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CONTRIBUTION TO THE MODELING AND AUTOMATIC CONTROL OF THE VIRGIN OLIVE OIL ELABORATION PROCESS

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Ph.D. Thesis

Pablo Cano Marchal
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SUMMARY

The VOOEP is a somewhat complex industrial process, with several variables involved and dichotomic production objectives. The quality of the produced oil depends on the characteristics of the incoming olives and on the values of different process variables. Usually, the values of the process variables that promote the quality of the VOO tend to penalize the quantity of the produced oil. Besides, as the harvesting season advances, the maximum potential quality of the oil decreases, so the relevance of the constraints imposed by the objective of obtaining high quality also diminishes.

Bearing this in mind, the first relevant question to be addressed when elaborating VOO, therefore, is to establish a good elaboration objective based on the characteristics of the incoming olives. Once this objective is set, the next stage is to define how to attain it. More precisely, the values of the technological variables that allow to reach that particular production objective should be established. However, more likely than not, the values of the output variables will not be exactly those planned, due to the effect of the small modeling errors and the disturbances affecting the process. Here, the application of feedback is the key to modify the values of the process variables so that the outputs eventually reach the desired objectives.

The challenging problem this thesis contributes to is that of developing a **comprehensive decision support system** to assist the operator of the *almazara* in each of the decisions to be made during the VOOEP:

1. What production objective should be chosen, given the olives to be processed?
2. What set points of the process variables allow to attain that objective?
3. How to modify the set-points to counteract the disturbances and assure the achievement of the objective?
4. When should the harvest the olives be done in order to maximize the season profit?

In this Thesis, fuzzy logic and expert knowledge are employed to model the VOOEP from a global point of view. Then, based on these models, optimization problems are posed and solved to determine the optimal elaboration objective for a given batch of olives, and the optimal set points of the process values that enable achieving the objective.

The application of standard feedback techniques to the higher level of the VOOEP process is difficult, due to the unavailability of reliable online sensors. However, the existence of at-line equipment and approximate values provided by expert operators allow to have some information about the system behavior that could be used to apply some sort of feedback to the process. Even though that the VOOEP is not completely of batch nature, run-to-run control is proposed as a candidate for this end.

Finally, the season-wide production planning is approached by means of the definition of an optimization problem where the available model of the VOOEP is extended with simple models of the evolution of the properties of the olives in the orchards, and some business-related characteristics of the organization carrying the activity are included.

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Pablo Cano Marchal
Jaén, 2014.

A mi familia,
especialmente, a Beatriz.

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Motivation

1.1 Introduction

The production of virgin olive oil (VOO) is an important economic activity carried out in more than 20 countries. The world average VOO production in the period 2008–2013 was 2,843,000 t, which supposes a 1.5% increase over the average of the 2001–2007 period [Council, 2014], and that tendency is expected to continue, as young orchards planted during the last decade continue to increase their productions. This production, valued at the average bulk sale price of the period 2008–2013, 2100 € per ton, renders the production of VOO as a 5970 million per year worldwide activity [Poolred, 2014].

The quality of the VOO is bounded by the quality of the olives to be processed, and further determined by the influence of the process variables during the actual elaboration. Obviously, the amount of VOO produced also depends critically on the characteristics of the incoming olives and the values of the process variables. Quality and quantity represent a trade-off, since the values of the process variables that preserve the quality tend to lessen the amount of VOO produced, and vice versa [Di Giovacchino et al., 2002].

Given this tradeoff between quality and quantity, besides the palpable interest of lower-level control of the different stages of the virgin olive oil

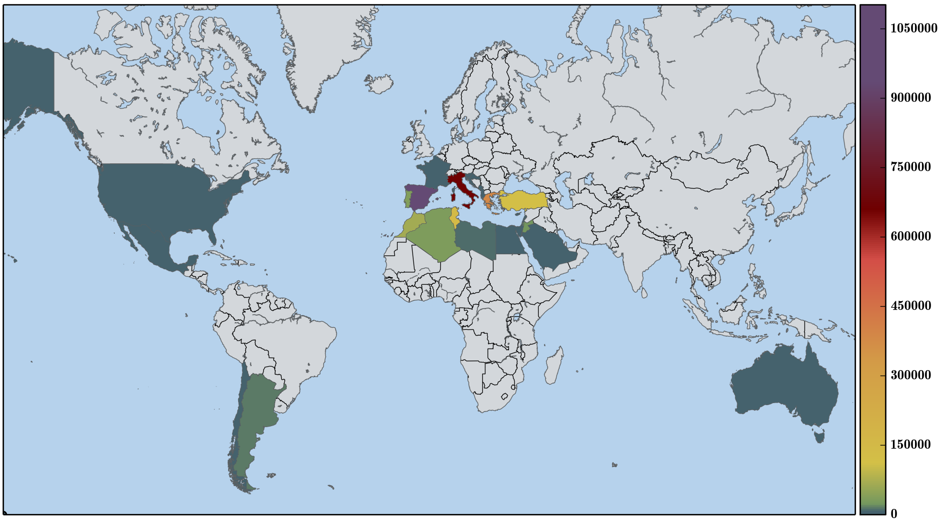


Figure 1.1: Geographical distribution of the average 2008–2013 VOO production in the world.

elaboration process (VOOEP), a higher level layer, concerned with handling the implications of this global relations in the VOOEP, emerges as a promising candidate to contribute to the overall improvement of the process.

The objective of this Chapter is to present some context and the motivation of this Thesis. Next Section presents some data about the relevance of the VOO production, with Sect. D.3 briefly sketching the VOOEP. Sect. D.4 introduces the main ideas and motivation of this Thesis, while Sect. D.5 advances its structure.

1.2 Virgin Olive Oil Production Data

The geographical distribution of the production of VOO can be seen in Fig. D.1 and Table D.1. As depicted there, the main production area is the Mediterranean area, which represents almost the 98% of the total world production. Some production is found in countries outside this area that have regions of Mediterranean climate, such as Argentina, Chile and Australia.

The countries outside the Mediterranean area are increasing very rapidly their production. Chile and Australia tripled their production from the 2001–2007 to the 2008–2013 period. Despite these remarkable rates, the

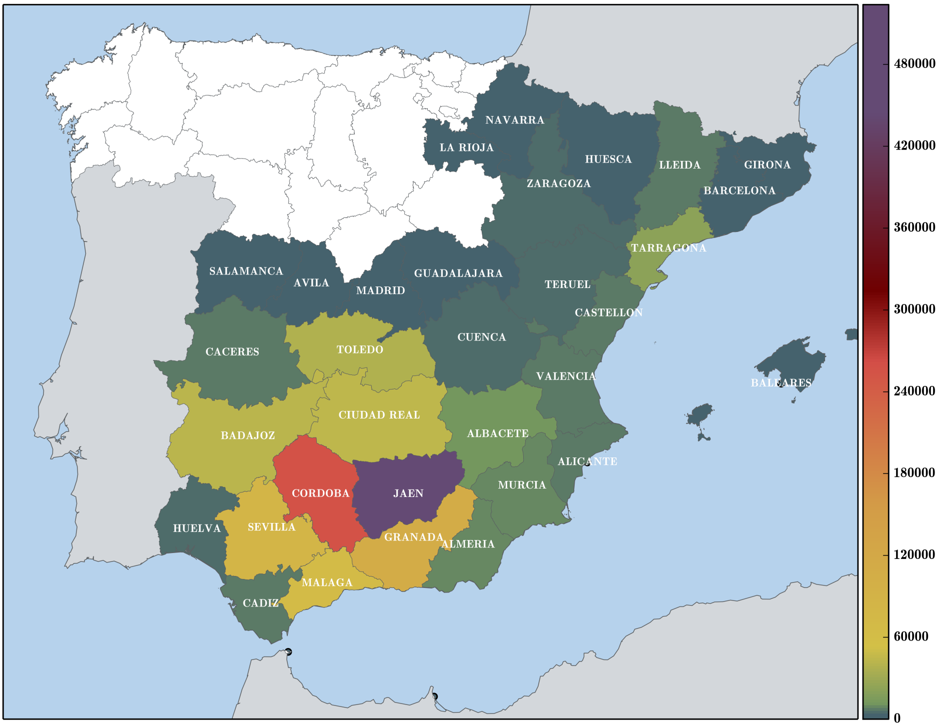


Figure 1.2: Geographical distribution of the average 2008–2013 VOO production in Spain

weight of the VOO production of these countries in the global figures is still small.

Within the Mediterranean region, the European Union is the major VOO producer, representing more than 70% of the total world production. Spain, Italy, Greece and Portugal are, in decreasing order, the four main producers. Outside the European Union, Tunisia, Turkey and Syria are the major actors in the industry.

As emphasized by Fig. D.1 Spain is the largest producer of VOO in the world, representing the 42% of the total production. The geographical distribution of the VOOEP production in Spain in included in Figure D.2, with Table D.2 showing the precise distribution. As depicted in the Figure, the production of VOO extends through the whole country, except for the north-western region.

However, the production is not evenly distributed throughout this area, but presents a few areas with very high production rates. Andalucia and

Table 1.1: VOO Production in World (t).

Country	Avg. Prod. 2001-2007	% 2001-2007	Avg. Prod. 2008-2013	% 2008-2013
Albania	0	0.00	7,300	0.26
Algeria	32,800	1.17	47,400	1.67
Argentina	15,100	0.54	22,700	0.80
Australia	4,800	0.17	14,600	0.51
Chile	5,000	0.18	15,400	0.54
Croatia	4,800	0.17	4,800	0.17
Cyprus	6,800	0.24	0	0.00
Egypt	4,000	0.14	5,800	0.20
France	4,200	0.15	5,300	0.19
Greece	384,900	13.73	317,600	11.17
Iran	3,200	0.11	4,800	0.17
Israel	6,000	0.21	9,200	0.32
Italy	663,500	23.67	455,800	16.03
Jordan	25,800	0.92	20,800	0.73
Lebanon	6,000	0.21	14,800	0.52
Libya	9,800	0.35	14,700	0.52
Mexico	1,900	0.07	0	0.00
Montenegro	500	0.02	500	0.02
Morocco	67,500	2.41	110,000	3.87
Palestine	17,700	0.63	14,900	0.52
Portugal	35,300	1.26	58,400	2.05
Saudi Arabia	0	0.00	3,000	0.11
Slovenia	300	0.01	500	0.02
Spain	1,102,100	39.32	1,215,100	42.74
Syria	132,700	4.73	159,300	5.60
Tunisia	149,500	5.33	167,000	5.87
Turkey	117,700	4.20	149,200	5.25
USA	1,000	0.04	4,300	0.15

Castilla-La Mancha are the major production regions, with Córdoba and, particularly Jaén clearly standing out. The production of Jaén represents around 40% of the Spanish production, leading to its being responsible for almost a fifth of the world VOO production.

With more than 300 olive oil factories in Jaén, the olive oil industry is a major economic activity in the region, being *the* major activity in its rural area. With 55% of its 664.916 inhabitants living in municipalities of less than 20000 residents, the importance of the virgin olive oil elaboration process (VOOEP) in the economy of Jaén is indisputable [{Instituto Nacional de Estadística}, 2014]. Considering the average 2100 € per ton price, the VOO production of Jaén equals a yearly average amount of 1100 million €.

Table 1.2: VOO Production in Spain (t).

Region	Avg. Prod. 2001-2007	% 2001-2007	Avg. Prod. 2008-2013	% 2008-2013
Albacete	6,725	0.61	10,281	0.79
Alicante	7,618	0.69	7,891	0.61
Almeria	6,976	0.63	9,464	0.73
Avila	1,003	0.09	1,053	0.08
Badajoz	34,268	3.11	41,134	3.17
Baleares	199	0.02	430	0.03
Barcelona	586	0.05	800	0.06
Caceres	9,283	0.84	7,687	0.59
Cadiz	6,240	0.57	7,632	0.59
Castellon	7,950	0.72	7,837	0.60
Ciudad real	27,807	2.52	44,371	3.42
Cordoba	222,386	20.16	256,342	19.78
Cuenca	5,799	0.53	5,165	0.40
Girona	726	0.07	811	0.06
Granada	83,635	7.58	108,576	8.38
Guadalajara	2,021	0.18	1,943	0.15
Huelva	4,321	0.39	5,503	0.42
Huesca	1,786	0.16	1,840	0.14
Jaen	465,844	42.23	523,818	40.42
La rioja	699	0.06	1,288	0.10
Lleida	5,880	0.53	8,097	0.62
Madrid	3,457	0.31	3,850	0.30
Malaga	56,358	5.11	65,926	5.09
Murcia	6,205	0.56	8,597	0.66
Navarra	2,250	0.20	3,642	0.28
Salamanca	265	0.02	208	0.02
Sevilla	65,704	5.96	85,329	6.58
Tarragona	22,329	2.02	22,104	1.71
Teruel	5,442	0.49	4,270	0.33
Toledo	27,078	2.45	38,175	2.95
Valencia	7,747	0.70	7,125	0.55
Zaragoza	4,526	0.41	4,755	0.37

1.3 Brief Description of the Virgin Olive Oil Elaboration Process

The VOOEP begins with the reception of the olives in the factory. These olives are washed in order to remove the dust, small pebbles and leaves that arrive with them. After this preliminary stage, the olives are stored in hoppers and fed into the mill, where they are crushed to form the olive

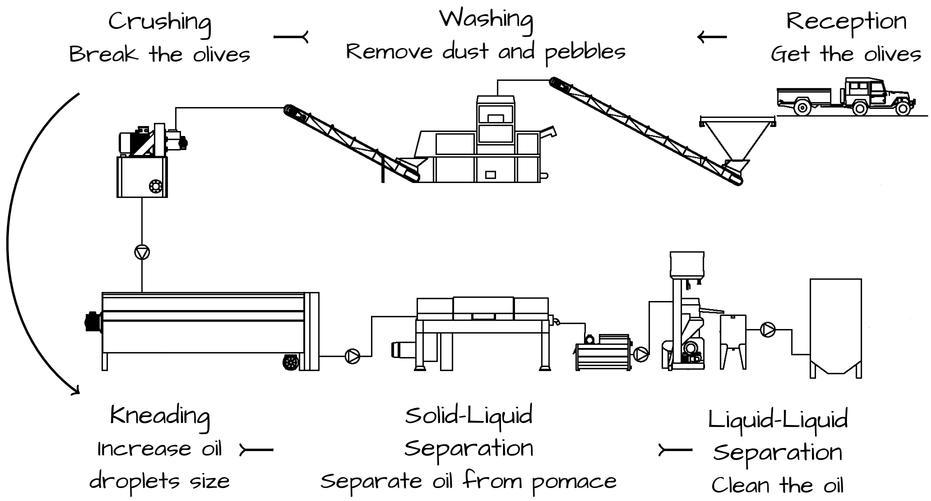


Figure 1.3: Virgin Olive Oil Elaboration Process Diagram

paste. This paste in this state would allow poor separation of the oil, so it is pumped into a thermomixer to be slowly stirred and heated in order to better its conditions for the oil separation. This separation is carried out in a decanter, and yields olive oil and pomace as by-product. The humidity and impurity content of this oil is still undesirably high, so further separation in a vertical centrifuge or a settling tank is performed. After this operation, the oil might be filtered or directly pumped to its final tank to be stored. Fig. D.4 shows a picture of a typical factory and Fig. D.3 shows a block diagram of the process.

This elaboration process may be divided into three major operations: the paste preparation, the effective separation of the oil from the rest of the components of the paste and the further humidity and impurities removal. The paste preparation involves the storage of the olives, the crushing, and the stirring and heating performed in the thermomixer. The effective separation includes the operation held in the solid-bowl centrifuge, and the humidity and impurity removal is constituted by the remaining operations.

The two major global output variables of the process are the quality of the obtained oil (q) and the yield (y). These two variables have an upper bound imposed by the properties of the olives to be processed, and the actual value obtained is influenced by different variables of the process. The paste preparation greatly determines the quality of the obtained oil, and imposes an upper bound on the achievable yield. In turn, the separation

Figure 1.4: Picture of a virgin olive oil elaboration factory.

phase affects the obtained yield, achieving sub-optimal yields if the process is not carried out properly. The humidity and impurities removal has minor influence in both quality and obtained yield [Civantos, 1998a].

The following Subsections detail a little further each stage of the process and highlight the relevant process variables and their interplay.

1.3.1 Definition of Virgin Olive Oil Quality

Virgin Olive Oil is the oil obtained from the olives using exclusively mechanical means for its extraction [Vilar, 2013]. That is, no chemical extraction nor refining processes are carried in its production. Consequently, VOO is actually olive juice.

The Collins dictionary defines *quality* as *a distinguishing characteristic, property, or attribute* [Dictionaries, 2012]. There are several different characteristics relevant to the VOO and some clarification is in order.

The first notion of quality of a VOO is that of its regulated technical quality. The classical technical characteristics, along with their values for

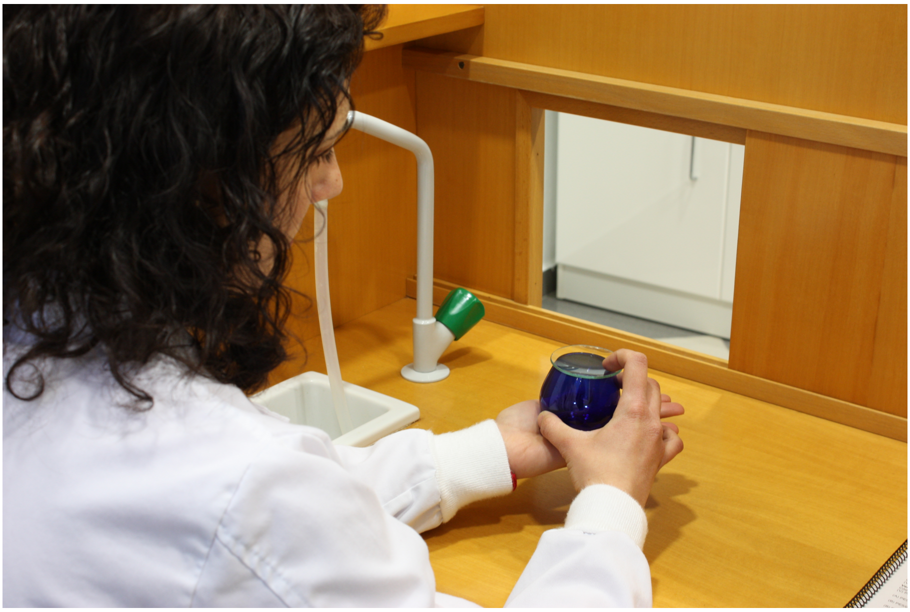


Figure 1.5: Taster performing an organoleptic evaluation of a VOO.

each of the three grades of virgin olive oil quality –extra virgin olive oil, virgin olive oil and *lampante* olive oil–, can be found in the European Norm 2568/91. The parameters included here can be classified into two major groups: physico-chemical and organoleptic. Physico-chemical parameters are determined by chemical means, while the evaluation of organoleptic characteristics is performed by a panel of expert tasters. Figure D.5 shows a taster performing an organoleptic evaluation of a VOO.

The physico-chemical parameters can be further classified into quality-oriented and purity-oriented parameters. Quality-oriented parameters are mainly intended for the classification of the oils in the different qualities, while the main purpose of purity parameters is to avoid the fraud of mixing the relatively expensive VOO with cheaper vegetable oils. Examples of quality-oriented parameters are acidity, peroxide index and K270, while wax content and sterols content are examples of purity-oriented parameters.

Organoleptic parameters are divided into positive and negative attributes, the latter also known as *defects*. There are only three positive attributes: fruity, bitter and pungent. They are said to be positive attributes because they are expected to appear in VOOs properly elaborated from healthy fruits [Civantos, 1998a]. In turn, there are many more negative attributes, being the most common *fusty, mustiness–humidity* and *rancid*. Negative attributes arise whenever the fruit is not in perfect conditions or the elaboration process has not been carried out with enough care. Depending of the flaw of the process or the olives, one defect or another arises.

A group of characteristics of the VOO whose relevance in the industry is increasing lately, are those related to the healthy properties of the VOO. Polyphenols, tocopherols and other minority components of VOO have been found to be responsible for many of the beneficial effects of VOO in human health [Covas et al., 2006], so high concentrations of these components represent a desired feature in produced VOOs. However, the values of these parameters are not considered for the classification of the VOO into the different commercial qualities.

A subtle distinction could be made between *technical quality* and *consumer-oriented quality*, since desirable characteristics from a technical point of view may not always align with consumer preferences [Delgado and Guinard, 2011, Predieri et al., 2013] and characteristics valued by the consumer might not be a technical quality requirement. A prototypical example is the average consumer reaction to high values of the organoleptic attributes *bitter* and *pungent*. From a technical point of view, they are classified as positive attributes, but research on the topic [Delgado and Guinard, 2011] and some personal experience suggest that consumers do not always find them attractive features in a VOO. Another example is the color of the VOO: it is not a regulated quality parameter, but consumers do show different attitudes and preferences depending on it.

As deduced from the above paragraphs, several parameters could be regarded when generically referring to VOO *quality*. For Picual cultivar, which is the main cultivar in Andalucia, the most limiting factors in the quality of a VOO are the organoleptic ones. Consequently, whenever an unspecified reference is made to the *quality* of the VOO, we are referring to its organoleptic characteristics, and mainly the fruity attribute. Whenever we wish to address any other of the quality parameters, we will explicitly state them.

Lastly, as a side note, it could be mentioned that *Virgin* and *Extra Virgin Olive Oil* are not the only types of olive oil that a consumer might buy in a store. Olive oil, without any accompanying adjectives, is also available in the market. Olive oil is a blend of virgin or extra virgin olive oil with *refined olive oil*. Refined olive oil is *lampante* olive oil, the lowest quality of VOO, that has undergone a chemical refining process in order to remove the undesirable odors and flavors that it contains.

Figure 1.6: Olives in different ripeness stages.

1.3.2 Olive Properties and their Evolution in the Orchards

Although the VOOEP itself can be considered to begin with the reception in the *almazara* of the olives, the characteristics of these olives play such a fundamental role in the process that the definition of which are those properties, along with some regard to their evolution in the orchards is mandatory.

The ripeness is the characteristic that indicates the stage of development of the fruit. The ripeness evolution of the olives begins once the fruit has developed its final size, typically 25 weeks after the blooming. This stadium is known as *green stage*, since the fruit presents green color. As the season advances, chlorophyll pigments in the skin are replaced by anthocyanines [Beltrán et al., 2004], which makes visible the evolution of the ripeness of the fruit through its color change. The fruit sequentially passes through the *spotted stage*, the *purple stage* and finally reaches the *black stage* [Beltrán et al., 2004]. Although some other methods to assess the ripeness of olives have been proposed in the literature [Mickelbart and James, 2003, Garcia and Yousfi, 2005, Cherubini et al., 2009], the main method used is the color index method [Hermoso et al., 1997]. Figure D.6 shows olives in different ripeness stages.

The ripeness of the olives is a major parameter in the determination of the quality of the olives and the influence of this parameter on different aspects of the quality of the obtained oil has been studied in several works [García et al., 1996b, Gutiérrez et al., 1999, Salvador et al., 2001, Jiménez Herrera et al., 2012].

The acidity index increases with the maturity, while the total polyphenol and pigment contents decreases [García et al., 1996b, Gutiérrez et al., 1999, Salvador et al., 2001, Jiménez Herrera et al., 2012]. Furthermore, the firmness of the olives decreases as the ripening advances, which facilitates the mechanical damage and pathogenic infection of the olives, and thus favours the decrease in the overall quality of the olives [García et al., 1996b]. This deterioration of the quality usually results in the increase of the acidity index and the appearance of organoleptic defects.

Regarding the organoleptic parameters, the fruity attribute reaches it maximum during the early stages of the ripening process, and remains practically flat until a ripeness index of around 3.5, when a decline in the observed values start to appear. There are minor variations between cultivars, but the behavior is roughly equivalent [Jiménez Herrera et al., 2012]. Bitter and pungent attributes decrease with the ripeness index, which is coherent with the well known good correlation between these parameters and the total polyphenols content [Gutiérrez et al., 1999].

The evolution of the oil content expressed as percentage in dry weight is reported to be quite flat once that the fruit has reached a ripeness index of around 3.5 [García et al., 1996b, Beltrán et al., 2004]. Other works, however, present a continuous increase until a higher index is attained [Gutiérrez et al., 1999, Salvador et al., 2001]. In any case, the oil content expressed as percentage of fruit weight do increases along the maturity stages, due to the loss of humidity that takes place [Beltrán et al., 2004].

Finally, it is worth noting that the retention force of the olives decreases as they ripen, so as the season advances, higher amounts of olives can be found on the ground [García et al., 1996a]. These fallen olives are subject to processes that degrade their quality, suffering an increase in the acidity index and the appearance organoleptic defects [García and Yousfi, 2007].

1.3.3 Harvesting and Reception

As a general principle, the longer the time elapsed between the olive leaving the tree branch and its being processed, the worse the expected quality of the obtained VOO [García and Yousfi, 2007]. The deterioration rate is increased if the fruit skin is broken, which is promoted by two factors:

- Low firmness of the fruit, due to its being in an advaced ripeness state,
- The transportation and storage of the olives in large containers, which imply high pressure on the olives in the bottom.

The harvesting methods can be classified in two major groups:

- Methods that separate olives coming from the tree from olives already in the ground, and
- Methods that mix olives coming from the tree and the ground.

As commented in the previous Subsection, olives that have fallen to the ground present poor quality characteristics, due to the chemical reactions that begin to take place [García and Yousfi, 2007]. Therefore, methods that mix olives cause a decrease of the potential quality that could be obtained if only olives coming from the tree were to be harvested. However, these methods tend to offer lower costs, since they require lower manual labor [Vilar Hernandez et al., 2010].

Although different non-mixing harvesting methods have been reported to show different effects on the quality of the obtained VOO [Yousfi et al., 2012], the effect of mixing or separating the different types of olives is far greater.

Once the olives arrive to the factory, the leaves and small sticks are removed by means of forced air currents in a so-called *cleaning machine*, while the dirt and pebbles are removed using water in the so-called *washing machine*.

Leaving some leaves to be processed with the olives is reported to provide greener color to the elaborated VOOs, however it does no influence the total polyphenol content [Di Giovacchino et al., 2002].

Traditionally, due to the low processing capacity of the factories relative to the income of fruits, olives have been stored for long periods of time, even months, in huge piles. García, quite graphically, states "*Traditionally, olives have been treated from the moment of harvesting until their processing with the same sensitivity that construction material such as sand or gravel might receive*" [García and Yousfi, 2007].

Nowadays, olives are no longer stored in piles, but are fed into hoppers, typically of around 50000 kg. of capacity. Besides, the processing capacity of modern *almazaras* renders it unusual having to store olives due to lack of processing capacity. Still, the time that the olives are stored in the hoppers is an important parameter in the VOOEP.

During the storage, olives lose moisture along with firmness, since degradation processes take place. This effect is negative for the quality of the olive oil, since acidity is incremented, fruity intensity is decreased and organoleptic defects may arise [Vichi et al., 2009,Clodoveo et al., 2007]. However, the extractability of the olives increases with the storage time [Uceda and Hermoso, 1997]. This behavior makes storage time an interesting parameter to be taken into account in the trade-off between quality and quantity.

1.3.4 Crushing

The objective of crushing is breaking the olive cells and freeing the oil. There are different types of mills used in the industry, however, the metallic hammer mill is, by far, the most used nowadays in Spain.

The main parameters that determine the performance of the milling operation for this type of mill are the geometry and hole size of the sieve and the rotational speed of the mill.

Variations in the milling conditions are reported not to affect acidity, peroxide index, K and fatty acids composition. However, smaller sieve sizes and higher speeds tend to accentuate the temperature increase experimented by the olive paste, as well as to increase the total polyphenol content [Di Giovacchino et al., 2002, Inarejos-García et al., 2011]. In line with the good correlation between polyphenol content and bitter attribute, this organoleptic parameter also increases in these conditions. The drawback is the decrease in the content of volatile compounds in the oil.

The sieve size and the firmness of the fruit determine the average size of the particles that constitute the olive paste, along with the degree of breakage of the cells. This parameter exerts direct influence in the industrial yield obtained, and it is important to select a good value for it. Smaller sieve sizes and less firm olives tend to provoke a high degree of breakage of the cells, contributing to obtain better yield. However, smaller sieve sizes require higher power consumption for the process, and contribute to the formation of emulsions if the moisture content of the olives is high.

The humidity of the olives plays an important role during the milling process. Very low humidity levels may cause a decrease in the processing capacity of the mill, and may eventually lead to its blocking. High levels of humidity provoke the formation of emulsions [Civantos, 1998a], which strongly provoke a decrease in the obtained yield if not corrected during the paste preparation in the thermomixer.

1.3.5 Kneading

The objective of the kneading process is to increase the size of the oil droplets and to break the emulsions that might have taken place in the milling, in order to facilitate the separation of the oil from the rest of constituents of the paste inside the decanter.

This operation is of key importance both for the obtained yield and the quality of the VOO. The bioprocesses that take place in this stadium of the process greatly influences the final quality of the oil. Two main effects influence this operation: the partition phenomena of components between oil and water, and the catalytic activity of the enzymes released during the crushing stage [Clodoveo, 2012].

The main technological variables in the kneading stadium are the temperature of the paste, the duration of the process and the addition of coadjuvants.

The usual temperature range in the VOOEP is between 25 °C and 40 °C. Higher temperatures tend to increase the obtained yield, while decreasing the content of volatile compounds [Inarejos-García et al., 2009]. Contradictory results exists on the sign of the influence of the temperature in the total polyphenol content and bitter and pungent attributes [Clodoveo, 2012]. For some cultivars, acidity, peroxide index and K increase when temperature rises from 30 to 35 °C [Ranalli et al., 2001], however, for some other cultivars the influence of temperature in the rest of quality characteristics is reported to be negligible, but for some tendency of high temperatures of increasing the values of purity-related parameters [Clodoveo, 2012].

