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Ranking of Shelf life models based on Smart Logistic Unit using the ELECTRE III method

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Abstract
The aim of this paper is the evaluation of Shelf Life (SL) models based on Smart logistic unit to support the management of the food supply chain in order to guarantee the shelf life of products in agreement with logistic efficiency and system sustainability. For this purpose, the main shelf life equations based on parameters that influence the quality of perishable products were defined and the correspondent acquiring and gathered system has been developed. The selection of the optimal SL model was carried out by means of the multi-criteria decision-making procedure ELECTRE III.

Keywords: Shelf life models, Perishable product, Smart Logistic Unit, ELECTRE III.

Introduction

The need to cope an increasing world population makes it mandatory to reduce the millions of tons of perished waste along the food supply chain. Based on an analysis of the data from the Food and Agriculture Organization of the United Nations [1] one-third of food produced for human consumption is lost or wasted globally. Non-optimal food chain processes and management cause a significant part of these losses. Mathematical models, technologies and applications to monitor changes in the product shelf life, defined as the time remaining until the quality of a food product drops below an acceptance limit, can be useful tools for reducing food losses. During the last years, several models have been developed for shelf life prediction of perishable products, most of them based on the growth of specific spoilage organisms (SSO) [2, 3, 4]. Such studies, however, can hardly be exploited to improve the supply chain management, as long as the data obtained for developing shelf life models, are not released from the laboratory test. The real time knowledge of the quality of the products, at the different stages of the supply chain, on the contrary, is nowadays considered a fundamental information for improved operations management as recent studies on the shelf life based supply chain management policies confirm [5, 6, 7, 8]. For these reasons, in the last years, different models have been developed for the establishment of shelf-life, mainly based on the detection of extrinsic factors changes, like for example temperature, Relative Humidity (RH), CO_2 and VOCs concentration [9, 10, 11, 12, 13, 14. The traditional approach consists of setting a cut-off point along the storage period at the time when the shelf life measured exceeds a pre-established limit. The cut-off point has been traditionally referred as quality limit.

Technological advancements in recent years in the field of sensor development has allowed the design of sensor network providing high performances in terms of sensitivity, immunity of electromagnetic interferences, low intrusively and high multiplexing features [15]. However the implementation of a logistic unit that takes into account the contemporary influence of all the environmental factors previously mentioned could lead to high costs in real life applications. In this paper the main equations used for measuring the remaining shelf life of perishable product are compared by means the multi criteria decision making methodology Electre III in order to develop an economically affordable smart logistic unit that can be integrated in the crate. In this way, it would be possible not only to reduce the number of sensors but also the size of the system itself, making it more suitable for large-scale applications. Different criteria have been identified and a prototype of a smart logistic unit has been developed in order to compare the shelf life measured with the different equations. The remainder of this paper is organized as follows. Section 2 refers the main shelf life models based on environmental factors. Section 3 describes the logistic unit developed for monitoring the shelf life parameters, Section 4 shows the results obtained by the application of the Electre III methodology and finally, Section 5 concludes the paper with a short discussion on the proposed approach and an outlook into on-going research work.

Shelf Life Models

The aim of a shelf life model is to predict the time span that is left in total for transport, storage, display in the shop and storage in domestic fridges as a function of the environmental conditions to which the product was, or may be, exposed if such information is available. It is important to investigate the components required for the integration of shelf life modelling

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into supply chain management [9]. There has been a vast array of research on shelf life models in the past two decades. For example, Tijskens & Polderdijk [16] published a list of model parameters for 60 Fresh Fruits and Vegetables in 1996. A review of the existing shelf life models for berries, for example, can be found in [10].

The first phase of the present research focused on tests the SL models based on parameters that can be acquired in real time. In particular, to compare the different models, we have chosen strawberries as a specific perishable product.

