequency is preferred. Figures 30 and 31 show respectively components of a RFID system and its working scheme.

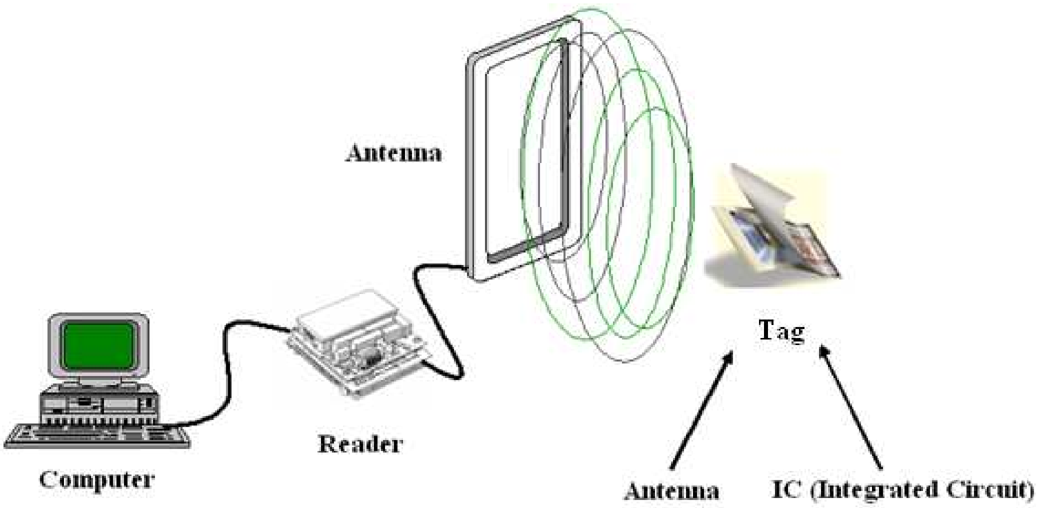


Figure 30

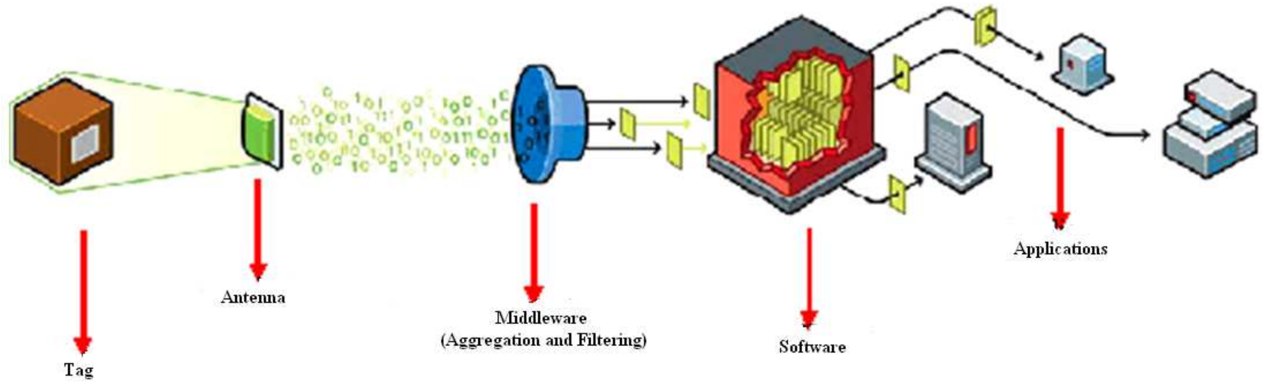


Figure 31

2.2. RFID components

2.2.1 Tags

The tag or transponder (derived from the terms “**trans**mitter” and “re**sponde**r”) is the part that collects real time data and then transmits the data via radio waves. A tag can perform some basic tasks like read or write data to its memory. When a tag is in a reader’s interrogation zone the data from its memory is retrieved and transmitted to the reader. Tags usually have two parts, an integrated circuit whit memory (a chip) and an antenna. Information is stored and processed by the chip while the antenna is used to receive and transmit the information. The chip, in most applications, is used to store information about a product or a shipment. The object, product or shipment that is being tracked, is provided with a unique identifying number. This number is a part of the information that is stored in the chip that is embedded in the tag. Tags come in many shapes and sizes. Tags also differ in memory capacity and temperature survivability. Almost all tags are encapsulated for durability against shock, moist, dirt and chemicals, but there are also cheaper tags without encapsulation. The size of a tag depends primarily on two things, whether the tag have a battery or not and the size and shape of the antenna. The size and shape of the antenna depends on the frequency that is used (see paragraph 2.5).

2.2.2 Tag types

RFID tags can be divided in three types: passive, semi passive (or semiactive) and active.

Passive tags don’t have a battery; they use the energy that the electromagnetic wave from the reader induces in the antenna to power up the chip and to transmit the data back to the reader. Passive tags reflect energy from the reader or receive and temporarily store the energy in order to generate the tag response to the reader. Since they don’t have a proper source of power the lifetime is almost unlimited. An **Active** tag has its own power source, typically a battery, to run the chip and to transmit the data to the reader. An active tag allows very low-level signals to be received and can still generate high-level signal to be transmitted back to the reader. The active tag lies in sleep-mode until it gets a wake-up signal from the reader. As soon as the tag gets the wake-up signal the data carrier gets into operating mode. After the completion of the data transaction the tag gets into sleep-mode again. Because the active tag has a battery onboard they can transmit data without requiring a reader to power them. They have therefore much longer reading range then a passive tag. On the other hand because they have a battery they have finite lifetime. Semi-passive, or Semi-active tags, also have an onboard battery. The battery in this case is only used to power the sensor and recording logic (to operate the chip). In fact, unlike active tags, semi passive tags are not able to initiate communications with the reader. Like the passive tag it uses the energy in the electromagnetic field to wake up the chip and to

transmit the data to the reader. Sometimes semi-passive tags are equipped with a sensor enabling the detection of environmental factors (like temperature, humidity, light and concentration of gases).
The main operative differences between passive and active tags are due to the additional energy of active tags which has several advantages and consequences, in particular:

- Signal strength: active tags can receive very low power signals from the reader. Passive tags require very strong signals from the reader, up to 1,000 times the power level necessary for active tags, and the strength of the signal they return is very low.
- Initiation of the communication: passive tags require a reader to first send a signal in order to communicate. Active tags can initiate the communication. For example, active tags can be programmed to send data (e.g. environmental sensor data) at specific times or when external events occur.
- Tag-reader distance is shorter for passive tags than for active tags. Tags can be read from a few centimeters away, to a few meters for passive tags, and up to hundreds of meters for active tags. Reader distance depends on various factors including the antenna's size. In order to double the reading distance of a passive tag, 16 times more power is required from the reader. By contrast, doubling the reading distance of an active tag only requires four times the power, since active tags benefit from their onboard battery.
- Environmental sensors: passive and active tags can be associated with sensors to monitor the environment. However, passive tags can only use their sensor capability when a reader is sending a signal. By contrast, active tags can continuously monitor the environment, regardless of the presence of a reader field, store sensor data and timestamp information, and send it to a reader at a specific time or when requested.
- Read/Write capacity: technology is available to enable passive and active tags to store information sent by the reader. However, energy constraints typically limit data processing features for passive tags which, in addition, do not usually feature large memory space. Data processing capabilities for active tags can include the use of more complex protocols, which limits, for example, transmission errors.
- Tag memory capacity: Typical memory capacity of a cheap passive identification tag is 64 bits to 1 kilobyte. Active tags can hold more than 128 kilobytes.
- Frequencies: Typical frequencies of a passive tag are Low Frequency, High Frequency, Ultra High Frequency and Super High Frequency while for active tags are Ultra Wide Band

Table 18 summarize the fundamental differences between passive and active tags.

2.2.3 Tag memory

The memory of a tag can be of three types: Read Only (RO), Read and Write (RW), Write Once Read Many (WORM) and Electrically Erasable and Programmable ROM (EEPROM). A RO tag has a pre-programmed serial number written on its memory. The serial number is incorporated during chip manufacturing. The user cannot alter this serial number or write new data to the tag. When the tag enters a reader's interrogation zone it will instantly start to send out its unique identification number and it will do so continuously until it is out of the reading zone. With a RW tag you can write new information to the tag or write over existing information. It is only possible to write information to the tag when it is in a reader's interrogation zone. You can of course also read information from the tag. RW tags usually have a pre-programmed serial number that cannot be written over. But unlike the RO tags a RW tag also have a memory space where the user can put his own information. A RW tag has limited write cycles depending on which type of memory it is using. A WORM is a tag which is something between an RO and an RW. It is possible to write to the tag one time and read it as many as you like. When you have written to the tag the data the tag becomes locked and you can only read from it. An EEPROM tag is a tag whose memory can be written several times. The EEPROM memory capacity ranging up to more than 100 Kbytes; they can withstand up to 100,000 cycles of read/write and can retain data written up to 10 years.

	Passive RFID	**Active RFID**
Tag Battery	NO	YES
Tag Power Source	Energy transferred from the reader	Internal to tag
Availability of Tag Power	Only within the field of an activated reader	Continuous
Required Signal Strength from Reader to Tag	High (must power the tag)	Low (only to carry information)
Available Signal Strength from Tag to Reader	Low	High
Communication Range	Short o very short range (3m or less)	Long range (100m or more)
Tag Lifetime	Very long	Limited to battery life (depends on energy saving strategy)
Typical Tag size	Small	Large
Multi Tag Collection	– Collects hundreds of tags within 3 meters from a single reader – Collects 20 tags moving at 8 Km/h or shower	– Collects 1000s of tags over a 28000 m^2 region from a single reader – Collects 20 tags moving at more than 160 Km/h
Sensor Capability	Ability to read and transfer sensor values only when tag is powered by reader; no date/time stamp	Ability to continuously monitor and record sensor input; data/time stamp for sensor events
Data Storage	Small read/write data storage (Bytes)	Large read/write data storage (Kbytes) with sophisticated data search and access capabilities available

Table 18

2.2.4 Tag formats

Based on the paper of Weis it is possible to divide RFID-style tags into five broad classes: EAS (Electronic Article Surveillance), read-only EPC (Electronic Product Code), EPC, sensor tags, and motes. These will be referred to as classes A through E. These five classes are summarized in Table 19.

Class	**Name**	**Memory**	**Power Source**	**Features**
A	EAS	None	Passive	Article Surveillance
B	Read-only EPC	Read Only	Passive	Identification Only
C	EPC	Read/Write	Passive	Data Logging
D	Sensor Tags	Read/Write	Semi Passive	Environmental Sensors
E	Motes	Read/Write	Active	Ad hoc Networking

Table 19. Tag functionality classes.

EAS tags are the most basic RFID-type tag. They do not contain unique identifying information, so technically are not RFID tags. They simply announce their presence to a reader. EAS tags could be active or semi-passive, but the added cost of a power source would greatly outweigh adding unique identifying functionality. Because of their limited functionality, EAS tags are the simplest and cheapest to manufacture. Unlike EAS tags, read only **EPC** tags contain some identifying information. This information may be a product code or a unique identifier. Read only EPC tags have a single identifier that is written once when a tag is manufactured. Class B tags will likely be passively powered. Although they could be semi-passive or active, again the cost of a battery would greatly outweigh the cost of re-writable memory. Class C refers to simple identification tags offering write-once, read-many or re-writable memory. Rather than having an identifier set at manufacture time, identifiers may be set by an end-user. If an EPC tag offers re-writable memory, its identifier may be changed many time. Because of fact that these tags support non-volatile, writable memory they may be significantly more expensive than read-only EPC or EAS tags. **Sensor** tags may contain on-board environmental sensors, and may log and store data without the aid of a reader. These types of tags will be referred to here as class D. Sensor tags offer more than strict RFID functionality, and are typically not thought of as RFID. Many sensor tags may form a “sensor net” that monitors a physical area’s environmental properties. This may include temperature changes, rapid acceleration, changes in orientation, vibrations, the presence of biological or chemical agents, light, sound, etc. Because they operate without a reader present, sensor tags must necessarily be semi-passive or active. An on-board power source and sensor functionality comes at a much higher manufacturing cost. Class E tags, or “smart dust” **motes**, are able to initiate communication with peers or other devices, and form ad hoc networks. Motes are essentially general pervasive computing devices and are much more complex than simple EPC-style RFID. Because they are able to initiate their own communication, mote devices are necessarily active. Figures 32.a-32.d show the most common tag formats.

Figure 32.a Coin tag (EPC).

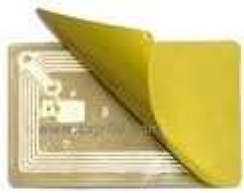


Figure 32.b Tag label (EAS or EPC).

Fig 32. c. Temperature Sensor Tag

Figure 32.d. Telosb mote

Figure 32

2.3. Readers

The reader is a radio frequency transmitter and receiver. It is composed by two parts: a control unit and one or more antennas. The first is a microprocessor which makes possible the communication with transponders

and provide for data elaboration. Antennas actually are the physic interface between tags and the control unit. Antennas are used to capture data from tags. The data is then sent further to a computer for processing. Readers come, like tags, in a large number of different sizes and features. Readers come in many forms, operate on many different frequencies, and may offer a wide range of functionality. Readers may have their own processing power and internal storage, and may offer network connectivity. Readers can be affixed in a stationary position, for example beside a conveyer in a factory, portable, integrated in a mobile computer, and even embedded in electronic equipment. In simple RFID systems, the reader’s energy pulse functions like an on-off switch. In more sophisticated systems, the reader’s radio-frequency signal can contain commands to the tag, instructions to read or write tag memory, and even passwords. In environments with many tags, a reader may have to perform an anti-collision protocol to ensure that communication conflicts do not occur. Anti-collision protocols permit readers to rapidly communicate with many tags in serial order. An important issue in the communication between the reader and the tags occurs due to the interference sources. The main interferences in the communication between readers and tags are due to the presence of liquid, (for example water), metal, foil, or other metallic objects, high humidity, extreme temperatures (very cold or very hot), motors and engines, wireless devices, such as cell phones, wireless computer or communication network, cordless phones.
How much these conditions affect a given RFID system’s performance depends on the operating frequency (see paragraph 2.5). One of the most significant roles in the success of a RFID deployment is the capability to address interference issues.
Figure 33.a and 33.b show some example of RFID readers, while Figure 34 shows the communication main components of the reader and the tag.

Figure 33.a. Reader for passive tag

Figure 33.b. Reader for active tag

Figure 33

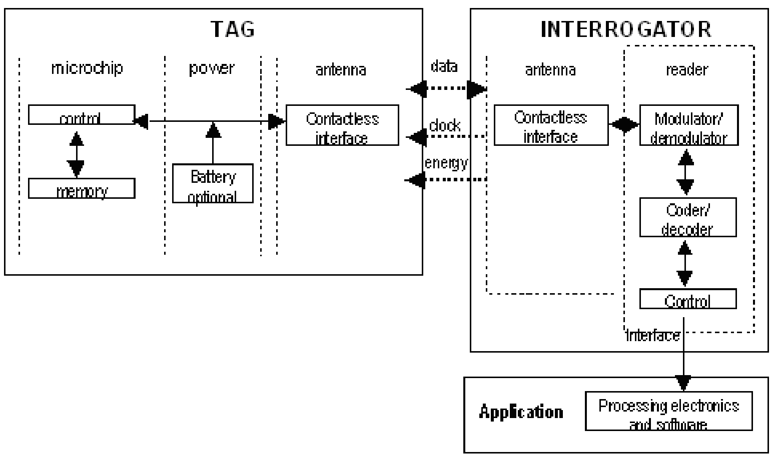


Figure 34

2.4. Antennas

An antenna is connected to a reader (transceiver) and sends out the reader's signals. Basically, the reader tells the antennas how to generate the proper RF field. This field can cover an area from a few centimeters up to 30 meter or more. How large that area can be is depending on the power output and the frequency. When a RFID tag moves into the antenna's radio field, it becomes activated. After the activation it sends back the information that is programmed into its memory. Through its array of antennas, the reader receives the tag's signal and decodes the signal. The decoded signal is then sent to the software system. A reader can also transmit special signals to a tag, for example telling a tag to come alive, synchronizing a tag with the reader or interrogating all or part of the tag's content. Antennas can act continuously or on demand. The continuously active system is used when tags are present regularly or for multiple tag reading in the antenna's detection field. This detection field can be activated only when needed by a sensor of some kind and is called the on-demand method. Normally one to four antennas can be attached to one reader. There are some readers where up to eight antennas can be attached.
Tag and reader power level can be considerably enhanced by the nature of their antenna and in particular its design and orientation. There are antennas which emit radiations in all directions equally (omnidirectional) and antennas which radiate in particular directions (unidirectional) with a longer range and better signal but must carefully be aimed towards a particular direction. When either the transmitter or the receiver is in movement, it may not be practical to use directional antennas at both ends of the communications link. Antenna design and orientation also influences tag and reader sensitivity. Tags' and readers' antenna sizes are also a key difference between induction and radio wave RFID. In general, electromagnetic induction tags require a smaller antenna than radio wave systems. Some examples of antennas are reported in the Figures 35.a-35.c.

Figure 35.a. HF antenna

Figure 35.b. HF antenna

Figure 35.c. UHF antenna

Figure 35

2.5. Frequency ranges

Each RFID system operates within a given frequency range. The frequency range in which a RFID system operates determines key capabilities and limitations in the system. For example, the higher the frequency, the shorter the wavelength and the harder for a radio signal to go around or through obstacles to reach a receiver. Unlike some radio communications systems that operate at licensed frequencies (such as mobile telephony or television), RFID systems operate at specific unlicensed frequencies that are not fully harmonized internationally, in particular in the UHF and microwave ranges. Different frequencies for RFID in different regions can be challenging for those who advocate the deployment of global RFID applications, although technical solutions can cope with a certain level of divergence of frequencies (See Table 20).

Frequency	Regions
Low Frequency (LF) **30 – 300 KHz**	125 - 134 kHz in Canada, Europe, Japan and the US
High Frequency (HF) **13.56 MHz**	In all the word
Ultra High Frequency (UHF) **300 MHz – 3GHz**	433.05 – 434.79 MHz in most of Europe, US, and under consideration in Japan 865 – 868 MHz in Europe 866 – 869 and 923 – 925 MHz in South Korea 902 – 928 MHz in the US 918 -926 MHz in Australia 952 – 954 MHz in Japan
Super High Frequency (SHF) **2 – 30 GHz**	2.4 – 2.5 and 5.725 – 5.875 GHz in Canada, Europe, Japan and the US
Ultra High Wideband (UWB) **3.1 – 10.6 GHz**	3.1 – 10.6 GHz in the US

Table 20

2.5.1 Low Frequency

One of the biggest advantages with LF is that it is not as affected by surrounding metal. Therefore it is ideal to use for identifying metal items. Depending on which reader being used and the size of the transponder, the reading range varies. It can be from a few centimeters up to a couple of meters. LF penetrates most materials, such as body tissue and water. One limitation is that electric motors may interfere with the LF system if it is used in the industry. Because of the antenna size, the LF transponders are normally more expensive than HF transponders. That makes this frequency best suitable for applications where the transponders can be re-used. Other limitations are that the data transfer is relatively slow, because the lower the frequency is the slower is the communication. One transponder at a time can be read in most LF systems and it does not support simultaneous read of multiple tags.

2.5.2 High Frequency

The frequency used for High Frequency (HF) RFID systems is 13.56 MHz. This is a globally accepted frequency meaning that any system operating at HF can be used world-wide. When using HF, the signal travels well through most materials, even water and body tissue. Compared to LF, it is more affected by surrounding metals. The advantages with HF, when comparing to LF, are lower tag costs, the communication speed is better and it is possible to read multiple tags at once. The antenna length is based on the length of the signal that is transmitted or received. You can say that the higher the frequency the shorter the wavelength is. Because of this, the antennas in a HF system are smaller than the ones used in a LF system. HF is designed for applications that require a communication range of one meter or less, with the current power regulations. One thing that has an impact on the communication range is the orientation of the tag with respect to the reader antenna. Both the reader antenna and the tag antenna should be parallel to get the best communication range as possible. If the tag is perpendicular to the reader antenna, then the communication range may be reduced. In HF RFID systems, the communication range is highly dependent on the reader design and the transponder antenna. Parameters on which the maximum communication distance is depended are RF power of the reader and specific antenna configuration. Factors that strongly influence range are tag tuning, antenna size and environmental factors. With 13.56 MHz systems, water does not interfere, but metal does. If there are metal between the reader and the tag, communication is impossible.

2.5.3 Ultra High Frequency

This frequency has become one of the dominating in RFID market space. One of the biggest reasons why UHF has become more popular is the read range. Even if LF and HF are well established and robust technologies, they fail where range of beyond one meter read is required. On the supply chain market where longer read distances are required, UHF systems are preferable. UHF range allows for shorter antennas and longer read distances. In UHF, the anti collision feature implementation is achieved, thus a higher number of tags can be read simultaneously. It is possible to read about 200 tags at once. Today's UHF systems do not work in presence of liquids and on metal. This condition poses a serious challenge. One problem with UHF is that it uses different frequencies in different regions of the world.

2.5.4 Super High Frequency (Microwaves)

The frequency 2.45 GHz is also called microwaves or Super High Frequency (SHF). This frequency ranges from 1 GHz and upward. For RFID systems, a typical microwave operates either at 2.45 GHz or 5.8 GHz. Microwave systems can use both semi-active and passive tags. One great advantage is that these systems have the fastest data transfer rate between the reader and the tag. Because it is in the UHF band, microwaves got the same drawback when using it in presence of metal or water, as UHF. The antenna length is inversely proportional to the frequency and because of that the passive tag's antenna has the smallest length comparing to the other frequencies discussed. That makes tags in microwave RFID systems, the ones with smallest size.

2.5.5 Ultra High Wideband (UWB)

Ultra-wideband (UWB) technology applied to RFID is fairly recent. Rather than sending a strong signal on a particular frequency, UWB uses low-power signals on a very broad range of frequencies. The signal on a particular frequency used by UWB is very weak, but in aggregate, communication is quite robust. In practice, some implementations of UWB operate from 3.1 to 10.6 GHz. The advantages of UWB are that it has a very long line-of-sight read range, perhaps 200 meters in some settings. UWB is also compatible with metal or liquids. Since the signal on a particular frequency is very weak, UWB does not interfere with sensitive equipment. Consequently, an early application was asset tracking in a hospital setting. A disadvantage of current implementations of UWB is that it must be active or at least semi-passive. However, since UWB tags broadcast very weak signals, they have relatively low power consumption.

Table 21 summarizes the main application fields for tag operating at different frequencies and their main characteristics.

Frequency	Main application fields	Type of tag	Metal	Moisture	Aiming of transponder during reading	Data rate	Tag dimension	Transmission of energy and data
LF (125 KHz)	Car immobilization Access control systems Gas readers Animal ID	Passive	No effect	No effect	Not necessary	Low (2- 10 kbps)	Medium/ small	Electromagnetic induction
HF (13.56 MHz)	Access control systems Contact –less credit cards ID badges Baggage handling Ticketing Tracking and tracing Multi access Library management Payment card	Passive	Approximately no effect	Approximately no effect	Not necessary	Good (10- 100 kbps)	Medium	Electromagnetic induction
UHF (868 MHz)	Tracking Supply chain management Inventory management	Passive	Strong reflection from metal	High absorption through liquids	Sometimes necessary	High (28 – 100 kbps)	Small	Radio waves
SHF (2.45 GHz)	Fleet identification Electronic tool Container tracking Production control	Passive Semi-passive Active	Strong reflection from metal	High absorption through liquids	Necessary	Very high (100 kbps- 1 Mbps)	The smallest	Radio waves
UWB (3.1 - 10.6 GHz)	Asset tracking	Semi-passive Active	No effect	No effect	Necessary	Very high (100 kbps- 1 Mbps)	The smallest	Radio waves

Table 21

2.6. Signal attenuation

In RFID, attenuation normally refers to reduction in the energy that is emitted by the reader or in the energy reflected back from the tag. A tag must be closer to the reader to be read if less energy is able to reach it. The energy emitted by the reader is naturally decreasing with distance. This rate of decrease is proportional to the inverse square of the distance. Passive UHF-tags reflect back a signal at very low power levels. Generally speaking Low Frequency signals penetrate liquids more easily because longer wavelength is less susceptible to attenuation. Therefore Low Frequency and High Frequency systems are better suited for tagging objects in environments containing water (like humans or animals). Metal stops radiofrequency signals and reflects them, creating interferences. Progress is being made regarding the management of interferences created by metallic environments. Low Frequency magnetic coupling systems can communicate in a metallic environment under certain conditions. A wide variety of error-correcting coding techniques can be employed to try to mitigate the effects of noise. The greater the complexity of noise avoidance, mitigation and reduction techniques in data channel engineering, the greater will be the cost of the tag.