Malaxion time typically ranges from 45 to 120 minutes. Higher malaxation time favors the increase of the industrial yield, but showing some saturation effect around 75 minutes or even a slight decrease in the yield [Ranalli et al., 2003]. Higher kneading times are reported to increase the volatile compound content, for both positive and negative attributes, and to reduce the polyphenol content [Inarejos-García et al., 2009, Ranalli et al., 2003]. However, other works report that the malaxation time does not significatively modify the organoleptic assessment of an oil [Di Giovacchino et al., 2002].

The addition of microtalc as coadjuvant is very useful in the breakage of emulsions, while it is reported not to affect the quality of the VOO [Cert et al., 1996]. The addition rate depends on the degree of emulsions in the paste, and the particle size of the product, with nominal addition values of around 0.5% for smaller size microtalcs, and 1% for bigger ones. The use of calcium carbonate as a coadjuvant has also been investigated and reported to offer good results [Moya et al., 2010], however, currently its use for the production of VOO is not accepted by the European normative, as there is some dispute wether there is or not some chemical activity of the substance on the oil.

When the moisture of the paste is low, it is common practice to add small amounts of water to compensate it, since the malaxation of very dry pastes is less effective than for those with an near optimal moisture content. Besides, the resistance opposed by the paste is also higher when the moisture is low, resulting in higher power consumption of the factory.

Finally, the atmosphere in contact with the paste is also reported to exert influence in the final quality of the produced oil. The use of nitrogen increases the phenolic compounds concentration and provokes an improvement on the organoleptic characteristics of the oil [Clodoveo, 2012]. However, this research is fairly recent, and quite some time is expected before this parameter is routinely considered in the industry.

1.3.6 Oil separation

The solid-liquid separation process held in the decanter is very important in the achieved yield, but does not play a major role in the quality of the obtained VOO [Civantos, 1998a].

Several factors influence the performance of the separation process, being the *kneading state* of the paste one of the most important ones. The kneading state refers to the way the olive paste has been prepared in the thermomixer for the separation. It comprises aspects such as having a good distribution of the oil drop sizes, not having emulsions and having a good moisture content.

If emulsions still remain in the paste after the kneading phase, there is not much else to be done to counteract its negative contribution to the obtained yield, besides from slightly reducing the input flow of paste into the decanter [Civantos, 1998a].

This input flow of paste into the decanter is a parameter that influences the operation in the decanter, since it determines the residence time of the paste inside the machine, and thus the available time for the oil drops to separate from the pomace.

The theoretical settling velocity of a sphere in a fluid where only centrifugal forces are acting, supposing a sufficiently small sphere diameter and laminar flow, is given by Stoke's Law:

$$v_c = \frac{D^2\omega^2 r(\rho_2 - \rho_1)}{18\mu}, \tag{1.1}$$

where:

- D: Diameter of sphere.
- ω: Rotational velocity.
- r: Distance of the sphere from the rotation axis.
- ρ_1 and ρ_2: Densities of the liquid and the sphere.
- μ: viscosity of the liquid.

This equation includes most of the parameters that influence the operation:

- Viscosity: lower values of the viscosity of both water and oil allow for higher settling velocities inside the decanter, and thus theoretically favoring higher yields for a given settling time.
- Drop sizes: bigger drops show bigger settling velocities, thus favoring the yield.
- Rotational speed: the rotational speed increases the force exerted on the drops, thus increasing the settling velocity and the yield.

A very important parameter in the separation process is the relative position of the theoretical inter-phase between oil and water and the outcome weirs of the decanter. This parameter influences the yield and the cleanness of the oil. The position of the inter-phase is determined by the paste composition, the input flow, and the screw-bowl differential velocity [Leung, 1998].

Having an inter-phase position substantially farther to the rotation axis of the machine that the weirs, supposes having very clean oil, but lower yields. A theoretical inter-phase position closer to the axis supposes obtaining the oil with higher amount of water, but achieving better yields. The theoretical optimum position of the inter-phase is that matching the weirs.

The liquid-liquid separation process can be held in a vertical centrifuge or in settling tanks. Parameters that influence the operation in the vertical centrifuge are the temperature of the addition water, which should be slightly higher than that of the oil in order not to harm the oil quality and avoid oil losses. The frequency of accumulated solid discharge is also important for the operation of the machine, to avoid harming the quality of the oil by not removing efficiently its impurities.

The main process parameters for the separation in settling tanks are the residence time in the tank and the frequency of impurities removal. Both parameters should be adjusted to allow sufficient removal of impurities, while assuring not harming the oil quality due to its being in contact with the moisture and solids.

1.4 Thesis Motivation

As highlighted by the previous Section, the VOOEP is a somewhat complex industrial process, with several variables involved and dichotomic production objectives [Civantos, 1998a]. The quality of the produced oil depends on the characteristics of the incoming olives and on the values of different process variables. Usually, the values of the process variables that promote the quality of the VOO tend to penalize the quantity of the produced oil. Besides, as the harvesting season advances, the maximum potential quality of the oil decreases, so the relevance of the constraints imposed by the objective of obtaining high quality also diminishes.

Bearing this in mind, the first relevant question to be addressed when elaborating VOO, therefore, is to establish a good elaboration objective based on the characteristics of the incoming olives. Two subsequent problems arise from this issue: determining which objectives are achievable given the batch to be processed, and which of those are considered *good*.

Once we have already defined what we intend to obtain, the next stage is to define how to attain it. More precisely, the values of the technological variables that allow to reach that particular production objective should be established. This, again, can be decomposed into finding the set of values that grant the fulfillment of the objective, and selecting those *good* out of them.

At this point, we would already know what we intend to produce, and even the values of the technological variables that would drive us to accomplish our mission. However, more likely than not, the values of the output variables will not be exactly those planned, due to the effect of the small modeling errors and the disturbances affecting the process. Here, the application of feedback is the key to modify the values of the process variables so that the outputs eventually reach the desired objectives.

Given a batch of olives in the reception yard of the *almazara*, we would know what to produce, how to produce it, and how to modify the values of the input variables so that we would *actually* produce it. But there is *one more thing* that could be said about the VOOEP: once a batch of olives has arrived to the factory, an upper bound on the quality has already been set by the decision of when those olives were harvested [Gutiérrez et al., 1999, Jimenez Herrera et al., 2012]. Since the quality of the olives evolves during the harvesting season, a pertinent question would be to consider when to harvest the olives in order to maximize the profit over the whole season.

Currently, the decision of when to harvest the olives is made by the owners of the olive groves, with the owners of the *almazaras* only influencing the decision indirectly with the prices paid for the different qualities of the olives.

The decisions to be made once the olives are in the factory, are usually made by the *maestro*, the chief operator of the factory, based on his experience.

The production objective is basically set attending the aspect of the olives, the ratio between installed processing capacity and income flow of olives, and maybe some directive from the management of the company regarding which production objective should be aimed at, specially during the early stages of the harvest season.

The selection of the set points of the process variables, along with their updates in case of mismatches between set objectives and obtained values, is entirely done by the *maestro* based on his experience.

In every case, the current decision-making process is mainly manual and relying on the expertise of one or several expert operators.

The challenging problem this thesis contributes to is that of developing a **comprehensive decision support system** to assist the operator of the *almazara* in each of the decisions to be made during the VOOEP:

1. What production objective should be chosen, given the olives to be processed?
2. What set points of the process variables allow to attain that objective?
3. How to modify the set-points to counteract the disturbances and assure the achievement of the objective?
4. When should the harvest the olives be done in order to maximize the season profit?

Although this last question is not for the operator of the factory to be answered, it is a relevant question in the overall picture of the VOOEP, since the harvesting decision conditions the rest of the process, and a holistic approach to be problem would not be complete without addressing the question.

As almost any other industrial process, the complete VOOEP system can be broken into two layers of dynamics:

- Higher-level dynamics: this layer deals with the relations existing between the variables of the system that are likely to be included in the production objective, and the set points of the technological variables relevant to the process.
- Lower-level dynamics: this layer deals with the dynamics governing the transformation from set point to actual value of the process variables that are not explicitly considered as a global outputs of the VOOEP system.

As an example, we may consider the paste temperature in the thermomixer and the fruity attribute of the obtained oil. Having a desired paste temperature is not a global objective of the VOOEP, but is required to having some selected value of fruity. Besides, the paste temperature is not a directly manipulable variable, but requires to select the values of valve openness and heating water temperature that allow for it to have the desired value. Here, the lower level system is that relating the valve aperture and heating water temperature with the paste temperature, while the relations between

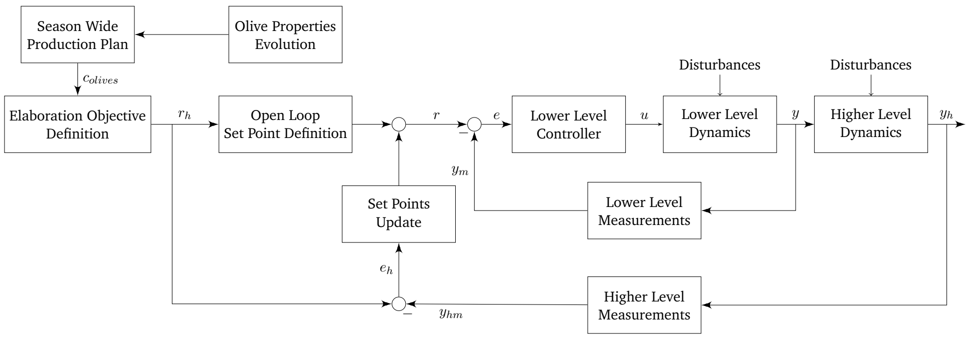


Figure 1.7: Block diagram of the VOOEP Global Control Approach.

paste temperature (assuming it is already guaranteed to obtain that value) and fruity constitute the higher-level dynamics.

Figure D.7 shows a conceptual block diagram for the global control of the VOOEP. In this scheme, the control of the lower-level layer can be addressed using standard or somewhat sophisticated feedback techniques, and, although there is some room for improvement, this problem can be regarded as essentially solved.

However, assuring that the technological variables of the process reach their defined set points despite the existence of disturbances, does not answer the posed questions. The higher-level dynamics play an obvious fundamental role when aiming to treat the problem globally, and thus must be considered and included in the system.

An important caveat is that, currently, there are no reliable sensors capable of providing accurate on-line measurements of the output variables of interest for the VOOEP. This fact, besides highlighting the necessity of the development of these sensors, renders it unfeasible to use standard system identification and feedback techniques to tackle this layer of the system. However, some at-line sensors exists, and experts operators may estimate the values of some of the variables based on their experience and visual inspection or directly by tasting the produced VOO, so some information of the process is available, although with a very limited sampling rate.

Under these circumstances, the usage of fuzzy logic and expert knowledge emerge like natural candidates to construct the required models of the higher layer of the VOOEP. In particular, Fuzzy Cognitive Maps [Kosko, 1986] are the formalism chosen for the modeling of the system.

Then, based on these models, optimization problems are posed and solved to determine the optimal elaboration objective for a given batch of olives, and the optimal set points of the process values that enable achieving the objective.

As discussed above, the application of standard feedback techniques to the higher level of the VOOEP process is difficult, due to the unavailability of reliable on-line sensors. However, the existence of at-line equipment and approximate values provided by expert operators allow to have some information about the system behavior that could be used to apply some sort of feedback to the process. Even though that the VOOEP is not completely of batch nature, run-to-run control is proposed as a candidate for this end.

Finally, the season-wide production planning is approached by means of the definition of an optimization problem where the available model of the VOOEP is extended with simple models of the evolution of the properties of the olives in the orchards, and some business-related characteristics of the organization carrying the activity are included.

1.5 Thesis Overview

This Thesis is organized as follows: Chapter 2 presents the state of the art of automatic control applied to the VOOEP, along with the results of a survey conducted to obtain a picture of the adoption of the already available control and automation technologies in the Spanish VOOEP industry. Brief reviews of the different techniques used in this Thesis are also included in this Chapter.

Chapter 3 deals with the modeling of the VOOEP. First, the selected model structure is discussed, along with the specific choices and details regarding the construction of the models. Then, the particular models are introduced, along with some comments and graphs of their outputs.

Chapter 4 focuses on the formulation and solution of the optimization problems to determine the optimal elaboration objective and the optimal set points of the process values that enable achieving the objective. The different problems considered are presented and the solutions provided to different particular VOOEP scenarios are discussed.

Chapter 5 treats the application of run-to-run control to include feedback in the higher-level layer of the VOOEP. The approach, based on the linearization of the previously fuzzy models, is presented and its application to different VOOEP scenarios is explored.

Chapter 6 considers the season-wide production planning of the VOOEP. Here, the required additional models are presented, along with the relevant business considerations. Then, the optimization problem is formulated and its provided solutions are presented for different scenarios.

Finally, Chapter F introduces the conclusions of this Thesis, summarizes the contributions and hints the future research lines.

2

STATE OF THE ART

This Chapter presents the state of the art, both from an academic and an industrial point of view. First, the main contributions in the literature on the application of automatic control techniques to the VOOEP are presented in Section 2.1, covering the contributed modeling approaches in Section 2.2. Then, a brief review of applications of expert systems to the agroindustry is presented in Section 2.3. Some notes on the evolution of the VOOEP in Spain are presented in Section 2.3, with the results of a survey conducted to study the degree of automation of the Spanish *almazaras* included in Section 2.5.

2.1 Automatic control techniques applied to the VOOEP

The works dealing with the application of automatic control techniques to the VOOEP can be classified into those dealing with the lower level loops, and those addressing the problem from a higher level perspective.

Regarding the control of the lower level layer of the different elaboration stages, the main contribution has been the controller proposed by Bordons and Cueli for the temperature of the paste in the thermomixer [Bordons and Cueli, 2004]. In this paper, a nonlinear model of the thermomixer is derived based on first principles of the physics of the system. The parameters of the model are identified minimizing the Root Mean Square of the errors

[Ljung, 1999] and the model is validated using fresh experimental data from a real plant. Then, a linear model is identified based on data obtained simulating the outcome of the nonlinear model when a step input is applied. An important feature of the system is the high delay in the temperature dynamics, and the relatively fast dynamics of the disturbances that affect this variable. In this scenario, a Model Predictive Control (MPC) [Camacho and Bordons, 2004] controller is designed including an auto-regressive model of the disturbances, given their predictable behavior. Finally, the obtained results are compared to those achieved using a PID controller and the attained improvement is highlighted.

Another paper that explicitly deals with the control of the lower layer of the VOOEP is a recent work by Altieri et al. [Altieri et al., 2013]. In this study, the control related part is the implementation of a low-level PID controller for the paste flow to the decanter, which the authors use to perform a series of test to characterize the relations between the solid-liquid separation process parameters and the obtained recovery efficiency.

The major contributions to the higher level control of the VOOEP can be found in a series of papers by Bordons and co-author [Scheffer-Dutra et al., 2002, Nunez-Reyes et al., 2002, Bordons and Núñez-Reyes, 2008], where the multiobjective aspect of the VOOEP is reflected.

In [Scheffer-Dutra et al., 2002], the authors propose a MPC controller with multiobjective prioritization for four performance criteria:

- keeping the thermomixer temperature as close to the reference as possible,
- maximizing the extracted oil,
- maintaining the paste flow into the decanter as close as possible to the reference set by the operator, and
- reducing the addition water flow.

The models used were of first-order-plus-dead-time (FOPDT) type, identified from experimental data. The multi-objective control was implemented employing a method that allows to prioritize the objectives to be fulfilled by the inclusion of prioritization constraints to the MPC formulation [Tyler and Morari, 1999]. The simulation results obtained were compared to those obtained using a Generalized Predictive Controller (GPC) with weighted objectives. The results were addressed satisfactory, with the biggest caveat being a somewhat abrupt response of the MPC controller. In turn, the main difficulty for the GPC approach was the lack of a systematic method to choose the weights of the objective function, having to resort to an heuristic ad-hoc method for their selection.

In [Nunez-Reyes et al., 2002], the same performance criteria are considered, and three approaches of accommodating the multi-objective nature were investigated:

- The first approach used a weighted combination of the squared difference of the desired and actual values of each variable considered in the criteria, plus a term penalizing the change in the control input.
- The second approach is the controller presented in the previously mentioned paper [Scheffer-Dutra et al., 2002].
- The third approach employs a decision list based in a set of if-then statements to select the current objective function that must be supplied to the MPC. The different objective functions had the same structure as the one employed in the first approach, with different weights for each of the functions.

The conclusions drew from the conducted simulations stated that the first alternative fulfills lower number of objectives than the other two approaches, with the difficulty of tuning the weights of the cost function as another disadvantage to be added to this controller. The main advantage found was the lack of need of additional software for its development.

The second approach offered the highest number of satisfied objectives without the need of tuning the weights. However, the requirement of using additional and complex software for its implementation was highlighted as a strong disadvantage.

The last option was considered as an intermediate approach, with the major disadvantage being some abrupt behavior in the switching between different objective functions.

Finally, a posterior paper by Bordons and Núñez-Reyes proposed a MPC controller focused on the global control of the plant with the objective of maximizing the industrial yield [Bordons and Núñez-Reyes, 2008] to provide the set points for lower-level PID controllers. The manipulated variables were the temperature of the heating water of the thermomixer and the paste and water addition flow rates into the decanter, while the output variable is the olive oil outflow from the decanter. Some of the multi-objectives concerns exposed in their previous papers were solved introducing constraints for the values of the process variables. Particularly, the consideration of the quality of the incoming oil in the system was introduced by means of constraints on the temperature of the paste in the thermomixer. The models used were FOPDT type directly identified on the plant, and the results obtained from tests carried out in a real plant showed an increase in the extraction performance.

2.2 Process models

To our best knowledge, the only dynamic models of the VOOEP proposed in the literature are those included in the already mentioned papers on VOOEP control by Bordons and coauthors [Bordons and Cueli, 2004, Nunez-Reyes et al., 2002, Scheffer-Dutra et al., 2002]. Studies relating the influence of different parameters of the process on several quality characteristics of the VOO are far more frequent. However, most of these studies usually aim at determining the existence and degree of influence of the effects, and are not usually claimed to be useful for prediction or simulation of the process. As already addressed, there are quite a few variables that influence the VOOEP, and these studies usually focus on a reduced number of them, making it difficult to employ these models for prediction, although they are very useful to qualitatively assess the influence of the variables studied. Examples of these works can be seen in the review about the influence of the process parameters in the malaxation stage by Clodoveo [Clodoveo, 2012] and the review addressing the whole process by di Giovacchino [Giovacchino et al., 2002]. Other references can be found in Section D.3, where a brief description of the VOOEP was presented.

On the other hand, some works explicitly aim at providing models susceptible of being used for prediction of the properties of the oil. A commonly used technique to construct these models is the Response Surface Methodology [Box and Wilson, 1951]. Espínola and coauthors [Espínola et al., 2011] investigate the influence on the yield and several VOO quality parameters of the kneading time and temperature at a laboratory scale for olives showing different ripeness indexes. The same authors also reported a similar study to assess the influence of the use of coadjuvants [Fernández Valdivia et al., 2008]. Kalua et al. [Kalua et al., 2006] also used this methodology to assess the influence of the kneading time and temperature on different characteristics of the VOO.

The use of artificial neural networks (ANN) to construct more sophisticated and comprehensive models of parts of the process has also been approached in the literature. The first reference on the usage of neural networks for the VOOEP can be found in [Bordons and Zafra, 2003], where a neural network was employed to infer the oil and moisture content of the pomace, using as input variables the temperature and input flow of the olive paste into the decanter and the temperature and flow of the addition water.

The usage of neural networks to infer the characteristics of the produced oil can be found in [Furferi et al., 2007]. In this work, ANN were used to predict the acidity and the peroxide index of the oil, using agronomic and process variables as inputs. The agronomic parameters considered were the ripeness and the integrity of the olives, while the technological parameters were the initial olive temperature, the kneading temperature and time, the degree of dilution of olive paste entering centrifugal decanter and the temperatures of the oil leaving centrifugal decanter and the wateroil separator. The results obtained estimated the quality properties of the oil providing an error within 10-15%.

In the same line of predicting the behavior of the plant using neural networks, Jiménez et al. built a network to predict the oil content in the pomace using as input variables the oil and moisture content of the incoming olives, along with several technological parameters, namely the kneading temperature, the addition of micro-talc, the paste inflow into the decanter, the moisture content of the paste and the position of the outcome weirs of the decanter [Jiménez Marquez et al., 2009]. The obtained network was able to predict the fat content on dried matter of the olive pomace and the oil moisture with a root mean square error of prediction (RMSEP) of 0.75% and 0.04%.

2.3 Expert systems in agroalimentary industries

The lack of appropriate sensors and detailed process models are difficulties common to most food industries when facing the automatic control of the processes [Perrot et al., 2006]. Consequently, operators in these industries usually play a fundamental role, as their responsibilities usually cover making evaluations of the sensory characteristics of the products and adjusting the process parameters accordingly [Perrot et al., 2006].

Regarding the control of food processes employing fuzzy logic, two approaches to the construction of the system are found in the literature: data-driven and expert based.

Most of the published works employing the data-driven approach are classical applications of the Takagi-Sugeno controller. An interesting paper is the work by Honda et al. [Honda et al., 1998], where they employ a fuzzy neural network (FNN) for controlling the temperature of the sake brewing process. They split the operation into four zones according to the indications of the experts, and the membership functions and the weights of the models were adjusted from experimental data using the backpropagation algorithm. Then, the product obtained employing the proposed fuzzy controller was compared to that produced by the expert, and the good results obtained were presented.

A more straightforward application of fuzzy control can be found in Alvarez et al. [Alverez et al., 1999], where the authors construct a fuzzy controller to control the temperature of the furnace employed in the hop pellet production process, using the voltage applied as the manipulated variable. The temperature was measured with a Pt-100 sensor and the error was fuzzified to feed a fuzzy controller, which provided the control action. In turn, O'connor et al. [O' Connor et al., 2002] used a similar apporach to construct a temperature controller for the fermenter in the context of the process of beer brewing.

All of these papers employed exclusively available data coming from sensors. A work by Davidson et al. [Davidson et al., 1999] developed a MISO fuzzy controller for the roasting of peanuts employing both data coming from sensors and data provided by humans. The sensor-provided data was the air temperature and roasted product color, being the peanut size the variable provided by the operator. The output of the system was the residence time of the peanuts, used to adjust the speed of the conveyor. The rules were derived from numerical simulations of the process, with trapezoidal membership functions being used and max-min composition for the inference.

Other application employing the expert knowledge for the construction of the systems are presented in [Ioannou et al., 2004a] and [Ioannou et al., 2004b]. In these two works, the authors develop a system to control the browning process employing exclusively human assessment, both for the construction of the system and for the supply of data from the process to the system, employing a Takagi-Sugeno mathematical structure for the decision model. A similar approach is employed by some of the authors in [Perrot et al., 2004], where the system developed is aimed at assisting the operators to control a cheese ripening process. In the same line of work, the authors propose a methodological guideline to handle expert-operator knowledge for sensory quality assessment of food products in [Allais et al., 2007].

Finally, it is worth mentioning a recent survey paper by Birle et al. [Birle et al., 2013], which includes a thorough review of the applications of fuzzy logic and neural networks to the food industry in the last twenty years. Of particular interest are the discussions of the authors about the promising potential of neuro-fuzzy approaches for the food control applications despite the scarcity of current applications of the technique.

2.4 Evolution of the VOOEP in Spain

The VOOEP in Spain has remarkably evolved along the years. The traditional technique employed in the *almazaras*, as are known the olive oil elaboration factories, consisted in the crushing of the olives using big conic stones called *empiedros*, kneading the resulting paste in a thermomixer and extracting the oil by pressing this paste. This process was of batch nature and required a high amount of manual labor [Ortega Nieto, 1943].

During the 1970s, the installation of the new so called *continuous systems* began. These systems replaced *empiedros* for metallic mills, and the presses for decanters that allowed to separate the oil from the paste using centrifugal forces. This technological change allowed the conversion of the VOOEP into a continuous process [Fuentes and Nickel, 2003].

These initial decanters are known as *three-phases* decanters, as these machines presented three output flows: oil, *alpechín* – the acquous phase– and pomace –the solid phase. These type of decanters required the addition of high amounts of water and, consquently, used to generate a great volume of *alpechín*. The *alpechín* is a very polluting by-product [Alba, 1997], and this situation eventually became a major environmental problem.

In the early 1990s a new type of decanter is introduced: the *two-phases* decanter. This new technology did not require the addition of substantial amounts of water and presented only two outflows: oil and *alpeorujo*, a high-moisture pomace that contained both the solid and aqueous phases.

The generalized installation of these machines meant an increase in the processing capacity of the *almazaras*, while allowing a reduction in the number of workers required to operate the plants.

Along with this technical change, a conscience of the importance of improving the quality of the obtained olive oils began to develop [Civantos, 1998a], which brought an increase in the research efforts on this topic. The impulse received by this research, together with the transference from the scientific community to the industry of best practices of VOO elaboration, fructified in an improvement of the average quality of the obtained oils [Uceda et al., 2006].

Despite this important evolution, the research, development and transference to the industry of automatic control techniques is a field where there is still a long way to go.

2.5 Survey on the VOOEP Automation in Spain

A survey was conducted with the objective of evaluating adoption level of the different automation and control technologies for the VOOEP in the spanish factories. The next Section details the design of the survey and the most relevant results.

2.5.1 Survey design and sample

The survey was composed of three major sections. The first section enquired about the structure of the organization: size and legal nature, so that these parameters could be taken into account in the study of the distribution of the automation adoption level.

The second section, which constituted the core of the survey, analyzed the adoption of the different automation technologies in each stage of the VOOEP. An exhaustive review of the available techniques was carried out, and a closed yes/no question list was built upon these techniques grouped by elaboration stadium.

The last section addressed the date of the investment in the automation technologies, along with the pros and cons and future necessities that the survey respondent found in the automation technologies. Analogously to the previous section, yes or no questions were included for each of these topics. Every section of the survey also included open questions to allow the inclusion of technologies, advantages or drawbacks not explicitly included in the survey.

Table 2.1: Geographic distribution of almazaras in Spain.

Region	Number of Almazaras
Andalucía	819
Aragón	103
Baleares	11
Castilla-La Mancha	241
Castilla y León	15
Cataluña	203
Extremadura	117
Madrid	19
Murcia	38
Navarra	16
País Vasco	4
La Rioja	22
C. Valenciana	129

The different automation adoption levels were computed based on the data gathered from the surveys. In particular, the adoption level was computed as the ratio between the adopted techniques and the total number of available ones, as expressed in the formula:

$$G = \frac{\sum_{i=1}^{n} s_i}{n \cdot t}, \tag{2.1}$$

where s_i is the number of adopted techniques in the i survey, t is the total number of techniques and n is the total number of surveys. Accordingly, to compute the global automation adoption level, t is the total number of existing techniques, while for the computation of the reception automation level, t includes all the techniques in that zone.

According to the data provided by the Spanish Olive Oil Agency for the year 2009, there are 1737 *almazaras* in Spain, geographically distributed as included in Table 2.1. The survey was mailed to each of these organizations, according to the list obtained from the web of the Agency. 292 filled out surveys were received, which represents a 17.68% response rate.

The distribution of the received surveys, grouped by geographic area and organization type is depicted if Fig. 2.1. As expected from its high number of organizations, Andalusia in the region with the highest number of received surveys, followed by Catalonia and Castilla-La Mancha. Regarding the organization type, 57% of the received surveys came from cooperatives companies and 43% from private ones.

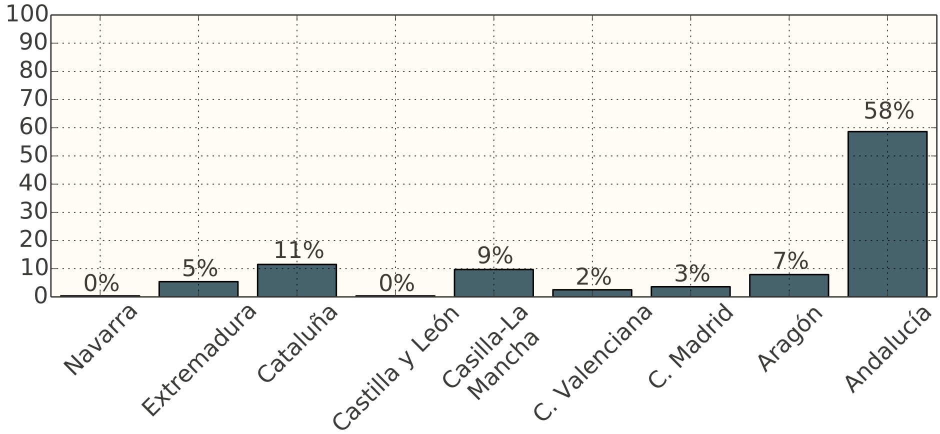


Figure 2.1: Geographic distribution of received surveys.

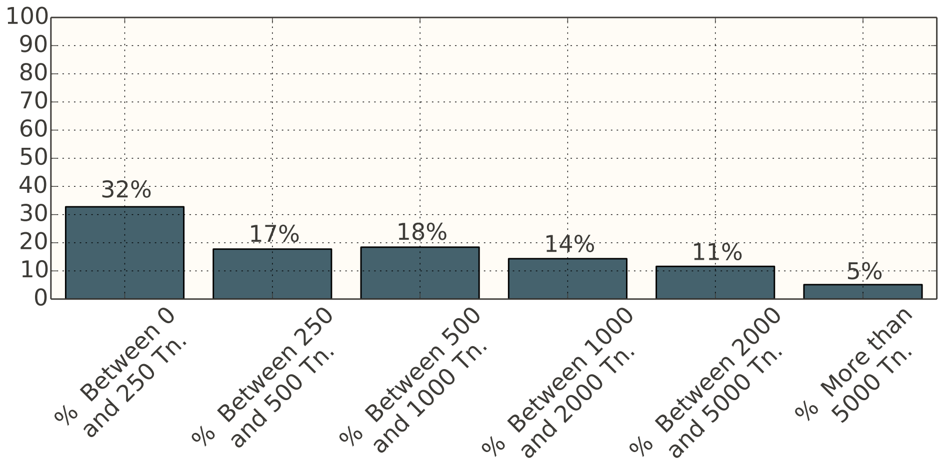
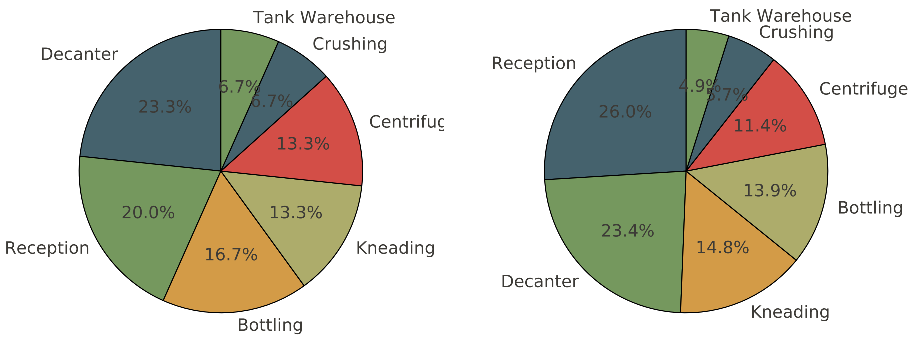


Figure 2.2: Distribution of the organization production capacity of received surveys.