Unnecessary losses of shelf life can be found in any part of the chain, especially with regard to temperature management, hence, the first model considered is the Arrhenius law. Considering *q* as the parameters employed to measure the quality of the product, the change of *q* with time *t* can be expressed as [17]

$$(\pm)\frac{dq}{dt} = kq^n \tag{1}$$

Where *k* is the reaction rate constant and *n* is the reaction order. It is possible to develop a kinetic-mathematical model that describes the evolution of the rate constant *k* of chemical reaction depending on storage time at different temperatures *T* for a specific activation energy E_a, according with the Arrhenius law:

$$log\frac{k_2}{k_1} = -\frac{E_a}{R}\left(\frac{1}{T_2}-\frac{1}{T_1}\right) \tag{2}$$

Where *R* is the universal gas constant (8, 31 J/mol K).

Since the deterioration rate can be considered inversely proportionate to the storage time of the product, then the equation (2) can be rearranged as follow by means of equation (3) that allows calculating the shelf life values at different temperature:

$$SL_1 = SL_0 exp\left(\frac{E_a}{RT_i}\right) \tag{3}$$

Where SL_1 is the Shelf life at temperature *Ti* and SL_0 is the shelf life at a reference temperature. The activation energy for strawberries is 64.2 KJ/mol [18] and at the temperature of about 4 °C the shelf life of the product is about 7 days (http://postharvest.ucdavis.edu/).

It is therefore possible to calculate the fraction of consumed SL (f_c) and residual SL (f_t) at the time *t* as [19]:

$$f_c = \sum_{i=1}^{n}\left(\frac{\Delta t_i}{SL_i}\right)_{T_i} \tag{4}$$

$$f_t=1-f_c \tag{5}$$

Another common approach is to relate shelf life to respiration activity [10]. It is assumed that the speed of ageing processes increases proportionally to the increase in the CO_2 production rate at higher temperatures.

In Gong et al. [20] the amount of CO_2 from respiration rate (TCO_2) is linearly correlated to the shelf life value by means the following equation:

$$SL_2=b_{co2}-a_{co2}*TCO_2 \tag{6}$$

where b_{CO2} and a_{CO2} represent shelf life constants. This shelf life model is only based on a single attribute [20].

However, in order to cover a wide range of environmental conditions, multiple quality factors should be considered. It is well recognized that the respiratory demand of fresh, harvested product is a function of temperature, oxygen availability and, in some case, CO_2 concentration. A convenient way to measure respiration is to seal the product in closed space and monitor gas concentration. We calculated the coefficients of the equation of Guevara et al. [21], wrote for prickly pear cactus cladodes, for strawberries. In the equation (7) R_{CO2} represents the CO_2 respiration rate, *T* the temperature and *RH* the humidity rate.

$$Ln(R_{CO_2}) = \left(27299\times\left(\frac{1}{273.15+T}\right)\right)+0.41\times RH + 60.65 \tag{7}$$

Guevara et al. wrote the equation in order to calculate R_{O2}, while equation (7) is modeled as a function of CO_2; it is possible because O_2 and CO_2 are closely related, furthermore the sensor of the SLU allows to measure CO_2, so the equation could validate comparing the values modeled with those measured.

Respiration was modelled according to the following equation:

$$R_{CO2}=RQ*R_{O2} \tag{8}$$

Where *RQ* is the respiration quotient and this value for strawberries is 0.8 [18]. Since there is a chemical bond between O_2 and CO_2 :

$C_{16}H_{12}O_6+ 6O_2 \rightarrow 6CO_2+6H_2O$+energy

In this way, knowing *RH* and *T* from SLU, using equation (7) we can calculate R_{CO2}, related to R_{O2} with (8). The R_{O2} value is necessary to calculate *SL* by means of the following equation:

$$SL_3 = \frac{O_{2,max}}{V_1\cdot\frac{1}{W}} \tag{9}$$

where $O_{2,\,max}$ represents the critical concentration of oxygen in the surrounding unfilled volume [cm^3*g^{-1}], V_1 the rate of oxygen inlet (related to the oxygen permeability of the package) and *W* the mass of product [g] [22].