2.7. RFID costs

The cost of RFID tags was about a dollar each in 2000. Many researchers believed hat extensive use of RFID would not be possible unless tag unit cost reduces drastically. There is a widespread view in the industry that the tag cost would have to come down to 5 cents each before the RFID industry could really take off because ‘‘companies cannot afford more than five cents worth of added cost’’. The five cent tag is not yet a reality, even though the price is decreasing continually. It came down to 12.9 cents of US$ in 2005 and currently the passive UHF tags sell for about 10 cents each as found in Zhu and al. (2011). As regard to the readers the cost varies from US$100 (for LF readers) to US$1,000 (High-frequency reader modules) for readers of passive tags, from US$1,000 to US$3,000 or more for readers that communicate with active tags over long distances. Finally the antenna costs range between 150$-2,000$ depending on frequencies adopted and applications.

Today the better way to determine if an investment on RFID is affordable is to verify if it will add value for the company. If there is no added value, then even a two-cent tag will not be attractive. The added value would come from the effective use of all the information that can be collected from the tags with no additional labor cost. The data can be used to improve on-shelf availability, tracking life-saving items or parts movement. All these have tangible value that can be quantified. If this value, for a given company, is higher than the tag cost (whatever it is), then RFID is available implementation. Table 22 summarizes the tag costs divided by frequency.

Frequency	Type of tag	Unit cost (US$)
LF (125 KHz)	Passive	1
HF (13.56 MHz)	Passive	0.50
UHF (868 MHz)	Passive	0.10
SHF (2.45 GHz)	Passive, Semi- passive, Active	25
UWB (3.1 – 10.6 GHz)	Semi- passive, Active	5

Table 22

2.8. Application fields

The information gathering, storing and transmitting capability of the RFID tag makes a variety of usage possible. Passive RFID tags, for example, are commonly used in product tracking, building access control, airline baggage tracking, while the US Department of Defense has successfully used active tags to reduce search and loss in logistics and to improve supply chain visibility. In this sense fields of application of RFID are very diverse. RFID technology is mainly applied for:

- **Retailing industry**. Effective implementation of the quick response system requires an efficient inventory management system and depends on consolidation, integration, and analysis of data collected from different supply chain players such as, supplier, manufacturer, distributor, wholesaler, shipper and retailer. Traditionally, the methods of stocking shelves and managing inventory were used, but these are labor intensive, time consuming, and error-prone. RFID can be of immense help in this operation. A product with an RFID tag could be tracked immediately after it is delivered to the store. Using this information, backroom inventory can be minimized and at the same time shelves can be kept full. This will also improve store security and analysis of sales data.

- **Smart shelf operations**. Smart shelves can detect RFID tags affixed to individual items. These can then be transmitted to the information system which can place a replenishment order either from the stock room to the shelf or from the manufacturer to the retailer for a new shipment.
- **Retailing industry-apparel**. In this sector the use of RFID solution may help to reduce the inventory shrinkage.
- **Food and restaurant industry**. In this industry, the inventory generally is perishable with limited life. If not handled properly while transporting, it may get spoilt and its useful life reduces. This has a number of repercussions. First, the saleable life is reduced thereby reducing the revenue generating window of the product. Second, an outdated (or expired) product can be delivered to a customer with disastrous results. RFID enabled product identification can reduce such spoilage substantially. RFID system can track the items in real time without product movement, scanning or human involvement. Active RFID tags can dynamically update information on the product. RFID can also be used to integrate agricultural firms into the food chain and reduce product recall costs.
- **RFID in health care industry**. A number of applications of RFID technology are already found in the health care industry. They use it to improve patient monitoring and safety, increase asset utilization with real-time tracking, to reduce medical errors by tracking medical devices, and to enhance supply-chain efficiencies.
- **Logistics industry**. In the logistic sector the RFID can improve the ‘‘shipping,’’ ‘‘receiving,’’ and ‘‘put-away’’ processes; these technologies can cancel, automate, or automatically trigger some business processes; they foster a higher level of information sharing/synchronization between supply chain members.
- **Travel and tourism industry**. A major application of RFID came into play when the US Government included RFID chips in US passports in 2006. The chips store the same information that is printed within the passport like the information about the traveler, including name, gender, date and place of birth, and a digital picture of the passport holder. Apart from this huge application in passports, there are many other RFID applications in travel and tourism industry, as the interactive museum and hands-free access to ski lifts.
- **Library applications**. In this field RFID is applied embedding books with RFID chip which includes all relevant information. Since RFID tags can be read through an item, borrowers can check out several books at one scan. RFID could help staff speed up inventory management process, reduce human errors and increase the accuracy of inventory records. A whole shelf of materials can be counted within seconds, reducing time of ‘‘shelf-reading’’ and other inventory activities. Smart Shelves are used to pinpoint the exact location of books in a library saving thousands of dollars in misplaced and therefore lost books.

2.9. RFID standards

The two most relevant RFID standards are the International Organization for Standardization’s (ISO) and EPC global’s standards. RFID ISO standards cover 4 different areas: technology (e.g. ISO 18000 series), data content (e.g. ISO 15418), conformance and performance (e.g. ISO 18046), and application standards (e.g. ISO 10374). The ISO standards are defined at a very high level, focusing on the interface rather than on the data which is transported. As a result, ISO standards are generic, being able to be supported by any system and in any context, irrespective of the data that is being carried. In contrast with ISO RFID standards which are generic standards, EPC standards are specific. EPC standards describe the tag and the air interface depending on the data being carried. EPC standards prescribe the physical implementation of the tags and readers, rather than specifying their generic characteristics. EPC global defines specifications for EPC-type tags operating in the UHF range. The EPC global protocols assume the tag carries a unique identifier, the electronic product code (EPC). EPC's can be either 64 or 96 bits long (longer ID's are available for future use), and are partitioned into a header describing the EPC structure, some information about the 'manager' (typically a company owning some ID space), and other information about the type of object marked and the serial number. The standards are also much more limited in their scope, for example where the ISO standards for air interface cover all the frequency range, EPC operates only within the UHF between 860-930MHz with one standard for 13.56MHz.

The ISO standard are divided in:

1. ISO Standards for Proximity Cards: ISO 14443 for “proximity” cards and ISO 15693 for “vicinity” cards both recommend 13.56 MHz as its carrier frequency. These standards feature a thinner card, higher memory space availability and allow numerous cards in the field to be read almost simultaneously using anti-collision, bit masking and time slot protocols.
   - ISO 14443 proximity cards offer a maximum range of only a few inches. It is primarily utilized for financial transactions such as automatic fare collection, bankcard activity and high security applications. These applications prefer a very limited range for security.
   - ISO 15693 vicinity cards, or Smart Tags, offer a maximum usable range of out to 28 inches (70cm) from a single antenna or as much as 4 feet (120cm) using multiple antenna elements and a high performance reader system.

2. ISO Standards for RFID Air interface. The ISO 18000 series is a set of proposed RFID specifications for item management that could be ratified as standards during 2004. The series includes different specifications that cover all popular frequencies, including 135KHz, 13.56 MHz, 860-930 MHz and 2.45 GHz.
   - 18000 - 1 Part 1 – Generic Parameters for Air Interface Communication for Globally Accepted Frequencies
   - 18000 - Part 2: Parameters for Air Interface Communications below 135 KHz
     ISO standard for Low Frequency
   - 18000 - Part 3: Parameters for Air Interface Communications at 13.56 MHz
     ISO standard for High Frequency
     Read \ Write capability
   - 18000 - Part 4: Parameters for Air Interface Communications at 2.45 GHz
     ISO standard for Microwave Frequency
     Read \ Write capability
   - 18000 - Part 5: Parameters for Air Interface Communications at 5.8 GHz
   - 18000 - Part 6: Parameters for Air Interface Communications at 860 – 930 MH
     ISO standard for UHF Frequency
     Read \ Write capability
     Targeted for same markets as EPC standards.
   - 18000 - Part 7: Parameters for Air Interface Communications at 433.92 MHz

3. ISO Standards for Animal Identification
   - ISO 11748 / 11785

4. ISO Supply Chain Standards

These are used to identify different types of logistics containers and packaging, in addition to individual items.

- ISO 17358 - Application Requirements, including Hierarchical Data Mapping
- ISO 17363 - Freight Containers
- ISO 17364 - Returnable Transport Items
- ISO 17365 - Transport Units
- ISO 17366 - Product Packaging
- ISO 17367 - Product Tagging (DOD)
- ISO 10374.2 - RFID Freight Container Identification

Table 23 summarizes the ISO and EPC Global standard for frequencies adopted by RFID technology.

Frequency	**Type of tag**	**ISO standard**	**EPC Global standard**
LF (125 KHz)	Passive	18000 - 2	Not treated
HF (13.56 MHz)	Passive	18000 - 3	Not treated
UHF (868 MHz)	Passive	18000 - 6	Yes
SHF (2.45 GHz)	Passive, Semi- passive, Active	18000 - 4	Not treated
UWB (3.1 - 10.6 GHz)	Semi- passive, Active	Not treated	Not treated

Table 23

CHAPTER 3

3.1. The case study: Introduction

The case study here presented deals with the analysis of the logistic chain of perishable products. Some typical perishables products are bread, meat, fresh fruit, ready-to-cook vegetables, dairy products, etc. The characteristic that has the greatest impact on the storage life and safety of fresh perishable is the temperature. Effective temperature management is in fact the most important and simplest procedure for delaying product deterioration (Nunes and al., (2006)), although the deterioration rate also depends on other parameters as relative humidity, solar irradiation, acidity, microbial growth, endogenous enzyme activities (Alasalvar and al. (2001), Howard and al. (1994), Riva and al. (1999)). A way of delaying perishables deterioration is to properly organize the cold chain. Products harvested must be immediately transported to the warehouse and stored at their optimal temperature (Jedermann and al. (2007)). In fact the storage at optimum temperature condition typically retards the aging and softening of fruit and vegetables, their textural and color changes, as well as their metabolic process, the moisture loss, and pathogen invasion. However even when the cold chain is adequately organized products can anyway be subject to temperature abuses due, for example, to the harvest phase and the loading and unloading phases which are performed outdoor and to the fact that different supply chain stages are performed at different temperatures. The variation of environmental conditions affects the product by triggering deteriorative processes. Such processes lead to the decreasing in the product quality attributes which ultimately result in no longer marketable products. In absence of control of product quality level these products could flow through the supply chain and reach the consumer. In such case the members of the chain incur in deterioration costs due to the wasted products, recall costs and consumers dissatisfaction. In order to reduce inefficiencies related to deteriorative processes affecting perishable products a suitable solution is given by the possibility of monitoring thermal conditions which characterize the product life from the harvest to the consumer and applying stock management policies based on the current quality level of a product. In fact the monitoring and controlling of storage temperature allows to determine the SL of perishable products. The effective application of this approach requires the modeling of the SL from the temperature. The literature reports several models which aim to determine the quality level of a product in terms of its Shelf Life starting from its thermal history. These models have been discussed in Chapter 1 and deal with the combined use of kinetic of reaction and the Arrhenius law. The accuracy with which these relationships are measured influences the reliability of the models. Recently TTIs (temperature time integrators) have been used for various perishable foods including fruit and vegetables (Grisius and al. (1987), Singh and Wells (1987)) by means of compact temperature logging devices. With modern information technology, it is relatively cheap to continuously keep track and monitor the temperature of products. By using, e.g. Radio Frequency Identification (RFID) technology, it is possible to update the remaining lifetime continuously and thus to avoid the risk that outdated products are delivered to customers. The RFID can be attached to the object to be tracked and monitored, thus allowing to move from traditional stock management policies (First In First Out, (FIFO)) to new advanced policies based on the SL (Least Shelf Life First Out, (LSFO)). Studies show that the use of this new policy, consisting in release first those products with lower SL, can increase a retailer's profit (Giannakourou and Taoukis, (2003-b), Dada and Thiesse, (2008)) by reducing the amount of perished products and by implementing advanced pricing policies. Consumers in fact can be less likely to purchase perishable goods when their expiration dates are near. For this reason, retailers frequently implement a discount pricing policies when the products are reaching their expiration dates (Sezen). In this study the kinetic equations discussed in Chapter 1 were used to set up a mathematical model to predict the shelf-life and an experimental campaign, using Stock Keeping Units (SKUs) labeled with RFID tags, were carried out to validate the model. In the case study here presented a RFID system has been employed to monitor the time-temperature history of peaches fruit, Elegant Lady variety, from the harvest phase until the product reach the final destination. A RFID tag with temperature sensor incorporating a memory, a battery and a clock to record sensor data in memory at constant intervals has been used. The two alternatives policies (FIFO and LSFO) were compared with regard to their effects on the quality of the products in terms of remaining SL, as well as to the impact on the economical performance of the system. The present study reports the technical/economic analysis related to the employment of a RFID warehouse management system in an agro-industrial supply chain, based upon the experimental validation of the theoretical shelf-life model and referred to actual product flows.

3.2. The proposed methodology

The case study here presented deals with the supply chain of peaches which are monitored from the harvest to the final destination. The monitoring consists in applying a RFID sensor to SKUs and recording the time-temperature history of the product when it moves through the supply chain. When the product reaches the final destination the data detected are downloaded from the sensor and transferred to a computer for processing. In order to verify the applicability of the Arrhenius model to data detected at first an analysis of SL dependence of peaches fruit from the temperature has been assessed. As explained in Chapter 1 the quality loss for a perishable product can be evaluated through the decay of those attributes which define its sensorial profile. With regard to these attributes the quality decay can be evaluated through a measurable parameter correlated to chemical-physical reactions which determine the decay. The variation of the quality with time can be expressed as in eq. (12). When the product is subject to variable temperatures the relation between the measurable parameter and the time can be expressed by the Arrhenius law (eq. (30)). This relation rearranged as in (45) can be related to the Q_{10} which defines the factor of speed of the reaction acceleration when the temperature varies of 10 °C. Based on relation (32) the use of Q_{10} can be defined as in (37). The knowing of the Q_{10} factor at different temperatures and of the SL value of peaches at a certain temperature can be used to determine other values of the SL of peaches. This allows to plot the SL values vs 1/T and determine whether data plotted follows the Arrhenius law.

Once the validity of the Arrhenius model has been verified the data processing phase is performed consisting in determining the SL of peaches on the basis of the experimental data gathered by applying the Arrhenius law. Finally the SL values have been used to determine the fraction of SL consumed f_c and residual f_r as in eq. (49) and (50). In order to show the usefulness of the monitoring system deployed in this study the attention is focused on the effect of a SL based management system on the assessment of quality of products reaching the final destination. For this reason the comparison between two alternative picking policies (FIFO and LSFO) has been performed on products stored. Results show that the knowing of residual quality of products at any stage of the supply chain contributes to optimize the decision process allowing to early withdraw perished products and the application of SL based picking policy allows to reduce the fraction of products which perish in the storage phase.

3.3. The case study proposed

3.3.1 The RFID system deployed

The detection of thermal conditions to which a product is subject when it moves through the supply chain is a central question in the application of the deterioration model proposed in the previous paragraph. It is necessary to record data related to the time-temperature history of the SKUs and associate each SKU to its time temperature history. In this way it will be possible to uniquely associate the SL calculated to each SKU. To achieve this goal the RFID technology can be properly used. As seen in Chapter 2 RFID systems allow the reading of an unique identification code referred to an object when it passes in proximity of a reader. Since a tag can be equipped with a sensor the RFID allows the detection of time-temperature history of the product. In order to monitor the temperature conditions at each stage of the supply chain it is necessary that each actor of the chain adopts a proper RFID system. However for the case study here presented a unique RFID system has been deployed at the final destination. The RFID system deployed consists in both centralized and remote tools. Centralized tools are fundamentally constituted by a reader, an antenna, tools for data transfer and systems able to process data and software and middleware needed to implement the SL model and to realize data transmission. Remote tools are constituted by the tags fixed on the SKUs under examination. The main components of the RFID system implemented are illustrated in the following paragraphs.

3.3.2 Components of the RFID system deployed

3.3.2.1 The reader

The i-PORT 3 reader is an Intelligent Long Range (ILR) interrogator. ILR provides highly accurate, real-time data collection with minimal human intervention in wireless applications such as: identification, tracking and tracing and localization of assets or people. Using UHF radio frequency technology, the i-PORT 3 transmits and receives data at distances from 6-100 meters. It has a anti-collision multi-tag-handling algorithm which allows communication to tags even when thousands of tags are within the interrogator's read zone. The i-PORT 3 comes with a software package, which is based on an industrially proofed Real Time Operating System (RTOS). The built-in software features allow various functions such as the communication with ILR tags, the concurrent management of 4 parallel antennas, the concurrent signal strength measurement (Signal strength measured simultaneously on all 4 antennas can be used as parameters for position determination of tags), the possibility of identify simultaneously 2,000 tag, the communication to host system via Ethernet interface, the integration of external devices (e.g. GSM, GPS, modem ...) via serial interface, the data processing. The i-PORT 3 includes an internal real-time clock to provide accurate time stamps for data captured from the tags. (see Figure 36 and Table 24 for the technical characteristics of the reader).

Figure 36. The i-PORT 3 reader

Fixed UHF Interrogator i-PORT 3	
Performance	
Read Range	100m
Write Range	100m
Max response time	<150ms
Read rate – ID only	100 tags/s
Read rate – 128 bit data	35 tags/s
Multiple tag handling	Up to 2,000 tags in the read zone
Communication	
Frequency	868MHz or 915 MHz
Certification	EN 300 220 (EC); FCC part 15 (US)
Number of antennas	5
CPU	
Data memory	128KB SRAM
Configuration Memory	8KB EPROM
Electrical	
Power Consumption	7.5 W maximum
Environmental	
Operating Temperature	0°C to 50°C
Humidity	90% non condensing

Table 24. Technical data of the i-PORT 3 reader

3.3.2.2 The antenna

The i-A9185 is an elliptically polarised UHF read /write RFID antenna meets all the requirements for ranges of up to 100 meters. Together with the i-PORT 3 fixed interrogator, this antenna creates a very powerful combination for data communication. Because of the wide apex angle (120º), a large read zone is achieved, which is desirable when a large quantity of tags needs to be read at the same time, or when tags moving at great speeds need to be interrogated. The antenna features have been chosen so that even tags in hard-to-reach places or mounted behind metal surfaces can be read and written to. Since the antenna's polarisation is elliptical, the direction of the tag relative to the antenna does not matter. The antenna is designed for use in industrial environments as well as in extreme temperatures and damp surroundings (see Figure 37 and Table 25 for the technical characteristics of the antenna).

Figure 37. The i-A9185 antenna

UHF read/write Antenna i-A9185	
Electrical	
Working Frequency	850 – 930 MHz
Amplification (min.)	5 dBic
Emission Angle	Azimuth: 360°
	Elevation: 120°
Polarisation	Elliptical
Environmental	
Wind Stability	150mph
Operation Temperature	-40°C to 70°C
Humidity	90% non condensing

Table 25. Technical data of the Antenna i-A9185

3.3.2.3 The tag

The i-Q32T tag is a Long Range (ILR) active RFID tags. ILR provides highly accurate, real-time data collection without human intervention in wireless applications such as the identification, the tracking and tracing, the localization and the temperature monitoring. Using advanced UHF radio frequency technology, i-Q tags transmit and receive data at distances of up to 30 meters from a handheld device or up to 100 meters from a fixed interrogator. The anti-collision multi-tag-handling algorithm allows communication to tags even when thousands of tags are within the interrogator's read zone (2,000 tag can be identified simultaneously). Because of its very low power consumption, the tag can operate effectively for over 6 years. The battery memory is of 32,000 Byte. The i-Q32T tag contains an internal sensor for temperature monitoring in order to measure and log the temperature of goods in definable intervals. With its LED, the tag supports visual recognition, such as, for example, for "pick by light" applications (see Figure 38 and Table 26).

Figure 38. The i-Q32T tag

Active UHF Tag i-Q32T	
Performance	
Read Rate	Up to 100 tags/s (Identification Code only)
	Up to 35 tags/s @ 128 bit data reading
Max Response Time	< 150 ms (single tag)
Multiple Tag Handling	Up to 2,000 tags in the read zone
Communication	
Read Range to i-PORT 3	Up to 100 m free air*
Write Range i-PORT 3	Up to 100 m free air*

Operating Frequency	868 MHz (EC) or 915 MHz (NA) ISM Band
Data Rate (download to tag)	115.2 kbits/s
Data Rate (upload to reader)	115.2Kbit/s
Maximum transmission power	0.75 mW ERP
Standards / Certification	EN 300 220 (EC); FCC Part 15 (US); Industry Canada
Electrical	
Power source	Lithium battery (not replaceable)
Expected battery life	> 6 Years @ 600 times 128 bit readings/day
Battery monitoring	Yes
Temperature Logging	
Number of samples:	13,312
Interval	User definable in intervals from 1 to 255 minutes
Accuracy	±0.5 °C (1 °F) over a range of –20 to +50 °C (–4 to 122 °F); ±1 °C over entire range
Metering range	–40 to +85 °C (–40 to +185 ºF) with internal sensor –127 to +127 °C (–197 to +261 ºF) with external sensor, optional
Resolution	0.25°C (0.5 °F)
Data	
Data retention	> 10 years without power
Write cycles	100,000 writes to a tag
Memory size	5,791 bytes, user definable
Identification code	48 bit fixed ID
Environmental	
Operating temperature	–40 to +85 °C (–40 to +185 ºF)
Shock	50 G, 3 times DIN IEC 68-2-27 Multiple drops to concrete from 1 (3 ft)
Vibration	3 G, 20 sine wave cycles, 5 Hz to 150 Hz, DIN IEC 68-2-6 5 G, noise 5 Hz to 1000 Hz, 30 minutes DIN IEC 68-2-64

Table 26. Technical data of the i-Q32T tag

3.3.3 Stock rotation systems for perishable products

The supply chain of fruits and vegetables is characterized by transport and storage phases which alternate from the field to the final destination. With regard to the transport phases the focus must be on keeping the correct temperature; while the load and unload phases should be rapidly performed in order to reduce the time the product passes at environmental temperature which can trigger the deterioration process. Concerning the storage phases the optimization of the quality of products stored depends not only from the keeping of proper temperature but also from the stock rotation system adopted. The most employed picking rule used to manage perishable products is the FIFO rule. This rule assumes that the obsolescence of products is strongly correlated to their arrival order in the warehouse. This is true for example for packaged product in which the expiration date increases with the order of arrival of food in the warehouse. In this case in order to optimize the quality of products stored it will be useful to release first (First Out) those products which are arrived first (First In) (see Figure 39.a). This is not the case of fruit and vegetable which due to the intrinsic variability of the maturation level at the harvest phase have different SL when they enter the cold chain. In this case it is preferable to release the products from the warehouse on the basis of their actual quality as in the LSFO rule. The possibility to gather information on actual quality level of products allows to implement SL based picking rules. In this case those products having a shorter SL (Least Shelf Life) will be released first (First Out) (see Figure 39.b). Singh and Wells (1987) were among the first to publish an issuing policy based on the actual quality of an item. Motivated by temperature-aware chemical sensors, so called Time-Temperature Indicators (TTI), they developed a type of Shortest-Remaining-Shelf-Life (SRSL) issuing policy. Their policy took into account that every individual item can have a different deterioration history and thus a different remaining shelf life. They conducted computer simulations and showed that for frozen goods the SRSL policy outperformed LIFO and FIFO policies. The results outlined the value of sensor-based strategies for the special case of frozen goods. 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.