Attending the size of the companies, small production capacity ones (0-250 t) represented a third of the received surveys, while companies with big processing capacity represented only 5% of the total. This distribution is not surprising, as is similar to the size distribution of VOOEP factories in Spain.



(a) Available automation technology distribution.

(b) Adopted automation technology rate distribution.

Figure 2.3: Available and adopted automation technology distribution grouped by VOOEP stadium.

2.5.2 Most adopted automation technologies

This Section shows the most relevant results concerning the adoption of the different automation techniques available in the market. Figure 2.3a shows the distribution of available techniques grouped by process stage, and Fig. 2.3b depicts the actual adoption distribution. The decanter is the stage with highest number of available techniques, while the reception leads the number of adopted ones.

Figure 2.4 displays the automation adoption rate for each stage of the process, and highlights he tendency already exhibited in the previous Figures: the reception clearly stands out as the stage with a highest automation adoption rate. Then, with around a 40% rate, the kneading, bottling and decanter stages are found. Lastly, centrifuge, crushing and tank warehouse shows rates around 30%.

Figure 2.6 shows the adoption rate of each of the automation and control technologies included in the survey. As depicted in the Figure, there are four technologies whose adoption rate is above 80%, followed by a 20 point gap before the next technology is found. From this point on, the adoption rate drops at almost constant rate from one technology to the next.

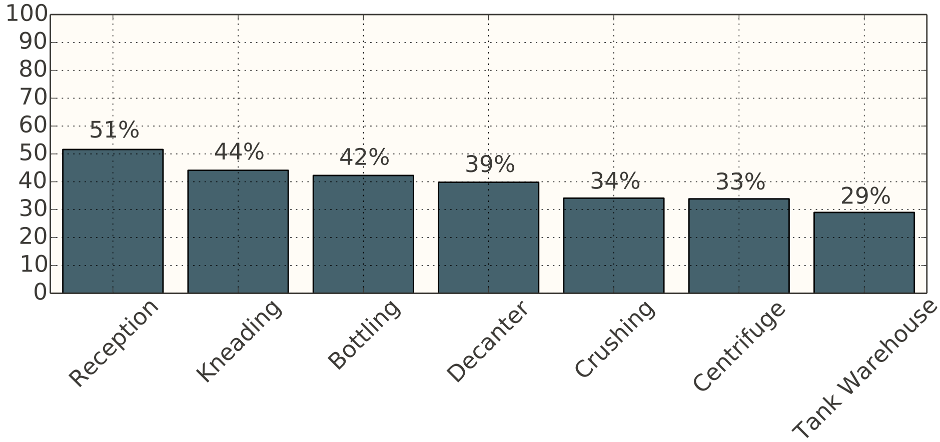


Figure 2.4: Adaption rate for each stage of the VOOEP.

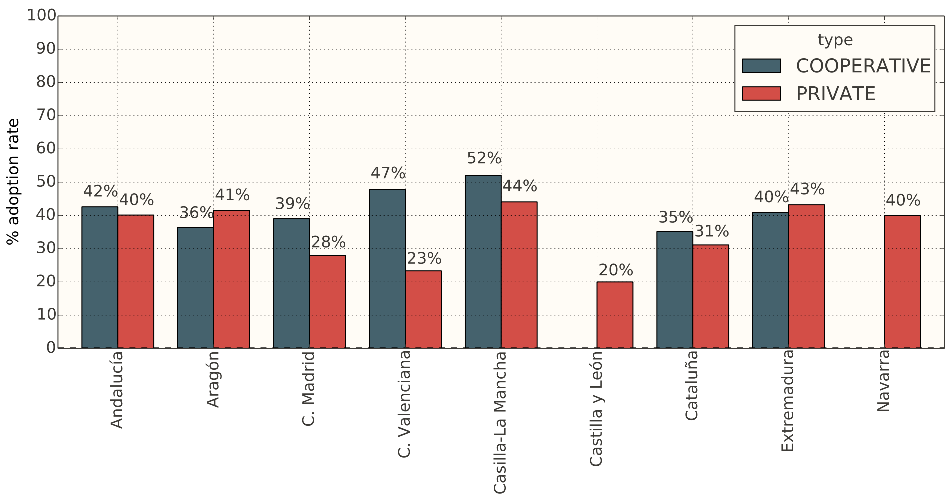
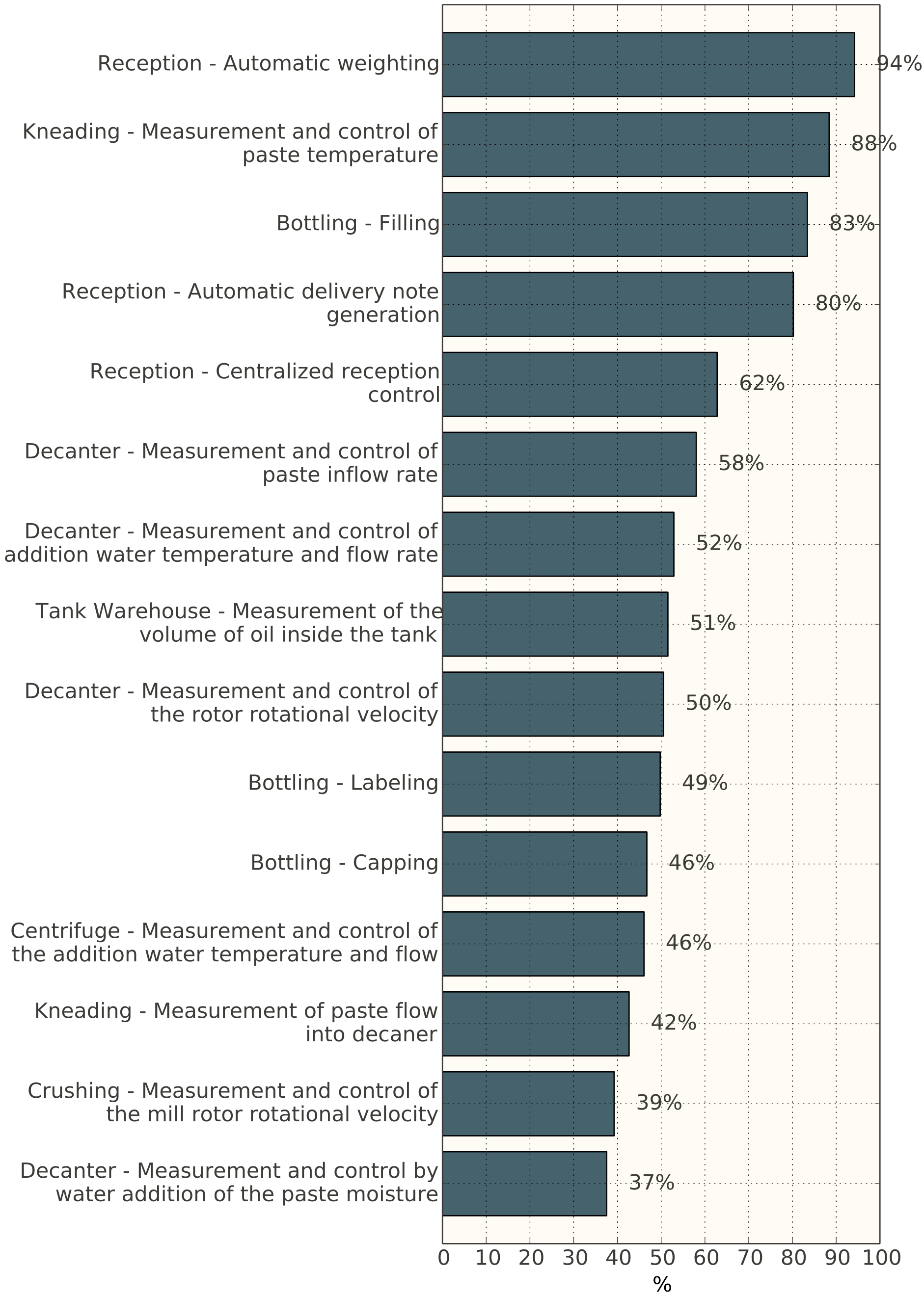
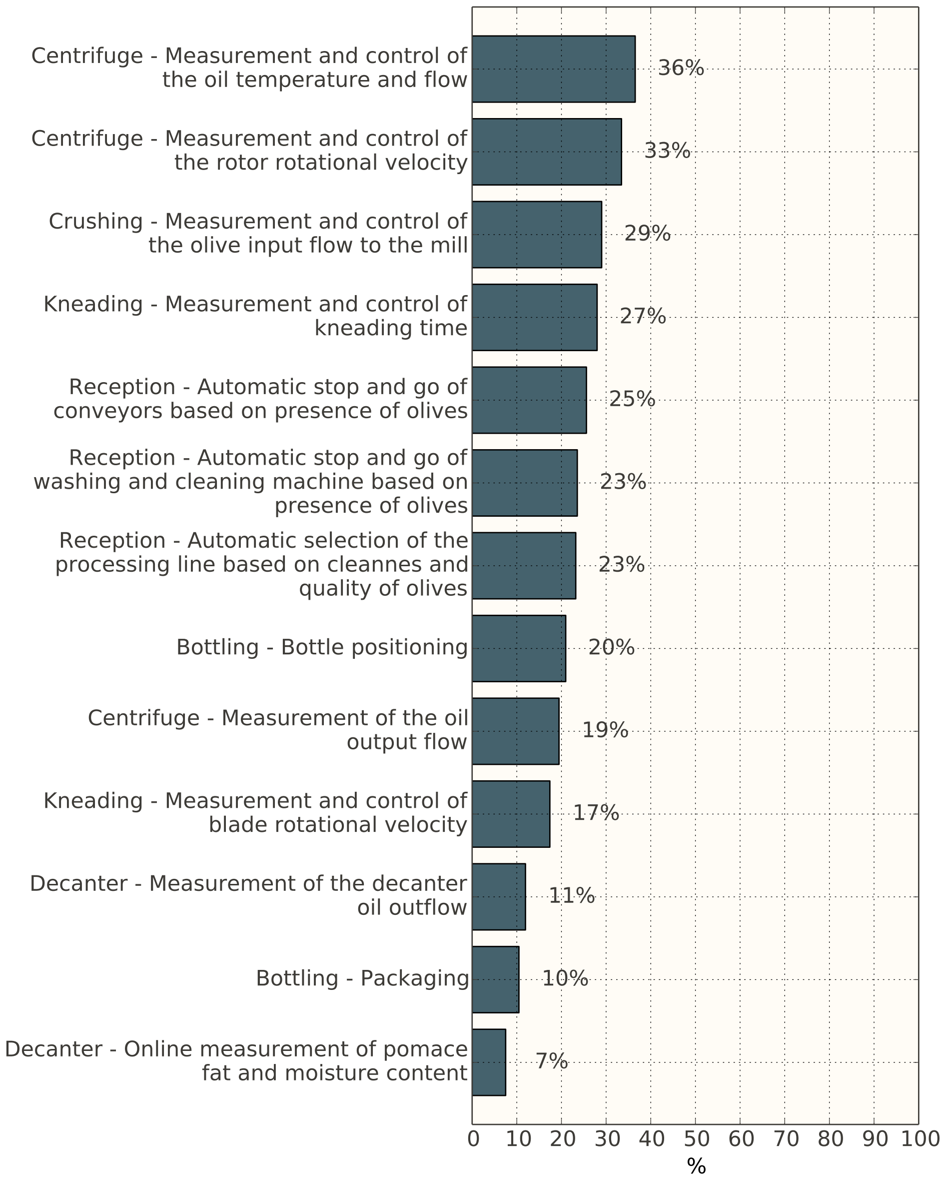


Figure 2.5: Geographic distribution of the global automation techonology adoption rate.



(a) Most adopted automation techniques.



(b) Least adopted automation techniques.

Figure 2.6: Adoption rate of all available automation technologies in the VOOEP.

It is worth commenting the common features of the most adopted techniques: all of them automate tasks common to other industries, and they are relatively cheap to implement. The automatic weighing and delivery receipt emission of raw goods are ubiquitous in every industry. In this particular case, it is also worth noting that the automation lies basically in the use of an information system, without requiring much different hardware than the one needed for a manual operation. In turn, temperature control is carried out using a simple low-level feedback loop, with the aperture of a valve typically as manipulated variable, and is a widespread technology in any process industry. Finally, the automatic filling of bottles is a feature included by almost every modern bottling machine.

The ratio between the adoption rate of technologies applied to the inflows to the decanter and those to its outflows is remarkable. The high rate of the former, and the low of the latter highlights the open-loop nature of the control of the decanter. The actual outputs of interest of the operation are the output flows of the decanter, but a low-level loop is closed on the inflows of the decanter. The control of the outflows remains responsibility of the operator of the factory, with his control action being the adjust of the set points of the inflow variables.

2.5.3 Automation adoption rate of the almazaras

This Section includes the most interesting results regarding the adoption rate of automation technologies. Figure 2.5 depicts the adoption rate grouped by region and type of organization. Castilla-La Mancha, Comunidad Valenciana and Extremadura are the regions with the highest adoption rates. Also, cooperative organizations show slightly greater adoption rates than private factories.

Figure 2.7 portrays the adoption rate grouped by organization size, and highlights a direct correlation between size and adoption rate. This correlation may explain the greater rate presented by cooperative organizations, as they usually are bigger than private factories. According to data provided by the Olive Oil Agency, cooperative organizations process the 67% of the total VOO production, while they represent the 56% of the number of entities.

Finally, Fig. 2.8 reproduces the distribution of organizations according to their adoption rate. It can be seen that 35% of the companies show an adoption rate above 50%, but that hardly a 6% exceeds 70%. On the other hand, 30% of the entities exhibit rates below 30%. This figures hint that the basic technologies are quite extended, but organizations are still reluctant to incorporate the rest of technologies available in the market.

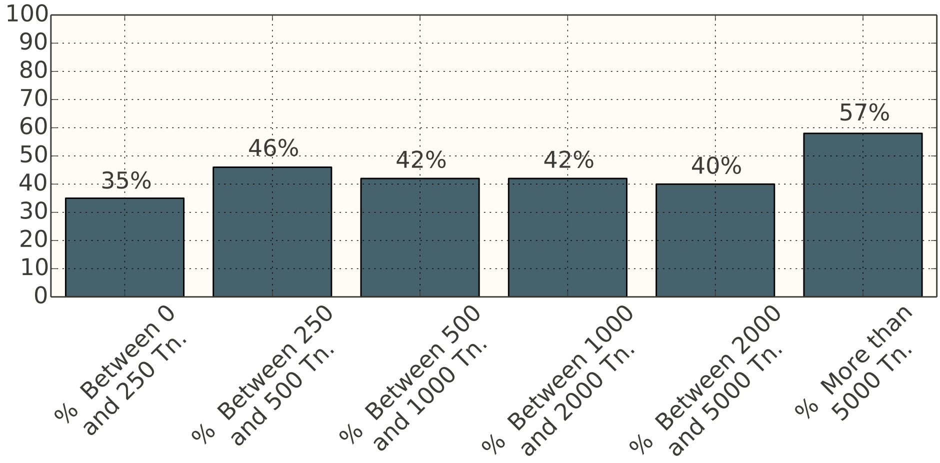


Figure 2.7: Automation technology adoption rate grouped by organization production capacity.

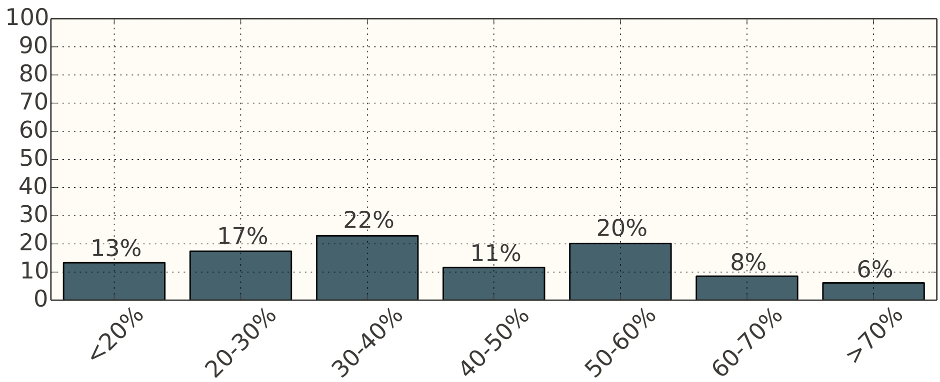


Figure 2.8: Distribution of entities grouped by automation technology adoption rate.

2.5.4 Advantages and disadvantages of automation

Figure 2.9 sketches the advantages that the survey respondents find in automation. Almost 70% of the respondents considered that automation and control of the VOOEP allow to increase the industrial yield, and 64% indicated that they increase the quality of the obtained product.

Regarding the disadvantages, as portrayed in Fig. 2.10, 61% point to the high investment required. However, only 5% considered that the results are

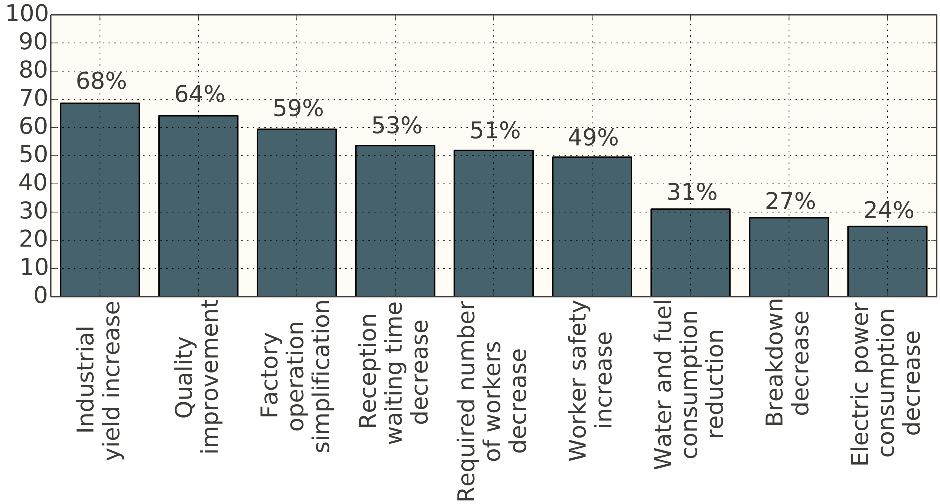


Figure 2.9: Advantages of VOOEP automation according to survey participants.

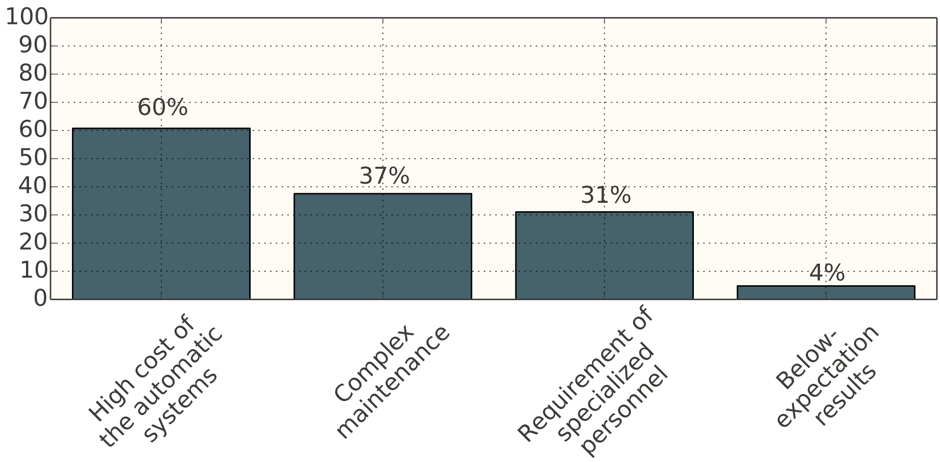


Figure 2.10: Drawbacks of VOOEP automation according to survey participants.

below their expectations.

Concerning future automation plans, 46% considered that they would invest in the tank warehouse and 43% in the VOOEP itself, as depicted in Fig. 2.11. On the other hand, only 30% contemplated new investments in the reception area. These data reflect the tendencies that might be expected attending to the current automation levels, showing the reception area and

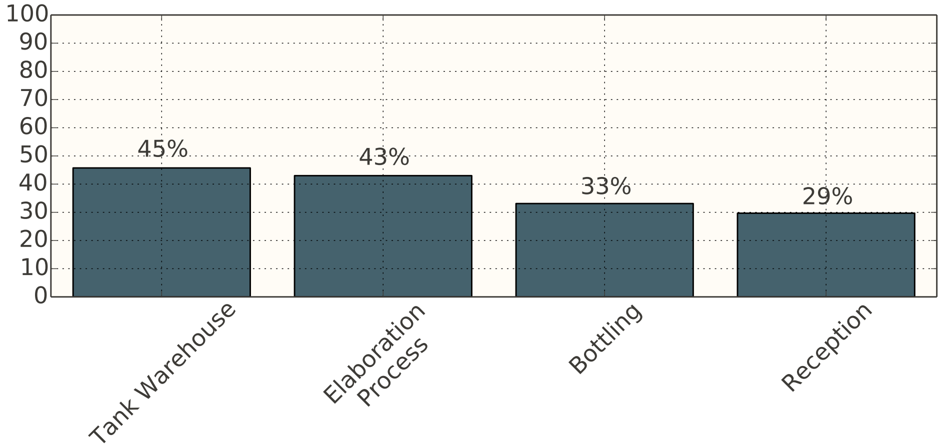


Figure 2.11: Future automation investment VOOEP stadiums as expressed by survey respondants.

the tank warehouse as the zones with the greatest and smallest adoption rates, respectively. It is also worth noting the intention of increasing the investment in the elaboration zones, which is in line with the advantages perceived by the respondents.

2.5.5 Discussion on the survey results

The first conclusion that might be found is the elevated rate of the reception area, as compared with the rest of zones of the *almazara*. This fact can be explained by the high requirement of workers of this zone of the factory and the reduction that the automation might achieve. Also, a reduction in the time needed for the grower to unload the olives is directly perceived as an increase in the service offered by the factory to them.

Another noticeable aspect is the high adoption rate in the bottling process, even higher than that in the decanter. This is remarkable, since usually the bottling process is a small part of the activity of the factories, and thus, represent small labor cost in the overall picture. A possible reason for this high rate might be that the technologies applied in this area are quite matured, since they are also applied in a myriad of other industries, and thus the required investment is low.

It is also noteworthy that the two major advantages indicated by the participants are the increase of the yield and the quality of the oil. In this line, it is interesting to remark that the second most adopted technique is the measurement and control of the temperature of the paste in the thermomixer. As pointed out in Section D.3, this is a very important parameter in the VOOEP, and this adoption rate reflects this importance. However, some other very relevant parameters show much lower rates, being particularly noticeable that of the on-line measurement of the oil content in the pomace. This may be related to the high cost of the sensor, and to the lower reliability of the on-line sensor versus the at-line alternative. Without this sensor, the automatic control of the VOOEP is reduced to isolated low-level feedback loops, requiring the intervention of a skilled operator to establish the set points of the different process variables in an adequate and consistent manner.

3

Fuzzy Modeling of the Virgin Olive Oil Elaboration Process

3.1 Introduction

The VOOEP is a fairly complex industrial process, with several variables involved and different production objectives. The outcome of the process, namely the quantity and the quality of the produced oil, depends on the characteristics of the incoming olives and on the values of different process variables. Usually, the process variables influence more than one output variable, which encourages to regard the process as a coupled MIMO system, and not just a collection of decoupled SISO systems.

The global modelling of the VOOEP is a challenging problem mainly due to three factors:

- The number of variables involved in the system is not small, there are may interrelations between them and the same variable may exert positive and negative influence on the same output variable through different means – for instance, the olive moisture of the olives or the sieve size.

- The current lack of reliable sensors capable of measuring the relevant output variables of the process on-line. NIR sensors are a promising technology, and they are routinely used to assess oil and water content in olive paste in laboratories. They are even reported to be capable of providing approximate results on some parameters of the quality of the VOO. However, their providing reliable data on-line for the VOOEP is still an unresolved technical challenge. Thus, approaching the problem with a traditional system identification approach would face the problem of dealing with scarce and expensive to obtain data.

- Finally, the limited period of availability of olives during the year, and the even more limited period of availability of olives of *some specific properties* during the year, represent a major hurdle when facing the VOOEP modeling task.

In this context, the selected approach is to rely on fuzzy modeling techniques to make full use of the knowlegde about the VOOEP expert operators enjoy. Moreover, the formulation proposed enables the use of eventually available data from the process to further refine or fine-tune the models.

The structure of this Chapter is as follows: Section 3.3 present the details of the chosen model structure, along with the posibility of using experimental data for the fine tuning of the models. Section 3.5 deals with the specific aspects of the model construction, with Sections 3.6 and 3.7 presenting the models for the paste preparation and solid-liquid separation stages of the VOOEP, respectively.

3.2 Brief Overview of Fuzzy Cognitive Maps

A cognitive map is signed directed digraph which allows the existence of feedback between their nodes. Each node represents a concept and the existence of an arc represents a causal relation among the concepts connected. Nodes take values in the $\{0, 1\}$ set, and the arcs are defined by a sign: positive defining increase and negative meaning decrease of the successor node. They were developed by Axelrod [Axelrod, 1976] to represent political and social systems.

The technique was further extended by Kosko [Kosko, 1986] by allowing the nodes to take values in the continuous $[0, 1]$ interval and substituting the sign by a number in the $[-1, 1]$ interval representing the intensity of the relation among the nodes.

3.2.1 Simplified Dynamic Cognitive Networks

Simplified Dynamic Cognitive Networks (sDCMs) were introduced in [Miao et al., 2010] as a simplification of Dynamic Cognitive Networks (DCNs), which, in turn, were developed in [Miao et al., 2001] as an extension to FCM to overcome some of its limitations.

The common idea of these formalisms is the use of a directed graph where the nodes represent the concepts relevant to the model at hand, while the directed arcs connecting the nodes stand for relations between those concepts.

This representation has the main advantage of allowing an easy visualization of the relations between the different variables in the system, and is thus a powerful tool in the modeling of a system using expert knowledge.

As presented in [Miao et al., 2010], sDCMs are defined as a tuple:

$$\mathrm{M} = \langle \mathrm{V}, \mathrm{A} \rangle, \tag{3.1}$$

where V is a collection of nodes and A is a collection of directed arcs connecting pairs of nodes.

Each arc a_{ij}, which connects the nodes v_i and v_j, has associated a fuzzy weight ω_{ij} which is the description of the relation between the two concepts.

For each node v_i in the system, the following properties are defined:

- f_{v_i}: the activation function of the node defined as follows:

$$f_{v_i}(u) = f_{v_i}\left(\sum_{j=1}^{n} \omega_{i,j} \times x_j\right) \tag{3.2}$$

$$u = \sum_{j=1}^{n} \omega_{i,j} \times x_j \tag{3.3}$$

  with u defined as the total impact received by the node.

- $S(v_i) = \{x_i^1, x_i^2, \ldots, x_i^{R_i}\}$: the state set of the node, with R_i being the number of values of the concept. As is the case with DCNs, different value set definitions are allowed for different nodes.

3.2.2 Fuzzy Inference Cognitive Maps

Fuzzy Inference Cognitive Maps (FICM) were proposed in [Jones et al., 2004], as an extension to FCM in general, and to Rule Based Fuzzy Cognitive Maps (RBFCM) [Carvalho and Tome, 2001] in particular. While in RBFCM the relation among nodes is modeled using Fuzzy Inference Systems (FIS) based on expert knowledge exclusively, FICM employ adaptive neuro-fuzzy inference systems (ANFIS) [Jang, 1993] as models. This type of models have the advantage that some parameters of the model can be *adapted* or *identified* from available input-output data of the particular relation. This allows to set up the structure of the model using expert knowledge, and fine-tune the final values of the parameters based on available experimental data.

3.3 Method

The tool employed for the modeling of the VOOEP is the Simplified Dynamic Cognitive Network (sDCM) class of models [Miao et al., 2010]. The following Subsections briefly present the general form of sDCMs and the particular choices and modifications employed.

3.3.1 Modified Simplified Dynamic Cognitive Networks

The class of models employed for the actual implementation of the system presents some differences with sDCMs, as detailed below. We shall refer to the model as MsDCM from this point on.

3.3.1.1 Definition of Nodes

Analogously to sDCM, MsDCM are composed of a collection of nodes and arcs representing the relations between those nodes. For each node v_i of the system, the following properties are defined:

- U_{v_i}: the universe of discourse of the node, defined as the set that contains all the possible crisp values of v_i. The nodes are supposed to have scalar crisp values, so, $U_{v_i} \subseteq \mathbb{R}$.