The last analysed model is based on VOCs concentration. Considering a Δt, where t_0 is the initial time and *t** is the marketability limit of the product and assuming that the trend of VOCs concentration in this interval is linear, it is possible to carry out a change of variable. Under these assumptions the VOC values corresponding to $SL(t_0)$ and $SL(t^*)$ are $VOC(t_0)$ and $VOC(t^*)$, that are the values measured by the SLU in t_0 and *t** respectively. The shelf life can be, hence, calculated through the following expression:

$$SL_4 = VOC(t)\cdot a + b \tag{10}$$

Where *SL(t)* and *VOC(t)* are respectively the shelf life and the VOC value measured at the generic *t* time and *a* and *b* are described by the following equations:

$$a = \frac{[SL(t^*)-SL(t_0)]}{[VOC(t^*)-VOC(t_0)]} \tag{11}$$

$$b = SL(t_0) - VOC(t_0)\cdot a \tag{12}$$

More complex models can provide better accuracy, but in general they contain more parameters that have to be evaluated experimentally. The selection of a model is therefore also a question of the amount of available data or the budget to carry out laboratory tests as well as the technical capabilities of the monitoring hardware for recording and processing the environmental data. It is important to note that different pre-harvest conditions influence factors that could not be measured and biological variance causes a certain

amount of uncertainties in the shelf life prediction, which even complex models cannot remove.
However, assigning deliveries based on a shelf life prediction overlaid with uncertainties is always better than performing the same job ignoring the shelf life loss because either no record or no method to compare and evaluate the data are available.

Smart Logistic Unit
The system proposed allows real time monitoring of parameters such as temperature, relative humidity, CO_2 and VOC concentrations to determine the quality of the perishable products in real time. The choice of these parameters is based on the review of the existing literature, which shows the correlations between the above-mentioned parameters and the quality of perishable products. The system proposed is described below and the main features of the sensors employed are given in table 1:

TABLE.1. Sensor Characteristics

Sensor	Specification	Value
VOC's sensor: **MiCS – 5524** (from e2v)	Measurement Range	1 ~ 1000 ppm
	Air Resistance	100 ~ 1500 KΩ
	Sensitivity	1.8 ~ 6 mV
	Response Time	30 seconds
	Supply Voltage	2.1 ~ 5VDC
	Operating Temperature	- 30 ~ 85 °C
	Average Consumption	32 mA
Temperature sensor: **MCP9700A** (from Microchip)	Measurement Range	- 40 °C, + 125 °C
	Output Voltage (0°C)	500 mV
	Sensitivity	10 mV/°C
	Response Time	1.65 seconds
	Accuracy	± 2 °C (range 0°C ~ +70°C) ± 4 °C (range -40°C ~ +125°C)
	Supply Voltage	2.3 ~ 5.5 V
	Typical Consumption	6 µA
	Maximum Consumption	12 µA
Humidity sensor: **808H5V5** (from Sencera Co. Ltd)	Measurement Range	0 ~ 100% RH
	Output Signal	0.8 ~ 3.9 V (25°C)
	Accuracy	< ± 4%RH (at 25°C, range 30 ~ 80%) < ± 6%RH (range 0 ~ 100%)
	Supply Voltage	5VDC ± 5%
	Operating Temperature	- 40 °C ~ + 85 °C
	Response Time	< 15 seconds
	Typical Consumption	0.38 mA
	Maximum Consumption	0.5 mA
Carbon Dioxine CO2 sensor: **TGS4161** (from Figaro)	Measurement Range	350 ~ 10000 ppm
	Voltage at 350 ppm	220 ~ 490 mV
	Sensitivity	44 ~ 72 mV (variation between the voltage at 350 ppm and at 3500 ppm)
	Supply Voltage	5V ± 0.2 VDC
	Operating Temperature	- 10 ~ 50 °C
	Response Time	1.5 minutes
	Average Consumption	50 mA