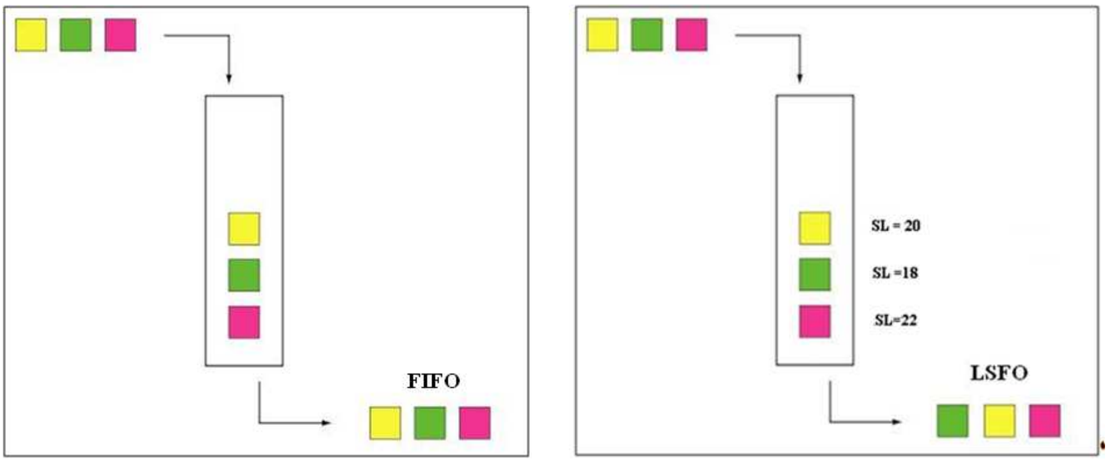


Figure 39.a **Figure 39.b**

Figure 39. FIFO and LSFO policies

In this study the two aforementioned picking policies have been taken into consideration to show the effectiveness of the monitoring system proposed in the case of fresh produces. For this reason the two picking policies were compared in order to show the increasing in quality of products stored achievable by implementing SL based policies instead of traditional policies.

3.3.4 Experimental analysis

The case study is applied to the supply chain of peaches fruit, Elegant Lady variety. The supply chain under study is composed by the production, transport and storage phase, as illustrated in Figure 40.

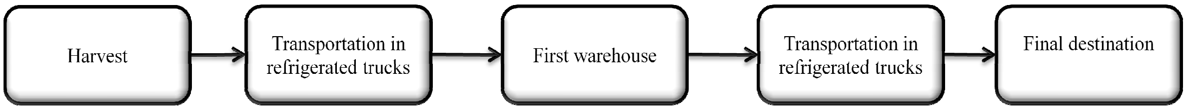


Figure 40. The supply chain under study

The experimental analysis carried out consisted of applying the RFID tags illustrated in the previous paragraph immediately after the harvest phase, when the logistic unit is built. At this moment some SKUs are equipped with the RFID tag to record the thermal history of products. Thus the product is transferred to the first warehouse where it is stored at a temperature of 5°C. In the successive phase the product has is sent in a truck freezer to the final destination which is the market where the product will be sold to the consumer. In this moment the tags have been removed from the SKUs, temperature data have been downloaded from the tags and transmitted to the centralized system.
The following Figure 41 reports the average time-temperature history for SKUs tested with the experimental analysis. These SKUs can be considered as a sample representative of the population. Data reported show that the variability in temperature is mainly due to the initial harvest phase. This variability affects the initial SL of products. In fact even though products have been harvested about at the same maturation level, the variability due to times required to harvest products and environmental conditions which cannot be controlled causes that products to have a different SL. This results in an intrinsic variability in the SL of products entering the cold chain, characterized as well by variable transport and storage times. At last the effect of such variability elements results in a different SL values of SKUs reaching the final consumer. As results from Figure 41 the monitoring has been carried out for 120 hours after harvest, consisting of 5 hours (first stage) to complete the harvesting phase and transportation to the first warehouse, 50 hours (second stage) in storage in a refrigerated warehouse, 40 hours (third stage) of transportation, in which temperature of truck freezer was higher than warehouse temperature, and 25 hours (fourth stage) of storage at ambient temperature when the product is arrived at destination.

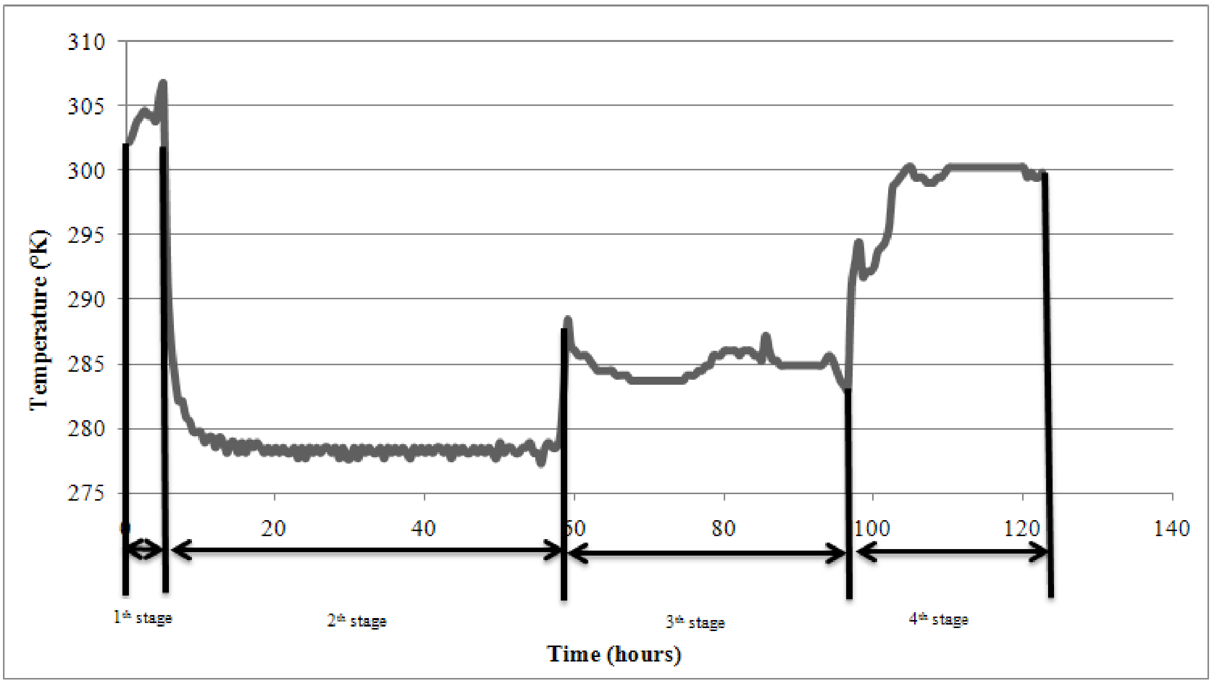


Figure 41

Once detected the time-temperature history of the product it is required to apply a temperature-dependent deterioration model to determine the SL of the product at any stage of the supply chain. For this reason the next step of the study involved the determination of the deterioration model which can represent the quality loss of peaches with time as a function of temperature. Thus in order to apply the Arrhenius law (discussed in the Chapter 1) it is required to evaluate whether the deterioration process follows the equation (30). To do this by considering eq. (33) it must be demonstrated that the SL of the product considered linearly depends from the temperature. This assumption can be showed by plotting some SL values vs 1/T and verifying whether they interpolate a straight line. By remembering the meaning of the Q_{10} value (discussed in the Chapter 1) and by considering information reported in Table 27 referred to peaches fruit (see Testoni and al. (2006)), it is possible to determine the SL for different values of temperature. Table 28 reports the Q_{10} values for several temperatures.

Fruit	Ea (J/mol)	SL (Days)	T (°C)
Peach	77,900	22	0.5

Table 27

	T=10	T=20	T=30
Q_{10}	2.5	2.5	2.0

Table 28

SL values are reported in Table 29.

T(°C)	SL (hours)
0.5	528
5	334
7	278
10	211
20	84
25	60
30	30
35	24

Table 29

The plot of $ln(SL)$ versus $1/T$ is reported in Figure 42.

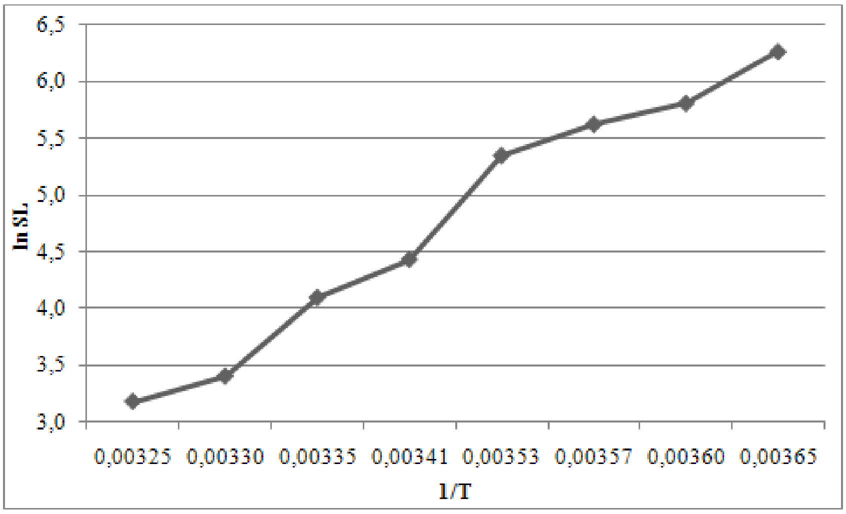


Figure 42

By performing a linear regression of $ln(SL)$ versus $1/T$, the determination coefficient R^2 resulted equal to 0.975. This value confirms that the $ln(SL)$ varies linearly with $1/T$. This means that the deterioration process of the product under consideration follows the Arrhenius law. Thus in the experimental analysis carried out the $ln(SL)$ has been calculated with Arrhenius equation and by considering data reported in Table 27 and the time-temperature history of the product showed in Figure 41, and the fraction of SL consumed f_c and the fraction residual f_r have been determined by using eq. (49) and (50). Results are showed in Figure 43 where the f_c is represented.

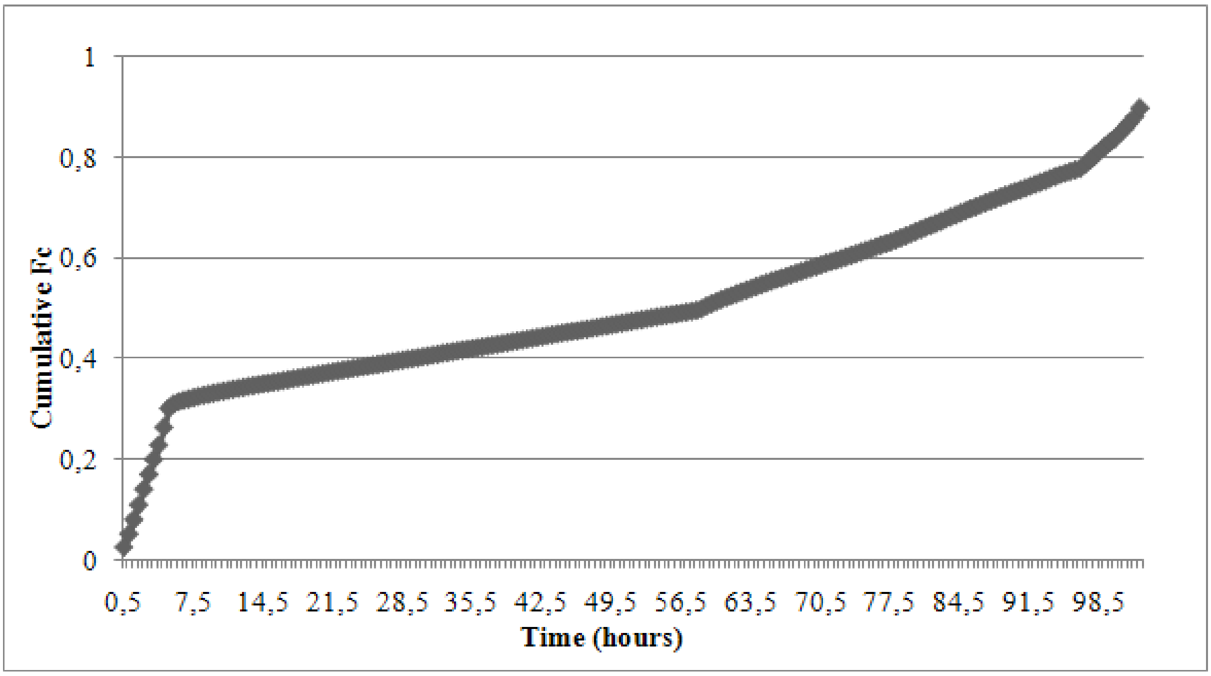


Figure 43

Figure 43 shows that the f_c increases until it reaches about the value of 1 which corresponds to the end of the marketability of the product. This figure also shows that about the 80% of the SL has been consumed within the cold chain and the remaining life of the product when it reaches the final destination is about of 20 hours. This information which can be simply get by means of a RFID system allows to establish, at each stage of the chain, the quality limit of the product beyond which the sending of the product is not more convenient, since would be high the probability the product arrives perished at destination. In this study a f_c limit has been fixed equal to 0.7, which means that those products which present a f_c equal or greater than this threshold at the time of the shipment from the first warehouse are considered not suitable for the target market, since even if they were maintained at their optimum temperature conditions during the following phases, they would arrive perished at the final destination. In such a situation it could be possible to send these products in an alternative market where they are considered still suitable for consumption thus achieving a salvage value in this alternative market.

3.3.5 Economic Analysis of SL based warehouse policies

Once the evaluation of the shelf life has been performed another important issue is related to the possibility of applying a SL based picking policy to products leaving the warehouse instead of the FIFO picking policy. In this study this comparison has been done on products leaving the first warehouse, however the choice made about the picking policy affects the entire cold chain. In order to show the impact of the picking policy the f_c of products entering the cold chain has been determined equal about to 25% in average, having a normal distribution with a standard deviation of 0.06 which is attributable to the harvest phase. The study has been conducted on the basis of the actual replenishment cycle (Figure 44) of the season 2009. The demand rate has been considered equal to 15 tons at fixed intervals of 4 days.

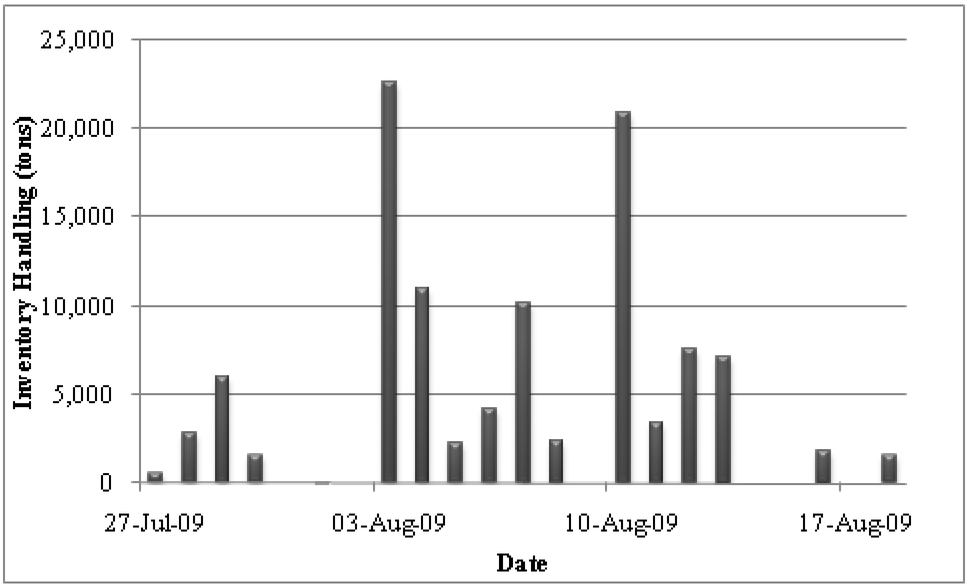


Figure 44

Given these considerations an economical analysis has been performed by fixing a selling price $V_0 = 0.6€/Kg$ and a threshold $f_c = 70\%$, considering that with a lower residual SL even in optimal storage and transportation conditions the product will be perished at the end of the supply chain. The production cost of peaches is $C_p = 0.1€/Kg$. Subsequently according to the constant demand considered, outgoing SKUs are selected according to the FIFO rule in the first case and to the LSFO rule in the second case. When SL is not monitored and the FIFO policy is adopted all products would be eventually delivered through the supply chain and the perished products would be detected at the end of the supply chain when they are not sellable anymore. The price of the perished products at the end of the supply chain is simply considered null and transportation and waste costs are neglected. The economic loss for perished products can thus be determined. When the LSFO policy is adopted products which achieve a residual SL value minor than 0.7 in the first warehouse are immediately discarded, and they do not enter the supply chain. In such conditions their transportation cost is avoided and a salvage value could be considered since they are still sellable in the local market. In this study however salvage value and transportation costs are not considered hence the profit is only related to the reduction of the quantity of perished products achieved by selecting the outgoing SKUs with relation to their SL value. Results of the economic analysis carried out for 20 days show that by moving from the FIFO to the LSFO policy it is possible to achieve a saving in terms of perished products of 5,549Kg (equivalent to 3,884€) which corresponds to a reduction of 32.25% of fraction of perished products as showed in Table 30.

FIFO		**LSFO**	
Kg	**€**	**Kg**	**€**
17,068	11,948	11,519	8,063

Table 30

It is clear that the wastes due to the deterioration have a little influence on the revenue at the starting of the season but they become very onerous when the production increases involving the stratification of stocks. Finally another aspect which should be taken into account is related to the increasing of the average value of initial SL consumed as the season progresses and the products ripen, but this aspect is not considered in this study.

3.3.6 Conclusions

The study presented is related to the application of RFID systems to the supply chain of perishable products. The advantage attainable by the automatic monitoring of environmental conditions affecting the quality level of products concerns the possibility to early identify the perished units and the withdrawal thus avoiding the related transport and disposal costs. The use of a RFID system specifically deployed also allows to apply SL based picking policy to products stored thus reducing the fraction of perished product and increasing the quality of products stored. In order to validate these affirmations a case study has been carried out in which the supply chain of peaches has been analyzed. The time-temperature history of products along the supply chain has been recorded. Once the deterioration model has been validated the fraction of SL consumed at each stage of the supply chain has been determined in order to know the residual quality level of products. Two different picking policies (LSFO and FIFO) have been applied to products leaving the first warehouse and the technical-economical analysis conducted showed the improvement achievable by applying the SL based picking policy instead of the traditional policy.

SECTION 3: DECISION MAKING IN A WAREHOUSE MANAGEMENT SYSTEM

INTRODUCTION

As discussed in the Section 2 the management of perishables throughout the supply chain is a critical issue due the limited life of such products. In the previous section we discussed the importance of the monitoring of the actual quality level of products through the supply chain and the results showed that the information related to the SL of the products at any stage of the supply chain can be of great help in the decision process involving the possibility to locally distribute those products that are soon to expire and to more distant locations less deteriorated products. Furthermore the knowledge of the SL of products in conjunction with the SL based picking policy allows to reduce the fraction of perished products in the storage phase. In this section the attention is focused on the storage phase and a warehouse management system for perishable products is presented. The warehouse management is essentially characterized by the replenishment policy (Economic Order Quantity, (EOQ)) and the issuing policy established by the distributor which must be specifically chosen in relation to the characteristics of products managed. These choices affect the warehouse performance in terms of quality of products stored and profit achieved. Other elements which affect the warehouse management are represented by external parameters, as for example, the demand rate, which cannot be controlled. With regard to the replenishment policy, traditional warehouse management systems are based on the Wilson's model, while the issuing policy relies on the choice between First In First Out (FIFO) or Least In First Out (LIFO). The choice of the proper picking policy is usually related to the maximization of the utility of products stored, the minimization of perished product or the maximization of the profit achievable from the products sold. However the management of perishable products is not always properly carried out by traditional replenishment and issuing policies especially when the obsolescence of the product cannot be correlated to the arrival time of the product in the warehouse. This is the case of fresh produce as fruits and vegetables having a random lifetime. In this case, knowing the quality conditions of the product entering the warehouse and monitoring of quality decrease during the storage phase is of fundamental importance in order to optimize the quality of products leaving the warehouse. The possibility of the real time detection of product quality is today enabled by innovative technologies as discussed in the Sections 1 and 2. In this section the attention is focused on the assessment of a warehouse management system for perishable products with the aim to show that once the warehouse goal has been defined, the optimization of the stock management is closely related to the picking policy adopted, the decisions about the replenishment policy and the monitoring of deterioration process during the storage phase. In particular this study aims at -proposing a methodology to quantify the benefits achievable by enforcing a SL based issuing policy rather than a traditional policy based on the arrival order (FIFO). In order to apply this policy the quality level of products stored must be closely monitored by means, for example, of the RFID technology and by applying the methodology already showed in the Section 2 allowing the determination of the SL. In order to take into account the deterioration process of products during the storage phase a replenishment policy including the deterioration costs is proposed in the present study. To show the improvement achievable with the LSFO policy to respect the FIFO policy the methodology proposed is the design of simulation experiments where the warehouse replenishment cycle is simulated on the basis of an experimental plan in which the input factors are the average RSL of product entering the warehouse, the demand rate and the initial deterioration rate and they vary on two levels. The response of the plan consists in the average Remaining Shelf Life (RSL) of product leaving the warehouse. The experimental plan has been replicated in order to ensure a desired precision of the interest measure. The section is organized as follows: Chapter 1 presents a literature review of issuing policies and EOQ models for perishable products; a taxonomy of the main characteristics of the EOQ models for perishable is done in order to explain the fundamentals of the perishable inventory theory. Chapter 2 presents the design of simulation experiment in order to illustrate the tool employed and finally Chapter 3 presents the warehouse management system proposed by means of a case study.

CHAPTER 1

1.1. The inventory management for perishable products

The choice of the optimal batch size (EOQ) and of the issuing policy are strongly related to the strategic goal of the warehouse and to the product characteristics. In fact given the goal it is necessary to take into account the lifetime of the products which can be deterministic and fixed or random. It is clear that for a fixed-life commodity, the issuing of the oldest units first (FIFO) minimizes expected outdating (Nahmias (1982)). However, in many real systems the user determines the issuing policy and when the utility of new units is higher, LIFO issuing will be the result. An example is retail food distribution where consumers observe an expiration date on shelf items and choose the newest. Significant research has been done to describe the optimal stocking policies for items with a fixed lifetime. The issuing problem, as originally formulated by Derman and Klein (1958), is to determine an optimal sequence to remove items from a stockpile of finitely many units of varying ages. It is assumed that an item which is issued at age *s* has a "field life" of *L(s)*, where *L* is some known function. An item is issued only when the previous item issued has expired so that the total field life of the stockpile will depend upon the sequence in which items are removed from the stockpile. The general approach has been to specify conditions on *L* for which issuing either the oldest units first (FIFO) or the newest units first (LIFO) is optimal. Derman found that given *U(S)* the expectation of *L(S)*, if *U(S)* is a convex function, then LIFO is an optimal policy in order to maximizes the total field life obtained from the stockpile. He also found the optimality condition for FIFO policy consisting in the form of the *L(S)* function (linear and decreasing) (Nahmias (1982). Veinott (1965) treats periodic review and known demand. He examines three distinct problems: (1) determining an optimal ordering policy when the disposal and issuing policies are given, (2) determining optimal ordering and disposal policies when the issuing policy is given, and (3) determining optimal issuing and disposal policies when the ordering policy is given. (Disposal refers to the reduction of stock levels without satisfying demand.) For problem (1) he shows that when the field life function is nonincreasing in the item's age at issue and a FIFO issuing policy is used, an optimal policy will order an amount equal to demand over a sequence of periods (Fries (1975)). Fries and especially Nahmias (1975) have studied fixed lifetime models for products with arbitrary but fixed lifetimes under the assumptions of first-in-first-out (FIFO) issuing policy and fresh supply. Chazan and Gal (1977) considered a Markovian model for perishable products inventory. They proved that in the case in which the daily demand is a discrete random variable the expected outdating in the steady state is a convex function of the order up to level *S*. In addition, they provide a rigorous proof that cumulative outdating is minimized under a FIFO issuing scheme. Cohen and Pekelman (1978) examined the effect of LIFO and FIFO accounting systems on inventory control policies. Although that paper does not deal directly with perishables, considering the age levels of the different stock is necessary for tax purposes. One very interesting result is that the optimal inventory policy does not vary greatly with the valuation scheme used (but does depend strongly on the explicit inclusion of taxation). Cohen and Prastacos (1978) deal specifically with the effect of FIFO versus LIFO depletion policies on both the system performance and ordering decisions. The analysis is restricted to $m = 2$ lifetime periods. The critical numbers obtained were relatively insensitive to the choice of the issuing policy even though the optimal expected cost was significantly higher for LIFO. This result is important in that it suggests that the relatively simple approximations derived in Nahmias which assume FIFO could also be used effectively in the more complex LIFO case as well.