- H_{v_i}: the collection of terms (fuzzy sets) $L^j_{v_i}$ defined in U_{v_i}, together with the membership function for each term:

$$L^j_{v_i} = \{\langle x, \mu_{L^j_{v_i}}(x)\rangle \; : \; x \in U_{v_i}\}, \tag{3.4}$$

$$H_{v_i} = \{L^j_{v_i}, \; j = 1, 2, \cdots, n_{v_i}\}. \tag{3.5}$$

- $S_f(v_i)$: the state of the node, defined as an array containing the degree of membership of v_i to each fuzzy set L_{v_i} defined in H_{v_i}:

$$S_f(v_i) = [\mu_{L^1_{v_i}}, \cdots, \mu_{L^{n_{v_i}}_{v_i}}]^T. \tag{3.6}$$

- $S_c(v_i)$: the crisp value of the state of the node, computed using a defuzzification function on S_f, according to the definition of the elements in H_{v_i}.

3.3.1.2 Definition of Arcs

For each arc a_{ij} the following properties are defined:

- R_{ij}: causal relationship matrix. It is defined as a matrix that maps the the degree of membership to each label of the antecessor, to contributions for the grade of membership of the sucessor to its labels. The size of the matrix is $n_i \times n_j$, with n_i and n_j being the number of labels in H_{v_i} and H_{v_j} respectively. The entries of these matrices are required to be non-negative.

- ω_{ij}: absolute value of the intensity of the relation between the nodes connected by the arcs.

As will be evident when the computation of the value of the node is addressed in Sec 3.3.1.3, the definition of ω_{ij} is not strictly required. The reason to separate a specific ω_{ij} for each relation, is that it arguably clarifies the relative importance of each antecessor in the computation of the final value of the node, than the alternative of implicitly including it in the entries of R_{ij}.

The introduction of the relation matrix allows greater flexibility in the definition of the relations between the nodes than that found in sDCMs. They allow the introduction of level-dependent and asymmetric relations between the nodes [Koulouriotis et al., 2005]. These matrices can also be thought of as a compact way of representing fuzzy if-then rules of the type:

- `If node` i `is` L_k, `then node` j `is` L_m

along with a weight representing the relative strength of the rule compared to others.

The structure of the matrix determines the influence of the antecessor on the successor. Positive and negative relations are considered, along with three types of relations:

- Bivalent relations: for a positive (negative) bivalent relation, a low value of the input variable tends to decrease (increase) the value of the output, and a high value of the input tends to increase (increase) the value of the output. The following matrices R are examples of positive and negative, respectively, bivalent relations for a system with three defined labels per node:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}. \tag{3.7}$$

- Univalent relations: these are asymmetric relations, in the sense that some level of values of the predecessor exert some influence on the successor, while others exert none. Besides, the influence of the node always tends to increase (or decrease) the value of the successor. The following matrices are examples of univalent relations that always tend to decrease and increase, respectively, the value of a node:

$$\begin{bmatrix} 0 & 0.5 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0.5 & 1 \end{bmatrix}. \tag{3.8}$$

  The arranging of the entries of the matrices in the first or last rows guarantees that the influence of the corresponding predecessor will be that of increasing (or decreasing) the value the node would have had if this node were not to exert influence.

  It should be noted that, in order to make sense, nodes exerting this influence on a successor are required not be the only predecessors, since that would either leave the value of the node undefined (if the incidence of the node is zero), or always having a extreme (maximum or minimum) value. However, this requirement is in line with the intuition that it is natural to think of a relation that moves the value of a variable only when there is some other relation that establishes a reference value.

For the matrices presented above, higher values exert higher influence on the successor. The following two matrices illustrate analogous behavior, but the influence being exerted by lower values of the input:

$$\begin{bmatrix} 1 & 0.5 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0.5 & 0 \end{bmatrix}. \tag{3.9}$$

- Sweet-spot relations: a certain value of the input provokes the maximum (minimum) value of the output, with higher and lower values of the input resulting in lower (higher) values of the output. The following matrices exemplify a minimum and maximum sweet-spot relations:

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}. \tag{3.10}$$

Level dependent and saturation effects can also be easily expressed using these matrices, as exemplified in the following two matrices:

$$\begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}. \tag{3.11}$$

Here, the matrix on the left expresses a relation where the strength of the effect is magnified as the value of the input increases, while the matrix on the right shows a saturation for high values of the input, that results in the same effect on the output as the one provoked by the moderate level.

As an example to illustrate the difference between univalent and bivalent relations, we may consider the effect of adding coadjuvant to the thermomixer in the malaxing process. If there is a high level of emulsions, adding coadjuvant will effectively reduce that level, thus helping to achieve a better yield. However, not adding coadjuvant does not mean an increase in the level of emulsions and a subsequent decrease in the yield. This is an example of univalent relation.

An example of sweet-spot relation is the effect of the moisture of the paste during the kneading process. Values either too high or too low result in poorer perfomance of the process than that obtained when working with the right amount of paste moisture.

3.3.1.3 Computation of the State of a Node

The computation of $S_f(v_i)$ for each node v_i requires combining the influence of each predecessor node v_j according to its state $S_f(v_j)$, the type of relationship R_{ij} and its strength ω_{ij}.

Analogously to the definition of the impact received by a node proposed sDCM, i.e., Eq. (3.3), we define the impact received by the node i as:

$$\mathrm{w}_i = \sum_{j=1}^{n_i} \omega_{ij}\, R_{ij} S_f(v_j) \tag{3.12}$$

The first remark is that this equation is a vector equation, with one equality for each label defined in the universe of discourse of $S_c(v_i)$, so we can further explicit w_i as:

$$\mathrm{w}_i = [w_1\ w_2\ \cdots\ w_l]^T. \tag{3.13}$$

It is important to note that, since there is no requirement in the entries of R_{ij} other than their non-negativity, in general the elements of w_i do not add up to one. Thus, it is useful to define the normalized impact as:

$$\bar{\mathrm{w}}_i = \frac{\mathrm{w}_i}{\sum_{k=1}^{l} w_k},$$

which is guaranteed to observe this property.

The computation of the crisp value $S_c(v_i)$ of the node is performed using a weighted average combination of the value of the kernel of each label, using the entries of the normalized impact as weights. Let

$$\mathrm{m}_i = [m_1^i\ m_2^i\ \cdots\ m_l^i]^T$$

be the kernels of the labels defined in the universe of discourse U_i, then $S_c(v_i)$ is computed as:

$$S_c(v_i) = \bar{\mathrm{w}} \cdot \mathrm{m} = \sum_{k=1}^{l} \bar{w}_k^i\, m_k^i.$$

To retrieve the fuzzy state vector of the node $S_f(v_i)$, all that is left to do is to evaluate the membership function for each label defined:

$$S_f(v_i) = [\mu_1(S_c(v_i))\ \mu_2(S_c(v_i))\ \cdots\ \mu_l(S_c(v_i))]^T.$$

It is important to remark the difference between the normalized impact $\bar{\mathrm{w}}$ and the fuzzy state $S_f(v_i)$. Even though the defuzzification of both arrays render the same crisp value, both arrays are in general different.

The entries of $\bar{\mathrm{w}}$ will, in general, be less sparse than those of $S_f(v_i)$, since the former ones are the result of the impacts received by the node and, in general, may have several non-zero elements. In particular, if univalent relations are present, nonzero entries are expected in the first or last elements of $\bar{\mathrm{w}}$, which does not mean that the resulting crisp value of the node necessarily presents nonzero membership to the fuzzy associated with those elements.

For the propagation of the computations from node to node, it is important to use $S_f(v_i)$ instead of $\bar{\mathrm{w}}$, since if asymmetric or level-dependent relations are present, $\bar{\mathrm{w}}$ might activate spurious contributions that should not be activated according to the resulting value of the node. As an example, suppose that values for a node are given by:

$$\bar{\mathrm{w}} = [0.5\ 0\ 0.5], \quad S_f(v_i) = [0\ 1\ 0].$$

Then, for a relation matrix for a successor node to present a marked nonlinear behavior, such as:

$$\begin{bmatrix} 5 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \tag{3.14}$$

the impact given by $\bar{\mathrm{w}}$ would be $[2.5\ 0\ 0.5]$, while $S_f(v_i)$ gives $[0\ 1\ 0]$. The different contributions based on each of these vectors is noticeable.

3.4 Data-driven parameter adjust

In order to study the inclusion of mechanism to allow the adjustment of the parameters of the system based of eventually available process data, we focus our attention to a model consisting of n inputs and one output. A more complex network can be built connecting different subnets with the same structure as the one analyzed.

For simplicity, we further suppose that all the nodes in the net have the same number of fuzzy labels defined in their universe of discourse. This assumption does not affect the generality of the analysis and simplifies the notation. Figure 3.1 shows the graph being analyzed.

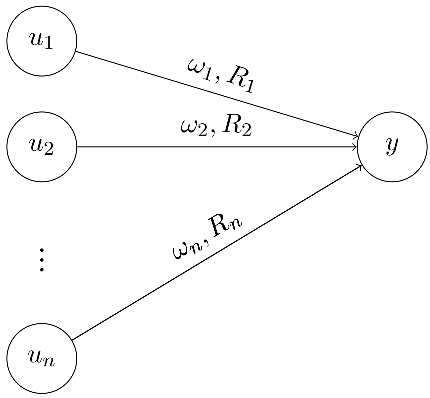


Figure 3.1: Generic multi-input single output graph.

The formula for the computation of the state of the consequent node, according to the FCM formulation is:

$$S_c(y) = f(\sum_i \omega_i R_i S_f(u_i)),$$

with $f(\cdot)$ being the function that maps the impact received by the node w_y to its final crisp state $S_c(y)$.

Let's define:

$$\mathrm{p}_i = \omega_i R_i S_f(u_i) = [p_{i1}\ p_{i2}\ \cdots p_{il}]$$

as the impact exerted by node u_i on the node y. Then, the total impact on y can be computed as:

$$\mathrm{w} = \sum_i \mathrm{p}_i.$$

Let μ_{ij} denote the membership grade of the i input to its j label, and F_{ij} the function that maps the crisp value of the node i to its membership value for the j label, i.e.:

$$S_f(u_i) = [\mu_{i1}\, \mu_{i2}\ \cdots\ \mu_{il}].$$

The first consideration is noting that we may split each node in the net into as many nodes as labels are defined in their universe of discourse, and construct a net that computes the state of node y based on these disaggregated nodes. Figure 3.2 shows the graph that implements these calculations, along with Fig. 3.3, which further details the computation of p_i from $S_f(u_i)$ and the properties of the relation ω_i and R_i, defining r_{kj} as the elements of the matrix R_i.

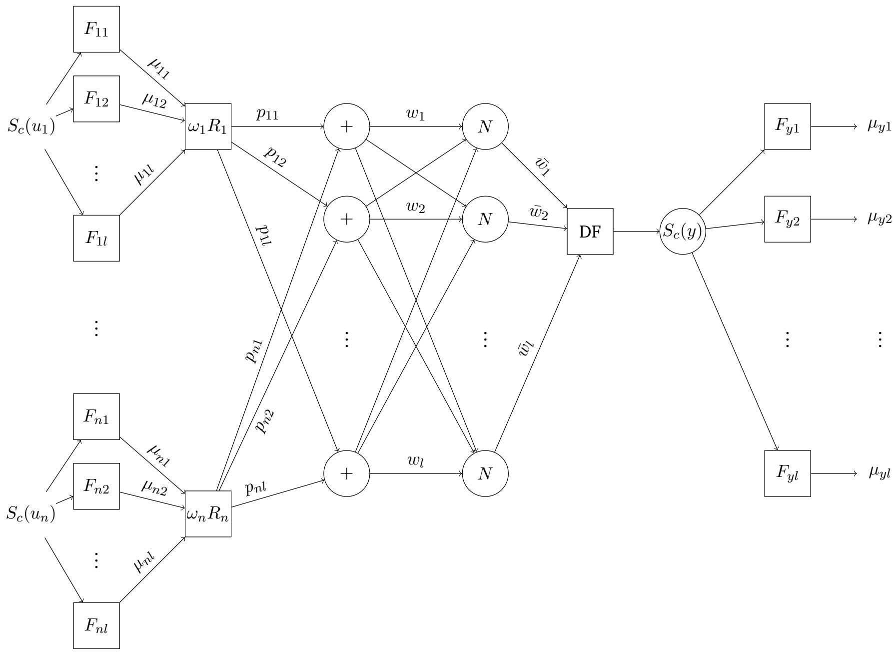


Figure 3.2: Detailed Expanded nodes graph.

In the graph in Fig. 3.2, p_{ik} represents the impact of node i to the k label of node y. Here, $i \in \{1, 2, \cdots, n\}$, with n being the number of input nodes, and $k \in \{1, 2, \cdots, l\}$, with l being the number of labels defined.

In turn, w_k represent the impact of *all* the input nodes to the k label of y. Again, $k \in \{1, 2, \cdots, l\}$.

The nodes N normalize the components of the impact, i.e.:

$$N(w_i) = \bar{w}_i = \frac{w_i}{\sum_{k=1}^{l} w_k}, \tag{3.15}$$

and play a similar role to the functions that normalize the firing strength a rule to the sum of all rules' firing strength in layer 3 of the ANFIS model detailed in [Jang and Sun, 1995].

Finally, the node DF computes the crisp value of y based on the normalized impact and the kernels of the labels as defined in the previous Section:

$$S_c(v_i) = \sum_{k=1}^{l} \bar{w}_k^i \, m_k^i.$$

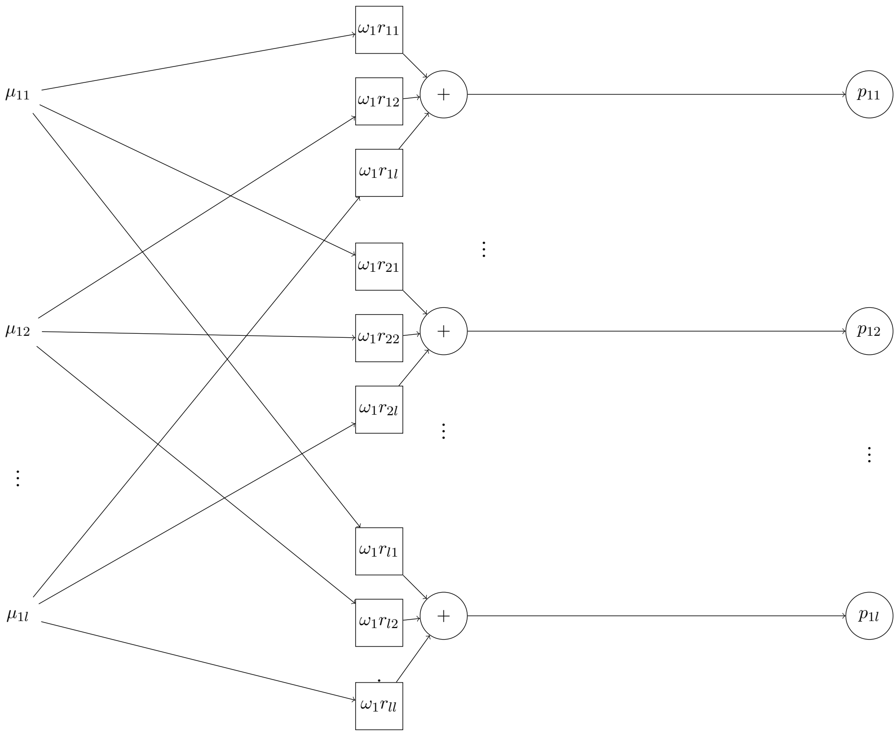


Figure 3.3: Detailed Computation of p_{il}.

Once the crisp value of y is computed, it can be used to compute the fuzzy state of the node $S_f(y)$, which in turn may be the input to a subsequent node in a net.

The net in Fig. 3.2 shows a similar structure to an ANFIS system. This structure allows the entries of the relation matrices can be computed to fit eventually available data from the process using the backpropagation algorithm, with the only limitation being the piecewise continuity of the membership functions to the fuzzy labels [Jang, 1993].

This approach enables the incorporation of a data-driven approach to the building or refining of the models. The relevant variables, along with the type of relations among the variables could be provided by experts, while the concrete values of the entries of the matrices R_{ij}, along with the weights ω_{ij} could be computed applying the backpropagation algorithm to the resulting graph.

Some caution is in order, since in general, FCM are allowed – even supposed – to have cycles in the graph, and thus the regular backpropagation algorithm could not be applied, but some generalization of it such as the *"backpropagation through time"* algorithm should be used [Chauvin and Rumelhart, 1995]. However, as justified in the following Section, the developed model of the VOOEP does not have any cycle, so it would be apt for the use of the simpler backpropagation algorithm.

3.5 Construction of the VOOEP Model

This Section elaborates the details of the construction of the VOOEP model, presenting in the following Subsections the design choices and particularities of the different variables and relations involved.

The construction of the system followed the expert-knowledge based approach. Interviews with a reduced number of experts on the VOOEP, along with an extensive review of the published literature on VOOEP and some years of personal professional experience in the industry were the foundations for the construction of the model.

In line with the different stages of the VOOEP, the construction of the model was approached by studying independently the paste preparation and separation processes. The connection between both models is carried out employing some output nodes of the paste preparation model as inputs to the oil separation one. The high flexibility and modularity inherent to FCMs favors this modeling approach.

Despite FCM usually having cycles in the graph, the developed VOOEP model does not include any cycle. The ultimate reason for this is the role of this model in the global approach of the VOOEP decision support system. We intend to use this model as the underlying source of relations among the system variables, and for this purpose we only need the *physical* relations among the variables. Given the selection of variables and the structure of the system, including cycles is not required to successfully reflect the relations among the variables.

3.5.1 Involved Variables

The nodes involved in the VOOEP model can be divided into two major groups, according to the nature of the value of the variable they symbolize:

- Nodes that represent typical physical variables, such as temperature, time, size, etc. These variables have a natural universe of discourse, namely their typical variation range for the process.

  Since the inference of the system is defined by relations between the different labels of the variables, it is important to have a good definition of the fuzzy sets and the labels defined over this universe of discourse. Experts were asked to provide a representative value for each label, and this value was used as the kernel of the membership function defining the label.

- Nodes that represent variables for which there are typically no available sensors, such as paste preparation (Kneading State (K_s)). These variables may be considered as inherently fuzzy, since it is the expert operator of the factory that determines their value based on indirect measurements, visual inspection, etc. For these variables, the input to the system is already provided fuzzified and the meaningful value of the output is also fuzzy, so the definition of the universe of discourse is arbitrary.

The nodes can also be classified according to the role of the variable they represent in the VOOEP:

- Properties of the incoming olives: this group includes Ripeness (R_f), Incoming Olive Moisture (H_o^I) and Fruit State (E_f). The value of these variables is determined by the evolution of the olives in the grove as influenced by cultivar and metheorological factors, the harvest date and the handling of the olives during the harvesting and transportation [García and Yousfi, 2007].

- Technological parameters: this group comprises all those variables whose set points are susceptible to be specified by the operator of the factory. Examples of these variables are Kneading Time (t_b) or Sieve Size (C_s).

- Auxiliary parameters: these are parameters whose value depends on other upstream variables, and thus cannot be chosen arbitrarily, but do not represent an output variable of the process. An example of this type of variables is Paste Emulsion (P_E).

- Output parameters: these are the variables that are usually included in the production objective of the process. Examples of this type are Yield (X) and Fruity (F).

This last classification of the nodes will be particularly relevant when addressing the optimization problems to find the production objective and its corresponding set points. Appendix A includes all the considered variables in the system.

Five labels were considered for the partition of the universe of discourse of each variable. This number was selected as it represented a balanced trade-off between resolution of the model and complexity. Triangular membership functions that intersect at 0.5 membership grade were used for each term of the model for simplicity reasons, and to guarantee that the sum of the elements in $S_f(v_i)$ adds up to one, so that the relative weights defined in the relations are not altered due to this factor.

3.5.2 Definition of Relations

The elicitation of the relations between variables was carried out using a two-step approach:

1. A first characterization of the relations is elicited, and a prototype system is built upon these.
2. The behavior of the system is studied and the relations of nodes that do not show satisfactory results are fine tuned.

For the first step, experts were asked to define the type, the sign and the strength of the relation between the nodes. As is common practice in the construction of FCM from expert-knowledge [Stach et al., 2010], experts were asked to describe the strength using a linguistic term, which was afterwards mapped to a numerical value according to Table 3.1. Also, experts were asked if any nonlinear effect, such as saturation, thresholds, etc., were to be included in the relations, explicitly asking for a mapping from input to output in case these effects were present. Regular relations were translated into R_{ij} according to the structure defined in Section 3.3.1.2.

The second step involved studying the values of the nodes as the predecessor nodes swept through their universe of discourse. These obtained values were plotted in contour plots and studied to find regions of odd behavior in order to fine tune the model accordingly.

Once this lower-level inspection of the system was finished, a more global approach was tackled, defining different scenarios of properties of the incoming olives and checking the output variables for different values of olive

Table 3.1: Definition of the weigth levels employed for the VOOEP model.

Influence	Value
Very Strong	1
Strong	0.75
Moderate	0.5
Weak	0.25

properties and process variables. The purpose of this study was to assure that the flow of effects accross the model was correct. Some examples of these plots are included in the next Section, along with the structure of the models and some comments.

3.6 Paste Preparation Model

The graph of the paste preparation model is included in Fig. 3.4, while all the relation matrices are included in Appendix B.

The properties of the incoming olives are defined by the nodes Incoming Olive Moisture (H_o^I), Ripeness (R_f), Pit-Flesh Ratio (R_p), Incoming Fruit State (E_f^I) and Olive Illnes (O_I). As commented in Sect. D.3, the values of these parameters depend on their evolution in the orchards, the moment the harvesting is carried out and the method used for the harvesting and the transportation. However, when olives arrive to the *almazara*, their values are already set, so in the model they are considered fixed value inputs.

Once in the factory, olives are fed into hoppers and the time they remain there effectively alter their properties. This effect is included in the system using the node Storage Time in Hopper (T_s), which reflects the time that olives are stored in the hoppers, and exerts influence on Fruit State (E_f) and Olive Moisture (H_o). These nodes represent the same physical variable as Incoming Fruit State (E_f^I) and Incoming Olive Moisture (H_o^I) respectively, but at the moment the olives are taken from the hoppers and fed to the following stage in the VOOEP. The storage of olives in the hoppers decreases Olive Moisture (H_o) and Fruit State (E_f), as depicted in Figures 3.5a and 3.5b. These effects favor having a low level of Paste Emulsion (P_E), which in turn helps having good Kneading State (K_s). The price to be paid is the increase in Defect (D) and a slight decrease in Fruity (F), which decrease the quality of the obtained oil [García and Yousfi, 2007].

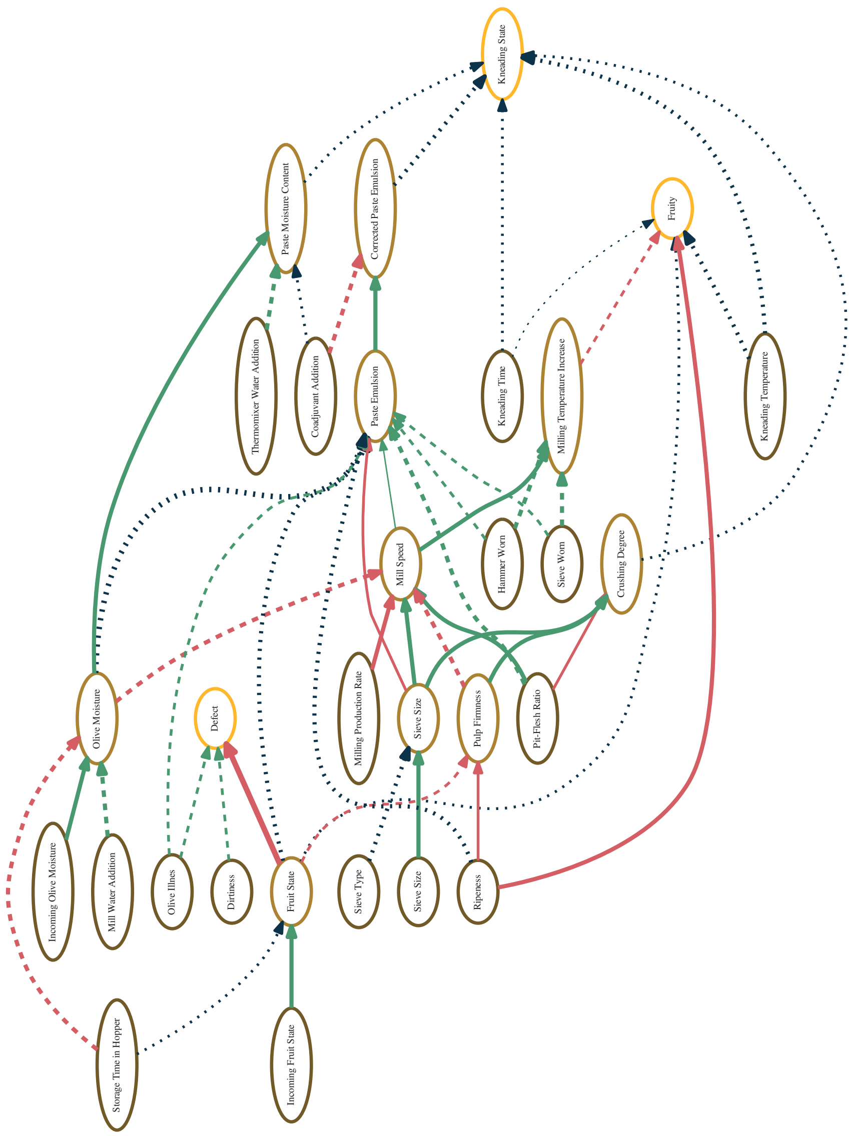
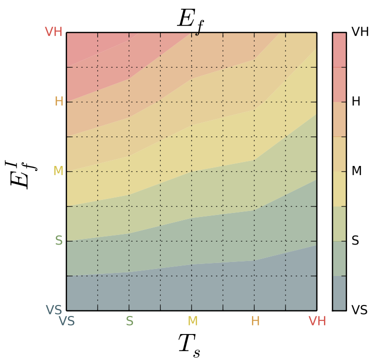
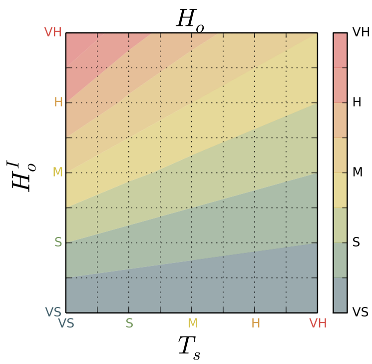


Figure 3.4: Graph of the VOOEP paste preparation model. Green (red) arcs represent positive (negative) relations, continuous (dotted) lines stands for bidirectional (unidirectional) relations, and greater width of the line indicates greater value of the relation weight. Blue arcs represent relations defined by matrices of non-standard form.



(a) Fruit State (E_f)



(b) Olive Moisture (H_o)

Figure 3.5: Influence of Storage Time in Hopper (T_s) on Fruit State (E_f) and Olive Moisture (H_o), respectively. The vertical axes represent Incoming Fruit State (E_f^I) (a) and Incoming Olive Moisture (H_o^I) (b).

The crushing process is responsible for the breaking of the olive cells and thus freeing the oil. Different crusher technologies are available for the VOOEP, but, by far, the most extended is the hammer crusher. Focusing on just this type of crusher, there are still alternatives in the type and size of the sieve to be used. This alternatives are included in the nodes Sieve Type (S_t) and Sieve Size (C_s), respectively. Sieve Type (S_t) presents only three possible values, one for each of the alternatives existing in the industry. The effect of these variables is combined into an intermediate node denominated Sieve Size (C_{se}), which in turn exerts its influence on the subsequent nodes.

Crushing Degree (G_m) is the variable that represents the resulting particle size of the olive paste, and it has a strong influence on the final yield. It depends on Sieve Size (C_{se}), as well as on some olive properties, namely Pulp Firmness (P_F) and Pit-Flesh Ratio (R_p). Pulp Firmness (P_F) is a characteristic of the olives, but can be related to Ripeness (R_f) and Fruit State (E_f), and since Fruit State (E_f) is affected by Storage Time in Hopper (T_s), the value of this parameter is inferred based on these two properties of the olives. In turn, Pit-Flesh Ratio (R_p) is a characteristic of the incoming olives that is defined mainly by their variety, and is another input variable to the system. Figure 3.6 renders the values of Crushing Degree (G_m) as a function of Sieve Size (C_{se}) and Pulp Firmness (P_F) for three different values of Pit-Flesh Ratio (R_p).

Besides Crushing Degree (G_m), Paste Emulsion (P_E) is another important parameter whose value is defined by the crushing process. It is affected by

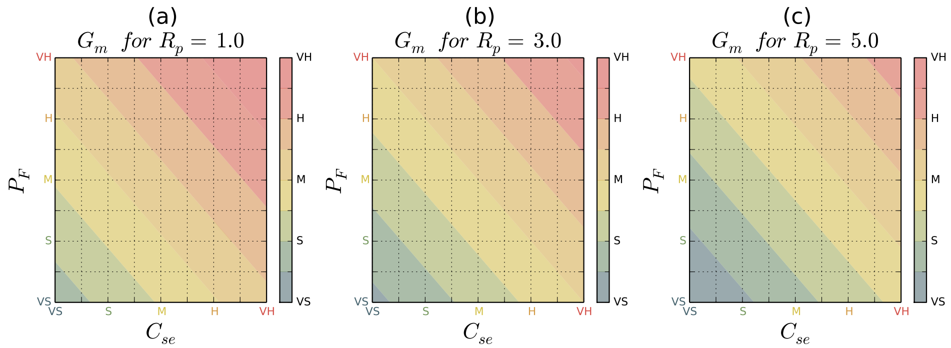


Figure 3.6: Values of Crushing Degree (G_m) as a function of Sieve Size (C_{se}) and Pulp Firmness (P_F) for three different values of Pit-Flesh Ratio (R_p).