The probes are connected to the SLU where the main board, the battery, the GPS and 3G modules are allocated. The JN3 GPS module from Telit allows to track the position of the logistic unit along the supply chain. The sensitivity of the GPS module is -147 dBm for acquisition, -160 dBm for navigation and -163 dBm for tracking, with a positional accuracy error < 2.5 meters and a speed accuracy < 0.01 m/sec. The GPS has the capability to receive signals from the systems such as EGNOS (European Geostationary Navigation Overlay System), WAAS (Wide Area Augmentation System), GAGAN (GPS Aided Geo Augmented Navigation) and MSAS (Multi Functionally Satellite Augmentation System). The SIM 5218E 3G module from SIMCom is employed to send the collected data over the internet. The 3G module uses the standard UTMS that enables downlink transfer speed of up to 7.2 Mbps (HSDPA) while uplink transfer speed of up to 5.76 Mbps (HSUPA). Such features allow the module to perform several activities such as: sensing/receiving SMS, HTTP and HTTPS service, FTP Service (downloading and uploading file), sending/receiving email (SMTP and POP3). This hardware is also characterized by a low-power consumption, high-modularity and it allows monitoring, processing and communicating the parameters that affect the shelf life to a remote database. The dimensions of the sensor box are reported in figure 1, the weight is 600 grams and the battery power is 6600 mAh.

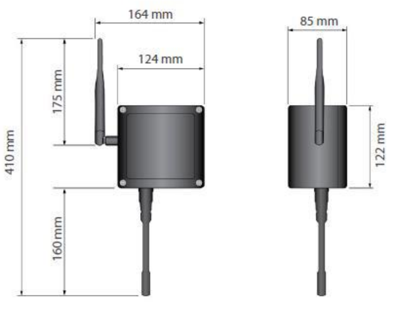

Figure. 1 The Smart Logistic Unit

The data gathered by SLU are forwarded to a cloud platform that is accessible via web interface by means the 3G module using an HTTP protocol. This platform lets developers write applications that run in the cloud and/or use services provided for the cloud. Gathered data can be used for further processing via PC or mobile devices as shown in figure 2.

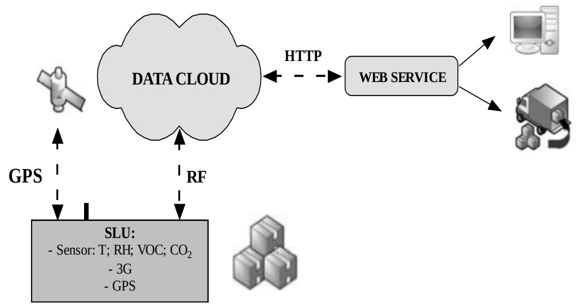

Figure. 2 Architecture of the proposed system

The cloud platform allows centralized data storage and on line access to computer service and resources, the data are available in real time for stakeholders that have a shared access to the system. A free web hosting service with php and mysql support (Altervista) was used to store and manage the data collected from the sensors and to make them available both in a graphical and numerical format.

ELECTRE III to rank the shelf life models

The faced problem regards the choice of the shelf life model that represents the best compromise, among a set of alternatives, with respect to different criteria. As said before, the proposed models are able to estimate the residual shelf life of the strawberry fruit.

Strawberries are in fact highly perishable and heavily sensible to mechanical injuries that occur during post harvest handling and transportation. This fruit is characterized by a high level of respiration, by a sensibility to fungal spoilage and by a thin skin that implies a rapid loss of water in low humidity environments [23, 24].

In the present section a real case is shown. In particular, a structured methodology, based on the multi-criteria decisional methods, is proposed with the aim to rank the different shelf life models, described in sections 2. In detail, with the aim to take simultaneously into account the aspects previously described and reflect the preferences of the decision maker in the ranking procedure, it is suggested the ELECTRE III method [25]. This technique permits to order the SL models, respect to different criteria conflicting each other. The choice of the proposed methodological approach is based on the properties that mark the ELECTRE III. In particular, this method is based upon pseudo-criteria. That is, using proper thresholds, pseudo-criteria allow to take into account the uncertainty and ambiguity that can affect the evaluation, so that, if the difference in the score of two alternatives is minimal, according to a specific criterion, such alternatives can be considered indifferent. Another peculiarity that differentiates ELECTRE III from other methodologies is that this multi-criteria decisional method is not compensative, which means that a very bad score of an alternative with respect to a criterion is not compensated by good scores on other criteria, contrarily for example, to Analytic Hierarchy Process (AHP) decisional method. In other words, the decision maker will not choose an alternative if it is very bad compared to another one, even on a single criterion. In particular, the non compensative characteristic occurs if the difference between the values of the scores of two alternatives is greater than a value, established by a fixed threshold, called veto threshold. Furthermore, ELECTRE III is based upon the outranking relation. The latter states that an alternative outranks another one if sufficient reasons exist to assert that the first is as good as the second one and good reasons to reject such assertion do not exist. Outranking relation is based upon concordance/discordance principle. This principle is founded on the verification of the existence of a concordance of criteria in favour of the assertion that one alternative is as good as another and that a verifiably strong discordance among the scores values that may reject the previous assertion does not exist [26].