As you can see the literature mentioned is about entirely related to the problem of optimal order quantity under FIFO and LIFO policies when the lifetime of the products can be considered known and fixed. On the other hand for many inventories the exact lifetime of stock items cannot be determined in advance. Items are discarded when they spoil and the time to spoilage may be uncertain. Fresh produce is a typical example. In this case it is necessary to define the probability function of a product of surviving at certain time *t*. The most known probability functions employed are the binomial, exponential and Weibull deterioration functions. The deterioration function must be taken into account in both the issuing policy and the EOQ model. As regards the issuing policy this involves the possibility to move from the FIFO policy to the LSFO policy (as already discussed in the Section 2, Chapter 3, paragraph 3.3.3). Concerning the EOQ model, the exponential and Weibull distributions will be treated in more detail in the next paragraph in which the EOQ theory for perishable products will be illustrated. The aim of this study is to show that when the goal of the warehouse is to maximize the SL of products stored some important decisions involving the optimal batch size, the picking policy and the monitoring of the deterioration process must be taken. The goal of the present study is to show that an EOQ model including the deterioration costs, a methodology able to determine the RSL of products stored and a SL based picking policy allow to increase the SL of products stored compared to the traditional warehouse management system relying on the traditional EOQ model and the FIFO issuing policy.

1.2. A brief introduction on the EOQ theory

1.2.1 The traditional EOQ model

The replenishment policy aims at establish the optimal Order Quantity (EOQ) which minimizes the total cost related to the operative management of the warehouse. The first EOQ model is that of Wilson (as illustrated in Wilson (1934) and Roach (2005) in which such cost is the sum of production cost, holding cost and ordering cost. In this model the following assumptions are made:

- Demand is continuous and constant
- The process continues infinitely
- There are no quantity constraint (on order quantity or storage capacity)
- The replenishment is instantaneous
- No shortages are allowed
- Costs are time and quantity invariant

The model assumes the following notations:

- c is the product cost. This is the unit cost of purchasing the product as part of an order. If the cost is independent of the amount ordered, the total cost is cz, where c is the unit cost and z is the amount ordered. Alternatively, the product cost may be a decreasing function of the amount ordered.
- $c(z)$ is the ordering cost. This is the cost of placing an order to an outside supplier or releasing a production order to a manufacturing shop.
- K is the set up cost. A common assumption is that the ordering cost consists of a fixed cost, that is independent of the amount ordered, and a variable cost that depends on the amount ordered. The fixed cost is called the setup cost.
- h is the holding cost. This is the cost of holding an item in inventory for some given unit of time. It usually includes the lost investment income caused by having the asset tied up in inventory. This is not a real cash flow, but it is an important component of the cost of inventory. If c is the unit cost of the product, this component of the cost is $c\alpha$, where α is the discount or interest rate. The holding cost may also include the cost of storage, insurance, and other factors that are proportional to the amount stored in inventory.
- a is the demand rate. This is the constant rate at which the product is withdrawn from inventory.

- Q is the lot size or EOQ. This is the fixed quantity received at each inventory replenishment.
- T is the cycle time . This is the time between consecutive inventory replenishments is the cycle time. For the models of this section $T = Q/a$
- TC is the Total Cost per unit time. This is the total of all costs related to the inventory system that are affected by the decision under consideration.

The assumptions of the model are described in part by Figure 45, which shows a plot of inventory level as a function of time. The inventory level ranges between 0 and the amount *Q*. The fact that it never goes below 0 indicates that no shortages are allowed. Periodically an order is placed for replenishment of the inventory. The order quantity is *Q*. The arrival of the order is assumed to occur instantaneously, causing the inventory level to shoot from 0 to the amount *Q*. Between orders the inventory decreases at a constant rate a. The time between orders is called the cycle time *T*, and is the time required to use up the amount of the order quantity, or *Q/a*.

The total cost expressed per unit time is:

$$TC = Setup\ cost\ +\ Product\ cost\ +\ Holding\ cost = \frac{aK}{Q} + ac + \frac{hQ}{2} \qquad (55)$$

Where $\frac{a}{Q}$ is the number of order per unit time and $\frac{Q}{2}$ is the average inventory level. Setting to zero the derivative of TC with respect to Q we obtain and solving with respect to Q we obtain:

$$Q^* = \sqrt{\frac{2aK}{h}} \qquad (56)$$

and $T^* = \frac{Q^*}{a}$ (57)

The optimal batch size is showed in Figure 46. From equation (56) is clear that the optimal policy does not depend on the unit product cost. The optimal lot size increases with increasing setup cost and flow rate and decreases with increasing holding cost.

Substituting the optimal lot size into the Total Cost expression (55), we see that:

$$TC^* = \sqrt{\frac{ahK}{2}} + ac + \sqrt{\frac{ahK}{2}} = ac + \sqrt{2ahk} \qquad (58)$$

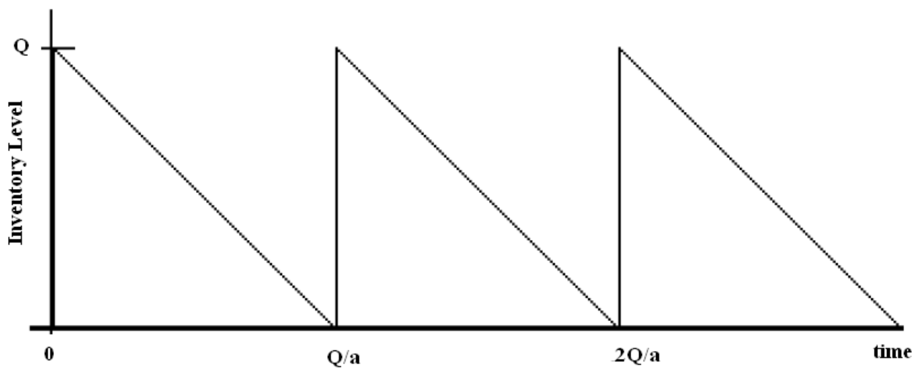


Figure 45

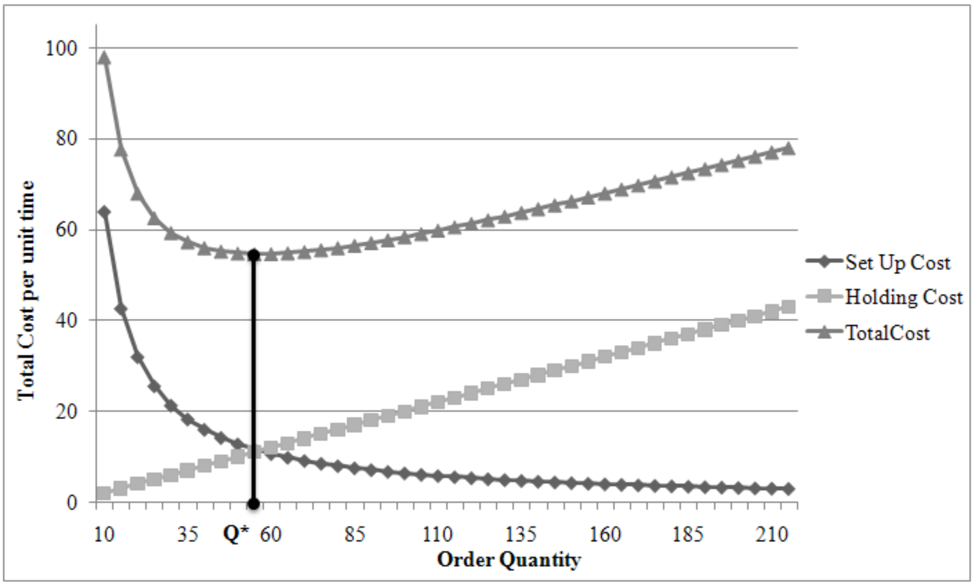


Figure 46

As seen the Wilson model is a deterministic model which aims at optimizing the lot size by balancing holding and ordering costs. In this model the depletion of the inventory level is only due to the demand. On the other hand when the products managed are perishable a more realistic condition is that the depletion in the inventory level is also due to the deterioration process occurring during the storage phase. In this case a suitable approach to the EOQ model is to consider the deterioration process of products and include the deterioration costs in the *TC* function. Furthermore the hypothesis of constant and deterministic demand results in a strong approximation not always verified. In fact in this case a warehouse orders a fixed quantity with the consequence that an order too much increases the storage costs and the risk of losses through obsolescence or spoilage, while an order too small increases the risk of lost sales and unsatisfied customers. This problem can be faced by considering the stochastic nature of the demand and by including the understock (or shortage) and overstock (or salvage value) costs as well as the cost due to the safety stock in the EOQ model. This problem consists in determine not only the optimal batch size but also the optimal inventory level (reorder point) at which to place an order. In the following paragraph the literature about the EOQ model will be presented in order to show the main characteristics of the most common existing models.

1.3. EOQ models for perishable products with random lifetime

As discussed in the paragraph 1.1 of this Chapter the analysis of deteriorating inventory items involves different concepts of deterioration. First, there are situations in which all items remaining in inventory become simultaneously obsolete at the end of the planning horizon, such as style goods in fashion merchandizing, or the classic newsboy problem. Second, there are those situations in which the items deteriorate throughout their planning horizon. This category can be further divided into two classes: (1) items with a fixed shelf life such as blood, and (2) items with continuous decay (random lifetime) such as radioactive materials. Fixed lifetime products have deterministic SL, i.e. if a product remains unused up to its lifetime it is considered to be out dated and must be disposed off. The products whose lifetime cannot be determined in advance while in stock are known as random lifetime products. A typical example is fresh produce whose time of spoilage is uncertain and as a result the lifetime is assumed to be a random variable. As discussed in the previous paragraph the Wilson model, as most of the existing inventory models, assumes that items can be stored indefinitely to meet the future demands. This assumption is not suitable for food products which have a limited life. In fact certain types of commodities, likes fruit, vegetables and meat, having a random lifetime, either deteriorate in the course of time and hence are unstable. If the rate of deterioration is not sufficiently low, its impact on modeling of such an inventory system cannot be ignored. Inventory problems for deteriorating items have been studied extensively by many researchers. Research in this area started with the work of Within (1957) who considered fashion goods deteriorating at the end of the prescribed storage period. An exponentially decaying inventory was developed first by Ghare and Schrader (1963). They observed that certain commodities shrink with time by a proportion which can be approximated by a negative exponential function of time. In this model the inventory level declines due to the simultaneous effects on both demand *D* and decay *θ* according to the ordinary differential equation:

$$\frac{dI(t)}{dt} + \lambda I(t) = -D(t) \tag{59}$$

Where $\boldsymbol{\lambda}$ is the constant failure rate equal to $\frac{1}{m}$ and *m* is the mean time between failures or to a failure.

When D(t) = R, independent of t, the solution obtained is:

$$I(t+u) = e^{-\lambda u}\left(I(t) + \frac{R}{\lambda}\right) - \frac{R}{\lambda} \tag{60}$$

This relationship may then be used to develop an expression for the cost incurred per unit time. The authors' procedure for determining the order quantity is based on approximating the exponential function by the first three terms of the Taylor series expansion. Successively Covert and Philip (1973) considered a two parameters Weibull deterioration function. The two parameters Weibull deterioration rate is expressed as:

$$\theta(t) = \frac{\beta}{\varepsilon}\left(\frac{T}{\varepsilon}\right)^{\beta-1} \tag{61}$$

where ε is the scale parameter, $\varepsilon > 0$, β is the shape parameter, β>0, t is time of deterioration, t>0. Equation (1) shows that the two-parameter Weibull distribution is appropriate for an item with decreasing rate of deterioration (β<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<β<2) only if the initial rate is approximately zero. Given the transformation:

$$\left(\frac{1}{\varepsilon}\right)^{\beta} = \eta \tag{62}$$

equation (61) become:

$$\theta(t) = \eta\beta t^{\beta-1} \tag{63}$$

where $0 < \eta \ll 1$

The approach of Covert and Philip also involves solving an appropriate differential equation. It is:

$$\frac{dI(t)}{dt} + \theta(t)I(t) = -R \tag{64}$$

The optimal order quantity is given by an infinite series expansion which can be approximated by Newton's method. Further extensions of Ghare and Schrader's model were considered by Shah (1977) and Tadikamalla (1978). Tadikamalla assumed that the lifetime of individual units is governed by a gamma rather than Weibull distribution, while Shah considered the case of an arbitrary distribution, say *φ(t)*. In the general case the differential equation governing changes in stock levels has the same form as above except that *φ(t)* replaces *θ(t)*. As will be clear from the paragraph 1.5 the *η* parameter corresponding to the caracteristic life of the product can be expressed by means of the Arrhenius law. Since the work of Covert and Philip and Ghare and Schrader considerable work has be done on deteriorating inventory system, which are summarized in Nahmias (1982) that presented a review of early 60s and 70s referred to fixed and random lifetime models. Nahmias suggested describing the lifetime with a general life-time function instead, and argued that the investigated issuing policies were limited to Last-In-First-Out (LIFO) and First-In-First-Out (FIFO) approaches due to the focus on the fixed-life perishable problem. Both types of policies are time-based strategies which prioritize items according to the total elapsed time (i.e. age) that an item has been in storage regardless of the goods' actual quality conditions (see Ilic and al. (2008)). Thus Raafat (1991) dealt of 70s and 80s in relation to continuously deteriorating items, and Goyal and Giri (2001) extended the review at 90s. Table 31 summarizes the main assumptions characterizing the deteriorating inventory models for perishable products present in the literature.

Deteriorating items could also be classified with respect to their value or utility as a function of time. Constant-utility perishable goods do not face an appreciable decrease in value during their usable lifetime, for example prescription drugs. Decreasing-utility perishable goods loss value throughout their lifetime, for example fresh produce or fruits. For these products the degree of deterioration can be treated as a penalty cost. Increasing-utility perishable goods increase in value, for example some wines that appreciate in value Raafat (1991. Hwang and al. Hwang and al. (2005) treated of ameliorating and deteriorating food products in the case in which the ameliorating/deteriorating rate follows a Weibull distribution. They develop an EOQ model under the two issuing policies FIFO and LIFO with the goal of minimizing the amount ameliorated per unit time. They determine an equation for the inventory level under the two policies and shows that the FIFO policy outperforms the LIFO policy in minimizing the inventory level in the case of deteriorating items, while the LIFO policy outperforms the FIFO policy in minimizing the inventory level in the case of ameliorating items. The aim of the present study is to show that an appropriate EOQ model including deterioration costs in conjunction with a SL based picking policy allows to optimize the quality of products stored in the case of random lifetime products. The optimization is in relation with the possibility to monitor the residual quality of the products stored.

					Reference
		Uniform	Constant	$D(t) = R$	Chiu (1995), Mahata and Mahata (2009) , Mishra and Shah (2008) , Patra and al, (2010)
			Power demand rate (exponential)	$D(T) = a * e^{bt}$ $a > 0, b \text{ arbitrary constant}$	Chand and Dye (1999)
	Deterministic demand	Time-varying	Linear demand rate		Chakrabarty and al. (1997) , Gosh and Chandhuri (2005),Chen (1998)
			Quadratic demand rate	$D(t) = a + bt + ct^2$ $a > 0, b > 0, c > 0, t > 0$	Begum and al. (2010-b)
Demand (unit/unit time)		Time dependent (other forms)			Manna and Chandhuri (2006),Giri and al. (1996), Tripathy and Pradhan (2010), Teng and Ouyang (2005) , Lee and Wu (2002)
		Stock-dependent consumption rate	$D(t) = a + bQ(t)\ a > 0, b > 0, t > 0$	It has been observed that in a supermarket a large pile of goods attracts more costumers. For this reason a retail may display each of items in large quantities to generate great demand. When the products are perishable this task is very complex.	Panda and Basu (2008), Chang and al. (2006), Sana and Chandhuri (2004), Arya and al. (2009), Mandal and Phaujdar (1989), Vallaithal and Uthayakumar (2009)
		Price-dependent	$V_t = V_0 e^{-\lambda t}$; $D(t) = a + V_0 e^{-\lambda t} - p$ $V_i = value\ at\ time\ i$, $p = selling\ price$	Generally speaking the lot size is affected by demand which in turn is dependent on the price of the product.	Liu and al. (2008) Begum and al. (2010-a) Dye and al. (2007)

	Stochastic demand	Known probability distribution Unknown probability distribution Arbitrary probability distribution			Chiu (1995) ; Chung and al. (2009)
SL (unit time)	Fixed lifetime	Defined by a fixed number	All order units arrive fresh . it is assumed that no loss or decrease in utility occurs before a certain unit of time		Hariga (1997) ; Chiu (1995),
	Random lifetime	Defined by a stochastic distribution			Liu and al. (2008)
Deterioration rate $\boldsymbol{\theta(t)}$ (Number of units which deteriorates in the unit time)	Constant rate	Exponential	$\theta(t) = \theta$	For items having a constant deterioration rate	Chand and Dye (1999), Hariga (1997), Panda and Basu (2008), Mahata and Mahata (2009), Chang and al. (2006), Teng and Ouyang (2005), Patra and al, (2010)
	Time varying rate	Linear	$\theta(t) = \lambda + \mu t$, $0 < \lambda, \mu \leq 1, t > 0$, $\theta(t) = \alpha t$, $0 < \alpha \ll 1, t > 0$		Manna and Chandhuri (2006),Giri and al. (1996), Gosh and Chandhuri (2005), Arya and al. (2009), Sing and al. (2009)
		Quadratic	$\theta(t) = a + bt + ct^2$ a *initial deterioration,* b *initial rate of change of deterioration* c *acceleration of deterioration*		Sana and Chandhuri (2004)
		Two parameters Weibull distribution	$\theta(t) = \alpha\beta(t)^{\beta-1}$	For items having a deterioration rate increasing/decreasing with time	Begum and al. (2010-b), Chen (1998), Tripathy and Pradhan (2010), Lee and Wu (2002),

					Mishra and Shah (2008)
		Three parameters Weibull distribution	$\theta(t) = \alpha\beta(t-\gamma)^{\beta-1}e^{-\alpha(t-\gamma)^{\beta}}$ $0 < \alpha \ll 1$ $scale\ parameter, \beta > 0$ $shape\ parameter, t \geq \gamma$	For items having a deterioration rate increasing/decreasing with time	Tripathy and Pradhan (2001), Begum and al. (2010-a)
		Gamma distribution	$\theta(t) = \frac{e^{kz-e^{z}}}{t\Gamma(k)\left(1-\Gamma_1(k;e^{z})\right)}$ $K > 0$ $shape\ parameter\ z = \ln(t) - \mu$ $where\ -\infty < \mu < \infty\ and\ e^{\mu}\ scale\ parameter$		Chakrabarty and al. (1997)
Shortage (loss of sales)		Allowed/	In the case of perishable products it is need to find the tradeoff between deterioration costs of overstocked products and shortage costs due to the lack of products		Chand and Dye (1999), Hariga (1997), Chiu (1995), Chang and al. (2006), Chakrabarty and al. (1997), Manna and Chandhuri (2006), Begum and al. (2010-a), Gosh and Chandhuri (2005), Arya and al. (2009), Mandal and Phaujdar (1989), Chen (1998), Tripathy and Pradhan (2010), Lee and Wu (2002), Patra and al, (2010), Chiu (1995), Chung and al. (2009), Begum and al. (2010-b), Shah and Pandey (2008)
		Not allowed			Panda and Basu (2008), Mahata and Mahata (2009), Liu and al. (2008), Sana and Chandhuri (2004), Begum and al. (2010-b), Giri and al. (1996), Teng and Ouyang (2005), Mishra and Shah (2008)
Backloggin		Partial/complete	Suppliers usually offer some credit periods to		Chang and Dye (1999), Hariga

g (possibility to delay payments)			the retailers in order to stimulate the demand for the products they produce.		(1997), Chang and al. (2006), Chakrabarty and al. (1997), Begum and al. (2010-a), Giri and al. (1996), Gosh and Chandhuri (2005),Arya and al. (2009), Mandal and Phaujdar (1989), Chen (1998), Tripathy and Pradhan (2010), lee and Wu (2002), Patra and al. (2010), Dye and al. (2007), Sing and al. (2009)
		Not allowed			Panda and Basu (2008), Liu and al. (2008), Teng and Ouyang (2005)
Deteriorati on costs					Chiu (1995), manna and Chandhuri (2006), begum and al. (2010-b), Ghosh and Chandhuri (2005), Arya and al. (2009), Tripathy and Pradhan (2010), lee and Wu (2002), Mishra and Shah (2008), Patra and al. (2010), Chiu (1995)
Price		Price increase	Usually when the price of the commodity being replenished is expected to increase by a fixed amount from some future date the suppliers are prone to increase the lot size. In this case the purchase and ordering costs decrease, but the holding cost increases. When the products managed are perishable the problem become more complex.		Huang and Kulkarni (2003)
		Price discount	Empirical observation in the market place		Panda and Basu (2008), Liu and

			indicate that a price reduction results in an increase in demand. This discount price motivates the retailers to increase their order quantity and the retailers in turn offer a price discount to their customers to increase the demand. Moreover, in order to reduce the loss due to deterioration a discount price policy is implemented by the suppliers to enhance sales.		al. (2008)
Replenishment rate (number of units available at certain time)	Finite	Dependent on the on-hand inventory level Q(t) and demand rate D(t)	$R(t) = \alpha - \beta * Q(t) + r * D(t), \alpha, r \geq 0, 0 \leq \beta \leq 1$		Begum and al. (2010-a), Begum and al. (2010-b)
	Infinite				Chang and Dye (1999), Hariga (1997), panda and Basu (2008), Mahata and Mahata (2009), Chang and al. (2006), Sana and Chandhuri (2006), Giri and al. (1996), Gosh and Chandhuri 82006), Arya (2009), Tripathy and Pradhan (2010), Lee and Wu (2002), Mishra and Shah (2008), dye and al. (2007), Sing and al. (2009)

Table 31

In the next paragraph an EOQ model taking into account a Weibull deterioration model is presented. This model has been employed in the warehouse management system proposed.