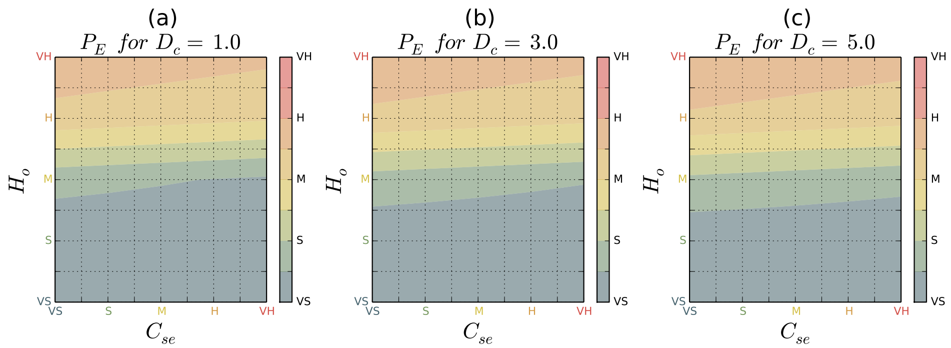


Figure 3.7: Values of Paste Emulsion (P_E) as a function of Sieve Size (C_{se}) and Olive Moisture (H_o) for three different values of Sieve Worn (D_c).

all the parameters that influence Crushing Degree (G_m), plus Olive Moisture (H_o), which plays a major role in its value. Values of Olive Moisture (H_o) below a certain threshold completely inhibit the emergence of emulsions, while higher values of the parameter dramatically contribute to their formation [Cert et al., 1996]. Besides this, Sieve Worn (D_c) and Hammer Worn (D_h) also exert some influence in the final value of Paste Emulsion (P_E). Figure 3.7 renders the values of Paste Emulsion (P_E) as a function of Sieve Size (C_{se}) and Olive Moisture (H_o) for three different values of Sieve Worn (D_c). This Figure highlights the major influence of the Olive Moisture (H_o), while the influence of Sieve Worn (D_c) is very slight.

Although the nominal spinning velocity of the hammers is usually fixed, the actual value of the velocity depends on Milling Production Rate (M_R), Sieve Size (C_{se}), Pit-Flesh Ratio (R_p), Pulp Firmness (P_F) and Olive Moisture (H_o). It is a parameter whose value is important, since, besides from slightly affecting Fruity (F) through Milling Temperature Increase (Δ_{Tm}),

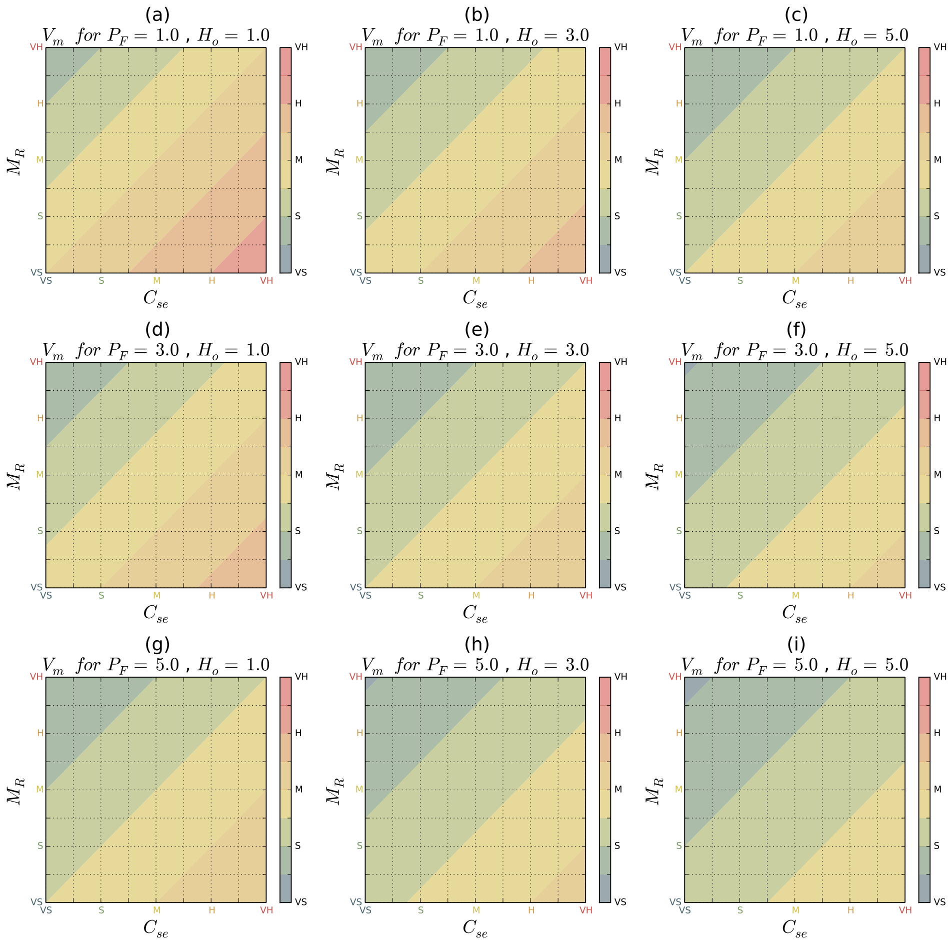


Figure 3.8: Values of Mill Speed (V_m) as a function of Milling Production Rate (M_R) and Sieve Size (C_s) for three different values of Pulp Firmness (P_F) and Olive Moisture (H_o).

having lower values may cause problems in the operation of the plant, eventually leading to broken sieves.

This consideration is important, since it enables the inclusion of a common practice in the VOOEP that would be unexplained if this parameter is not considered: the addition of water to the crusher when olive moisture is too low. This variable is represent by the node Mill Water Addition (M_W). The addition of water at this stage of the process favors the emergence of emulsions, and wields no influence on the quality of the oil. The reason for this practice is found in the requirement of assuring adequate working conditions for the crusher. Figure 3.8 includes values Mill Speed (V_m) for

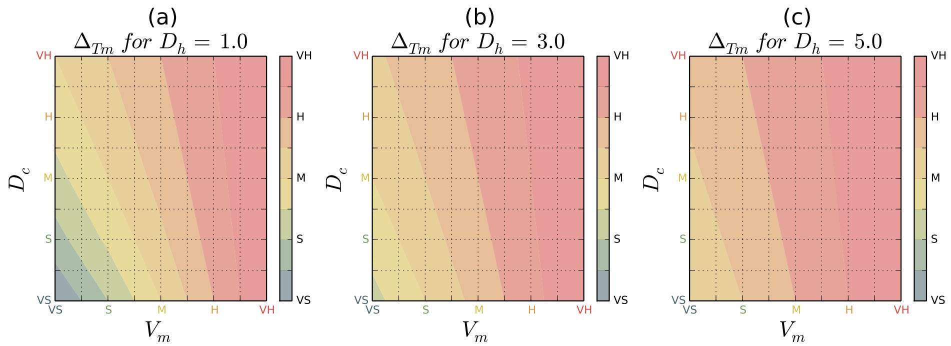


Figure 3.9: Values of Milling Temperature Increase (Δ_{Tm}) as a function of Mill Speed (V_m) and Sieve Worn (D_c) for three different values of Hammer Worn (D_h).

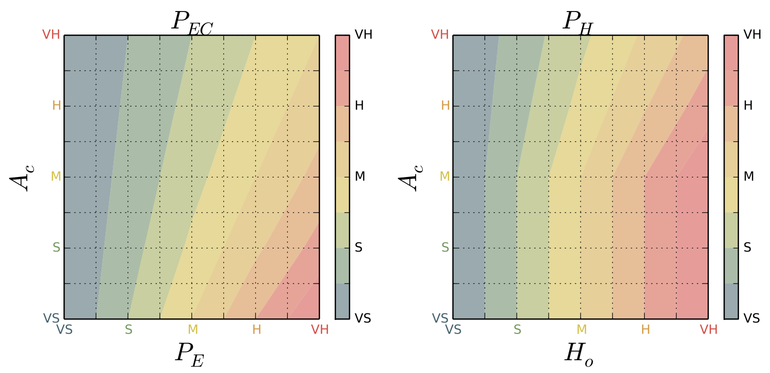
different values of its predecessors nodes, while Fig. 3.9 depicts Milling Temperature Increase (Δ_{Tm}) as a function of Mill Speed (V_m) and Sieve Worn (D_c) for three values of Hammer Worn (D_h).

The final step in the paste preparation process is the kneading of the paste inside the thermomixer. This is probably the most important part in the whole VOOEP, due to the influence it presents on both quality and yield [Clodoveo, 2012].

If the value of Paste Emulsion (P_E) is high, then coadjuvants are added to the paste to reduce this value. The node Coadjuvant Addition (A_c) represents the amount of coadjuvant added to the paste, and Corrected Paste Emulsion (P_{EC}) symbolizes the resulting level of emulsions in the paste after the addition of the coadjuvants. Figure 3.10a shows this influence of Coadjuvant Addition (A_c) on Corrected Paste Emulsion (P_{EC}).

The value of Paste Moisture Content (P_H) is also very important in the process, with values too high and too low affecting negatively the Kneading State (K_s). If Paste Moisture Content (P_H) is low, then some water can be added at this stage of the process, as represented by Thermomixer Water Addition (A_B) node. If Paste Moisture Content (P_H) is too high, then the addition of coadjuvant may moderately attenuate its negative influence on the yield, as depicted in Fig. 3.10b.

Lastly, Kneading Temperature (T_b) and Kneading Time (t_b) are the par excellence parameters that influence the kneading process. Higher values of both variables tend to increase Kneading State (K_s) and penalize Fruity (F), with a stronger influence shown by Kneading Temperature (T_b). Some nonlinear behavior of the parameters is considered, as reflected by the entries of the corresponding relation matrices included in Table **??**.



(a) Corrected Paste Emulsion (P_{EC}) (b) Paste Moisture Content (P_H)

Figure 3.10: Effect of Coadjuvant Addition (A_c) on Corrected Paste Emulsion (P_{EC}) and Paste Moisture Content (P_H)

Figure 3.11 and 3.12 illustrate the influence of Kneading Temperature (T_b) and Kneading Time (t_b) for a combination of 3 values of Paste Moisture Content (P_H) and Corrected Paste Emulsion (P_{EC}) on Kneading State (K_s). This Figure shows that Kneading State (K_s) is worse for low and high values of Paste Moisture Content (P_H), as well as the negative influence exerted by Corrected Paste Emulsion (P_{EC}). Also, the higher weight of Kneading Temperature (T_b) compared to Kneading Time (t_b) is patent in the almost vertical transition lines shown in these plots.

Finally, Figure 3.12 shows the values of Fruity (F) as a function of Kneading Temperature (T_b) and Kneading Time (t_b) for a combination of 3 values of Ripeness (R_f) and Milling Temperature Increase (Δ_{Tm}). The Figure clearly illustrates the requirement of having an adequate value of Ripeness (R_f) for having high values of Fruity (F), as well as the relative low range of possible process values if very high values of Fruity (F) are to be obtained.

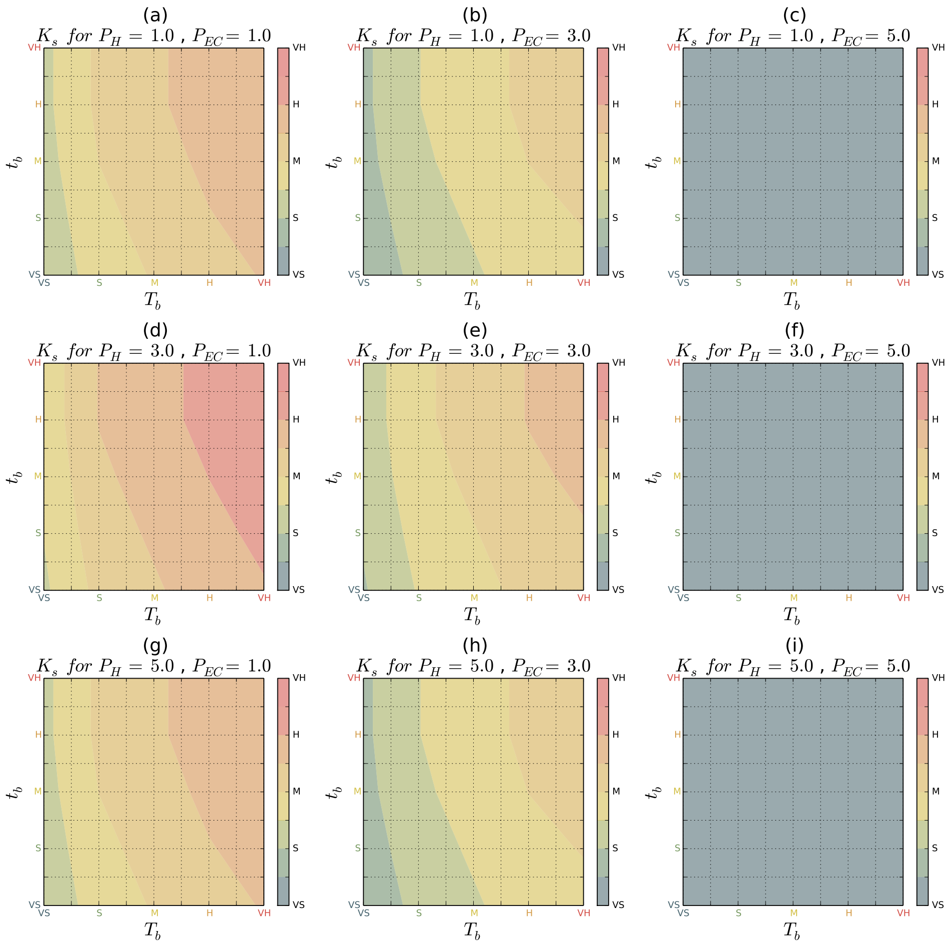


Figure 3.11: Values of Kneading State (K_s) as a function of Kneading Temperature (T_b) and Kneading Time (t_b) for three different values of Paste Moisture Content (P_H) and Corrected Paste Emulsion (P_{EC}).

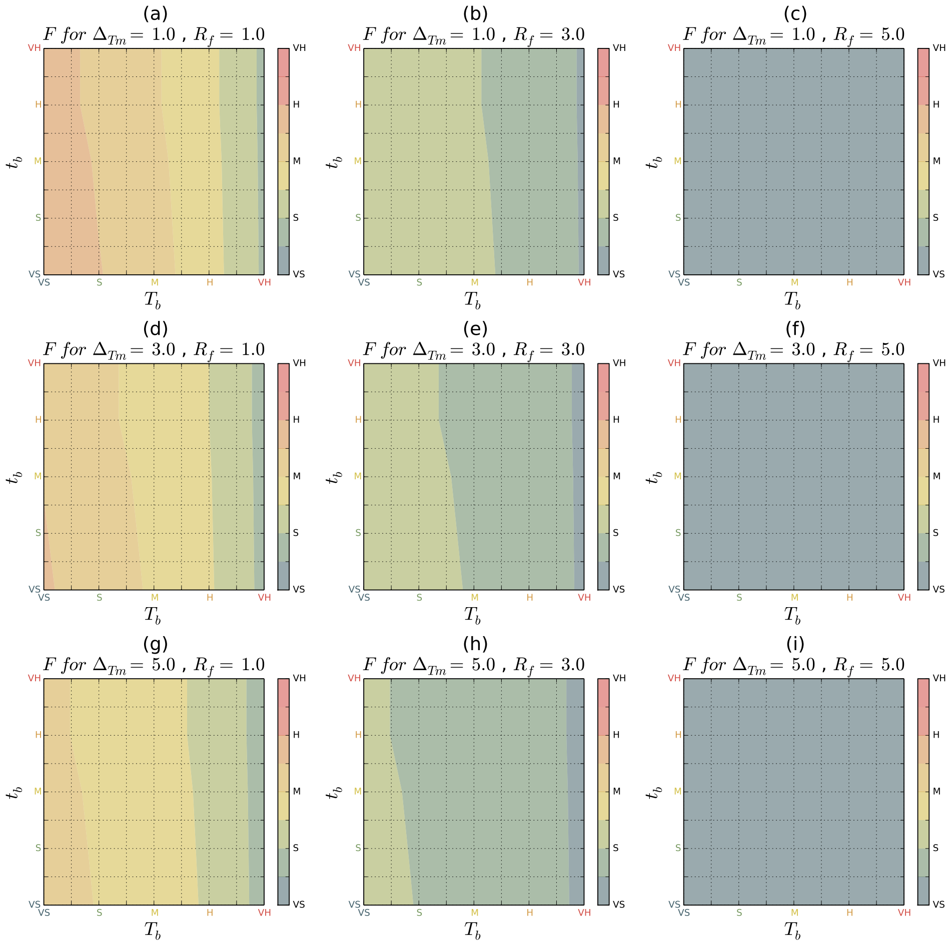


Figure 3.12: Values of Fruity (F) as a function of Kneading Temperature (T_b) and Kneading Time (t_b) for three different values of Ripeness (R_f) and Milling Temperature Increase (Δ_{Tm}).

3.7 Solid-Liquid Separation Model

The graph of the paste preparation model is included in Fig. 3.13, while all the relation matrices are included in Appendix C.

The model of the solid-liquid separation performed in the decanter is founded on the notion that the key element that greatly determines the separation efficiency of the decanter is the relative position between the theoretical oil-water interphase and the oil weirs. The variable that represents the offset between these elements is called Weirs-Separation Line Offset (Δr). Having Overflow Weirs Position (r_1) closer to the rotation axis than Separation Line (r_s) means that there is going to be a big pool of oil inside the decanter, which helps obtaining good values of Oil Cleannes (O_c), but diminishes Yield (X), since part of the oil goes with the pomace. In turn, having a theoretical position of Separation Line (r_s) closer to the rotation axis than Overflow Weirs Position (r_1) means obtaining good Yield (X) at the expense of having poor values of Oil Cleannes (O_c).

Overflow Weirs Position (r_1) is fixed by the operator of the plant, while Separation Line (r_s) depends on several operation parameters. A mass conservation analysis on the decanter helps to intuitively understand the dependence of Separation Line (r_s) with these parameters.

If we think of the decanter as a simple settling tank, it is intuitive to see that the outflow of pomace depends of the height of the pond and the axial velocity. Then, a simple model of the outflow of pomace from the decanter is:

$$q_{out} = \alpha \cdot \Delta\omega \cdot r_s,$$

since Differential Speed $(\Delta\omega)$ is the parameter that influences the velocity at which the pomace is traversing the decanter. Here, α is some unknown positive constant.

If we suppose that Differential Speed $(\Delta\omega)$ is constant, an increase of Production Rate (F) provokes a rise of Separation Line (r_s), as the total mass must remain constant inside the decanter after the transient state decays, and consequently the outflow of pomace must increase. Conversely, if Production Rate (F) remains constant and Differential Speed $(\Delta\omega)$ increases, Separation Line (r_s) decreases. The same argument applies for an increase of Water income flow (F_w) and Solid income flow (F_s). Figure 3.14a presents the values of Water Pool Width (h_w) as a function of Water income flow (F_w) and Differential Speed $(\Delta\omega)$, illustrating the commented behavior.

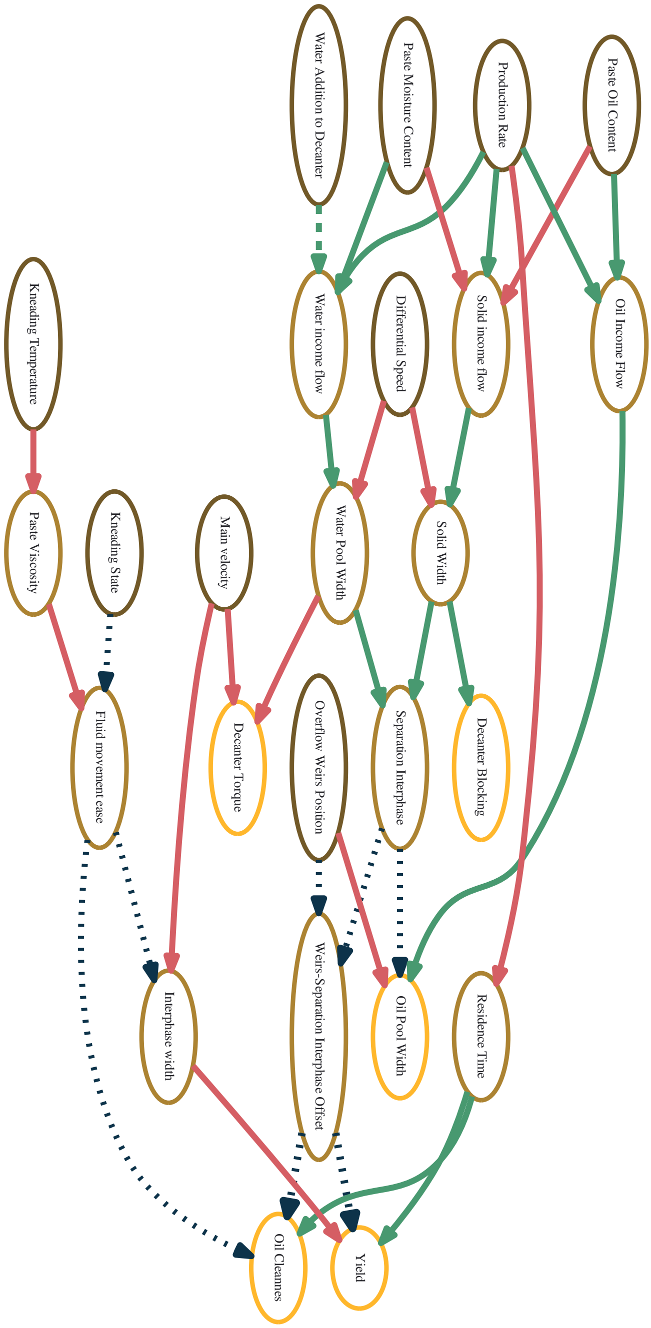
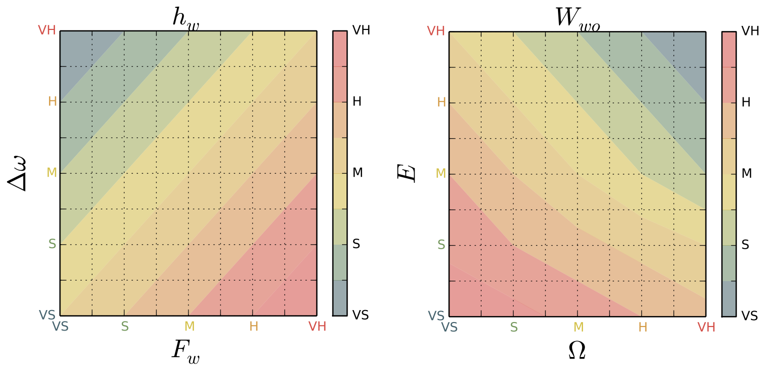


Figure 3.13: Graph of the VOOEP solid-liquid separation model. Green (red) arcs represent positive (negative) relations, continuous (dotted) lines stands for bidirectional (unidirectional) relations, and greater width of the line indicates greater value of the relation weight. Blue arcs represent relations defined by matrices of non-standard form.



(a) Values of Water Pool Width (h_w) as a function of Water income flow (F_w) and Differential Speed $(\Delta\omega)$.

(b) Values of Interphase width (W_{wo}) as a function of Main velocity (Ω) and Fluid movement ease (E).

Figure 3.14: Values of Interphase width (W_{wo}) and Water Pool Width (h_w)

Another important parameter in the efficiency of the separation is the width of the oil-water interphase (W_{wo}). This parameter decreases when Main velocity (Ω) increases, as the forces acting on the particles rise, according to Stoke's Law [Civantos, 1998b]. The other factor that influences this parameter is Fluid movement ease (E), a fuzzy variable that takes into account the influence of Kneading State (K_s) and Paste Viscosity (mu_p). The higher Fluid movement ease (E), the lower Interphase width (W_{wo}). Figure 3.14b shows the values of Interphase width (W_{wo}) as a function of Main velocity (Ω) and Fluid movement ease (E).

The third major parameter influencing Yield (X) is Residence Time (t_r). As is intuitive, higher Residence Time (t_r) enables achieving better Yield (X), as more time is granted for the particles to separate.

Figure 3.15 shows the values of Yield (X) as a function of Interphase width (W_{wo}) and Weirs-Separation Line Offset (Δr) for three different values of Residence Time (t_r). As commented above, values of the Weirs-Separation Line Offset (Δr) representing Overflow Weirs Position (r_1) closer to the rotation axis than Separation Line (r_s) offer poor Yield (X). Also, lower values of Interphase width (W_{wo}) offer better values of Yield (X). In turn, Figure 3.14b show the dependence of Oil Cleannes (O_c) with Weirs-Separation Line Offset (Δr) and Fluid movement ease (E). Here, values of Weirs-Separation Line Offset (Δr) representing Overflow Weirs Position (r_1) closer to the rotation axis than Separation Line (r_s) show better Oil Cleannes (O_c), with the parameter being favoured also with higher values

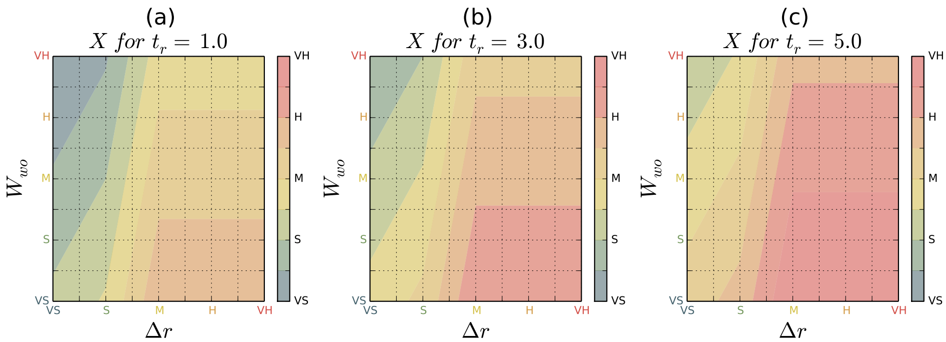


Figure 3.15: Values of Yield (X) as a function of Interphase width (W_{wo}) and Weirs-Separation Line Offset (Δr) for three different values of Residence Time (t_r).

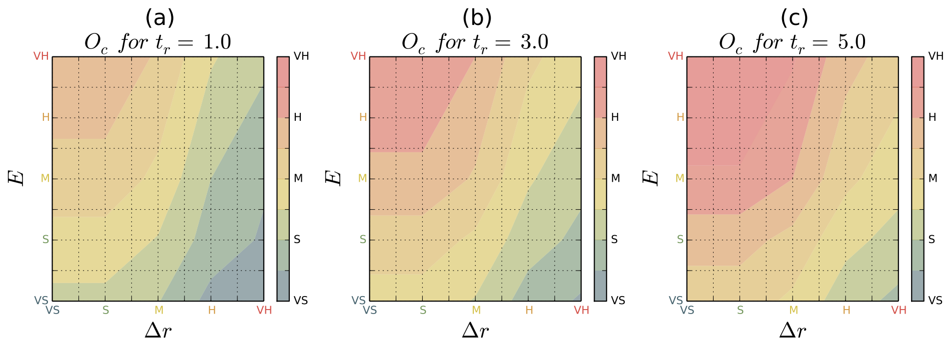


Figure 3.16: Values of Oil Cleannes (O_c) as a function of Fluid movement ease (E) and Weirs-Separation Line Offset (Δr) for three different values of Residence Time (t_r).

of Fluid movement ease (E).

Finally, the influence of the paste preparation stage on the operation of the decanter is depicted more clearly in Figures 3.17 and 3.18, where Yield (X) and Oil Cleannes (O_c), respectively, are shown as functions of Kneading State (K_s) and Weirs-Separation Line Offset (Δr) for three values of Kneading Temperature (T_b). As expected, both Kneading Temperature (T_b) and Kneading State (K_s) help obtaining good values of both Yield (X) and Oil Cleannes (O_c), as both parameters favor Fluid movement ease (E).

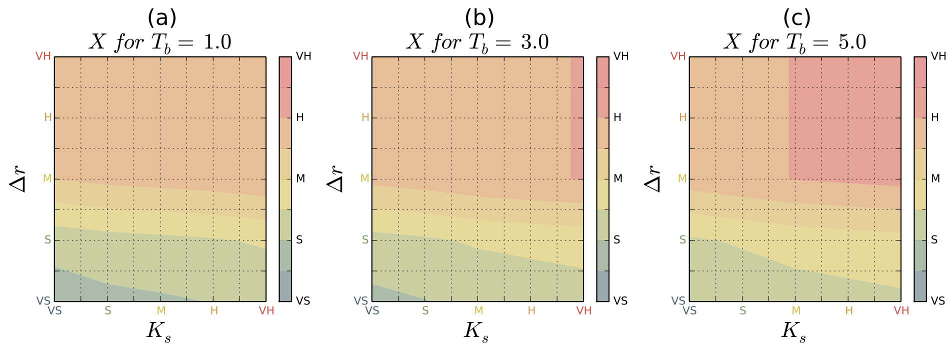


Figure 3.17: Values of Yield (X) as a function of Kneading State (K_s) and Weirs-Separation Line Offset (Δr) for three different values of Kneading Temperature (T_b).

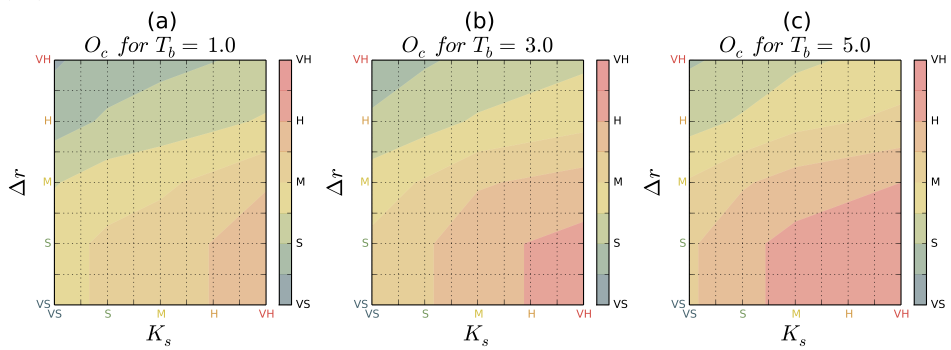


Figure 3.18: Values of Oil Cleannes (O_c) as a function of Kneading State (K_s) and Weirs-Separation Line Offset (Δr) for three different values of Kneading Temperature (T_b).