In detail the following criteria, able to evaluate the different proposed shelf life models, are considered:

- C_1: percentage error (%);
- C_2: cost (€);
- C_3: response time (sec);
- C_4: consumption (mA);
- C_5: accuracy [1-5];
- C_6: initial quality [1-5].

The first criterion represents the percentage error evaluated between the shelf life value obtained by means of a microbiological analysis and that characterizing the different models. In particular, the microbiological analysis have been carried out basing on the study reported in La Scalia et. al [14] and SL value was calculated by means of equation proposed by Dalgaard [27].

The values of SL models alternative were calculated by applying the equations 3, 6, 9 and 10. Furthermore, the input values of the parameters T, RH, CO_2 and VOC were gathered by the SLU described in section 3.

C_2, C_3 and C_4 represent respectively the cost, the response time and the consumption of the sensor used to implement the related shelf life model. C_5 and C_6 represent respectively the accuracy of the measure system and the initial quality of the analysed sample. The accuracy is defined as the ability of each sensor to correctly acquire a specific parameter (generally this ability is worst in measuring gas concentration) while the initial quality as the capability of the mathematical model to take into account different pre-harvest conditions (i.e. different initial shelf life). The score of the alternatives with respect to these last two criteria has been assigned by a panel of experts using the rating scale [1-5], where 1 is the worst value. Among these criteria, C_1, C_2, C_3, C_4 have to be minimized and thus they are characterized by a decreasing preference versus, while C_5 and C_6 have to be maximized, otherwise their preference versus is increasing.

The relative importance of criteria is evaluated taking into account the judgments of the panel of experts [28] by applying the AHP method [29] In the present case the experts have different priority in the decisional process and specifically equal to 0.3 for the expert 1 and the expert 2, equal to 0.4 for the expert 3. The weighted geometric mean is applied to synthetize the pairwise comparison judgments of experts in a unique matrix (reported in table 2). Furthermore, in table 2 are shown the weights of the criteria obtained on the base of the related pairwise comparisons judgments.

TABLE.2. Pairwise comparison judgments matrix and criteria weights

	C_1	C_2	C_3	C_4	C_5	C_6	Weights
C_1	1.000	1.390	3.031	2.781	1.390	1.000	0.246
C_2	0.719	1.000	2.885	1.911	1.202	0.793	0.193
C_3	0.330	0.347	1.000	0.545	0.379	0.467	0.073
C_4	0.360	0.523	1.835	1.000	0.793	0.644	0.116
C_5	0.719	0.832	2.639	1.260	1.000	0.644	0.161
C_6	1.000	1.260	2.144	1.552	1.552	1.000	0.211

Table 3 shows the evaluation matrix.

TABLE.3. Performance matrix of SL models

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
SL_1	4.28 %	19	1.65	0.012	4	2
SL_2	7.11 %	67	1.5	50	2	5
SL_3	6.91 %	58	15	0.512	4	4
SL_4	5.16 %	31	30	32	3	5

As said before, in order to obtain the ranking of the alternative is herein suggested the ELECTRE III method that needs of different parameters to derive the aforementioned outranking relation.
Among these parameters, the values of three threshold have to be determined according the practice of concrete problems and the risk attitude of the decision-makers [30].
In detail, for each criterion *k* considered, belonging to the set *K* of criteria, the following thresholds have to be set:
q_k indifference threshold;
p_k preference threshold;
v_k veto threshold.
Where $0 < q_k < p_k < v_k \qquad \forall k \in K$
These threshold values can be expressed in terms of percentage of the scores differences assumed by the alternatives [31]. In particular, expression (13) is related to the adopted function to determine the range R_k in which the threshold values have to belong.