1.4. The proposed model

In the present study the attention is posed on the EOQ model developed by Mishra and al. (2008) and Shah and al. (2008) in order to define the replenishment policy of the warehouse system proposed. In this model the warehouse is replenished with the optimal batch size (EOQ) at time t=0. Thus the depletion of inventory level arises due to the perishability of the products stored and the demand rate. The products that deteriorate during the cycle time are considered still marketable in an alternative market and sold at a salvage value. The optimal order quantity is determined by starting from the total cost per unit time including the ordering cost, the holding cost, the deterioration cost and the savage value. The model is developed using the following notations:

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

The following assumptions are used:

- the demand rate of R_D units per time is assumed to be deterministic and constant. This assumption can be done by considering that the demand rate is known with certainty and it is not affected by seasonality.
- the system deals with a single item;
- the replenishment rate is infinite, i.e., the items are available at every time instant;
- the lead time is zero and shortages are not allowed. This assumption involves that at every time instant the inventory level is always greater than the demand rate;
- the deterioration rate of units follows the Weibull distribution function given by (63), where $0 < \eta \ll 1, \beta \geq 1, 0 \leq t \leq T_c$;
- 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:

$$\frac{dQ(t)}{dt} + \theta(t) * Q(t) - R_D = 0, \ \ 0 \leq t \leq T_c \tag{65}$$

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

This equation can be solved by taking series expansion and ignoring second and higher power of η (assuming η to be very small). The solution of the differential equation (65) using the boundary condition $Q(T_c) = 0$ is given by:

$$Q(t) = R_D \left[T_c - t + \frac{\eta T_c}{\beta+1}\left({T_c}^{\beta} - (1+\beta)t^{\beta}\right) + \frac{\eta\beta {T_c}^{\beta+1}}{\beta+1}\right] \tag{66}$$

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

$$D = Q_{opt} - R_D T_c = \frac{\eta R_D {T_c}^{\beta+1}}{\beta+1} \quad (67)$$

The cost of deterioration (CD) is:

$$CD = \frac{\eta C R_D {T_c}^{\beta+1}}{\beta+1} \quad (68)$$

The salvage value (SV) is:

$$SV = \frac{\eta \delta C R_D {T_c}^{\beta+1}}{\beta+1} \quad (69)$$

The per cycle inventory holding cost (IHC) is:

$$IHC = h * \int_0^{T_c} Q(t)dt = hR_D \left[\frac{{T_c}^2}{2} + \frac{\eta\beta {T_c}^{\beta+2}}{(\beta+1)(\beta+2)}\right] \quad (70)$$

The total cost per cycle is:

$$TC(T) = CD - SV + IHC + A \quad (71)$$

and the Total Cost per Time Unit is:

$$TC_u(T_c) = \frac{[CD - SV + IHC + A\,]}{T_c} \quad (72)$$

By deriving (72) with respect to T_c and solving it the optimal cycle time is determined and by equation (66) the corresponding optimal order quantity is calculated.

1.5. The Arrhenius-Weibull model

The study here presented deals with the simultaneous determination of optimal lot size and issuing policy to adopt in order to maximize the quality of products stored. For this reason the EOQ model presented in the previous paragraph has been used. In order to deal with perishable products such as fruits and vegetables it is required to take into account their random SL. In this respect the Arrhenius-Weibull life stress model can be of great help. The Arrhenius life-stress model (or relationship) is probably the most common life-stress relationship employed in accelerated life testing. It has been widely used when the stimulus or acceleration variable (or stress) is thermal (i.e. temperature). It is derived from the Arrhenius reaction equation seen in the section 2 (eq.30) and can be expresses as:

$$L(V) = Ce^{\frac{B}{V}} \quad (73)$$

where L represents a quantifiable life measure, such as mean life, characteristic life, median life, etc, V represents the stress level (formulated for temperature and temperature values in absolute units i.e. degrees Kelvin or degrees Rankine), C is one of the model parameters to be determined, *(C > 0)* and *B* is another model parameter to be determined. Depending on the application (and where the stress is exclusively thermal), the parameter *B* can be replaced by $\frac{E_a}{K}$, where *K* is the Botzmann's constant equal to $8.623 * 10^{-5}\ eV\ K^{-1}$. The life stress model of Arrhenius can be linked with the Weibull deterioration model by substituting the scale parameter η of equation (61) with *L(V)*. This means that in eq. (63) the *θ(t)*depends from the lifetime of the product treated, from the way the product deteriorates with time (defined by the β

parameter) and from the time. The scale parameter ε of equation (61) can be expressed as the inverse of the K constant of the equation (30) (see Oms-Oliu 2009) and represents the characteristic life of the product (Rahman and al. 2002, Abernethy 2004), defined as the age at which 63.2% of the units will have failed. For $\beta = 1$ the Mean Time to Failure (MTTF) and ε are equal, for $\beta > 1$ are approximately equal.

The arguments treated in this chapter can be summarized by saying that perishable products can be differentiated between products having a fixed or random lifetime. Concerning the latter it is necessary to take into account the deterioration process which can be constant or time varying. The Arrhenius-Weibull model underlines that the deterioration process is dependent upon the lifetime of the product for temperature-sensitive products. Information about the deterioration process must be included in the EOQ model to take into account the related deterioration costs . For this reason an EOQ model for deteriorating items has been presented when the deterioration rate follows a Weibull distribution. In this study a warehouse management system for perishable products is presented with the aim to determine the optimal operative parameters consisting in the EOQ and the picking policy to be employed. The goal is achieved by monitoring the lifetime of the product stored and applying a lifetime based picking policy (LSFO). The study also shows that the LSFO policy outperforms the traditional FIFO policy when the products release is done on the basis of their SL.

CHAPTER 2

2.1. The design of simulation experiments

The performance of a warehouse management policy is directly related to the operative parameters as for example the stock levels, the picking rule, etc. and to other uncontrollable elements which must be considered as sources of uncertainty. In this chapter the effect of the uncertainties on the performance of a 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.. They include predictable events like demand fluctuations, the variability of Remaining Shelf Life of products entering the warehouse and the deterioration process of products stored. In fact fluctuations on demand for a specific fruit or vegetable is due to the changes in consumer preferences and eating patterns, and by change of the season and in living standards. Moreover the year-round availability of processed vegetables (frozen, canned and, to a lesser extent, dehydrated) may reduce demand for the fresh products, particularly when prices are inflated. The availability of other products, which can be used as substitutes for a particular vegetable, may also play a role. The variability on SL is fundamentally attributable to the goodness of the prediction of harvesting date, to the fluctuations on timing of harvesting phases and to the fact that harvest and packaging phases are performed outdoor. Consequently since the degree of maturation at harvest date can vary from one product to another and due to the fact that the harvest and packaging phases cannot be controlled relatively to the environmental conditions, products entering the warehouse are characterized by different RSL. Finally the variability of the deterioration process is due to the initial SL of products and the storage temperature chosen. Since the SL is affected by the temperature as higher is the storage temperature as greater will be the speed of deterioration reaction. In traditional warehouse management systems, where the picking policies used are based on arrival time of SKUs (FIFO) and no system information management is adopted, such a situation has a strong impact in terms of quality of products leaving the warehouse.

In traditional warehouse management systems, where the picking policies used are based on arrival time of Stock Keeping Units (SKU) and no information management system is adopted, such uncertainties have a strong impact in terms of quality of products leaving the warehouse. In the present study the impact of warehouse operational decisions is studied considering the effect of these uncertainties, by evaluating the RSL distribution of the products leaving the warehouse when the two policies LSFO and FIFO are enforced. The study of warehouse system is carried out with the methodology of design of simulation experiments. A sensitivity analysis is also performed 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 the benefit achievable by the information about the RSL of the product in terms of improvement of the operational and tactical management decisions thus increasing the quality of the products delivered.

The design of simulation experiments starts by building the experimental plan including all parameters that affect the system behavior, thus the simulation model is realized to represent the actual system, and finally each configuration of the experimental plan is replicated through a simulation model and the average measures of interest are calculated. An experimental plan is generally designed to estimate how changes in the input factors affect the results, or responses, of the experiment. Experimental plans are typically employed in physical experiments but they can fairly easily be used in computer-simulation experiments as well, as described in Law and Kelton (2000). An experimental plan consists in a set of experiments in which each factor varies based on certain number of levels. This is called full factorial experimental plan. It can be of great help in any case in which you would evaluate the sensibility of the response value when the input parameters vary. As a basic example of such techniques, suppose that you can identify just two values, or levels, of each of your input factors. There is no general prescription on how to set these levels, but you should set them to be "opposite" in nature but not so extreme that they are unrealistic. If you have k input factors, there are thus 2^k different combinations of the input factors, each defining a different configuration of the model; this is called a 2^k factorial design. Referring to the two levels of each factor as the "-" and "+" level, you can form what is called a design matrix describing exactly what each of the 2^k different model configurations are in terms of their input factor levels. For instance, if there are $k = 3$ factors, you would have $2^3 = 8$ configurations, and the design matrix would be as in Table 32, with R_i denoting the simulation response from the ith configuration. For more details see Kelton and Barton (2003).

Run (*i*)	**Factor 1**	**Factor 2**	**Factor 3**	**Response**
1	-	-	-	R_1
2	+	-	-	R_2
3	-	+	-	R_3
4	+	+	-	R_4
5	-	-	+	R_5
6	+	-	+	R_6
7	-	+	+	R_7
8	+	+	+	R_8

Table 32. Design Matrix for a 2^3 Factorial Experiment

An important result given by 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. In practice to compute the effect of a factor it must apply the signs in the factor column of interest to the corresponding responses, adding, and then dividing by 2^{k-1}. Furthermore the possible interaction between the factors 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. To compute the interactions from the experimental results, you "multiply" the columns of the involved factors row by row (like signs multiply to "+", unlike signs multiply to "-"), apply the resulting signs to the corresponding responses, add, and divide by 2^{k-1}.

In order to execute the experimental plan designed a Simulation method is 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. In this study an event-based simulator has been built to reproduce the behavior of the real warehouse management 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. Once developed and validated the 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.

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 inputs in the model are random variables. In this case the outputs provided by the model can be considered only as an estimates of the true characteristic of the model. 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 replications 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:

$$\overline{\sigma_n^2} = \mathrm{MSE}\,(\overline{X_n}) = \frac{\sigma^2}{n} \tag{74}$$

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

$$n^{1/2}[\overline{X_n} - \mu] \to N(0, \sigma^2) \text{ as } n \to \infty, \tag{75}$$

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

$$P(\overline{X}_n \leq x) \approx P\left(N\left(\mu, \frac{\sigma^2}{n}\right) \leq x\right) = P\left(N(0,1) \leq \frac{x-\mu}{\sqrt{\frac{\sigma^2}{n}}}\right) \tag{76}$$

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

$$\left[\overline{X}_n - z_{\frac{\alpha}{2}}\left(\frac{\sigma}{\sqrt{n}}\right), \overline{X}_n + z_{\frac{\alpha}{2}}\left(\frac{\sigma}{\sqrt{n}}\right)\right] \tag{77}$$

where

$$P\left(-z_{\frac{\alpha}{2}} \leq N(0,1) \leq +z_{\frac{\alpha}{2}}\right) = 1-\alpha \tag{78}$$

and α denotes the error (width of confidence interval divided by the estimated mean) admitted in the measure. The statistical precision of measure performed 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:

$$w_a(\alpha) = \frac{2z_{\frac{\alpha}{2}}\sigma}{\sqrt{n}} \tag{79}$$

$$w_r(\alpha) = \frac{2z_{\frac{\alpha}{2}}\sigma}{\mu\sqrt{n}} \tag{80}$$

where α denotes the error (width of confidence interval divided by the estimated mean) admitted in the measure.

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

$$n_\alpha(\epsilon,\alpha) = \frac{4\sigma^2 z_{\frac{\alpha}{2}}^2}{\varepsilon^2} \tag{81}$$

$$n_r(\epsilon,\alpha) = \frac{4\sigma^2 z_{\frac{\alpha}{2}}^2}{\mu^2\varepsilon^2} \tag{82}$$

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 replications of each configuration are run, the confidence interval and initial level of precision are determined. Thus the number of replication is calculated through equation (81) or (82) by fixing the desired precision (Itami and al. (2005).

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:

$$y = f(x_1, x_2, \dots\dots. x_k) \tag{83}$$

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).

$$y = \gamma_0 + \sum_{i=1}^{k}\gamma_i g_i + \sum_{i=1}^{k}\gamma_{ii} g_i^2 + \sum_{i=1}^{k}\gamma_{ij} g_i g_j + \varepsilon \tag{84}$$

where the γ_j coefficients are unknown and must be estimated, and ε is a random error term representing the inaccuracy of the model in approximating the actual simulation-model response *y*. The parameters of the model are estimated by making simulation runs at various input values according with the experimental plan, recording the corresponding responses, and then using standard least-squares regression to estimate the coefficients.

In this study an event-based simulator has been built to reproduce the behavior of the real warehouse management system. 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. Once developed and validated the 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.

The goal of this study is to show that applying an EOQ model for perishable products (taking into account the deterioration rate) 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 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 (the RSL of products entering the warehouse, the demand rate and the deterioration rate) varies on two quantitative levels. Experimental plan has been replicated to ensure a desired precision of the measures.. The simulation 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. The results obtained show how the information about the RSL of the product and the employing of SL based issuing policies can improve the operational and tactical management decisions thus increasing the quality of the products delivered. The case study will be treated in the next chapter.

CHAPTER 3

3.1. INTRODUCTION

In this Chapter a model for a warehouse management system for perishable products having a random lifetime is presented consisting in the definition of the operational parameters characterizing the warehouse system as the replenishment policy and issuing policy to adopt and a methodology to monitor the deterioration of products stored. The EOQ model discussed in the Chapter 1 has been used to define the optimal batch size of incoming products. The deterioration process of products stored has been monitored through the methodology discussed in the Section 2 allowing the assessment of the SL of products stored at any time. Once the SL of outgoing products is known the SL based picking policy (LSFO) is applied to show the improvement in product quality achievable to respect the traditional policy (FIFO). In the present study the SL of products stored is the residual SL of products transferred from the field to the warehouse; this is named Remaining Shelf Life (RSL). 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. 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) (Van Donselaar and al. (2006)). In this study the RSL of products entering the warehouse is known and the RSL of products leaving the warehouse in determined by considering the methodology already discussed in the Section 2 and based on the Arrhenius law.

3.2. THE METHODOLOGY PROPOSED

3.2.1 The case study proposed: Experimental application

In this paragraph a numerical application is proposed referred to the avocado fruit. In particular a warehouse is considered for the allocation of a perishable product characterized by a Weibull deterioration model having η=0.0085 (corresponding to a Shelf life of 24 days at 10°C), β=1.5. On the basis of assumption referred to the model of Mishra discussed in the Chapter 1, paragraph 1.4, the optimal batch size is determined considering A=30€, R_D=16 SKUs/day and h=0.1€/SKU/period. The product cost *(C)* has been considered equal to 0.4 €/SKU and the salvage value of the perished product is δC=0.01€/SKU. Products that are considered perished at a generic instant of the warehouse cycle are sold at their salvage value.

In such conditions the TC_u is 10.30€ which corresponds to a cycle time T_c of 5.6 days. The optimal order quantity has been determined by equation (66) and is equal to 94 SKUs. The EOQ and the related optimal TC_u for different η values is reported in Figure 47, while the optimal TC_u as a function of the Cycle Time is reported in Figure 48. In this figure the β value has been fixed and the η value varies in order to show how the optimal TC_u and the cycle time T change by considering different products having different SL.

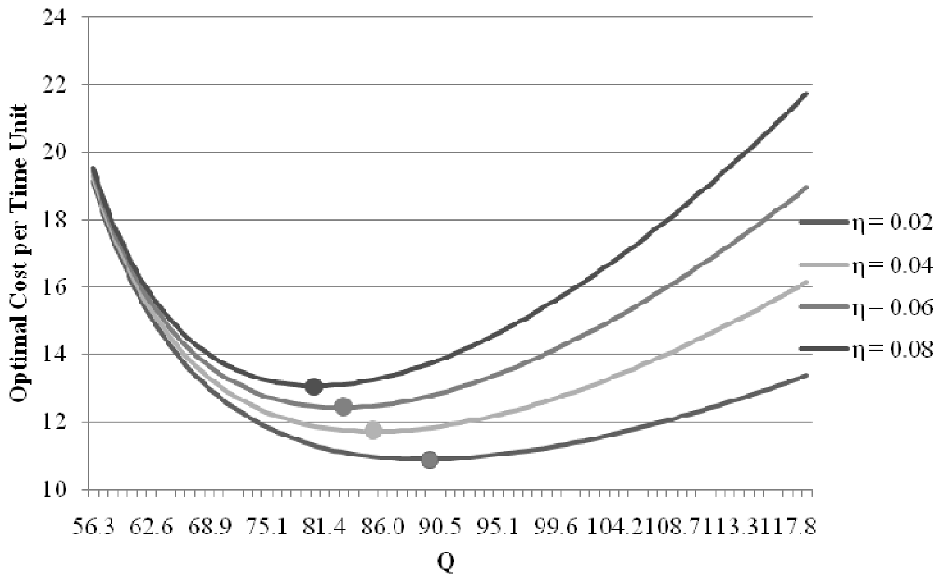


Figure 47. Total Cost per Unit Time as a function of Q for different η values.

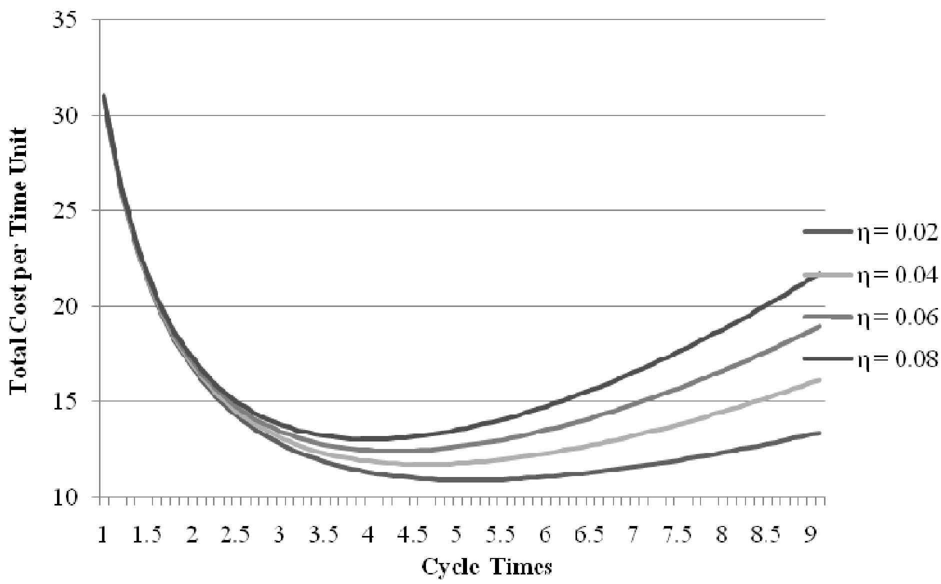


Figure 48. Total Cost per Unit Time as a function of the Cycle Time for different η values

For the same values of η and β the corresponding Inventory level I(t) is reported in Figure 49. Such figures confirm that the optimal order size decreases when η increases.

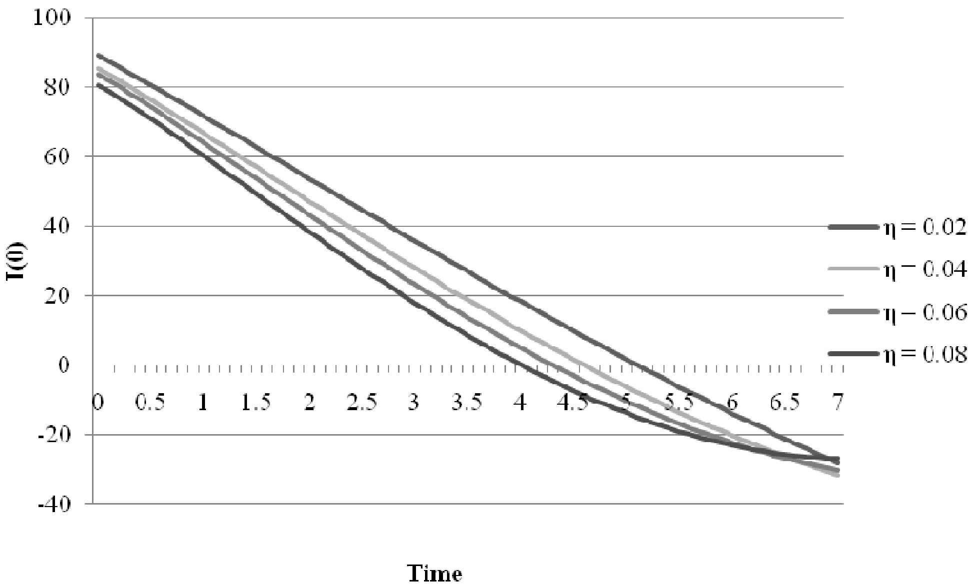


Figure 49.Trend of Inventory level for several η values.

The change in the values of parameters that affect the EOQ may happen due to uncertainties in any decision-making situation. In order to examine the implications of these changes, the sensitivity analysis will be of great help in decision-making. The sensitivity analysis of various parameters of the EOQ model presented here has been done, using the values reported in the previous. The results of sensitivity analysis are summarized in Table 33. The following inferences can be made:

1. When the demand rate (*R*) decreases or increases the ordering quantity (*Q*) and the total cost unit (TC_u) will also decrease or increase. Similarly, the ordering quantity (*Q*) and the total cost unit (TC_u) will also decrease or increase as the ordering cost (*A*) decreases or increases. That is changes in (*R*) and (*A*) will lead to the positive changes in (*Q*) and (TC_u).
2. The change in deterioration rate (θ) leads to a negative change on the ordering quantity (*Q*) and a positive change in the total cost unit (TC_u). That is *Q* decreases with the increase of (θ).Whereas (TC_u) increases with the increase of (θ).
3. Changes in carrying cost (*h*) and salvage value (γC) result in a positive change in the total cost unit (TC_u) and a negative change in the ordering quantity (*Q*).

Table 33 also reports the corresponding value of the T*, EOQ and TC_u calculated with the Wilson's model. As you can see the optimal batch size and the cycle time corresponding to the model including costs of deterioration is always less than that determined by the Wilson's model.

		Mishra			Wilson		
	Parameter value	**T**	**EOQ**	**TCu**	**T***	**EOQ**	**TCu**
A	30	5.6	93.64	10.30141	6.12	97.98	17.798
	60	7.7	132.15	14.80537	8.66	138.56	21.856
	90	9.2	161.17	18.35443	10.61	169.71	24.971
h	0.1	5.6	93.64	10.30141	6.12	97.98	17.798
	0.2	4.1	67.45	14.21824	4.33	69.28	21.856
	0.3	3.4	55.56	17.2704	3.54	56.57	24.971
R	8	7.7	66.08	10.30141	8.66	69.28	10.928
	16	5.6	93.64	7.402684	6.12	97.98	17.798
	24	4.6	114.10	12.52569	5.00	120.00	24.000
α	0.0085	5.6	93.64	10.43545	6.12	97.98	17.798
	0.011	5.5	92.99	10.30141	6.12	97.98	17.798
	0.017	5.2	89.91	10.73796	6.12	97.98	17.798
γ	0.01	5.6	93.64	10.30141	6.12	97.98	17.798
	0.1	5.6	91.86	10.32736	6.12	97.98	17.798
	0.3	5.5	91.86	10.38482	6.12	97.98	17.798
C	0.35	5.6	93.64	10.265	6.12	97.98	15.398
	0.7	5.5	91.86	10.51604	6.12	97.98	20.998
	1	5.3	88.32	10.72155	6.12	97.98	25.798

Table 33

3.2.2 Measuring the RSL of products stored

The RSL of products stored is monitored through the methodology discussed in the Section 2 by applying respectively the equations (31), (33) and (49). By equation (49) it is possible to determine the RSL_{exit} (rearranged from the formula found in the Chapter 3 of Steele (2004)):

$$RSL_{exit} = RSL_{entry} * (1 - f_c) \tag{85}$$

where the f_c represents the fraction of SL consumed during the storage period and the RSL_{exit} is the remaining quality of products leaving the warehouse.

3.2.3 The design of simulation experiments

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_{RSL}=24 days, σ_{RSL}=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 the warehouse performance. Such parameters are the average RSL of the incoming products, the demand rate and the deterioration rate. Based on the assumptions made in Chapter 2 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 34.

Configuration	Average RSL_{entry} (Days at 10°C)	θ (Unit/unit time)	R_D (Batch/Day)
1	20	0.01275	16
2	24	0.01275	16
3	20	0.0255	16
4	24	0.0255	16
5	20	0.01275	24
6	24	0.01275	24
7	20	0.0255	24
8	24	0.0255	24

Table 34. Experimental Plan

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 have also been investigated in two alternative scenarios. This aspect has been modeled by ranking the products according to their RSL, as they enter the warehouse (where perfect temperature control is assumed), and by using such rank in the picking list, when the LSFO policy is adopted (first scenario). 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 (second scenario). 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-D)/R_D. For each configuration the EOQ quantity arriving at the warehouse is determined by equation (66) based on the demand rate and the deterioration rate reported in Table 34. 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 on the basis of the Arrhenius law seen in the Section 2. The RSL at the shipping time is then determined based on equation (85), 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. Thus a number of SKUs corresponding to the demand rate is released on the basis of the two alternative picking policies LSFO and FIFO.