4

Production Objective and Set Points Selection

4.1 Introduction

We already have a base of model of relations among the different variables of the VOOEP. In this Chapter we use those models to find answers to following questions regarding the process:

1. Which production objectives are possible, given the batch of olives to be processed?
2. Which of those possible objectives should be selected?
3. What set-points of the process variables allow to reach that production objective?

The multi-objective nature of the VOOEP already became apparent in Section D.3 during the brief description of its operations: the opposite influence of several process variables on relevant process outputs supposes having to compromise the value of one output for the other. This multi-objective characteristic can be formalized by the definition of an objective vector, where each element of the vector represents a desiderable characteristic of the output of the process, such as having high fruity, good yield or low elaboration costs.

The existence of trade-offs between desirable characteristics of the VOO supposes that, in general, there is not an unique set of values of the process variables that concurrently optimize all the elements of the objective vector, but a Pareto boundary of non-dominated objective points [Ehrgott, 2006]. These Pareto points represent those situations where an improvement in the value of an objective necessarily means a decrease in the value of another [Ehrgott, 2006]. Finding this boundary answers a slightly improved version the first of the posed questions, namely *which efficient objectives are possible?*

The selection of just one of these Pareto frontier points as production objective depends on the relevance assigned to each of the components of the objective vector. For instance, depending on the characteristics of the incoming olives and the market, obtaining a high yield might be more important than preserving the fruity of the VOO, or obtaining a VOO without any organoleptic defect might be the first concern in the elaboration. This point is addressed in Section 4.5 and lead to answering the second question: *which of the possible objectives should be chosen.*

Finally, the answer to the last question, i.e., *which set points of the process variable should we use to obtain the defined objective,* emerges naturally from the mathematical structure used to answer the previous questions, as the decision variables in the optimization problems are, precisely, the values of those desired set points. The question of obtaining those optimal for a given production objective is discussed in Section 4.4.

The analysis of the models developed in the previous Chapter reveals an interesting aspect that simplifies the complexity of the models required for selecting the production objective and its corresponding set points: the solid-liquid operation does not present any trade-off for the output variables of the system, but those type of relations are included in the paste preparation process exclusively. This means that establishing the optimization of the yield as the objective for the solid-liquid operation is not in conflict with the achievement of any particular value of the VOO properties. This, in turn, reduces to problem to just that of optimal set point selection for the solid-liquid separation, and allows to obviate its relations among variables when facing the production objective selection problem.

The remaining of the Chapter is organized as follows: the following Section discusses the characteristics of the optimization problem to be solved.

In turn, the determination of the Pareto boundary is dealt with in Section 4.3, with Section 4.4 dealing with the process set points. Finally, Section 4.5 addresses the selection of a single production objective out of the possible ones.

4.2 Analysis of the optimization problem

The following Sections analyze different aspects of the optimization problem to be defined and solved in order to find the achievable production objectives and select the optimal set points for the VOOEP.

4.2.1 Analysis of the role of the nodes in the VOOEP models

As discussed in Chapter 3, the variables of the VOOEP can be classified according to their role in the process as:

- Properties of the incoming olives: this group included those variables that characterize the olives whose value is already fixed when the olives arrive at the factory.
- Technological parameters: all those variables whose set points are susceptible to be specified by the operator of the factory.
- Auxiliary parameters: these are parameters whose value depends on other upstream variables, and thus cannot be chosen arbitrarily, but do not represent an output variable of the process.
- Output parameters: these are the variables that are usually included in the production objective of the process.

For the set up of the optimization problems, we classify the VOOEP variables according to their role in the optimization problem as:

- Parameters (p): these VOOEP variables are considered to have a fixed value for the optimization problem at hand. They will usually include the properties of the incoming olives, along with some other process parameters whose value is justified to be fixed for the current problem.

- Decision variables (x): these VOOEP variables are the ones whose value is to be specified by the optimization problem. Usually, they will be a subset of the process variables.

- Objective variables (y): those VOOEP variables whose value is considered an output of the process and are included in the objective vector.

Since the values of the objective variables (y) depend on the parameters (p) and decision variables (x), we may represent these relations as:

$$\mathrm{y} = f(\mathrm{x},\ \mathrm{p}).$$

The VOOEP models obtained in the previous Chapter provide an approximation of this f function, as they relate the values of the output parameters with properties of the incoming olives and the technological parameters.

Following this notation, we may define the objective vector of the multi-criteria optimization problem as:

$$F(\mathrm{y},\mathrm{x} \mid \mathrm{p}) = \begin{bmatrix} f_1(\mathrm{y},\mathrm{x} \mid \mathrm{p}) \\ f_2(\mathrm{y},\mathrm{x} \mid \mathrm{p}) \\ \vdots \\ f_n(\mathrm{y},\mathrm{x} \mid \mathrm{p}) \end{bmatrix},$$

with $f_i,\ i \in \{1,\ 2,\ \cdots,\ n\}$ representing each of the objectives.

The problems we are to solve for the answer of the different posed questions have the general structure:

$$\begin{array}{rr} \text{"min"} & F(\mathrm{x} \mid \mathrm{p}) \\ \text{s.t.} & \mathrm{y} = f(\mathrm{x},\ \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \end{array}$$

with the meaning "min" being properly defined in each particular problem studied.

4.2.2 Analysis of the constraints imposed by the VOOEP models

The analysis of the computation of the state of a node in the model included in Section 3.3.1.3 sheds some light on the type of constraints imposed by the models in the optimization problem definition.

The computation of the impact received by a node i:

$$\mathrm{w}_i = \sum_{j=1}^{n_i} \omega_{ij}\, R_{ij} S_f(v_j) \tag{4.1}$$

is clearly linear, since there are no products among variables as the elements of R_{ij} and ω_{ij} are fixed parameters of the model.

The calculation of the crisp value $S_c(v_i)$, given by

$$S_c(v_i) = \bar{\mathrm{w}} \cdot \mathrm{m} = \sum_{k=1}^{l} \bar{w}_k^i\, m_k^i,$$

is also linear, since, again, the kernel of each label is also a fixed model parameter.

Obtaining the fuzzy state vector of the node $S_f(v_i)$ from its crisp value $S_c(v_i)$ is a little bit trickier, since the triangular membership functions used are piecewise continuous functions:

$$f(x;b,s) = \begin{cases} 0 & \text{if } x \le b-s \\ 1+\frac{x-b}{s} & \text{if } b-s \le x \le b \\ 1+\frac{b-x}{s} & \text{if } b \le x \le b+s \\ 0 & \text{if } x \ge b+s \end{cases}$$

However, this represents no major hurdle since, employing auxiliary variables, this constraint could also be cast into linear form. Given that the used membership functions add up to one in each point of the universe of discourse of the node, the following constraint is introduced:

$$\sum_k y_{ik} = 1.$$

With this constraint, we can use inequalities to bound the upper value that each membership value can reach, thus:

$$y_{ij} \le 1 + \frac{y^c - b_j}{s}$$

$$y_{ij} \le 1 + \frac{b_j - y^c}{s}$$

However, in order to assure the feasibility of the problem, a new set of non-negative auxiliar variables is required. The constraints regarding the membership values are finally:

$$y_{ij} - \delta_{ij} \leq 1 + \frac{y^c - b_j}{s}$$
$$y_{ij} - \delta_{ij} \leq 1 + \frac{b_j - y^c}{s}$$

with $\delta_{ij} \geq 0$. In order force that the value of each δ_{ij} is not zero only when required to assure feasibility, the objective function of the optimization problem must be augmented including a term that penalizes the value of each δ_{ij}:

$$\sum_{i \in \Omega} \delta_i.$$

Finally, we also enforce each membership value to lie between zero and one:

$$0 \leq y_{ij} \leq 1.$$

Using this trick, the constraints imposed by the membership have been transformed into linear ones.

The remaining relation to be addressed is the computation of the normalized impact given the impact received by the node:

$$\bar{\mathrm{w}}_i = \frac{\mathrm{w}_i}{\sum_{k=1}^{l} w_k}.$$

Unfortunately, this relation imposes a non-convex quadratic constraint, since the analysis of the eigenvalues of the associated matrix shows the existence of negative ones. Although all the variables in the system are guaranteed to be non-negative, they are not guaranteed to be positive, as the membership value to a label can be zero. Due to this property of the system, geometric programming could not be applied either [Boyd and Vandenberghe, 2004].

Once that the nonlinear and non-convex nature of the problem appeared unavoidable, its formulation aimed at using as little variables as possible to define it [Venkataraman, 2009]. The crisp value of the node $S_c(v_i)$ was the variable used, as it is the single variable that captures the state of the node, and the computations were lumped into a single function for each node.

This way, a problem with n nodes is composed of n variables, n nonlinear equality constraints and the corresponding $2n$ box-bounding inequalities.

Moreover, since there are no inequality constraints in the problem formulation beyond the box ones, the problem can be casted into a nonlinear box-constraint optimization by including all the required computations in the objective function, which was the final approach implemented when solving the problems. However, for the formulation of the problems in the text, the description using the nonlinear equality equations is preferred, and used in the remaining of the Chapter.

4.2.3 Solvers used for the optimization

Finding the solution of a nonlinear optimization problem is not a simple task in general [Nocedal and Wright, 2006]. Since the problem at hand is non-convex, finding the true global optimum solution is not guaranteed, as the solution found by the algorithm might be just a local optimum, dominated by some other point out of the awareness of the employed algorithm [Nocedal and Wright, 2006].

The majority of nonlinear solvers available are local solvers, meaning that they just look for a local optimum, and do not check if the solution is actually a global optimum. For these type of algorithms, providing a good initial point is very important, as the optimum solution found is to be *close* to it. The advantage of these type of solvers is that they are typically *faster* than global algorithm. A sensible way of employing these algorithms is by providing different initial points and checking if the optimum found coincides, which would provide some hint that if not the true optimum, at least a good solution for a wide area is found.

On the other hand, global solvers explicitly try to obtain the global optimum for the problem at hand. Different methods exist, such as particle swarm optimization, simulated annealing, ant-colony optimization or genetic algorithms [Hendrix et al., 2010].

The algorithm used for the solution of the posed problems was the implementation of a differential evolution algorithm [Price et al., 2005, Feoktistov, 2007] provided in the OpenOpt [Kroshko, 2007] open source optimization package. The differential evolution algorithms are based on genetic algorithms and are applicable to continuous optimization problems.

The main reason for the election of this particular algorithm was that the size of the problem at hand made tractable the use of global optimization solvers, and the tests carried out shown that this particular algorithm was the fastest of the global solver alternatives.

4.3 Achievable Production Objectives

This Section covers the determination of the Pareto boundary of possible production objectives given a set of fixed parameters of the process. In this optimization problem, it is natural to consider that p is composed of the properties of the incoming olives. However, any condition of the process variable whose value were to be regarded as fixed could also be included in the array, such as the cleanness of the factory.

Points belonging to the Pareto boundary can be found using different methods, such as Normal Boundary Intersection [Das and Dennis, 1998], Weighted Sum Scalarization and the ϵ-constraint method [Ehrgott, 2006].

For simplicity, the Weighted Sum Scalarization method was used to obtain the different plots included below. This method requires finding the solutions to the following problems:

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & J = \sum_{k=1}^{c} \omega_k f_k(\mathrm{y}, \mathrm{x}) \\ \text{subject to} \quad & \mathrm{y} = f(\mathrm{x}, \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \end{aligned}$$

for different combinations of scalarization weights ω_k.

The elements of the objective vector considered were the quality characteristics of the obtained VOO included in the paste preparation model developed in the previous Chapter, namely Fruity (F) and Defect (D), and Kneading State (K_s). This last node allows to take into account the industrial yield of the process since, as discussed in Sec. 4.1, the influence of the separation process can be disregarded for this analysis, as it does not contribute to the yield-quality trade-off.

An analysis of the paste preparation model shows that there is no real trade-off between Defect (D) and Fruity (F). The only node that influences both variables is Fruit State (E_f), and the effect of this parameter in both variables shows the same sign. Taking this fact into account, the value of both nodes was combined into a single objective in order to reduce the

Table 4.1: Value of the olive properties and fixed VOOEP paramaters for the Figures 4.1, 4.4 and 4.5.

	Value
Dirtiness (D_t)	VL
Hammer Worn (D_h)	VL
Incoming Fruit State (E_f^I)	VH
Incoming Olive Moisture (H_o^I)	M
Olive Illnes (O_I)	VL
Pit-Flesh Ratio (R_p)	M
Ripeness (R_f)	M
Sieve Type (S_t)	M
Sieve Worn (D_c)	VL

analysis to a bi-objective problem and facilitate the visualization of the results. As for the weight considering the relative relevance of Fruity (F) and Defect (D), a value of $\omega_q = 0.5$ was chosen to assign the same priority to both parameters. The influence of assigning different priorities to these variables is illustrated in Section 4.5, when dealing with the selection of a single production objective. This way, the objective vector analyzed was:

$$F(\mathrm{y},\mathrm{x}\,|\,\mathrm{p}) = \begin{bmatrix} f_1(\mathrm{y},\mathrm{x}\,|\,\mathrm{p}) & = & \omega_q\, F + (1-\omega_q)\, D \\ f_2(\mathrm{y},\mathrm{x}\,|\,\mathrm{p}) & = & K_s \end{bmatrix}.$$

4.3.1 Olive properties influence

In this Section we analyze the impact on the achievable production objectives and their trade-offs caused by the different properties of the olives.

- **Olive Moisture** (H_o). Figure 4.1 shows points in the Pareto front for different values of Incoming Olive Moisture (H_o^I), with the rest of olive characteristics considered defined in Table 4.1. The different starting points for the frontier in the highest achievable Fruity (F) area, showing lower values of Kneading State (K_s) for wetter olives illustrate the more challenging conditions of obtaining good yields from wet olives while preserving the quality. However, the most noticeable difference is illustrated in the plot relating Defect (D) and Kneading State (K_s), as obtaining high values of Kneading State (K_s) convey having a remarkable increase in Defect (D). A plot of the decision variables for the different problems solved is included in Figures 4.2 and 4.3. An inspection of these plots shows that main responsible for

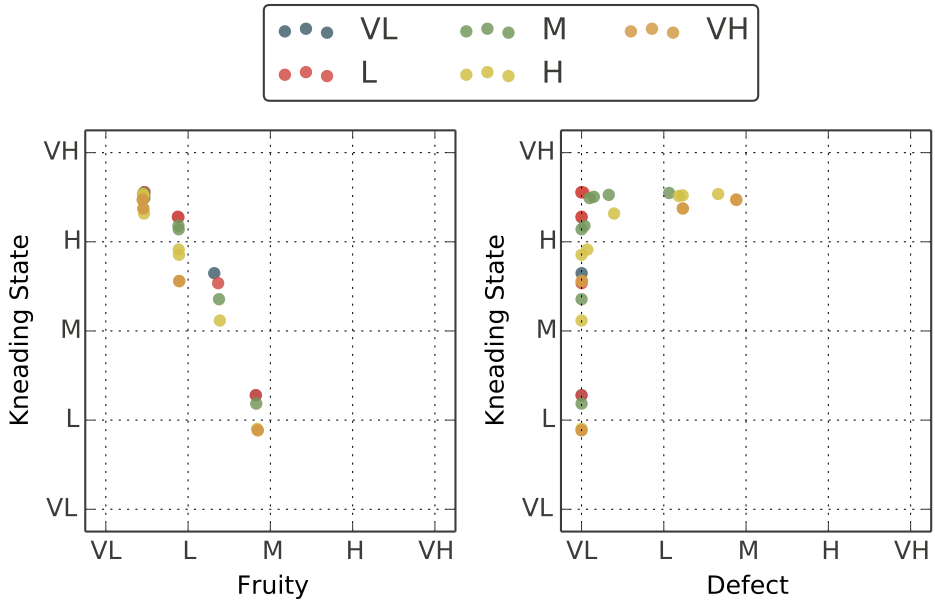


Figure 4.1: Points belonging to the Pareto boundary for the different values of Incoming Olive Moisture (H_o^I) specified in the legend, with the rest of the olive properties and fixed process parameters specified in Table 4.1.

this behavior is the increase in Storage Time in Hopper (T_s) required to decrease Corrected Paste Emulsion (P_{EC}) beyond the point that Coadjuvant Addition (A_c) can provide. This behavior will be further explored when addressing the optimal values of the process variables set points.

- **Ripeness** (R_f). The main influence of Ripeness (R_f) is the different values of Fruity (F) which are achievable, with lower values of Ripeness (R_f) always offering higher values of Fruity (F) for every value of Kneading State (K_s). It is also worth noticing the reduction of choices for interesting process objectives as Ripeness (R_f) increases, patent in the increasing slope of the Pareto frontier showing that decreasing aimed Kneading State (K_s) yields smaller improvements of Fruity (F). This behavior will be mentioned again when dealing with the definition of a single objective point in Section 4.5.

- **Incoming Fruit State** (E_f^I). In turn, Incoming Fruit State (E_f^I) shows a milder, although noticeable, limiting effect on Fruity (F). The greatest effect, however, in effected on Defect (D), with the points in the plots almost parallel to Kneading State (K_s) and clearly separated

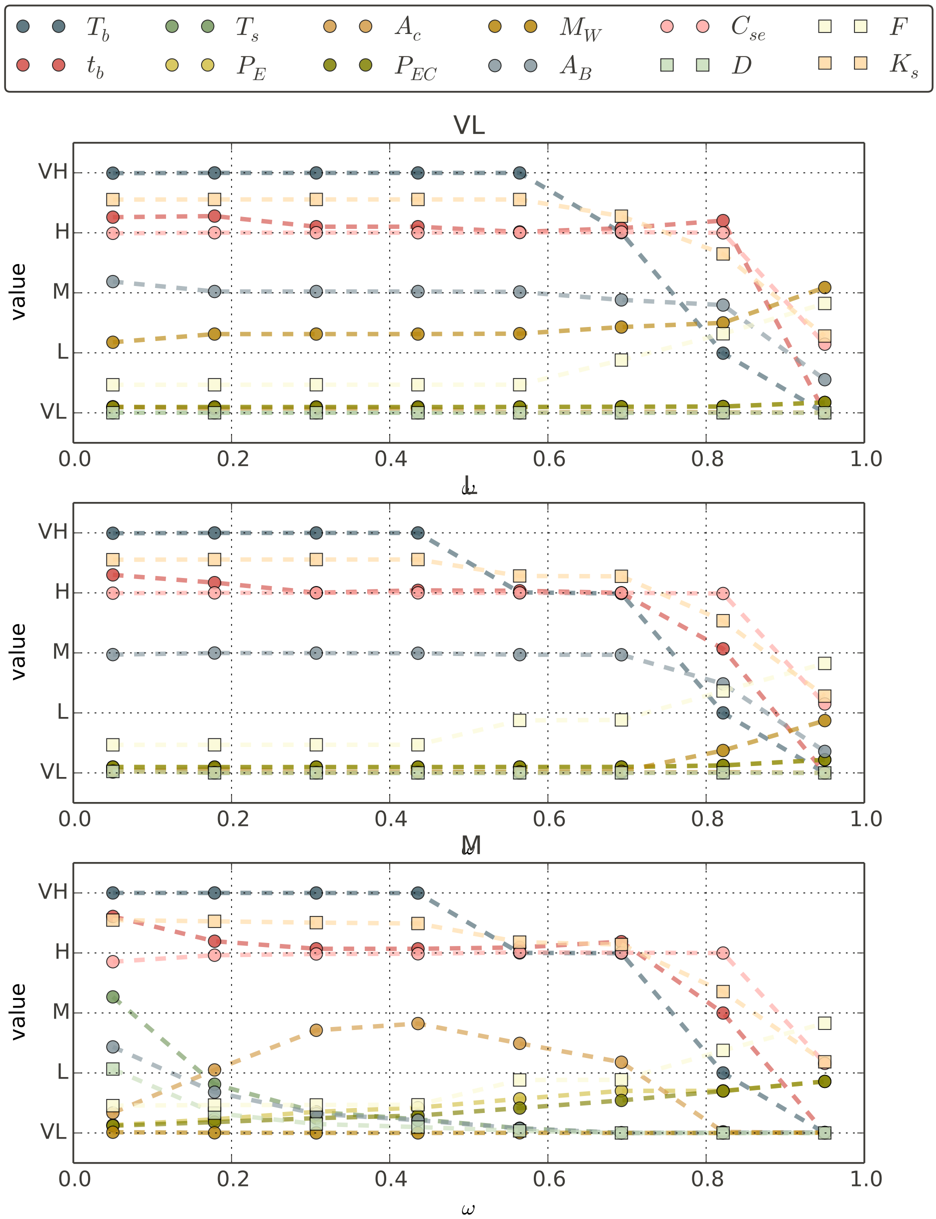


Figure 4.2: Process Set Points for the points in the Pareto boundary shown in Figure 4.1. The title of the subplot indicates the value of Incoming Olive Moisture (H_o^I) considered.

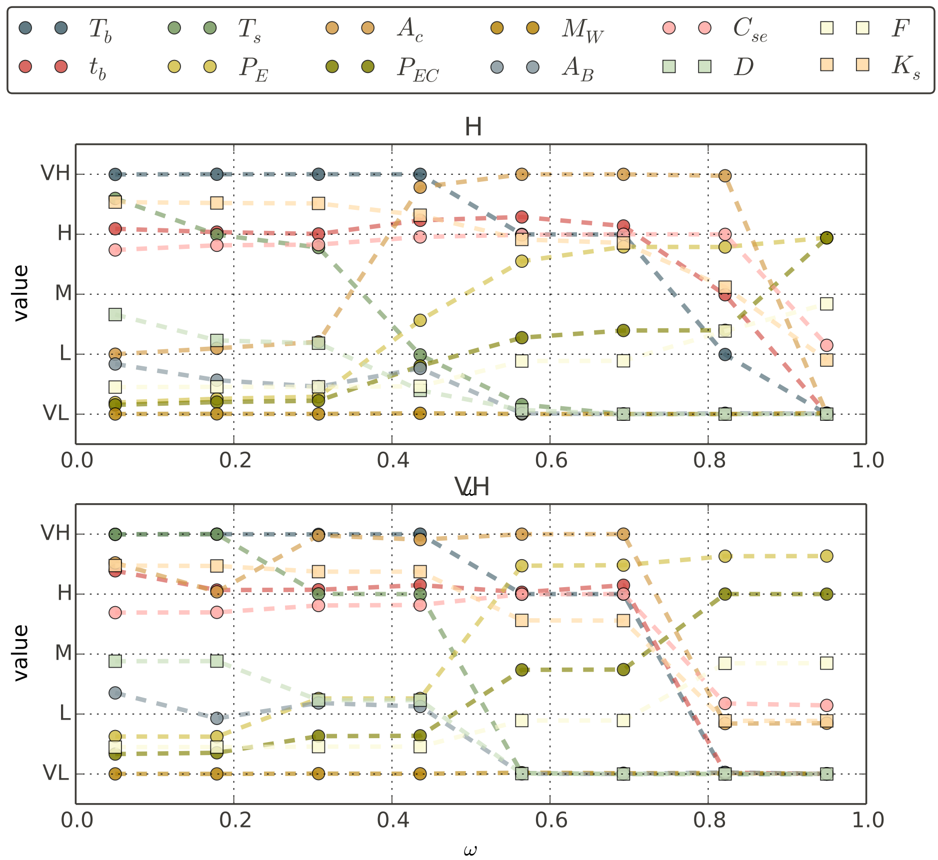


Figure 4.3: Process Set Points for the points in the Pareto boundary shown in Figure 4.1. The title of the subplot indicates the value of Incoming Olive Moisture (H_o^I) considered.

by values of Incoming Fruit State (E_f^I). The increase in Defect (D) for higher values of Kneading State (K_s) is similar to that found when visualizing the effect of Olive Moisture (H_o), and the reason is also the same: longer values of Storage Time in Hopper (T_s) which provoke a decrease in Fruit State (E_f) and contribute to higher values of Defect (D).

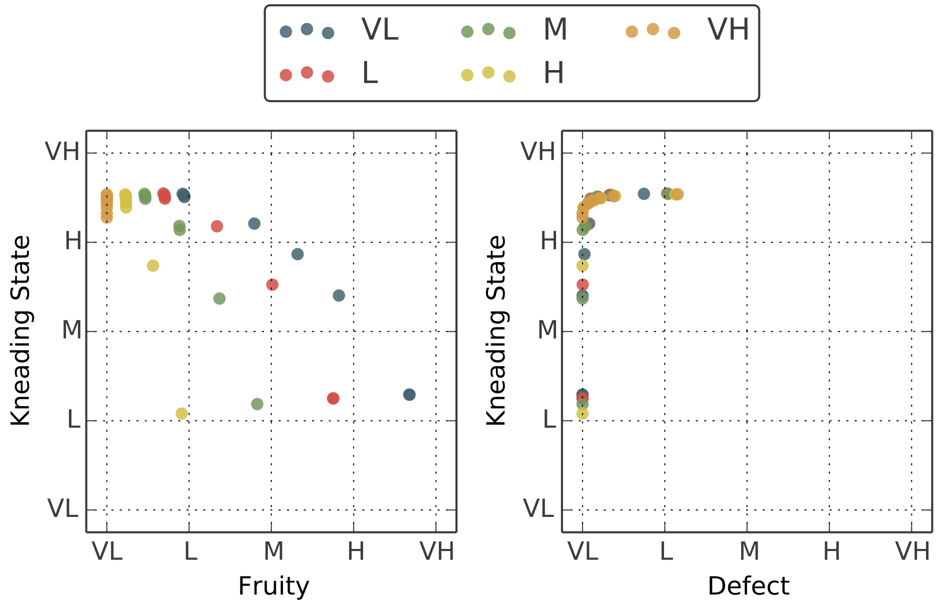


Figure 4.4: Points belonging to the Pareto boundary for the different values of Ripeness (R_f) specified in the legend, with the rest of the olive properties and fixed process parameters specified in Table 4.1.

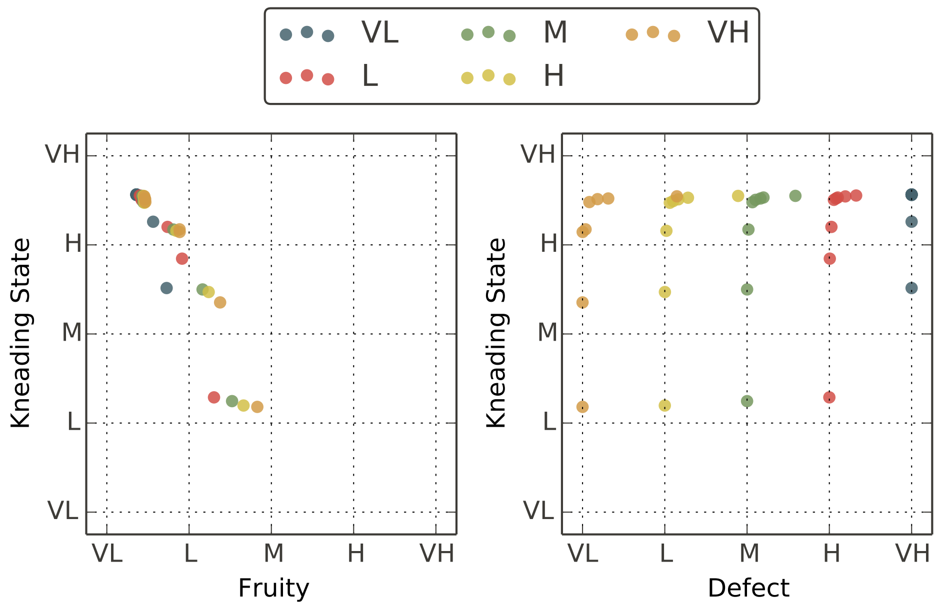


Figure 4.5: Points belonging to the Pareto boundary for the different values of Incoming Fruit State (E_f^I) specified in the legend, with the rest of the olive properties and fixed process parameters specified in Table 4.1.

Table 4.2: Value of the olive properties and fixed production parameters for each of the scenarios considered in Figure 4.6.

	November	December	January healthy	January damaged	February	March
Dirtiness (D_t)	VL	VL	VL	VL	VL	VL
Hammer Worn (D_h)	VL	VL	VL	VL	VL	VL
Incoming Fruit State (E_f^I)	VH	VH	VH	M	M	L
Incoming Olive Moisture (H_o^I)	VH	H	M	M	L	L
Olive Illnes (O_I)	VL	VL	VL	VL	VL	VL
Pit-Flesh Ratio (R_p)	M	M	M	M	M	M
Ripeness (R_f)	VL	L	M	M	H	VH
Sieve Type (S_t)	M	M	M	M	M	M
Sieve Worn (D_c)	VL	VL	VL	VL	VL	VL

4.3.2 Production scenario analysis

The previous Section showed the influence of the characteristics of the olives in the achievable Pareto points. However, although the properties of the olives are theoretically independent variables, they usually present some correlation in their values [Hermoso et al., 1997]. That is, some combinations of values of the properties are more likely to be found in a real scenario, while other are very unlikely. This Sections presents the achievable objectives for some typical combination of the properties of the olives through the season, as included in Table 4.2.