$$R_k = \frac{max_{\forall i}(a_{ik}) - min_{\forall i}(a_{ik})}{max_{\forall i}(a_{ik})} \tag{13}$$

where a_{ik} is the score of the alternative *i* with respect to the criterion *k*; moreover, set the value of indifference threshold on the base of the preference of the analyst, the following relations have been established among the three thresholds:

$$p_k = 2 \cdot q_k \; \forall k \in K \tag{14}$$

$$v_k = 3 \cdot q_k \; \forall k \in K \tag{15}$$

in order to obtain the values reported in table 4:

TABLE.4. Thresholds and R_k values

	C_1	C_2	C_3	C_4	C_5	C_6
Indifference (qk)	10 %	20%	25%	30%	15%	15%
Preference (pk)	20 %	40%	50%	60%	30%	30%
Veto (vk)	30 %	60%	75%	90%	45%	45%
R_k	39.80 %	72 %	95 %	100 %	50 %	60 %

With the aim to derive the alternatives ranking, the ELECTRE III implies descending and ascending distillation procedures. Firstly, the descending distillation places the best alternative (characterized by the highest qualification degree) in the first position and the procedure is completed when the worst alternative is allocated in the last position. On the contrary, the ascending distillation assigns the worst alternative to the last position and at the last step allocates the best alternative in the first position. The results of the descending and ascending distillations are shown in figure 3:

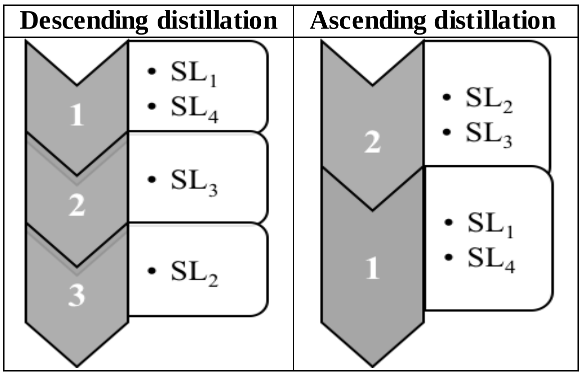

Figure 3: Descending and ascending distillation results

The final ranking is obtained through the combination of the two distillations ant it is reported in figure 4. It is possible to note, as SL1 and SL4 are in the first position in both rankings, thus they are indifferent. SL3 outranks SL2 in descending ranking, while they outrank each other's in the ascending ranking. Thus, SL3 is placed in the second position. Finally, SL2 takes the last position.

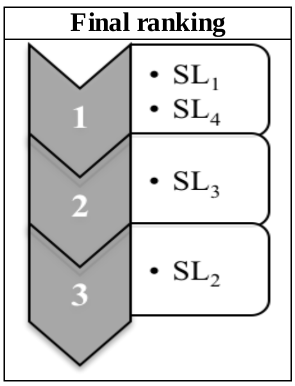

Figure 4: Final ranking

Conclusion

In this paper the application of a technical system that allows monitoring and controlling the supply chain of perishable products, in particular of strawberries, by using tracking and sensing technologies was proposed and different mathematical models, that are able to translate the monitored parameters into valuable information for supply chain management, were compared by means of a multi criteria decision making methodology. In particular, the ELECTRE III technique has been applied and the results show that the models based on temperature and VOCs concentration outrank the other two models considered. This information allows establishing the economically optimal sensor configuration of the SLU. In fact, in a real industrial application each crate should be equipped with sensors able to monitor the SL parameters while the GPS module for real time positioning during transportation and the 3G communication system for remote quality supervision and real time shelf life prediction, will be unique for all the crates inside the truck. It is important to note that different pre-harvest conditions cause a certain amount of uncertainties in the shelf life prediction and for this reason future developments could include the adoption of fuzzy numbers in the multi criteria analysis. The knowledge on the residual shelf life in real time could finally be exploited for developing advanced supply chain strategies based on GPS information.

Acknowledgements

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