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 (81) 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 (LSFO and FIFO issuing policies) (FIFO and LSFO). The performances of the warehouse system for the two policies analyzed are illustrated in Table 35 and Figure 50 where the distribution resulting from the two alternative scenarios for each configuration of the experimental plan and for each of the 23 replications are reported. In all configurations the LSFO policy corresponds to the distribution having a smaller variance and thus a greater number of batches with a RSL closer to the average.

Configuration	Average RSL (Days)		$б_{RSL}$ (Days)		Average Number of products with a RSL_{exit} equal to Average RLS_{exit} ±1		Average Number of products with a RSL_{exit} equal or greather then the Average RLS_{exit}	
	LSFO	FIFO	LSFO	FIFO	LSFO	FIFO	LSFO	FIFO
1	16.835	16.862	1.442	3.596	75	30	84	69
2	20.835	20.862	1.442	3.596	75	30	84	69
3	17.424	17.429	1.416	3.391	46	29	76	58
4	21.424	21.429	1.416	3.391	45	29	76	58
5	18.008	18.034	1.996	3.273	57	32	66	61
6	22.008	22.034	1.996	3.273	57	32	66	61
7	18.420	18.426	1.936	3.144	56	30	71	60
8	22.420	22.426	1.936	3.144	56	30	71	60
Average value	19.672	19.6875	1.697	3.35	58.375	30.25	74.25	62

Table 35. Results of the Experimental Plan

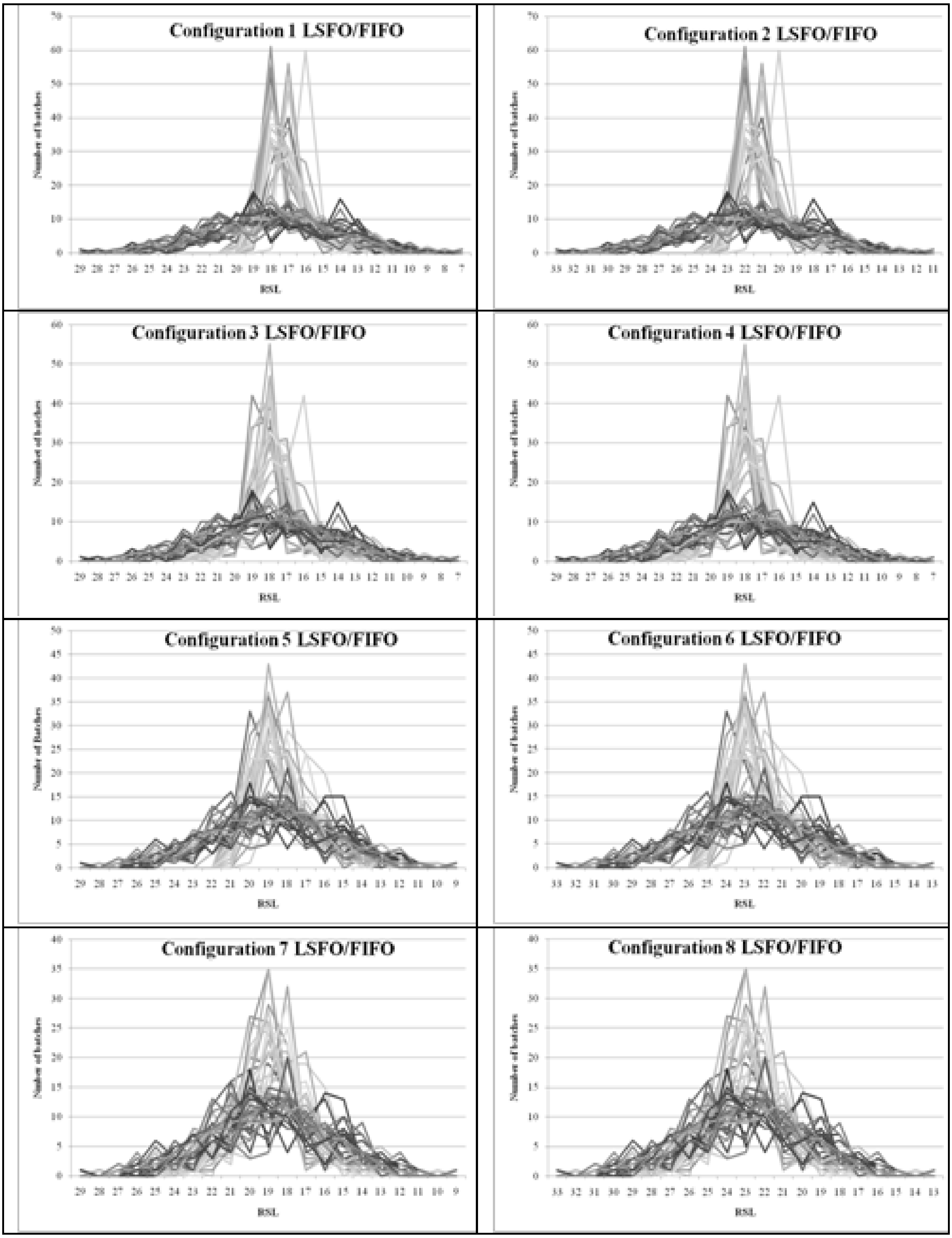


Figure 50. Average Number of products leaving the warehouse and their RSL for the two picking policies in each configuration of the Experimental Plan.

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 35. 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). The best value of the response is obtained when the input factors are at their high level (Scenario 8 of the experimental plan). Table 35 also shows that when the LSFO policy is applied a greater number of products have a RSL_{exit} about equal than the average RSL_{exit} value ±1 compared to the case in which the FIFO policy is applied. In the best case (corresponding to Configuration 1) this allows an improving in quality of 60%, while in the worst case (corresponding to Configuration 4) the improvement achieved is of 35.5%. The average quality improvement is of 48.18%. The average improvement in quality results of 16.5% if you consider only those products having a RSL greater or equal to the average RSL.

Based on the deterioration parameters and demand rate fixed by Table 34 the optimal order quantity and the number of perished products can be calculated respectively with equations (66) and (67) for different scenarios. Since the fraction of perished products is the same in the two cases in which the LSFO and the FIFO policy are applied the Minimum Quality Level of products sold can be determined as the minimum RSL_{exit} of non perished products leaving the warehouse. Results are shown in Table 36 in which it can be seen that when the LSFO policy is adopted the Average Quality Level of products sold is greater than in the case in which FIFO policy is adopted.

Configuration	**Picking policy adopted**	**EOQ**	**Fraction of Perished Products (%)**	**Minimum Average quality level of products sold (RSL_{exit})**
1	LSFO	93.63	4.30%	18
	FIFO	93.63	4.30%	17
2	LSFO	93.63	4.30%	22
	FIFO	93.63	4.30%	21
3	LSFO	93.076	5.45%	18
	FIFO	93.076	5.45%	17
4	LSFO	93.076	5.45%	22
	FIFO	93.076	5.45%	21
5	LSFO	114.1	3.24%	19
	FIFO	114.1	3.24%	18
6	LSFO	114.1	3.24%	22
	FIFO	114.1	3.24%	21
7	LSFO	112.61	4.09%	19
	FIFO	112.61	4.09%	18
8	LSFO	112.61	4.09%	23
	FIFO	112.61	4.09%	22

Table 36. Minimum Quality Level of products sold for the two picking policies LSFO and FIFO

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 37 and 38.

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 37. Factorial Analysis for LSFO and FIFO policy (average)

ANOVA		
LSFO	DF	SS
Main Effects		
RSL	1	32
θ	1	0.501
R	1	2.352
Total Main Effects	3	34.853
Residual Error	4	0.016
Total	7	34.869
FIFO		
Main Effects		
RSL	1	32
θ	1	0.460
R	1	2.352
Total Main Effects	3	34.8121
Residual Error	4	0.015
Total	7	34.827

Table 38. ANOVA for LSFO and FIFO policy (average)

Results reported in Table 37 show that in both cases the initial RSL, the demand rate and the deterioration rate have a positive 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 (Table 38). This means that the two-way interactions and the-three way interactions can be neglected.
The analysis of factors has been extended to the standard deviation of the response in order to study the impact of input factors on the standard deviation of the response in the two cases in which LSFO and FIFO policies are applied. Results are shown in Table 39 and 40.

LSFO	Effect	Coefficient	T	P
Constant		0.51	399.41	0.00
RSL	0	0	0	1.000
θ	-0.043	-10.7158	-5.06	0.007
R	0.537	0.067	63.18	0.000
FIFO				
Constant		4.677	352.74	0.00
RSL	0	0	0	1.000
θ	-0.2857	-41.6173	-8.79	0.007
R	-0.1670	-0.03562	-15	0.000

Table 39. Factorial Analysis for LSFO and FIFO policy (standard deviation)

ANOVA		
LSFO	DF	SS
Main Effects		
RSL	1	0.000
θ	1	0.0037
R	1	0.57674
Total Main Effects	3	0.5804
Residual Error	4	0.000578
Total	7	0.581014
FIFO		
Main Effects		
RSL	1	0.000
θ	1	0.055778
R	1	0.162450
Total Main Effects	3	0.2182
Residual Error	4	0.00288
Total	7	0.2211

Table 40. ANOVA for LSFO and FIFO policy (standard deviation)

Results reported in Table 39 show that in both cases the initial RSL, has no effect on the standard deviation of the response, the demand rate has a negative influence in the case of LSFO (the variability increases when the demand rate increases as well) and a positive influence in the case of FIFO and finally the deterioration rate has a positive influence in both cases (the variability decreases when the deterioration rate increases). This is due to the fact that when the deterioration rate increases (i.e. the initial SL decreases) the EOQ decreases. The factor mainly influencing the standard deviation of the response in the case of LSFO policy is the demand rate, while in the case of the FIFO policy is the deterioration rate. The ANOVA analysis (Table 40) shows that the three main factors are responsible for the 99.9% of the total variance. This means that the two-way interactions and the-three way interactions can be neglected. In particular the demand rate is the factor mainly affecting the variance of the standard deviation of the response both in the LSFO and the FIFO case followed by the deterioration rate, while the initial RSL is not responsible for the variance of the response.

Based on coefficients shown in Table 39 the response surfaces are determined for the experimental plan with equation (84) by considering only the first order terms. The two response surfaces referred respectively to the standard deviation of LSFO and FIFO policies are:

$$y = 0.51 - 10.7158\vartheta + 0.067R_D + \epsilon \tag{86}$$

and

$$y = 4.677 - 41.6173\vartheta - 0.03562R_D + \epsilon \tag{87}$$

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 ($\sigma_{RSLexit}$). This result can be employed to investigate the behavior of the response without the need to run further simulations thus allowing to gain fast information about the warehouse system behavior when the input parameters vary.

3.2.4 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 agro-industrial systems. In modern Agri-Food supply chains in fact some inefficiencies can be reduced exploiting the opportunities given by new technologies, which allow a detailed monitoring of the environmental factors over the entire chain. Enforcing a temperature monitoring system through the supply chain, may turn useful to immediately detect possible temperature abuses and system malfunctioning, but the resulting benefit is marginal unless gathered data are effectively exploited in the management policies. Optimizing the performance of such supply chains is thus a complex task, which involves a good knowledge of the deterioration processes and a detailed environmental control. 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 traditional management policy is compared with a Shelf-Life based management system. involving a Weibull deterioration model to determine the optimal stock level and a shelf-life based picking policy. In order to take into account the effect of uncertainties on the performance a simulation approach is proposed and an experimental plan is considered. The results of the experimental plan 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 compared to the case in which the FIFO policy is applied allowing an average improvement in the quality of 48.18%. Finally the response surfaces have 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.

SECTION 4: THE AFFORDABILITY OF RFID TECHNOLOGY ENABLING THE SUPPLY CHAIN TRACEABILITY

INTRODUCTION

In the previous sections the optimization of perishable management has been faced with regard the pre and post harvest phases and the results show that the innovative technologies such as the WSN and the RFID can be specifically employed for environmental detection. However the applicability of such technologies is strongly related to the possibility of establishing the economic impact of the technology itself. It is in fact well recognized that one the most important factor influencing the decision about the implementation of the RFID is the knowing of the profitability of the investment. As it has been already discussed in the Section 2 the costs related to the RFID are essentially referred to the antenna and reader which are fixed costs and to the tag which is a variable cost. In this section the problem of the economic impact of the RFID technology is addressed in terms of the variable costs involved. The aim of this section is to present an economic model for the assessment of the optimal batch size (Economic Order Traceability) and the optimal number of RFID tags to apply in order to minimize the total cost incurred.

CHAPTER 1

1.1.RFID traceability systems

As widely discussed in the previous Sections perishable management optimization is a topic extensively studied due the limited shelf lives of such products. In addition to this it should be considered that recent laws aiming at ensuring consumers about the food quality have introduced the obligation of traceability of product thus increasing producers attention about the products quality assurance. According to the ISO 9001:2000 standard, chain traceability is the ability to trace the history, application or location of an entity by means of recorded identifications throughout the entire supply chain. In practice, chain traceability is achieved if businesses keep records of suppliers and customers and exchange this information along the entire supply chain (Opara (2004)). It is an integrated end-to-end process, in which all supply chain members contribute to optimize the tracking activity. Traceability in food supply chain has attracted considerable attention in the last few years for a variety of reasons (Jansen-Vullers and al. (2003)). First of all, it has become a legal obligation within the EU since 1st January 2005 (Regulation n°178/2002 (2002)). Then, food companies tend to consider the significant expenditure required to build a traceability system as a long-term strategic investment to create consumer confidence both in the company image and in the specific product. Consequently, other requirements for traceability exist besides the legal ones. In fact, in addition to systematically storing information that must be made available to inspection authorities on demand, a traceability system should also take food safety and quality improvement into account (Food Standards Agency of United Kingdom, (2002)). This means, for example which the system should be able to trace back so as to discover the cause of a problem and to prevent it from happening again, or to trigger a proper recall of potentially unsafe products, thus protecting public health. The data recorded must univocally identify the product when it flows through the supply chain, the quantity or nature of product as well as the weight. In this context, traceability allows targeted withdrawals and the provision of accurate information to the public, thereby minimizing disruption to trade. Postharvest traceability of perishable goods at all levels of the supply chain is a goal and a practice already known and pursued by several years for most products. When products managed are perishable a traceability system involves the need to monitor the product quality. In fact the knowing of the current keeping quality of products allows the early identification of non conforming products and their withdrawal from the supply chain before they reach the consumer. This goal can be achieved by means of innovative techniques which are based on the environmental monitoring and which are discussed in the next paragraph.

1.2.Environmental factors influencing the keeping quality

In the previous sections the focus was on the influence of the temperature on the product quality and the main results showed that the monitoring of such parameter allow to determine the current state of the products. In this paragraph the attention is posed on the influence of the atmosphere composition on the product quality. In fact despite having been detached from the plant, harvested produce continues to respire throughout its postharvest life. The respiration rate of a product can be determined by detecting the O_2 consumption rate and/or CO_2 production rate. Because this process occurs from harvest to table, compounds that affect plant flavor, sweetness, weight, turgor (water content), and nutritional value are lost. In addition, storage conditions affect respiration, with higher temperatures leading to a faster rate of respiration. Because of the significant effect of temperature on respiration, the amount of time a harvested product is exposed to heat should be minimized; the fruit or vegetable should be quickly brought to its optimal storage temperature. A study conducted by UCD university shows that a delay beyond 1 hour in the storage of strawberries in refrigerated room reduces the percentage of marketable fruit of 20% (Albright 2008). Another important factor that affects the product quality in postharvest phases is represented by ethylene production. It triggers specific events during a plant's natural course of growth and development, such as ripening. Through this action, it induces changes in certain plant organs, such as textural changes, color changes, and tissue degradation. Some of these changes may be desirable qualities associated with ripening; in other cases, it can bring damage or premature decay (Silva (2008)). Depending on their response to ethylene fruits and vegetables may be classified in climacteric, in which ripening is accompanied by a peak in respiration and a concomitant burst of ethylene, and non-climacteric, in which respiration shows no dramatic change and ethylene production remains at a very low level (Alexander and Grierson (2002)). The climacteric or non climacteric behavior of a product affects strategic decisions in terms of the logistic life cycle, type of cold chain to be implemented to maintain the shelf life of the product and margin trading in sale phase. In fact the climacteric fruits can be stored longer and more efficiently because, thanks to controlled atmosphere and controlled administration of ethylene, it is possible to harvest them unripe and quickly take them to ripening when necessary. The most significant case is that of bananas harvested green and then matured after transport. On the contrary non climacteric fruits must be harvested at their optimal maturation level, immediately stored at appropriate conditions and sent to the destination to avoid the risk of quality decaying of products. The effect of ethylene is accumulative so continuous exposure to a low concentration of ethylene throughout marketing can cause significant harm (Jobling (2000)). Table 41 reports a taxonomy of most common fruit and vegetables devised by climacteric and non climacteric as well as their ethylene production rate and CO_2 emission rate.

Climacteric Fruit	**Ethylene sensitivity**	**Principal reaction to Ethylene Gas**	**Ethylene production µl/kg·hr**	**CO_2 emission ml/kg·hr**	**Non Climacteric Fruit**	**Ethylene sensitivity**	**Principal reaction to Ethylene Gas**	**Ethylene production µl/kg·hr**	**CO_2 emission ml/kg·hr**
Apple	High	Decay	2 to 4 (0°C)	4 - 6 at 0°C	**Cherry**	Low	Yellowing	Less than 1 (20°C)	3 – 5 (0°C)
Apricot	High	Decay	Less than 0.1 (0°C)	2-4 at 0°C	**Cucumber**	High	Brown, Spots	0.1 – 1 (20°C)	12 -5 (10°C)
Avocado	High	Decay	Greater that 100 (20°C)	10-25 at 5°C	**Eggplant**	Low	Mold	0.1 - 0.7 (12.5°C)	30-39 (12.5°C)
Banana	High	Mold	0.1-2 (13 °C)	10-30 at 13 °C	**Grape**	Low	Decay	Less than 0.1 (20° C)	1-2 (0°C)
Blueberry	Low	Yellowing	0.1-1 (5°C)	3 at 0 °C	**Grapefruit**	Medium	Mold	Less than 0.1 (20°C)	3-5 (10°C)
Kiwi	High	Mold	1.5-2 (0 °C)	Less than 0.1 at 0°C	**Lemon**	Medium	Russet spotting	Less than 0.1 (20°C)	5-6 (5°C)
Mango	High	Decay	0.1-0.5 (10 °C)	12-16 at (10 °C)	**Lime**	Medium	Russet spotting	Less than 0.1 (20°C)	3-5 (10°C)
Melon	Medium	Decay	40 (20°C)	2-3 (0°C)	**Mandarine**	Medium	Decay	Less than 0.1 (20°C)	2-4 (5°C)
Nectarine	High	Odor, sprouting	Less than 0.01-5 (0°C)	2-3 (0°C)	**Orange**	Medium	Decay	Less than 0.1 (20°C)	2-4 (5°C)
Papaya	High	Decay	0.1-2 (7°C)	3-5 (7°C)	**Watermelon**	High	Sleepness	0.1 - 1.0 (20°C)	3-4 (5°C)
Passion fruit	High	Decay	160-370 (20°C)	15-30 (5°C)	**Pineapple**	Low	Mold	Less than 0.2 (20°C)	2-4 (7°C)
Peach	High	Decay	Less than 0.01-5 (0°C)	2-3 (0°C)	**Strawberry**	Low	Mold	Less than 0.1 (20°C)	6-10 (0°C)

Pear	Low	Decay	0.1-0.5 (0°C)	2-3 (0°C)	**Raspberry**	Low		12 (0 °C)	0.1-1 (5°C)
Plum	High	Sprouting	Less than 0.01-5 (0°C)	1-1.5 (0°C)					
Tomato	High	Lose firmness	1.2 - 1.5 (10°C)	3-4 (5°C)					

Table 41

Given the importance that the rate of ethylene and respiration have in keeping of product quality level during postharvest phases, the literature has focused its attention on this topic by several years. Studies aim to relate the trend of these two important phenomena to the residual quality of the product. Don W. Brash and al. (1995) studied the relation between the respiration rate of a product stored at fixed temperature and its shelf life (Figure 51); X.Y. Zheng and Wolff (2000) focused on relation between remaining quality, expressed in terms of product deterioration rate, and ethylene production (Figure 52); Gäbler (2005) found a distinct relationship between time dependency of the gas concentration and remaining quality at examinations of lettuce and other fruits. This suggests the key role played by the rate of respiration and ethylene emission in determining the quality of the product and the importance of possibility to monitor these two parameters.

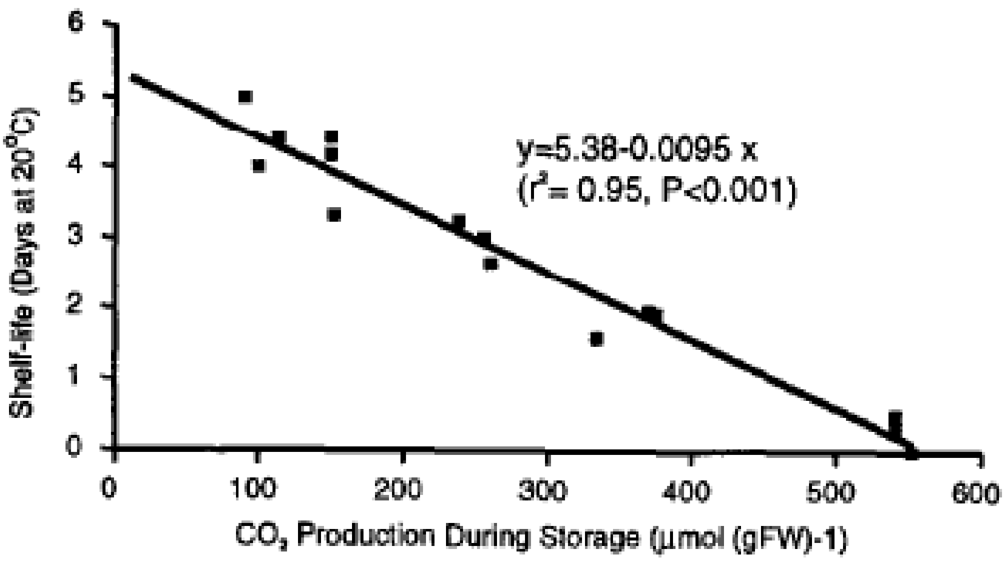


Figure 51. The effect of total CO_2 production of stored asparagus spears on subsequent shelf-life.

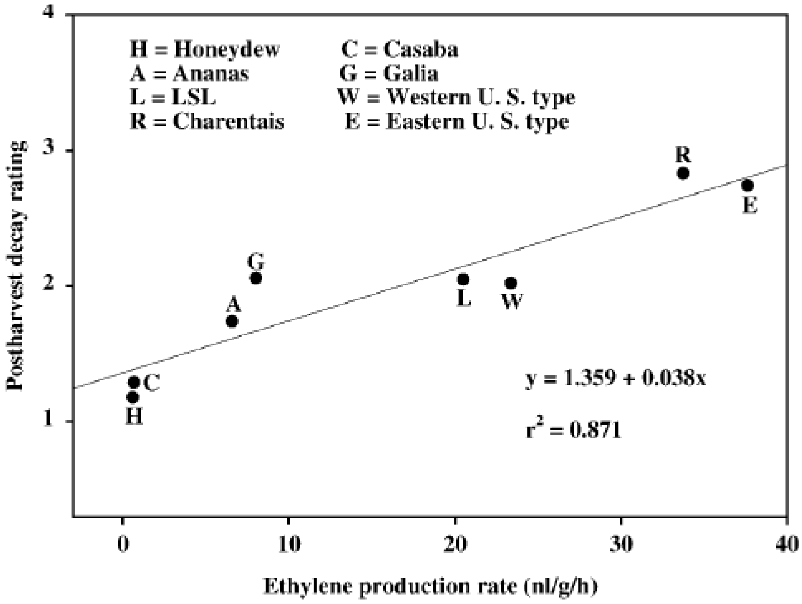


Figure 52

Linear regression of mean postharvest decay ratings on mean ethylene production rates (1994 and 1995 field experiments) of each market type of melon fruit. Melon fruits were harvested at horticulture maturity and stored at 27–30°C for 7 days before rating visually and mechanically for postharvest decay. A rating of 1 signified no evidence of softening or decay, ratings of 2, 3 and 4 indicated about 25%, 50% and 75% decay of the surface area, and 5 indicated complete rot and collapse of the fruit. (Zheng and Wolff (2000)).