Figure 4.6 shows the points of the Pareto boundary for each of these scenarios. A first inspection of this Figure draws the attention to the decrease of the maximum values for Fruity (F) and increase of the minima for Defect (D) for successive scenarios. As commented in the previous Section, the progressive increase of Ripeness (R_f) and decrease of Fruit State (E_f) are responsible for this behavior. This is coherent with the well known

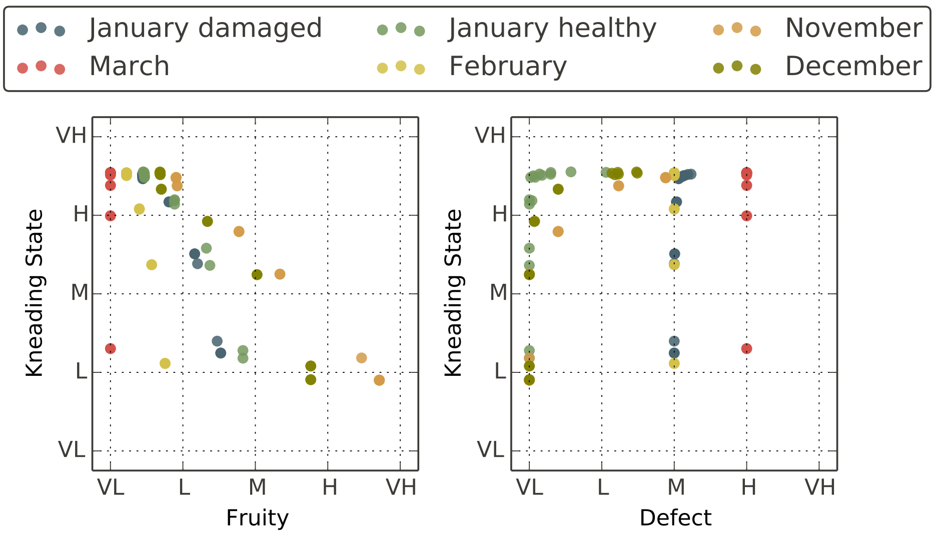


Figure 4.6: Points belonging to the Pareto boundary for the different scenarios specified in the legend, with the corresponding olive properties and fixed process parameters specified in Table 4.2.

fact in the industry that, in order to obtain good VOO quality, the olive conditions must meet some requirements, with the VOOEP not being able to compensate for the lack of quality of the olives.

When studying the conservation of the olives in low temperature storage, and referring to the inability of this technique to increase the quality of already damaged olives, García and Yousfi remark that "*Finally, it is necessary to take into account that cold storage is not a fruit hospital.*" [García and Yousfi, 2007]. The same could be said of the whole VOOEP process, as poor olive quality cannot produce good quality VOO, irrespective of the employed process variables. On the other hand, it is very possible indeed to obtain poor quality VOO from exceptional olives, if the correct values of the process variables are not employed. This is illustrated in the spread of the points for the scenarios where good quality olives are considered, and how it is possible to get to points were Fruity (F) is lower, and Defect (D) higher than they could be.

The increase in Defect (D) when approaching the higher Kneading State (K_s) values in the two first scenarios can be attributed to the higher Olive Moisture (H_o) considered and the associated increase of Storage Time in Hopper (T_s), a behavior already depicted in Figure 4.1. In turn, the vertical disposition of the points in the plot on the right of Figure 4.6 for the lower-

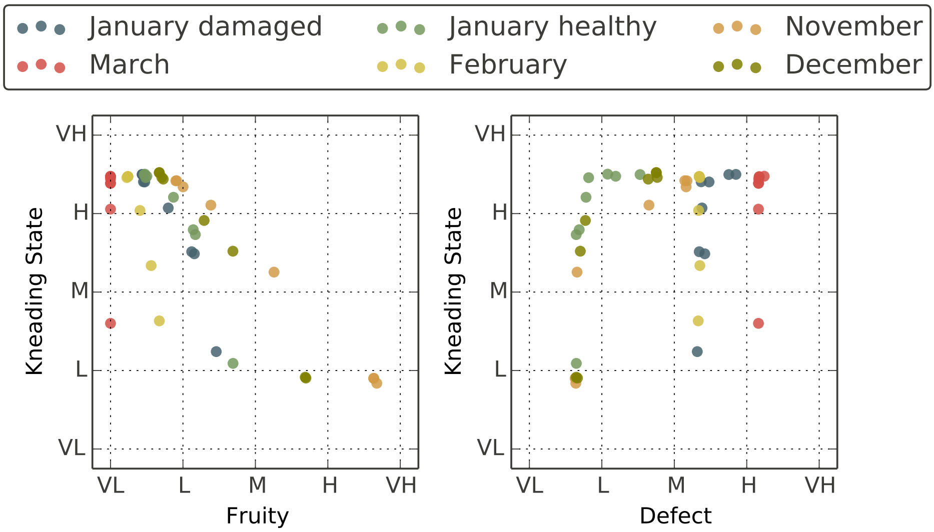


Figure 4.7: Points belonging to the Pareto boundary for the different scenarios specified in the legend, with the corresponding olive properties and fixed process parameters specified in Table 4.2, but for a value of of H.

quality scenarios reveals that good yields do not necessarily convey an increase in Defect (D), but a toll is paid in the decrease of Fruity (F).

The scenarios defined suppose that the *almazara* is very clean, that is, that is VL. It is interesting to explore how a different value of this parameter may affect the achievable production objectives. Figure 4.7 shows the Pareto boundary for the scenarios defined in Table 4.2 but considering a value of of H. The comparison of this plot with Figure 4.6 shows that Fruity (F) is not affected by the level of of the factory, but a difference is visible in Defect (D), where all the values are displaced towards the right. For the scenarios where Defect (D) was already noticeable, the change is not too important, but for scenarios where defect free VOO could be obtained, this offset represents a major concern, since it means a major decrease on the quality of the VOO. The implications of this effect will be examined when studying the optimal production objective attending to economic criteria in Section 4.5.

4.4 Optimal set points of VOOEP process variables

As commented in Section 4.1, the value of the set points of the process variables are given by the values of the decision variables that allow to achieve the production objective, no further actions are required to obtain the set points for the plant, as the solution of the problem posed to find the production objective already yields the corresponding set points.

However, since there are more process variables than outcome variables, we have a *fat plant* where we expect that several combinations of the values of the manipulated variables yield the same process outputs [Qin and Badgwell, 2003]. To deal with these additional degrees of freedom, it is natural to impose further conditions on the process variables to select just one combination of values out of all the possible ones.

The most straightforward of such conditions is to require the cost of the operation to be minimum. This condition can be implemented preserving the Pareto points found by resorting to a lexicographical optimization approach [Ehrgott, 2006].

The lexicographical order approach implies assigning an order of prevalence to the different elements of the objective vector, and solving a scalar optimization problem for each of them, augmented with a restriction on the value of the previously solved problem [Ehrgott, 2006]. If we assume that the elements of the objective vector are ordered according to this prevalence preference, the successive problems to be solved are:

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & J = f_j(\mathrm{y}, \mathrm{x}) \\ \text{subject to} \quad & \mathrm{y} = f(\mathrm{x}, \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \\ & f_i(\mathrm{y}, \mathrm{x}) \leq f_i^*, \; i = 1, \cdots, j-1 \end{aligned}$$

This way, the first objective is optimized without considering any of the following objectives, which are addressed afterwards an modify the solution of the problem just if there are extra degrees of freedom.

In our case, a first optimization is carried out without regard of process costs to find the points of the Pareto boundary – this is the optimal production objective problem, whose associated optimization problem was addressed in the previous Section. Then, a second optimization problem is posed to minimize the cost, subject to obtaining the production objective defined in the former optimization problem. This preference can be formalized using the following optimization vector:

$$F(\mathrm{y},\mathrm{x}|\mathrm{p}) = \begin{bmatrix} f_1(\mathrm{y},\mathrm{x}\mid\mathrm{p}) = \omega_i(omega_q\, F + (1-omega_q)\, D) + (1-\omega_i)K_s \\ f_2(\mathrm{y},\mathrm{x}\mid\mathrm{p}) = c(\mathrm{x}\mid\mathrm{p}) \end{bmatrix}.$$

with $c(\cdot)$ representing the cost function.

The introduction of these inequality constraints increase the complexity of the problem, and increment significantly the computation time required for its solution. In order to reduce this computation time, an alternative problem was posed whose solution is expected to be close to that obtained solving the above one.

The approach taken was a to formulate an optimization problem including both elements of F in the objective function, but assigning a weight to each element such that the first objective clearly prevails over the second.

With this modification, the second optimization problem considered is:

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & J = Hf_1(\mathrm{y},\mathrm{x}\mid\mathrm{p}) + f_2(\mathrm{y},\mathrm{x}\mid\mathrm{p}) \\ \text{subject to} \quad & \mathrm{y} = f(\mathrm{x},\mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \end{aligned}$$

with H representing a constant such that $H >> 1$.

4.4.1 Optimal Process Set Points for Different Production Scenarios

The values of the set points for each considered scenario and relative weight of the objectives are commented below:

- **November:** The values of the process variables for low values of ω, which represent the priority of Kneading State (K_s), reflects the traditional recipe for elaborating VOO without caring about its quality: high Storage Time in Hopper (T_s) to allow for the olives to lose moisture at the expense of increasing Defect (D), and high values of Kneading Temperature (T_b) and Kneading Time (t_b), which offer good Kneading State (K_s) while reducing Fruity (F). The high value of

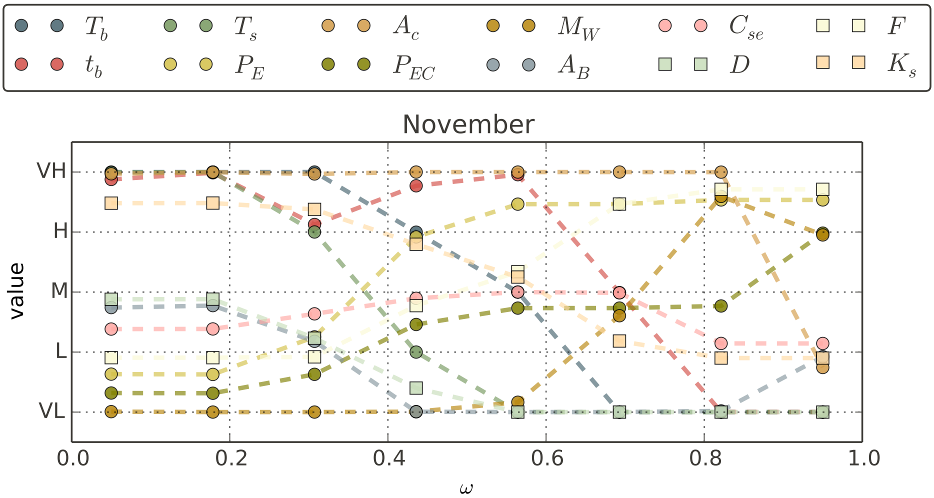


Figure 4.8: Process Set Points for different scalarization weights in the scenario *November*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

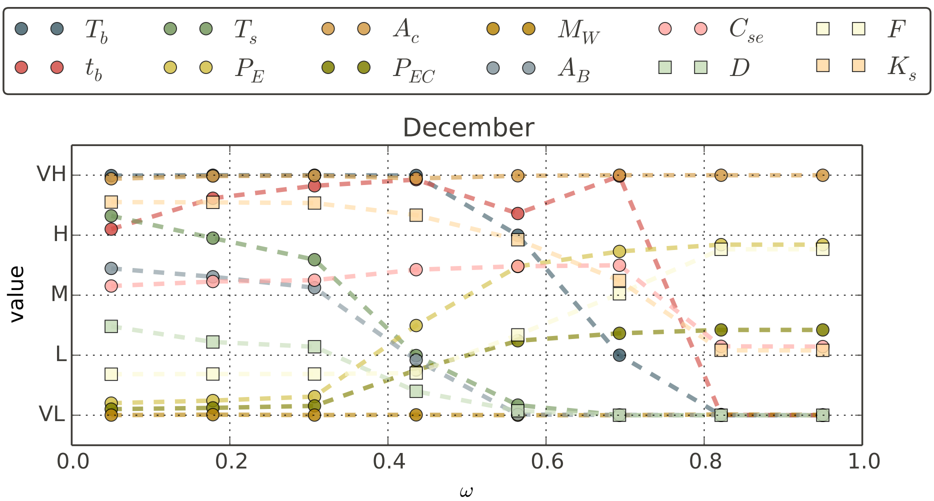


Figure 4.9: Process Set Points for different scalarization weights in the scenario *December*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

Coadjuvant Addition (A_c) is explained by the existence of emulsions even after the storage in the hopper.

As quality increases its weight in the objective function, the first variables to decrease their values are Storage Time in Hopper (T_s), as it affects both Fruity (F) and Defect (D), and Kneading Time (t_b), which favors a increase in Fruity (F) without affecting too seriously Kneading State (K_s). As ω keeps increasing, Kneading Temperature (T_b) begins to drop, initially being compensated with an increase of Kneading Time (t_b). Finally, when all the relevance is given to the quality, Storage Time in Hopper (T_s), Kneading Temperature (T_b) and Kneading Time (t_b) are assigned their lowest possible values.

- **December and January Healthy:** The evolution of the process set points is very similar in these scenarios to the November scenario. The values of Storage Time in Hopper (T_s) are lower, since Incoming Olive Moisture (H_o^I) is also lower than in the previous scenario, and less time is required for it to be reduced. This explains the lower values of Defect (D) of this scenario for equivalent values of Kneading State (K_s), as visible in Figure 4.6.

  It is also visible the tendency of requiring higher weights in the objective function for the process variables to adapt to values promoting the quality of the oil, as the final value of this quality decreases from one scenario to the next.

- **January damaged, February and March:** These scenarios represent conditions where olives already present values of Incoming Olive Moisture (H_o^I) which don't provoke problems related to the formation of emulsions. Because of this, the value of both Storage Time in Hopper (T_s) and Coadjuvant Addition (A_c) is saturated at its minimum value for all points. The low quality of the olives conveys the suggestion of set points aiming for favoring Kneading State (K_s) for almost every value of ω, what is also reflected in the higher concentration of the points in the Pareto plot of Figure 4.6.

4.5 Selection of the optimal production objective

Once that the points in the Pareto frontier have been found and the possible production objectives are available, it is for the decision maker to choose

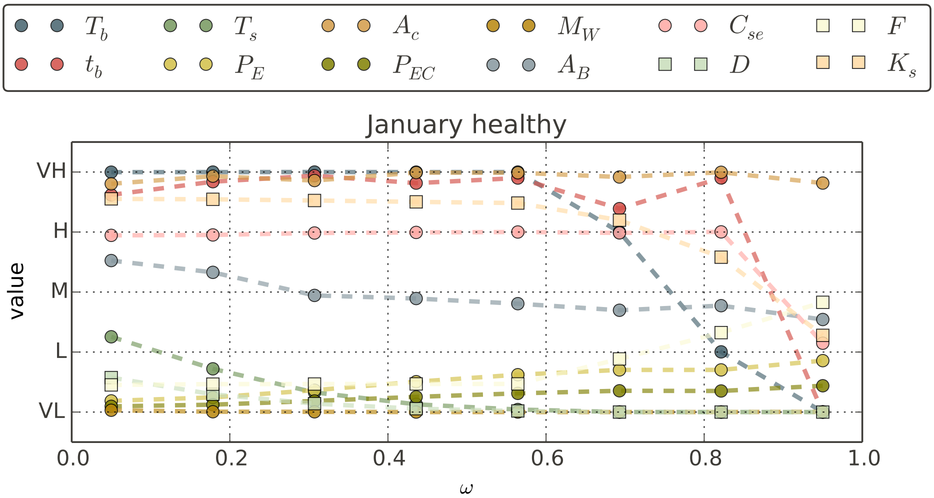


Figure 4.10: Process Set Points for different scalarization weights in the scenario *January healthy*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

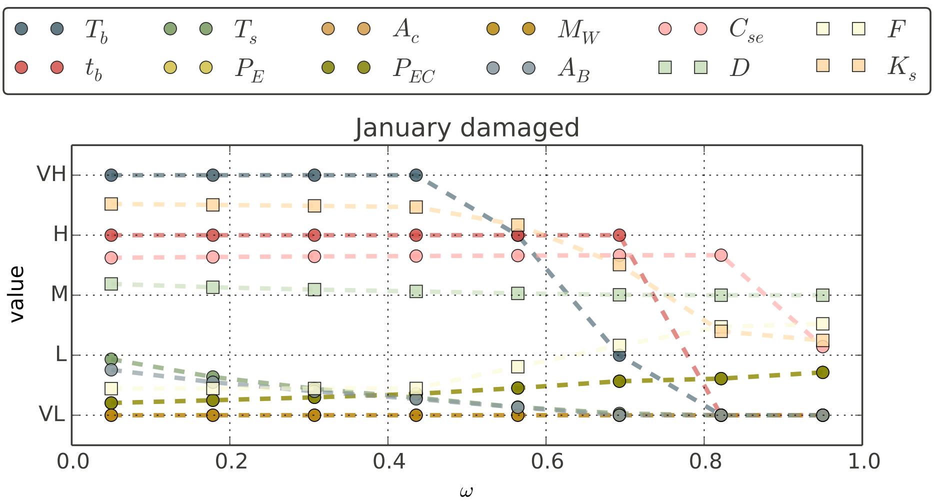


Figure 4.11: Process Set Points for different scalarization weights in the scenario *January damaged*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

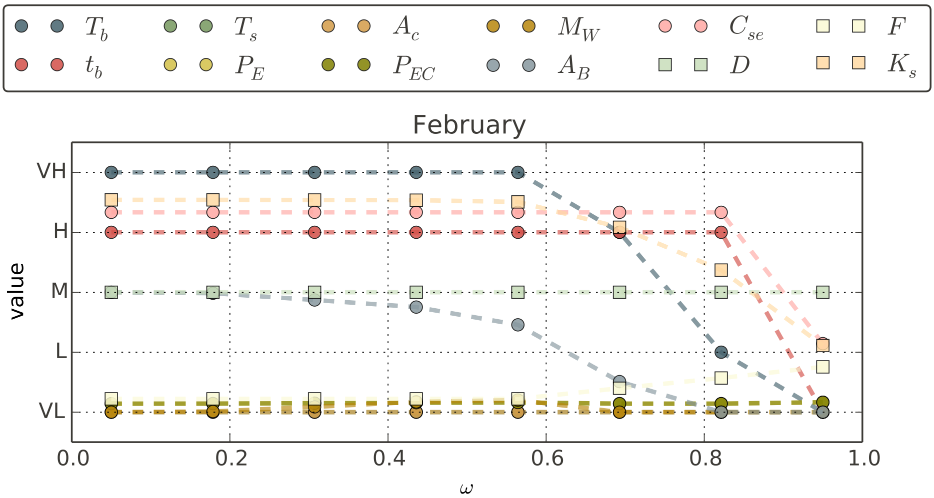


Figure 4.12: Process Set Points for different scalarization weights in the scenario *February*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

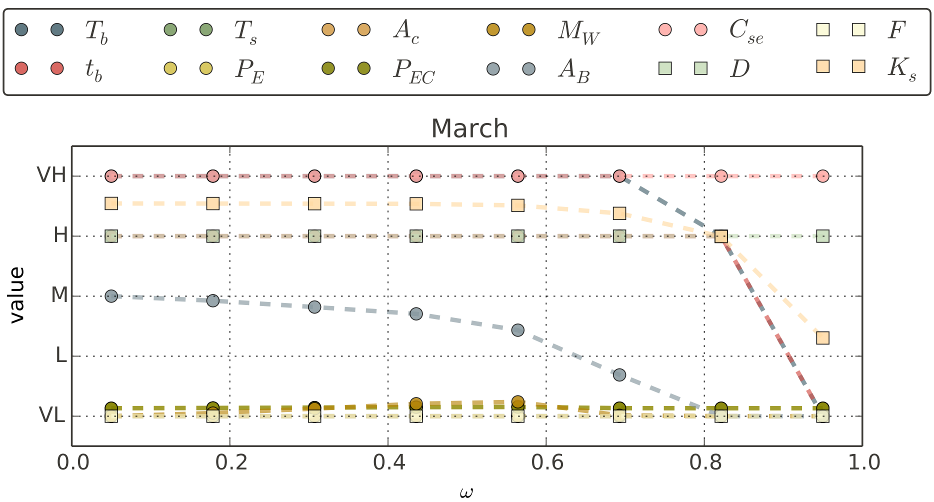


Figure 4.13: Process Set Points for different scalarization weights in the scenario *March*. The corresponding points in the Pareto boundary are shown in Figure 4.6.

which of these points should be aimed at, or to establish a criteria for its selection.

The weight assigned to each of the quality elements of the objective function is likely to change during the season. For instance, in the early season, when having defect is not unavoidable, keeping the defect as zero is likely to have the greatest importance for the process, as having a defect immediately means that the quality of the VOO is no longer Extra VOO, and consequently, the price might decrease substantially.

On the other hand, when some defect is unavoidable due to the olive properties, then it might not be so important to prevent increasing the defect if it remains below the bounds of *lampante*, which might leave room for focusing on obtaining better industrial yield.

An obvious approach to take into account the above discussion is to find the production objective that maximizes the income of the produced oil for each production scenario. Two evident factors affect the obtained revenue: the obtained quantity of VOO and its quality, as it affects its market price. A third factor to be considered could be the possibly different production costs of elaborating VOO of different quality.

To implement this approach, a function that maps the properties of the VOO to a price, a model that provides the industrial yield based on Kneading State (K_s) and a function providing the productions costs are required.

The current model of the paste preparation stage is useful when finding the Pareto optimal values, as obtaining good values of Kneading State (K_s) are known to provide good industrial yields. However, when selecting the optimal elaboration point according to a economic criterion, we need to know the value of industrial yield expected from the operation. This amount can be obtained employing the VOO separation model derived in the previous Chapter, assuming that the separation is carried out optimally.

Some comment on the way of considering the industrial yield is required. The total amount of oil obtained per mass unit of processed olives does not depend only on Yield (X), but also on the total amount of oil that the olives convey. It has already been metioned in Chapter D that there is an evolution of this amount of fat contained in the olives through the season, and that variation might be relevant if the additional freedom of when to harvest the olives is granted. In this Section, however, we embrace the hypothesis that the olives are already at the factory, which leaves the question of considering how much oil the olives contain irrelevant for the solution of the problem, as this quantity is fixed, and the same irrespective of what quality of VOO we finally produce. The selection of the optimal production objective when that hypothesis is relaxed is also an interesting problem, that is dealt with in Chapter 6.

As for the function that maps the properties of the VOO to its price, we may rely on the published bulk market price of the VOO according to its commercial quality, and consider a function that provides this quality based on the VOO characteristics. Such function, applying the European Norm 2568/91, is:

$$q(F,D) = \begin{cases} \text{EXTRA VIRGIN OLIVE OIL} & \text{if } D = 0 \text{ and } F > 0 \\ \text{VIRGIN OLIVE OIL} & \text{if } 0 < D \leq 3.5 \text{ and } F > 0 \\ \text{LAMPANTE OLIVE OIL} & \text{if } D > 3.5 \text{ or } F = 0 \end{cases}$$

Once that the income is available, the production cost should also be taken into account. This production cost can be estimated based on the values the optimal set points assigned for the objective, which are also available, as commented in the previous Section. A simple estimation of the unitary cost per resource allows to include this consideration.

Regarding the production cost, a similar comment to the one considering the total fat content of the olives can be made. One of the most important production costs of the VOOEP is that of the harvesting [Vilar Hernandez et al., 2010,AEMO, 2010]. Moreover, the harvesting method also influences the properties of the olives [García and Yousfi, 2007]. However, the assumption of having the olives already in the factory entails the irrelevance of this parameter for the problem at hand. Again, the influence of this aspect is taken into account in Chapter 6.

The above discussion suggests the following objective function of the problem to be solved:

$$J = X\, p(q(F,D)) - \sum_j c_j x_j, \tag{4.2}$$

where $p(\cdot)$ denotes the function that maps the commercial quality of the oil to its market price, and c_j is the unitary cost of the process variable x_j, with j indexing all the relevant process variables.

4.5.1 Analysis of Different Production Scenarios

In this Section we analyze the optimal production objective and their corresponding process set points for the scenarios presented in Table 4.2.

Table 4.3: Sale prices in each scenario (Euros/kg)

PRODUCT	Extra Sup.	Extra	Virgin	Lampante
PRICE	4	2.71	2.51	2.36

The sale prices have been taken from the average bulk sale prices for the Extra, Virgin and Lampante qualities from the Poolred system [Poolred, 2014] from the June-July period of 2013, and included in Table 4.3. A fourth quality, namely *Extra superior* not included in the official quality classification, is included in this Table. This category regards Extra VOO that possess high values of Fruity (F) of , and that, although they are technically classified as just Extra VOO, from a consumer-oriented quality perspective they are different from regular Extra VOO in that the market is willing to pay a higher price for them.

Figure 4.14 shows the optimal production points according to the application of a strict definition of the quality classification of VOO. Here, the November point aims at obtaining the characteristics for *Extra superior*, defined by requiring a minimum value of Fruity (F) of H. The December point, surprisingly, drops its Fruity (F) aim to L. This is a consequence of applying strictly the technical quality classification, as for a VOO to be Extra it is just required to have *nonzero* Fruity (F) and zero Defect (D). However, from a market oriented perspective, VOO with such low values of fruity would not be considered as Extra, and thus, would not be paid the corresponding price.

Figure 4.15 shows the production objective for a situation where a market-aware interpretation of the quality of the VOO is applied, considered as requiring minimum values of Fruity (F) for a VOO to be classified as Extra or Virgin. In turn, Figure 4.16 shows the corresponding set points of the process variables for those objectives.

The *November* scenario still aims at Extra Superior quality, with prescribed set points according to this objective: very low value of Storage Time in Hopper (T_s) so that no organoleptic defect is provoked on the oil and use of Coadjuvant Addition (A_c) to reduce the emulsions; low value of Kneading Temperature (T_b) and moderate of Kneading Time (t_b) to preserve the Fruity (F) of the oil.

The target in *December* is Extra VOO, as Fruity (F) would not be high enough to reach the threshold required for Extra Superior, as depicted in Figure 4.6. Since the objective of Fruity (F) is milder, a slightly more

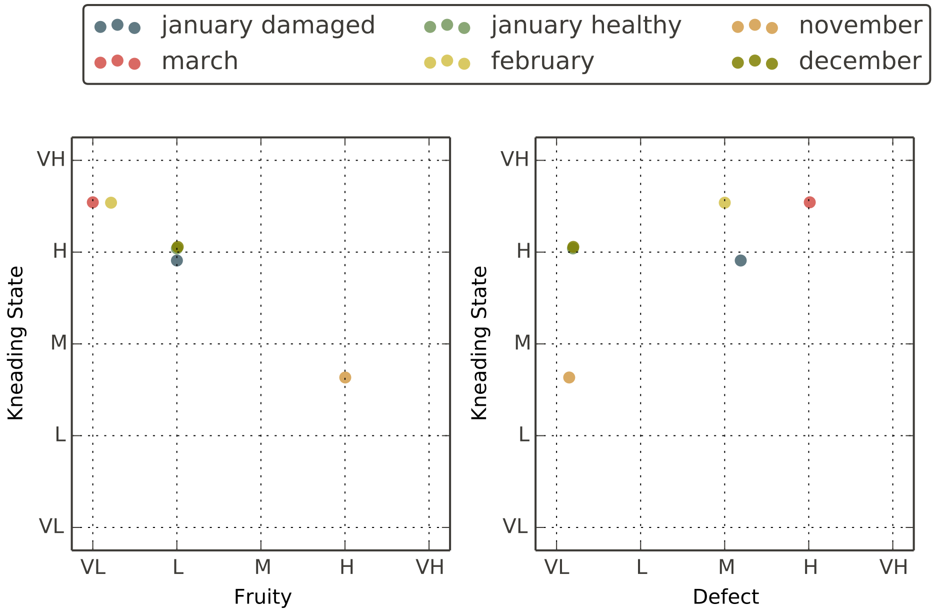


Figure 4.14: Pareto plot of the optimal production points according to the prices defined in Table 4.3, considering than Extra VOO is obtained with any positive value of Fruity (F).

aggressive conditions are prescribed for the elaboration, increasing slightly both Kneading Time (t_b) and Kneading Temperature (T_b).

The conditions for the both scenarios considered in *January* are very similar, being the objective in both producing Virgin VOO. Kneading Temperature (T_b) shows moderate values to preserve Fruity (F) into the limits for the prescribed quality. A slightly slower value of the parameter is set for *January damaged*, as the quality condition of the olives is worse.

Lastly, the objective for *February* and *March* are also very similar, and the process conditions prescribed identical. In these scenarios, the focus is on obtaining the highest possible quantity of oil, as the quality is already lost, consequently, high values of Kneading Temperature (T_b) and Kneading Time (t_b) are suggested.

It is interesting to see how the production objectives would change if the value of is H. This new scenarios are depicted in Figure 4.17, with their prescribed set points included in Figure 4.18. The unavoidable increase in Defect (D) caused by the value of completely changes the situation for the *November* and *December*, with the objectives collapsing into a common one

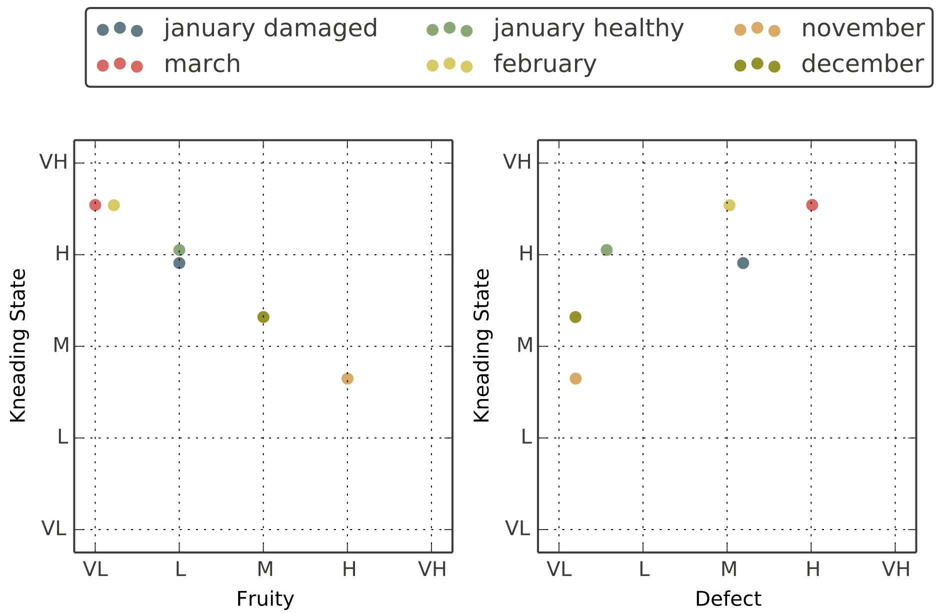


Figure 4.15: Pareto plot of the optimal production points according to the prices defined in Table 4.3, considering than a small minimum value of Fruity (F) is required for obtaining Extra VOO.

of maximizing the yield while preserving Fruity (F) just enough to remain Virgin VOO. The set points of the process variables also change accordingly, increasing Storage Time in Hopper (T_s), Kneading Time (t_b) and Kneading Temperature (T_b) while reducing Coadjuvant Addition (A_c).