1.3.Innovative techniques and technologies for monitoring parameters that affect product quality

As already discussed in the previous Sections the perishable quality monitoring arises from knowing the environmental factors responsible for products deterioration. Such factors are related to the environmental parameters as temperature, relative humidity, solar irradiation and atmosphere composition -in terms of CO_2, O_2 and ethylene concentration- which characterize the micro climate around the product at any postharvest stage and contribute to determine its quality. Traditional techniques for product quality monitoring are based on direct detection of parameter of interest, realized with chemical, physical and optical methods. Usually they are disruptive methods and therefore they can be applied only to a small sample of the production. These methods are based on sampling and analysis of product in order to evaluate the indexes that determine product quality such as the appearance (size, shape, color, brightness, defects), the kinesthetic features (softness and internal consistency, fibrous, juiciness, etc.) and the organoleptic characteristics (taste and aroma). The most common indexes are: consistency of pulp, sugar content, acidity, color and degradation of starch. Difficulties in the implementation of such techniques relates to the accuracy required in the stages of sample collection and to the considerable expertise required for those performing the evaluation. In fact the samples should be representative of production with reference to the homogeneity of the chemical-physical and organoleptic characteristics of products taken to ensure the validity of sampling and a thorough knowledge of the physiology of ripening is needed to ensure a proper evaluation of product characteristics. Recent requirements regarding the certification of the entire production make these traditional techniques inadequate to the monitoring of product quality. In this context new non-destructive techniques are emerging that can perform the complete evaluation of production through the method of indirect evaluation. This indirect evaluation is based on detection of a parameter responsible for the quality of the product such as the temperature, the rate of emission of ethylene or CO_2. Naturally such indirect measurement techniques are less sensible than direct measurements. In fact for their application it is necessary to consider that the physiological phenomena related to the parameter chosen can vary in the evolution of fruit ripening in manner not smooth and simultaneous. On the other hand, they allow to eliminate the imprecision in the evaluation due to the validity of sampling and the considerable costs related to destructive analysis. Furthermore it must be considered that the quality decreasing are often difficult to assess by using the sensorial analysis. In fact perceptible changes in color and consistency mostly become apparent only during the later stages of a product's life (i.e. mostly on the sales floor), and therefore human-sense-based examinations result unable to the fast identification of non conformity in the initial stage of the product management.

As discussed in the Section 2, today the innovative and pervasive technologies such the RFID make it possible the identification of products and the monitoring of their remaining quality by starting from the knowing of the environmental parameters thus enabling the indirect evaluation techniques. In this sense the RFID technology allows to implement a traceability system enabling the possibility to early identify the non conforming products. For details about the RFID technology see Section 2 Chapter 2. A RFID system essentially consists of a tag, a device able to the unique identification of item to which it is attached, an antenna and a reader, which allow the remote reading of tag. As a RFID tag “follows” the item while moving along the supply chain, the RFID devices allow to the dynamic monitoring of products from production site along the logistic chain into the hand of consumer thus enabling producers, logistics groups and costumers to trace their goods at any time. A RFID sensor tag can incorporate some important requirements that make it a suitable tool for quality monitoring. A RFID tag can be embedded with temperature, humidity, illuminance, gas and/or shock sensors, thus incorporating sensing capability in order to measure both physical and chemical parameters. Usually, it also incorporates a memory, a battery and a clock to record sensor data in memory at constant intervals. In this way the history of “when” a tag was “in which status” can then be accessed later by reading tag memory. A RFID sensor tag with embedded memory can measure and record the parameter of interest by itself thus allowing the automated data collection. The unique ID associated to each tag allows the identification of individuals items thus combining quality management with the inspection function (Ogasawara and Yamasaki (2006). In this way you can know either the localization of batch in every stage of the chain and its current quality conditions. Consequently the RFID enables you to realize a traceability system and perform an inspection system of the entire production. In recent years several research have addressed the topic about how RFID implementations can affect the production models. In fact RFID implementations incur additional costs, which is a disadvantage for organizations involved in the supply chain. Sounderpandian and al. (2007) discussed the conditions under which a RFID implementation is beneficial compared to a non-RFID implementation for existing inventory models. They argue that, in most cases, changes to an organization's inventory model are required for a RFID implementation to be beneficial. Lee and Byoung-Chan (2010) propose a Supply Chain RFID Investment Evaluation Model based on the classic economic order quantity (EOQ) model in which three unique RFID investment factors of ordering efficiency, Just-In-Time (JIT) efficiency, and operating efficiency are considered. The present study focuses the attention on the assessment of the economic impact of a traceability system RFID based on supply chain costs. As is well known the introduction of a RFID system allows achieve several advantage: the possibility to identify a product and the information related to its actual quality level allows the early detection of non conforming units and their withdrawal thus avoiding transport cost of products unsuitable for the target market; the knowing of the actual remaining quality level also allows to redirect non conforming products in an alternative market in which they are still suitable for sale allowing the producer to make a profit in this market and reducing disposal costs; finally the implementation of an automatic detection system allows to reduce the cost due to the amount of product samples and destructive tests needed to determine the actual quality of products. Naturally the RFID implementation involves some costs both fixed and variable. Fixed costs are essentially infrastructural costs related to hardware -as readers and antennas- and software for the initial installation while variable costs are referred to the devices that must be applied. The goal of the present study is to assess the impact of RFID implementation on the optimal order quantity. In this study an economic model is presented in which costs involved in supply chain management are considered including the infrastructural costs due to RFID and the optimal order quantity which minimizes the total cost is determined. The model proposed will be discussed in Chapter 2.

CHAPTER 2

2.1. The proposed methodology

The methodology here proposed employs the RFID technology for the detection of environmental parameters (such as the temperature, the CO_2 and/or ethylene concentration) of batches which are monitored when they move through the supply chain which is composed by a producer and a wholesaler. The goal is to determine the optimal batch size to transfer from the producer to the wholesaler. The device RFID can take trace of an interest parameter with time, and for this reason it allows to detect the exceeding of an acceptance threshold of the parameter itself. In the present study, a methodology is proposed in which an acceptance threshold is fixed consisting in a maximum level of deterioration rate allowed or minimum remaining shelf life. For each batch transferred from the producer to the distributor the remaining quality determined through the RFID detection can be compared with the threshold fixed thus performing a control test. According to the information given by the test, the producer will send to the wholesaler those batches whose remaining quality is greater than the minimum required by the target market. Regarding those batches which have not passed the test, information provided by the RFID allows the producer to decide whether to send them to an alternative market in which they are still suitable for sale. In the present study a cost model is presented to assess the economic impact of the application of the discussed methodology to the monitoring of product quality. In the model presented the percentage of non conforming units in the production (that is the percentage of units which have an initial remaining quality such that they must be considered perished) is known, the acceptance threshold can be fixed in terms of maximum percentage of non conforming units allowed in a batch and the probability of a batch leaving the producer exceeds the threshold can be determined as well as the related costs.

2.2. The probabilistic model

In the present section we present a probabilistic model, with the assumption that the percentage of non conforming units in the production is known. Such a model starts by establishing the probability a batch of size *n* not passes the control test, i. e. the probability that the RFID tag shows the condition of exceeding of the acceptance threshold. It is supposed that the RFID tag is not affected by detection error, that is the hypothesis of perfect control is done. For this purpose suppose a population of size *P* devised in batches of size *n*. The percentage of non conforming units in *P* is *p*. As we can assume that each product in *P* has the same probability *p* to be non conforming, the non conforming units in a batch is *n*p*. Let *th* be the fixed acceptance threshold, that is the maximum allowable percentage of non conforming units which determine the acceptance or the rejection of the batch. Suppose also you want to fully inspect the batches based on the methodology previously explained in the paragraph 2.1 to determine the quality level of products in order to decide if they can be sent to the target market or in an alternative market. Products quality monitoring with RFID technology can be compared to an acceptance test performed by extracting products and verifying the keeping conditions of each batch. The acceptance condition is that within the batch tested the percentage of defective products detected is less than the threshold *th*. The probability this happening can be represented by a binomial random variable *X* in which the acceptance probability is equal to the sum of probability that by executing *n* tests the number of defects observed is less than *n*th*, i.e.:

$$P(X \leq th * n) = \sum_{k=0}^{th*n} \binom{n}{k} p^k (1-p)^{n-k} \qquad (88)$$

The probability a batch fails the test can be calculated from (88) as follows:

$$P(x > th * n) = 1 - P(x \leq th * n) \quad (89)$$

Since the computation of binomial distribution becomes more and more difficult when the size of batch increases in order to simplify the calculation it is possible to use a continuous approximation of the binomial. The approximation here proposed is the standard normal distribution function with the following parameters:

$$X \sim N(\mu, \sigma) = N\left(n * p, \sqrt{(n * p) * (1 - p)}\right) \quad (90)$$

The probability a batch passes the test can be expressed through the standard normal as follows:

$$P(x) = P(x \leq th * n) = \int_{-\infty}^{x} \frac{1}{\sigma * \sqrt{2\pi}} * e^{-\frac{z^2}{2}} dz \quad (91)$$

where $z = \frac{x-\mu}{\sigma}$ and $x = n * th$

The probability of rejecting a batch can be determined as in (89). As the batch size is unknown the goodness of the approximation has been tested by calculating the error made when you use the normal instead of binomial. The results are reported in Table 42 and in Figure 53.

p	Th	Absolute error	Th	Absolute error	Th	Absolute error	Th	Absolute error
10%	20%	0.030244	40%	0.052813	60%	0.041927	80%	0.026321
20%		0.004647		0.036508		0.034278		0.020423
30%		0.015609		0.016005		0.029734		0.015198
40%		0.015398		0.01185		0.025276		0.011559
50%		0.008502		0.032422		0.010652		0.009503
60%		0.00172		0.031265		0.028364		0.008036
70%		0.004593		0.020718		0.062081		0.006246
80%		0.011039		0.009071		0.051422		0.084794
Mean Absolute Deviation		**0.011469**		**0.026331**		**0.035467**		**0.02276**

Table 42

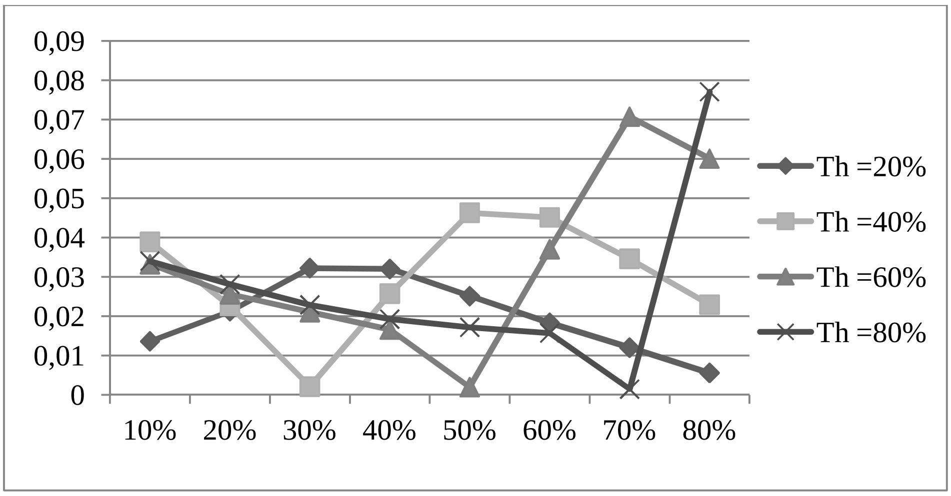


Figure 53

The results show that the MAD between the binomial distribution and its normal approximation is at most of 3.5%.

2.3. The model formulation

In this section the cost model is presented. The purpose of this model is to verify the impact of RFID technology on optimal batch size, when this technology is applied to the monitoring of products quality. The RFID is adopted for a full inspection of the production in order to verify the correspondence between the remaining quality level of batches with respect to the client requirements. In fact the client can fix a threshold representing the maximum level of non conforming units allowed in a batch. Accordingly to this only those batches whose non conforming level is less than the threshold may be sent to the client. The higher the threshold is the more non conforming products will be sent to the destination. The model here presented aims at determine the size of the transferring batch in order to minimize the total cost due to the technology adoption. In fact the real time evaluation of products quality allows the early identification of products non-conforming to client requirements; these products can be addressed in an alternative market where they are considered still suitable for sale; in this way the producer will achieve a revenue in this alternative market. The salvage value proportional to the non conforming identified decreases when the fixed threshold increases and for fixed threshold decreases when the batch size increases. Regarding to those products which pass the quality test they are sent to the wholesaler in the target market and for these products the producer will incur in a transport cost proportional to the amount of products shipped. Due to the fact that the quantity of non conforming products in the batches sent increases when the acceptance threshold increases the cost of transport increases with the threshold. The revenue resulting by products sold is proportional to the amount shipped. Since for fixed threshold the wholesaler will also receive non conforming products, he will incur in a disposal cost, proportional to the quantity disposed. This quantity is greater the higher the acceptance threshold. The application of RFID technology also involves an infrastructural cost consisting in operating costs relatively to tag and sensor costs. This cost is proportional to the number of tags applied. Under the hypothesis that the producer will apply a tag on each batch the decision that must be taken is about the batch size which minimizes the total cost.

The following notations are used in developing the model:

P: total product quantity managed by the producer

p: percentage of non conforming units in the total production P

n: batch size

n_{tag}: number of tag applied determined as P/n

th: threshold identifying the percentage of non conforming units present in the batch that determine the withdrawal of the batch from the producer

d_c: unit disposal cost

tr_c: unit transport cost

tag_c: unit tag cost

s_v: salvage value

pr: unit price

R: probability of rejecting a batch of size n when $n * th$ non conforming units are presented. From (91) we have:

$$R = P(\mathrm{x} > Th * n) = \begin{cases} 1 - P(x) & Th > p \\ P(x) & Th \le p \end{cases} \tag{92}$$

From (92) we can determine the expected number of products which have not passed the test for fixed *th* and *p*:

Expected number of rejected products= $R * n * \frac{P}{n} = R * P$ (93)

The Total Salvage value TS_v is:

$$TS_v = s_v * R * P \tag{94}$$

The Total Transport cost TTr_c is :

$$TTr_c = tr_c * P * (1 - R) \tag{95}$$

From (91) we can determine the total number of non conforming units in the rejected batches *nc*:

$$nc = F^{-1}(P = th) * \sigma + \mu \tag{96}$$

Thus the expected number of conforming products in the rejected batches *c* is:

$$c = n - nc \tag{97}$$

The Total Disposal cost TD_c is :

$$\mathrm{TD_c} = d_c * \left(P * p - nc * \frac{P}{n} * R\right) \tag{98}$$

The Total Infrastructural cost TI_c is:

$$TI_c = tag_c * \frac{P}{n} \tag{99}$$

Thus the Total Cost *TC* is:

$$TC = -TS_v + TTr_c + \mathrm{TD_c} + TI_c \tag{100}$$

The Total Revenue *TR* is :

$$TR = Pr * \left(P * (1 - p) - c * \frac{P}{n} * R\right) = \tag{101}$$

The Total Profit *Π* is:

$$\Pi = TR - TC \tag{102}$$

The objective function is to minimize the Total Cost to respect to *n*, in order to determine the optimal batch size. Since $n_{tag} = \frac{P}{n}$ the optimization to respect *n* also allows to determine the optimal n_{tag} to be attached to the batches. The analytical equation (100) is difficult to solve in closed form. However a graphic solution can be found. The optimal order quantity which minimize equation (100) is shown in Figure 54, in which the minimum cost is determined by taking $s_v = 0.6€$, $d_c = 0.1€$, $tag_c = 1.8€$, $tr_c = 0.3€$, $pr = 2€$, $p = 0.4$, $th = 0.5$, $P = 10000$. The optimal tag number results equal to 625 units and the optimal batch size results equal to 16.

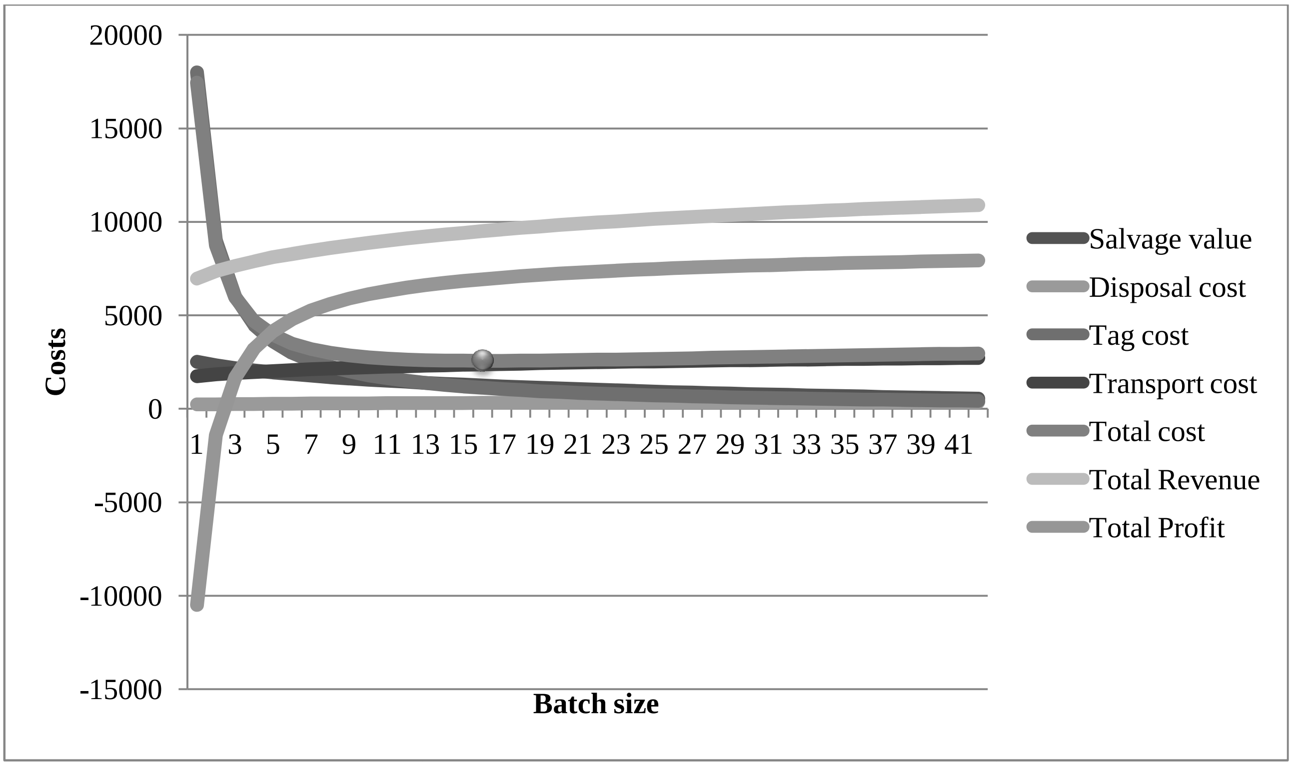


Figure 54

The analysis of Equation (100) has been carried out with a sensitivity analysis in order to examine how the minimum cost, the optimal quantity and the optimal tag number vary when the input factors vary as well. The computations needed to carry out the sensitivity analysis have been performed with a C++ code. To simplify the computational effort required, the equation (91) representing the standard normal probability an its inverse have been replaced by an approximation as follows (Aludaat and Alodat (2008)):

$$\Phi(\chi) = 0.5 + 0.5 * \sqrt{1 - e^{-\sqrt{\frac{\pi}{8}} * \chi^2}} \tag{103}$$

where $\chi^2 = z^2 = \left(\frac{x-\mu}{\sigma}\right)^2$ (104)

$$z = \sqrt{-\sqrt{\frac{8}{\pi}} * log\,(1 - (\Phi(\chi) - 0.5)^2)} \tag{105}$$

The sensitivity analysis has been carried out by varying each factor at a time and keeping the other fixed. The input parameter used for the analysis and the output of the analysis consisting in the optimal tag number for each test are reported in Table 43. As regard the tag cost the range has been chosen in order to include the cost of most common used frequencies (0.50€ for LF tag and 5€ for UWB tag).

<table>
<tr><th></th><th>Range</th><th>Δ(increment)</th><th>Fixed value</th><th colspan="2">Optimal order quantity (Range)</th><th colspan="2">Optimal tag number (Range)</th></tr>
<tr><td>P</td><td></td><td></td><td>10000</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 1</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td>0.1-5</td><td>0.05</td><td></td><td colspan="2">5-2</td><td colspan="2">2,000-5,000</td></tr>
<tr><td>tr_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tag_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>s_v</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>p</td><td></td><td></td><td>0.3</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>th</td><td></td><td></td><td>0.4</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 2</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tr_c</td><td>0.1-5</td><td>0.05</td><td></td><td colspan="2">5-2</td><td colspan="2">2,000-5,000</td></tr>
<tr><td>tag_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>s_v</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>p</td><td></td><td></td><td>0.3</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>th</td><td></td><td></td><td>0.4</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 3</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tr_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tag_c</td><td>0.1-5</td><td>0.05</td><td></td><td colspan="2">5-50</td><td colspan="2">2,000-200</td></tr>
<tr><td>s_v</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>p</td><td></td><td></td><td>0.3</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>th</td><td></td><td></td><td>0.4</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 4</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tr_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tag_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>s_v</td><td>0.050-3.50</td><td>0.05</td><td></td><td colspan="2">6-2</td><td colspan="2">1,666-5,000</td></tr>
<tr><td>p</td><td></td><td></td><td>0.3</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>th</td><td></td><td></td><td>0.4</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 5</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tr_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tag_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>s_v</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td rowspan="2">p</td><td rowspan="2">0.05-0.95</td><td rowspan="2">0.005</td><td rowspan="2"></td><td>p>th</td><td>p<th</td><td>p>th</td><td>p<th</td></tr>
<tr><td>28-3</td><td>5-28</td><td>357-3,333</td><td>2,000-357</td></tr>
<tr><td>th</td><td></td><td></td><td>0.7</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Test 6</td><td></td><td></td><td></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>d_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tr_c</td><td></td><td></td><td>0.1</td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>tag_c</td><td></td><td></td><td>0.5</td><td colspan="2"></td><td colspan="2"></td></tr>
</table>

s_v			0.1				
p			0.7				
th	0.05-0.95	0.005		**th<p**	**th>p**	**th<p**	**th>p**
				28-3	4-28	357-3,333	2,500-357

Table 43

The graphs referred to each test are reported in Figures 55-60.

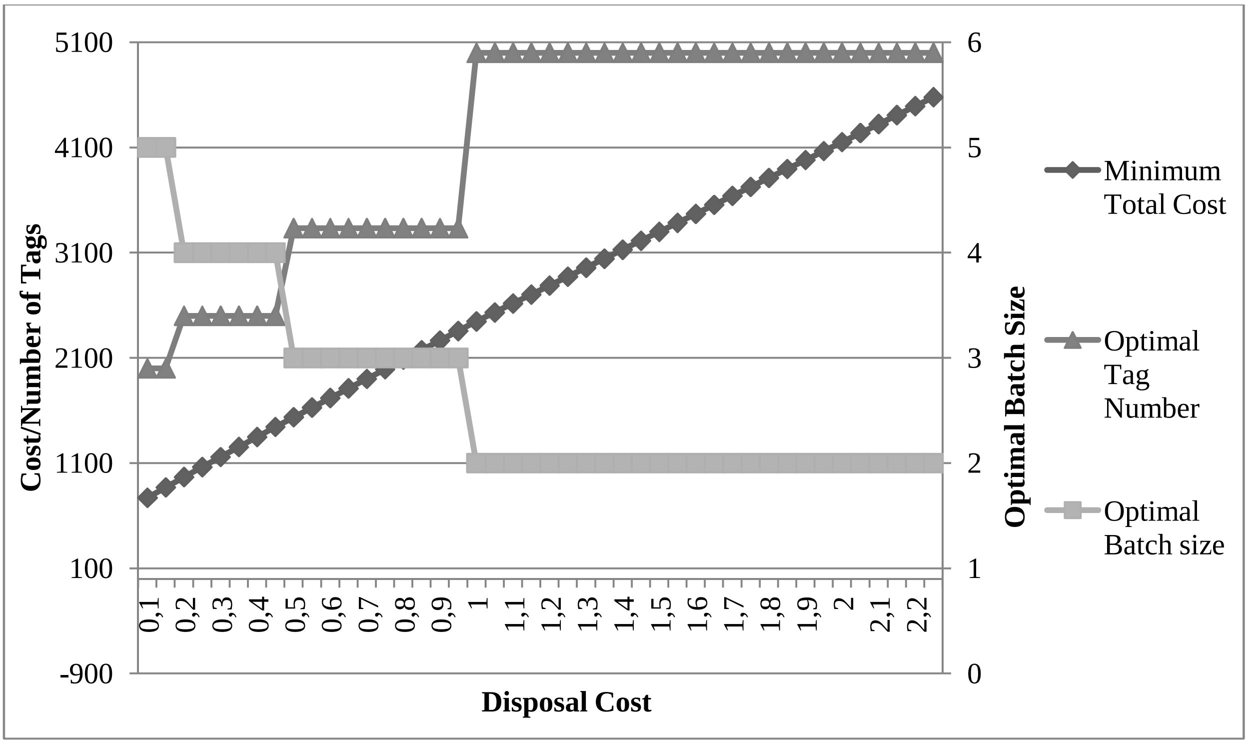


Figure 55. Test 1

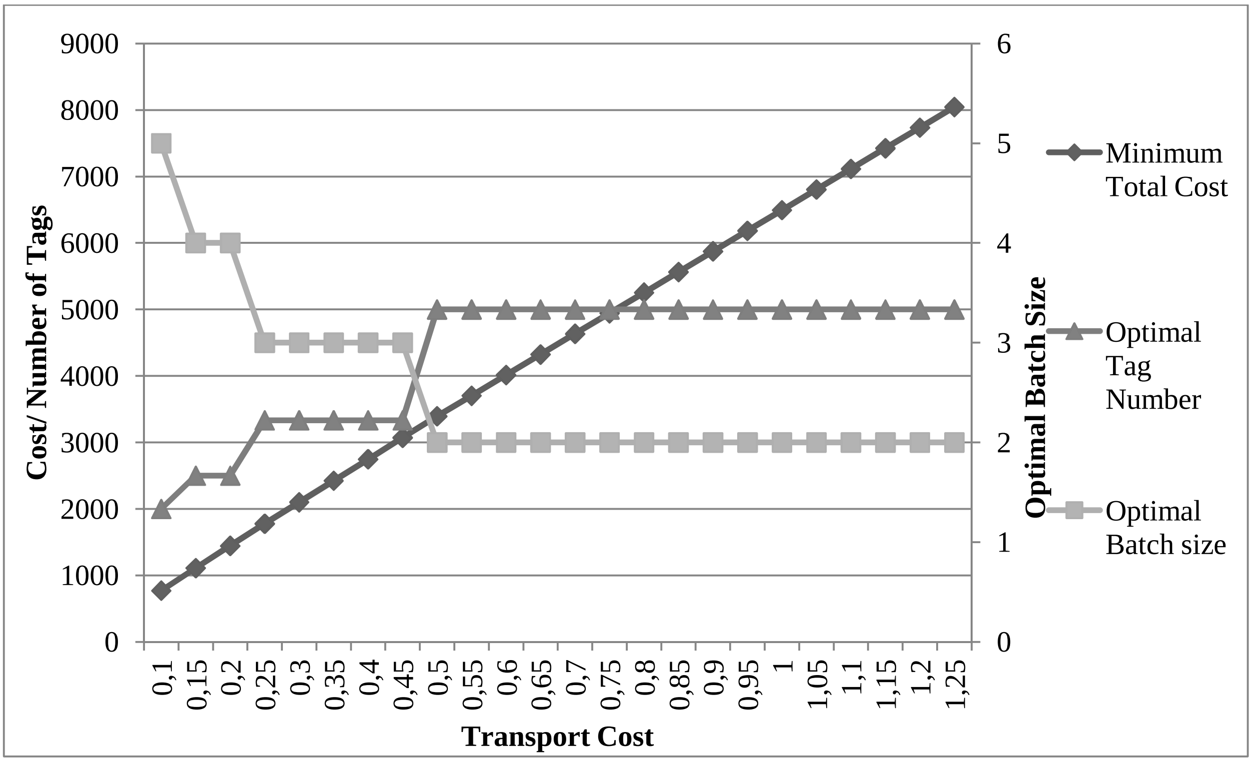


Figure 56. Test 2

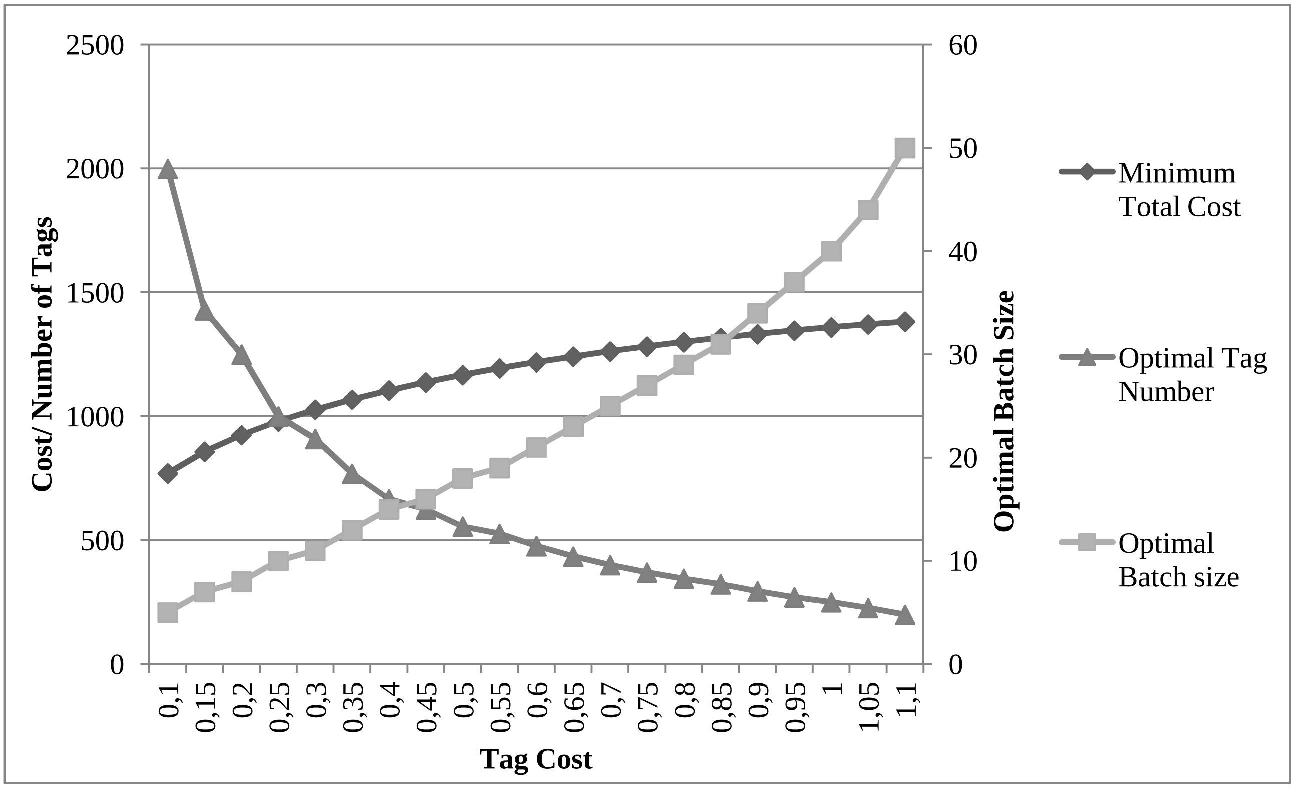


Figure 57 Test 3

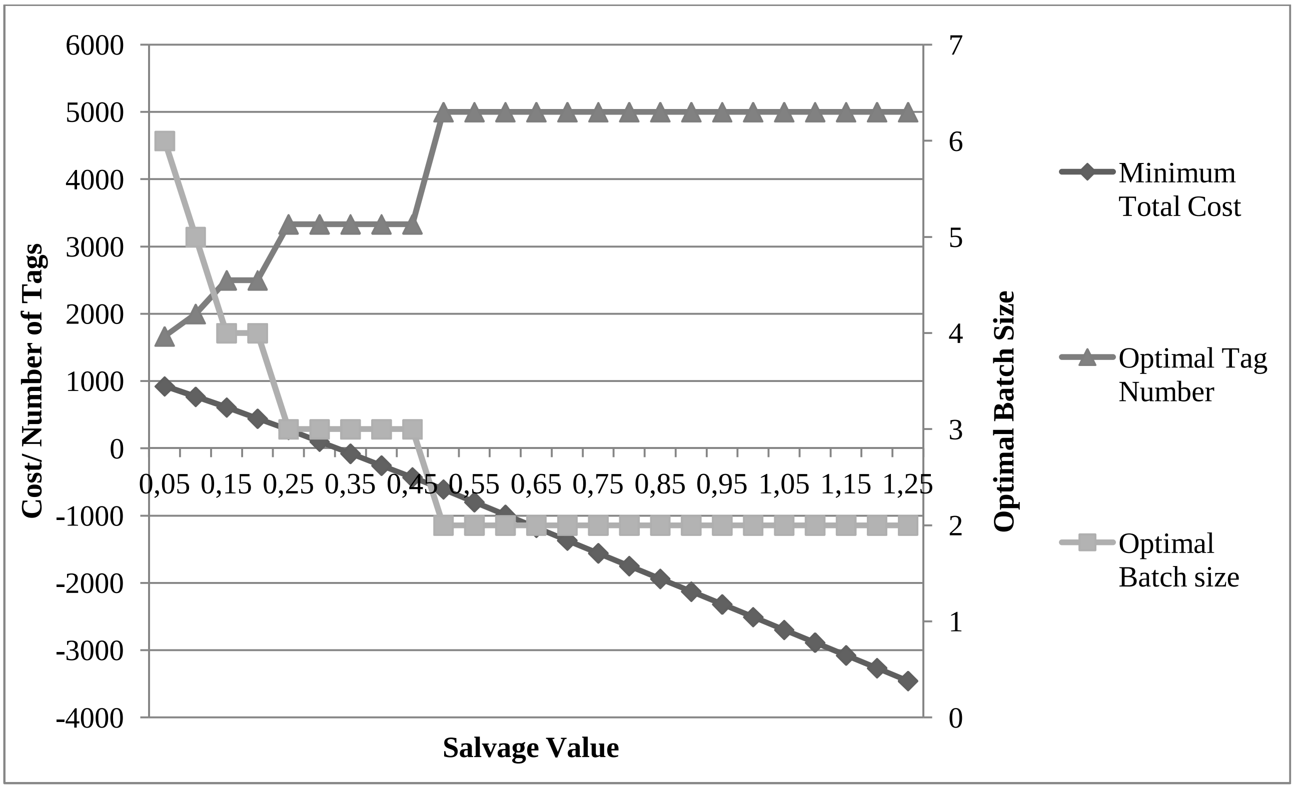


Figure 58. Test 4

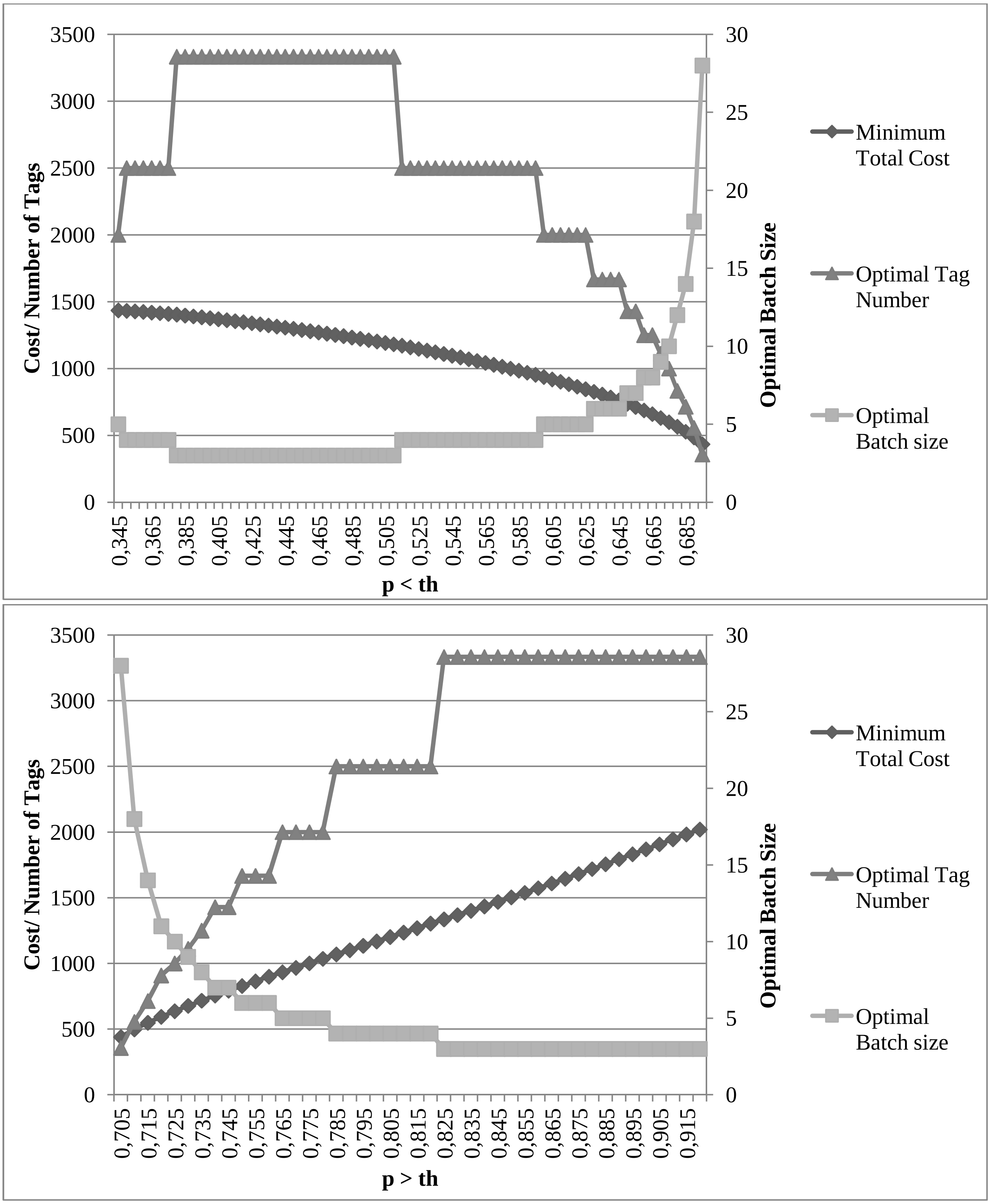


Figure 59. Test 5

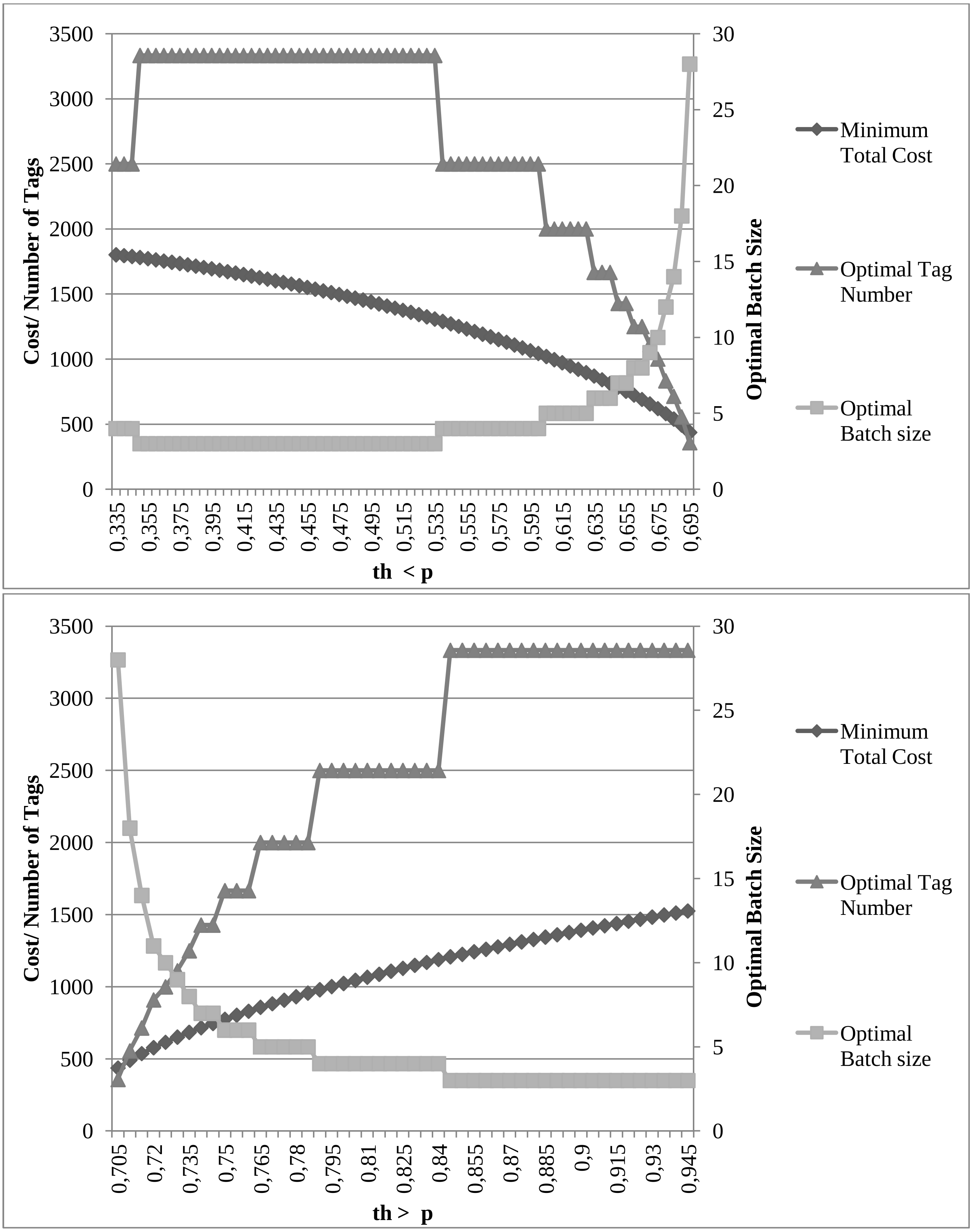


Figure 60. Test 6

Figures 55, 56 and 58 show that the increasing in d_c, tr_c and s_v costs cause an increasing in optimal number of tag (i.e. a decreasing in EOQ value), while an increasing in tag_c cost cause a decreasing in this number (i.e. a increasing in EOQ value) as shown in Figure 57. The variation of *p* and *th* (Figures 59 and 60) cause a decreasing of optimal number of tag (and than an increasing an EOQ value) if *th* is less then *p* and an increasing otherwise. From Table 43 it is clear that the input parameter mainly responsible for the variation of the optimal batch size are the tag cost, the initial percentage of non conforming units and the threshold fixed, while the disposal cost, the transport cost and the salvage value have not great influence on the optimal batch size. Based on the consideration expressed in the paragraph 2.7 of Section 2 about the tag costs, the model proposed allows to know the optimal batch size for tag ranging from the LF (Passive) to the UWB (Semi- passive, Active).

2.4. Conclusions

In this Section the problem of the affordability of a RFID system has been addressed. The RFID system allows to implement a traceability system able to know the current quality of products managed. This allows the fast withdrawal of non conforming units . the suitability of a RFID investment has been addressed by means of a mathematical model with the aim to determine the optimal batch size when the variable costs involved in such technology are included in the cost model. Results show that the tag cost is the cost mainly responsible for the variation of optimal batch size. The range of variation of RFID tag cost has been chosen in order to include the most common used frequencies (from passive to active tag) and the results show the optimal batch size for each of them.

SECTION 5: CONCLUSION

DISCUSSION AND FUTURE RESEARCH

In the present PhD thesis the use of innovative technologies was addressed in order to show their contribute to the optimization of efficiency/responsiveness of the supply chain of perishable products. The aim of the thesis was to show as the use of these innovative technologies makes possible to improve the decision making process involved in the perishables management. The study was conducted with reference to the pre and post harvest phases and finally the attention was posed on the affordability of the investment in innovative technologies.

Concerning the pre-harvest phase the monitoring of the grape berries during the ripening process allowed the possibility to make prevision about the incoming of different phenological phases. With this regard the goal was to built a decision making tool consisting in an Expert System able to automatically monitor the progress of the ripening process and forecast the start and the end of each phenological phase. The main result of this study was that the Expert System allows to reduce human intervention and disruptive sampling in the decision process related to grapes growth. The possibility to precisely discriminate the maturation level of grapes allows to improve the responsiveness of the supply chain in the early stages by allowing the optimization of the harvest phase scheduling . At the present the precision of the measure forecasted by the Expert System is affected by high variance, however this problem will be reduced over the years as the detection of the environmental factors will continue.

The study of post-harvest phases addressed two topics: the monitoring of product quality along the entire supply chain and the monitoring of storage conditions in particular.

With reference to the first argument the peaches fruits have been monitored in order to determine their actual SL at every stage of the supply chain. The goal in this context was to make information about the residual SL of products managed in order to effectively choose the final market on the basis of their SL. The main result was that the automatic monitoring of the SL actually represents a suitable decision making tool since it makes possible fast and precise decisions allowing to reduce the deterioration costs. This result can be improved by considering the possibility to apply picking policies SL based to the coming out products. Furthermore the knowing of actual quality level of products managed allows to the members to fast recognize the responsibility in terms of not proper product management. This improves the responsiveness of the chain by allowing the members to choice the destination of the products on the basis of their remaining quality and the efficiency of the chain itself by allowing the deterioration cost reduction. However the main issue in this context relates to the necessity of implementing the RFID system by all members of the supply chain involving the coordination of the chain itself.

The study of the post-harvest stages followed with the monitoring of perishable products in the warehouse system. The aim in this context was to show that traditional EOQ models and picking policies which not consider the perishability of products are unable to optimize the warehouse management system. In this case a warehouse management system based on an EOQ model including deterioration costs and a picking policy SL based were proposed in order to show the benefit achievable in terms of improvement in the quality of product managed. The main result was that the possibility to monitoring the quality level of products stored allows to define a decision making tool (a warehouse management system) consisting in a set of operative decisions concerning the stock level, the picking rule, etc able to improve average quality of products stored with respect to the traditional EOQ/picking policies. In this context the efficiency of the supply chain can ameliorate thanks to the analysis of costs involved in the storage process. As seen in the previous case also in this context the effective realization of such a system involve the necessity of the implementation of the monitoring system by all members of the supply chain in order to make information about the residual quality of products entering the warehouse. Further study in this field could interest the impact of pricing policies SL based on the optimal picking policy of the outgoing products.

Finally the attention was focused on the affordability of the investment in innovative technologies such the RFID. In this case the goal was to determine the optimal batch size (i.e. the optimal number of RFID devices) in order to minimize the total transferring cost by considering a supply chain with a producer and a supplier. An EOQ model including transport, disposal and device cost as well as the salvage value was presented in which information arisen from the RFID device allows for fast detection of non conforming units in the EOQ. The main result was that the cost mainly influencing the optimal batch size is the device cost. Information about the impact of the RFID technology on the supply chain costs allows the supply chain members to make decisions about the affordability of the RFID investment. In this sense the analysis proposed allows to improve the efficiency of the supply chain. In this context the future research can be addressed to the definition of an EOQ model which includes not only variable costs as in the model presented here but also fixed infrastructural costs.

In conclusion the study proposed allows to comprise how the use of innovative technologies can be of great help in the decision making process in order to improve the dual aspect of efficiency and responsiveness of the supply chain.

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