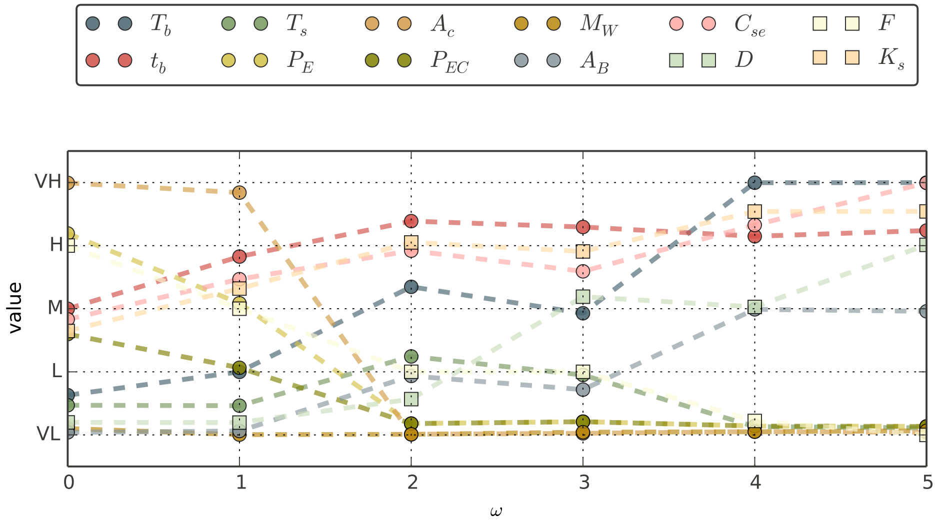


Figure 4.16: Values of the process set points for the optimal production points according to the prices defined in Table 4.3, considering than a small minimum value of Fruity (F) is required for obtaining Extra VOO.

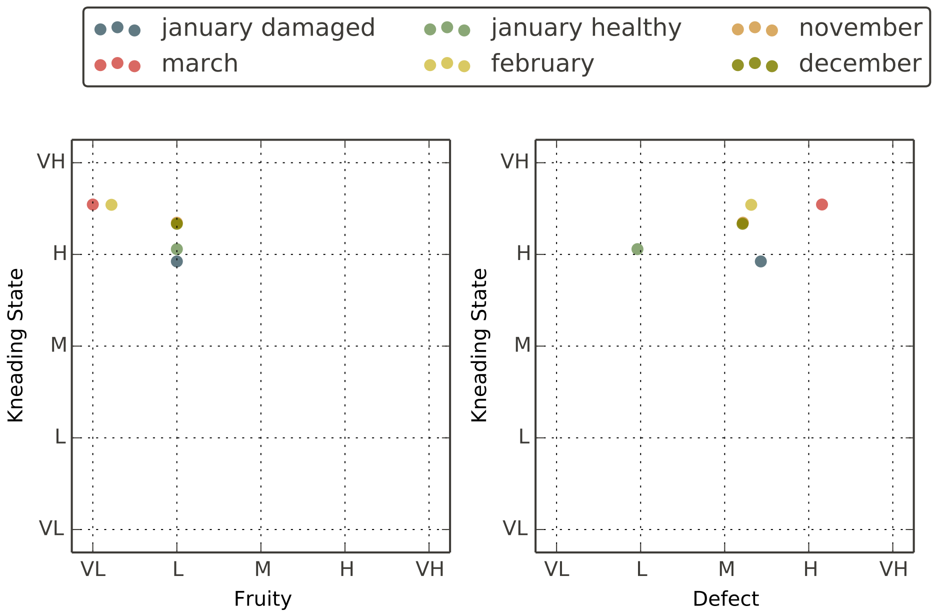


Figure 4.17: Pareto plot of the optimal production points according to the prices defined in Table 4.3, considering than a small minimum value of Fruity (F) is required for obtaining Extra VOO and that the value of is H.

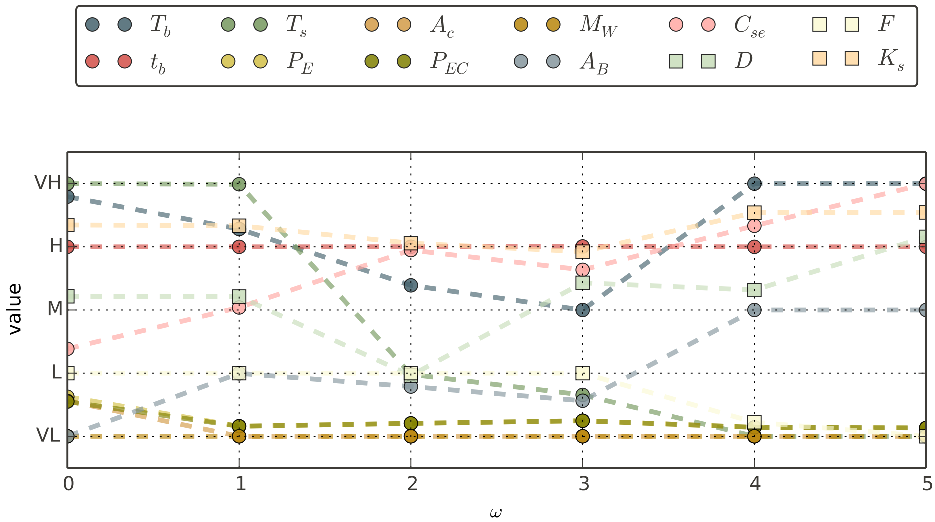


Figure 4.18: Values of the process set points for the optimal production points according to the prices defined in Table 4.3, considering than a small minimum value of Fruity (F) is required for obtaining Extra VOO and that the value of is H.

5
SET POINTS UPDATE

5.1 Introduction

The previous Chapter provided the production objectives given a batch of olives to be processed, along with the values of the set points of the process variables that allow to, theoretically, obtain it.

However, the proposed procedure to obtain these set point values rely on the precision of the underlying models employed in the optimization scheme. The existence of errors in these models imply obtaining set points that would not yield the desired output variables. Moreover, were the models perfect, errors in the estimation of the properties of the olives would also lead to missing the prescribed objectives.

In this scenario, the introduction of feedback in the decision support system would substantially improve its utility, as it would allow to eventually correct the deviations of the outputs from the targets. However, feedback requires measuring the controlled variable, and, as commented in Chapter D, currently there are not available sensors capable of providing sufficiently accurate and reliable on-line measurements of the relevant output process variables. This is a major difficulty for the automatic control of the VOOEP. There are, however, means of obtaining measurements or accurate estimations of the values of these variables in an at-line fashion, thus providing information from the process at a very low sampling rate, but providing information nonetheless.

The purpose of this Chapter is to propose a mechanism to incorporate this information to the decision support system, so that the set points of the process variables provided by the system are updated to correct deviations from the desired production objective.

Next Section presents a brief overview of run-to-run control, with Section 5.3 dealing with the specific aspects of the application of this control technique to the VOOEP. Lastly, Section 5.3.2 presents some simulation results to illustrate the proposed approach.

5.2 Brief overview of run-to-run control

Run-to-run control [Sachs et al., 1990] was first developed for the semiconductor manufacturing industry to control the height of the deposition of components, due to the unavailability of sensors capable of providing online measurements of this variable. Instead, after the batch was produced, an off-line measurement was carried out and the information was used to modify some parameters of the process in order to improve the following batch to be produced [Sachs et al., 1990].

The run-to-run controllers are usually model-based controllers augmented with an observer [Campbell et al., 2002]. The basic idea is to use the observer to estimate the disturbance acting on the system, and use the model of the system to compute the control action that allows to compensate for that disturbance. The following Sections present run-to-run controllers described in the literature for SISO and MIMO systems respectively.

5.2.1 SISO case

The Exponentially Weighted Moving Average (EWMA) controller is probably the best known run-to-run controller [Adivikolanu and Zafiriou, 2000]. This approach considers a linear process affected by a disturbance, according to the structure:

$$y_k = \beta\, u_k + \nu_k, \tag{5.1}$$

with u_k being the process input and ν_k denoting the disturbance acting in the k batch.

The model of the system is:

$$\hat{y}_k = b\, u_k + \hat{\nu}_k, \tag{5.2}$$

and the observer equation is defined recursively as:

$$\hat{\nu}_{k+1} = \omega\,\hat{\nu}_k + (1-\omega)(y_k - b\,u_k). \tag{5.3}$$

With this two elements, and considering T the target of the system, that is, the desired value of the output, the control action is computed by simple inversion of the plant:

$$u_{k+1} = \frac{T - \hat{\nu}_{k+1}}{b} \tag{5.4}$$

If the disturbance is an integrated moving average (IMA) process, as described by:

$$\nu_k = \nu_{k-1} - \theta\epsilon_{k-1} + \epsilon_k, \tag{5.5}$$

and the value of ω matches θ, then the observer provides the minimum mean square error estimate of the disturbance [Campbell et al., 2002]. Here, ϵ_k represents a zero mean random variable with variance σ. However, even in the case that the actual disturbance were effectively an IMA process, the value of θ would still be unknown, so ω is usually used as tuning parameter for the controller [Good and Qin, 2006].

The stability conditions for the controller can be derived casting the EWMA controller as an IMC controller [Adivikolanu and Zafiriou, 1997]. The conditions that must hold to ensure the stability is:

$$0 < \omega\frac{\beta}{b} < 2. \tag{5.6}$$

This relation shows that overestimating the value of the process gain, i.e., having ratios $\beta/b < 1$ is conservative for the stability of the controller.

5.2.2 MIMO case

Given the well-known advantages of MPC to deal with MIMO systems [Camacho and Bordons, 2004], it is natural to turn to an MPC approach for the MIMO run-to-run case.

The most straightforward extension is to conserve both the model structure and the observer used in the EWMA controller, and just change the control law, replacing the simple plant inversion for the computation of the input as the result of an optimization problem. Then, the application of just the first input and recomputing the solution with the updated observed value of the disturbance would implement the time-receding strategy, yielding an MPC controller.

A classical objective function for the optimization problem can be constructed using a weighted sum of the square of the deviations on the target, the control cost and the rate of change of the input variables. This approach yields the following MPC formulation [Good and Qin, 2006]:

$$\min_{u_k} \; J = (T - \hat{y}_k)^T \, Q \, (T - \hat{y}_k) + u_k^T R u_k + \Delta u_k^T S \Delta u_k \tag{5.7}$$

$$\text{s.t.} \;\; \hat{y}_k = b u_k + \hat{\nu}_k. \tag{5.8}$$

Here, Q weights the importance of the deviations from the target, R penalizes the value of the inputs and S restricts the changes in the input values. If no constraints on the values of the inputs are considered, then the solution of the optimization problem is [Good and Qin, 2006]:

$$u_k = \left(b^T Q \, b + R + S\right)^{-1} \left(S u_{k-1} + b^T Q \, (T - \hat{\nu}_k)\right).$$

If restrictions on the values of the inputs are considered, then the problem no longer has an analytic solution, and a numeric solution should be found.

The conditions for the stability of the controller for the unconstrained case and $S = 0$ can be found in [Good and Qin, 2006]. The closed-loop computation formula of the observed disturbance is:

$$\hat{\nu}_{k+1} = (I - (I - I\omega)\xi)\hat{\nu}_k + (I - I\omega)(\xi T + \nu_k), \tag{5.9}$$

with

$$\xi = (\beta - b)(b^T Q b + R)^{-1} B^T Q + I. \tag{5.10}$$

If we denote the eigenvalues of ξ as $\lambda_j = a_j + b_j i$, the stability criterion can be expressed as:

$$\frac{a_j^2 + b_j^2 - 2a_j}{a_j^2 + b_j^2} < \omega < 1. \tag{5.11}$$

5.3 Application of run-to-run control to the VOOEP

Although in many parts of the world the VOOEP is commonly conducted in a batch manner, in Spain it is usually carried out as a continuous one. Since run-to-run control is applied to batch processes, this means that the notion of *batch* employed is required to be clarified.

The available models of the higher-level layer of dynamics of the process, derived in Chapter 3, are, paradoxically, *static*. That is, these models provide just the steady-state value of the output variables, without any additional information of the dynamics of the relation. In these models it is tacitly assumed that the effect of the inputs on the outputs is not immediate, but that some time is required for the outputs to reflect the effect of the input. Thus, the dynamics of the system can be considered to be lumped into a delay τ_{min}, representing this time.

We will consider as a *batch* the amount of olives processed between measurements. Let τ denote this sampling rate, then a requirement for the models to apply is that $\tau > \tau_{min}$, that is, we should grant enough time between measurements to allow for the system to reach its steady state.

Thus, since we apply the input at time t, and obtain the output of the system at time $t + \tau$, we can express this model as a discrete time system, according to the structure:

$$y_{t+1} = g(u_t),$$

with t representing the sampling instant in a discrete formulation with sampling time τ.

However, as already reflected in the previous Section, in the run-to-run literature it is more common to use the index to denote the considered batch, not the time instant when the action of applying the input or measuring the output take place [Kosut et al., 1998]. According to this criterion, the relation between the elements of the recipe and the output of the system is expressed as:

$$y_k = g(u_k),$$

with k indexing the batch number.

A fundamental hypothesis for the method to apply is that the system must reach its steady state within the considered time, which also implies the stability of the system. The assumption of the existence of lower-levels controllers in the plant builds a ground to assume that eventual disturbances won't affect the process dramatically, thus easing the strength of the hypothesis.

Since the properties of the incoming olives heavily influence the outcome of the process, another requirement must be that these properties remain somewhat constant during the batch. From a practical point of view, several arguments could be considered in order to curb the harshness of this hypothesis:

- Usually, olives are classified according to whether they come from the ground or just from the top of the tree. Since *almazaras* usually receive olives from their close surrounding area, olives are quite homogeneous at each given harvest instant.

- Olives are fed into fairly big hoppers before they are processed, so additional mixing between the different lots of received olives takes place.

5.3.1 Run-to-run controller design

Most of the published results on run-to-run control are based on the assumption of linearity of the plants [Adivikolanu and Zafiriou, 2000, Adivikolanu and Zafiriou, 1998], with some results obtained for nonlinear plants with certain characteristics [Francois et al., 2003, Francois et al., 2005, François et al., 2011].

Since the majority of the work done and stability results on run-to-run control refers to linear processes and linear models, so it is in principle appealing to head for this approach.

Although the available models of the process are nonlinear, and supposed not to match the process exactly, it seems a sensible working hypothesis to assume that the models are *good enough* to propose initial set points such that the model operates *close* to the production objective, so that a local linearized model of the process provides a good approximation of it, useful for our feedback purposes.

However, even disregarding the implications of the linearization and assuming that the process is sufficiently well described by the local linear model, making full use of the convergence results for the linear MIMO case is not immediate using this approach, as the problem is constrained, and the result obtained are for unconstrained optimization.

On the other hand, the general structure of a run-to-run controller is based on a model of the system, an observer and a method to compute the control action based on these model and observer. In the previous Chapters we have already proposed a model and a method to compute the control action. It is tempting to augment the proposed system with an observer and stick to the nonlinear models. The downside of this approach is that no results on the convergence of the proposal are available.

Since the method is intended for a decision support system, which is supposed to provide guidance to an operator, although very desirable from a theoretical and rigorous point of view, the availability of rigorous proof of convergence is not of key importance from a practical point of view, since we can rely on the filtering of the operator were the system to provide strange results due to instability of the feedback algorithm.

With the above discussion in mind, the approach taken is the latter, that is, to augment the system with an EWMA-like observer, and maintain the nonlinear models. Using a quadratic objective function, the proposed run-to-run controller is:

$$\begin{aligned}
\underset{\mathrm{x}_k}{\text{minimize}} \quad & J = (\hat{\mathrm{y}}_k - T)^T\, Q\, (\hat{\mathrm{y}}_k - T)^T + \mathrm{x}_k^T\, R\, \mathrm{x}_k \\
\text{subject to} \quad & \hat{\mathrm{y}}_k = f(\mathrm{x}_k, \mathrm{p}) + \hat{\nu}_k \\
& \mathrm{p} = \mathrm{p}^0 \\
& \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \\
& \hat{\nu}_k = \omega\, \hat{\nu}_{k-1} + (1-\omega)\,(\mathrm{y}_{k-1} - f(\mathrm{x}_{k-1}, \mathrm{p}^0)),
\end{aligned}$$

where Q, R and ω are their tuning parameters.

Some discussion about the chosen structure of the observer is in order. Two main types of disturbances have been studied in the run-to-run literature: steps disturbances and process drifts. Steps disturbances model well sudden changes in the operating condition that remain constant for successive operations, while drifts are better for considering situations where some effect continuously varies from one batch to the next, such as accumulation of dirt [Lee et al., 2008].

This chosen observer structure is known to work well with step disturbances, not being so effective when drift disturbances affect the process. Selecting this observer structure implicitly assigns more relevance to step disturbances in the process than drifts. That is, indeed, the case for our application of the method to the VOOEP.

Since the models are static, a step disturbance is a good approximation for a mismatch of the gain of the process [Lee et al., 2008], which is the most appealing use case for the feedback approach. On the other hand, drift disturbances are less likely to occur to the process at the high-level layer. One possible drift could be the progressive moisture loss of the olives in the hoppers as they remain there, but this effect is already considered in the model, so updating the value of Storage Time in Hopper (T_s), this effect is already accounted for. In the proposed scheme, we suppose that the operator measures all the relevant process variables in the VOOEP in each batch, and these values are supplied to the system, thus providing some feedforward action for the change of these variables.

5.3.2 Simulation results

The following Section presents simulation results for different disturbances, controller parameters and production scenarios. The objective is two-fold: study the behavior of the controller and validate the proposed actions of the system for the different production scenarios.

5.3.2.1 Influence of the controller parameters

As commented above, the proposed run-to-run controller has three parameters susceptible of tuning: Q, R and ω. The first two parameters influence the assignment of relative importance to the errors in the output process variables and the control action, while the latter influences the way the observer estimates the disturbance affecting the system, thus influencing the convergence rate of the controller.

As test case to illustrate the influence of the process parameters, the scenario *December* is selected, as it presents a balanced situation between achieving good quality and good yield.

In Section 4.5 of Chapter 4, the optimal production objectives based on an economic criterion were found. Let us assume that the production objective for the scenario is given by that criterion. Let us further assume that there is a mismatch between the model used for obtaining the optimal production set points and the actual plant, modeled as an offset affecting Fruity (F).

If we apply the set points computed according to the method proposed in the previous Chapter, we will find that the process outputs do not exactly match the objective, as Fruity (F) is below the desired values. Iteration 0 of Figures 5.1, 5.2 and 5.3 show this behavior.

Given the multiobjective nature of the VOOEP, it is expected that in order to reduce the mismatch in Fruity (F), some toll had to be paid in the rest of outputs. So, a preference in the tolerance against deviations in the different outputs should be established, which is exactly the role of parameter Q in the controller.

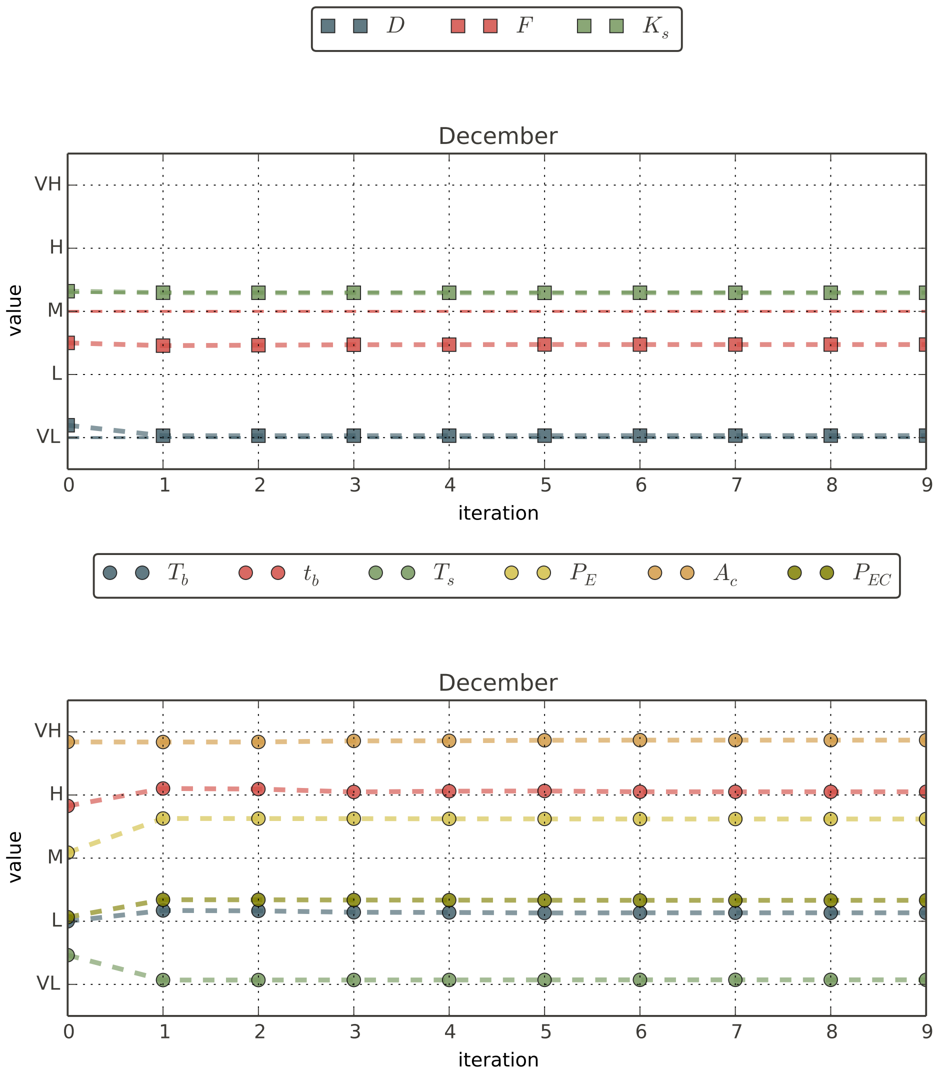


Figure 5.1: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.2$, when the priority is set to Kneading State (K_s) and a constant disturbance is acting on Fruity (F), for the *December* scenario.

Figure 5.1 shows the situation when the preferred output is Kneading State (K_s). Given that the desired value of the parameter is obtained, no major changes are suggested for the process variables, just a slight correction to further reduce Defect (D) which does not imply a change in Kneading State (K_s). The error showed in Fruity (F) is tolerated and no further actions are prescribed.

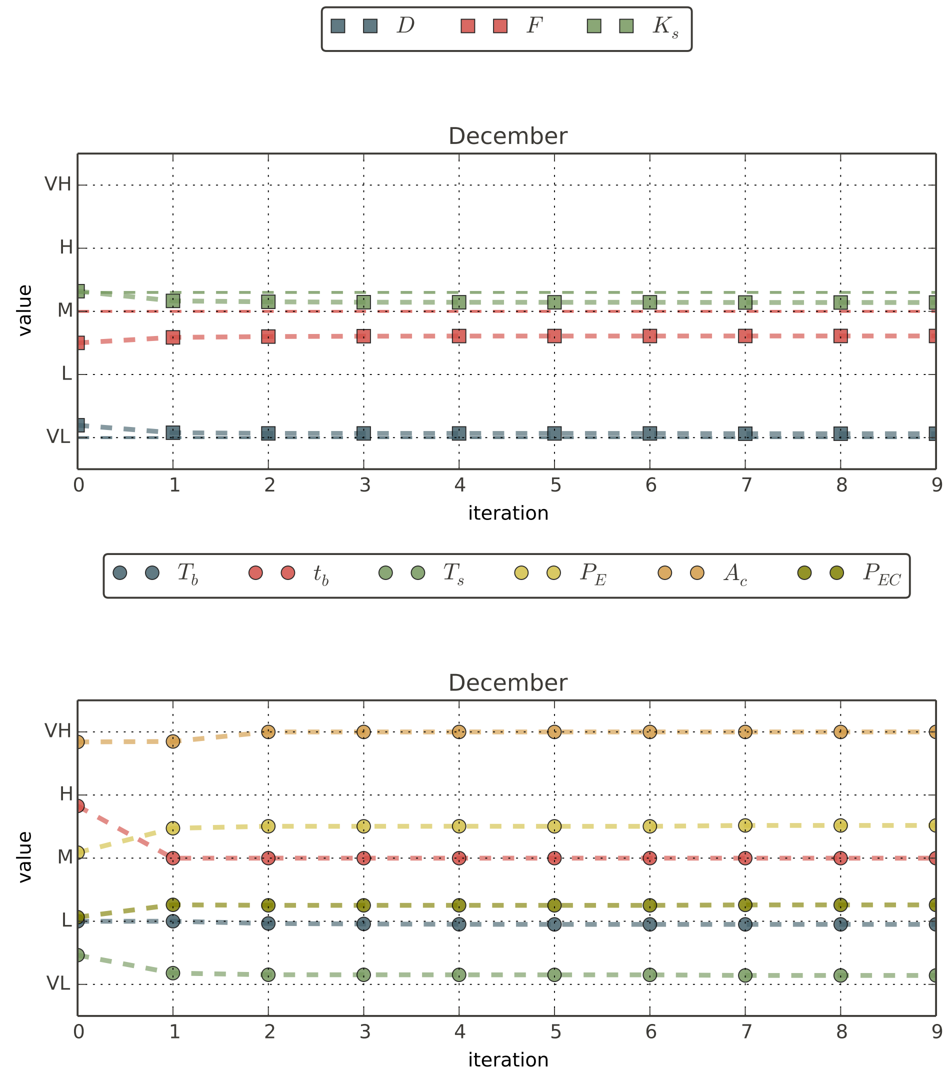


Figure 5.2: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.2$, when the priority is balanced and a constant disturbance is acting on Fruity (F), for the *December* scenario.

In turn, Figure 5.2 shows the case when the deviations in each of the process variables are equally penalized. As expected, the stipulated process set points are slightly modified to decrease the error in Defect (D) at the expense of lightly worsening Kneading State (K_s).

To complete the discussion, if the emphasis is put on achieving the prescribed Fruity (F), disregarding the decrease of Kneading State (K_s), the

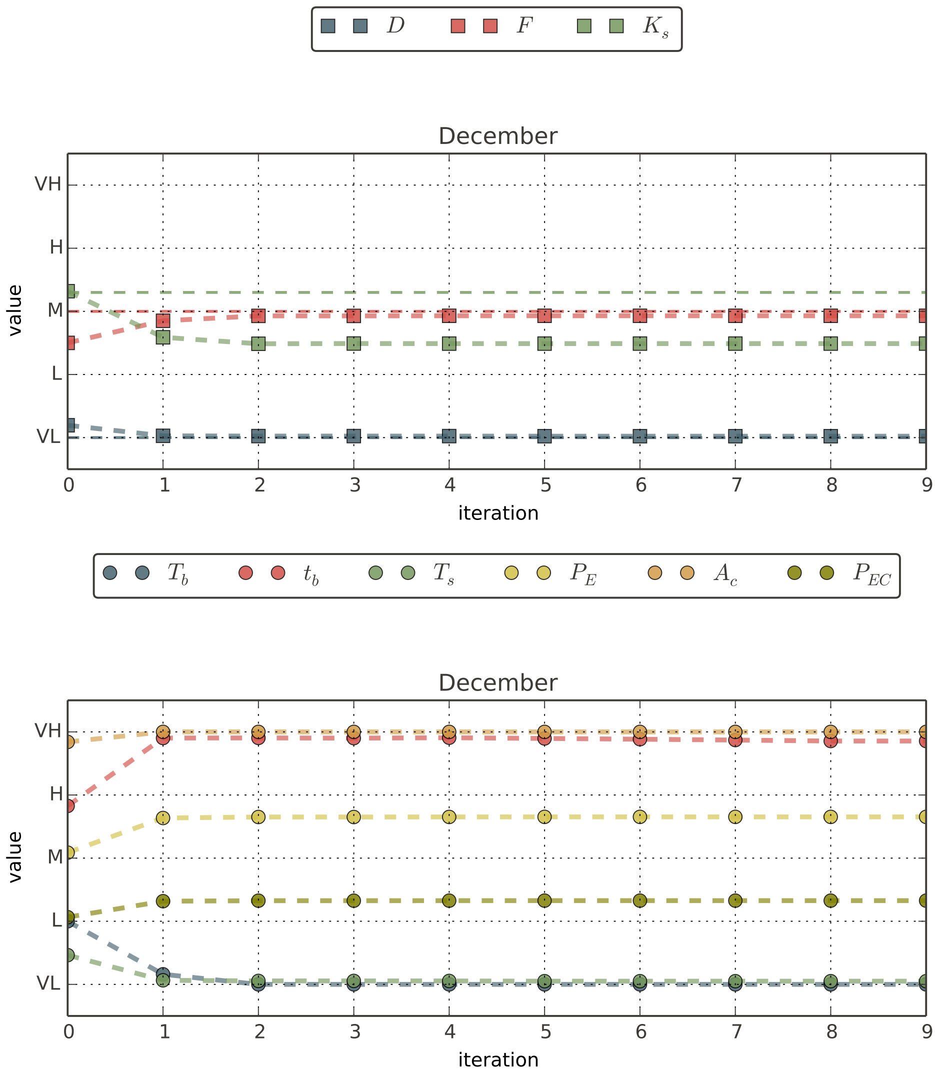


Figure 5.3: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.2$, when the priority is set to Fruity (F) and a constant disturbance is acting on Fruity (F), for the *December* scenario.

sequence of proposed set points by the algorithm is portrayed in Figure 5.3. In this scenario, the desired level of Fruity (F) is almost exactly achieved, at the expense of a higher decrease of Kneading State (K_s).

The influence of ω can be observed comparing Figures 5.3 and 5.4. In these plots Q and R have the same value, while ω is set to 0.2 and 0.8 respectively in each Figure. The final values of both the outputs and the

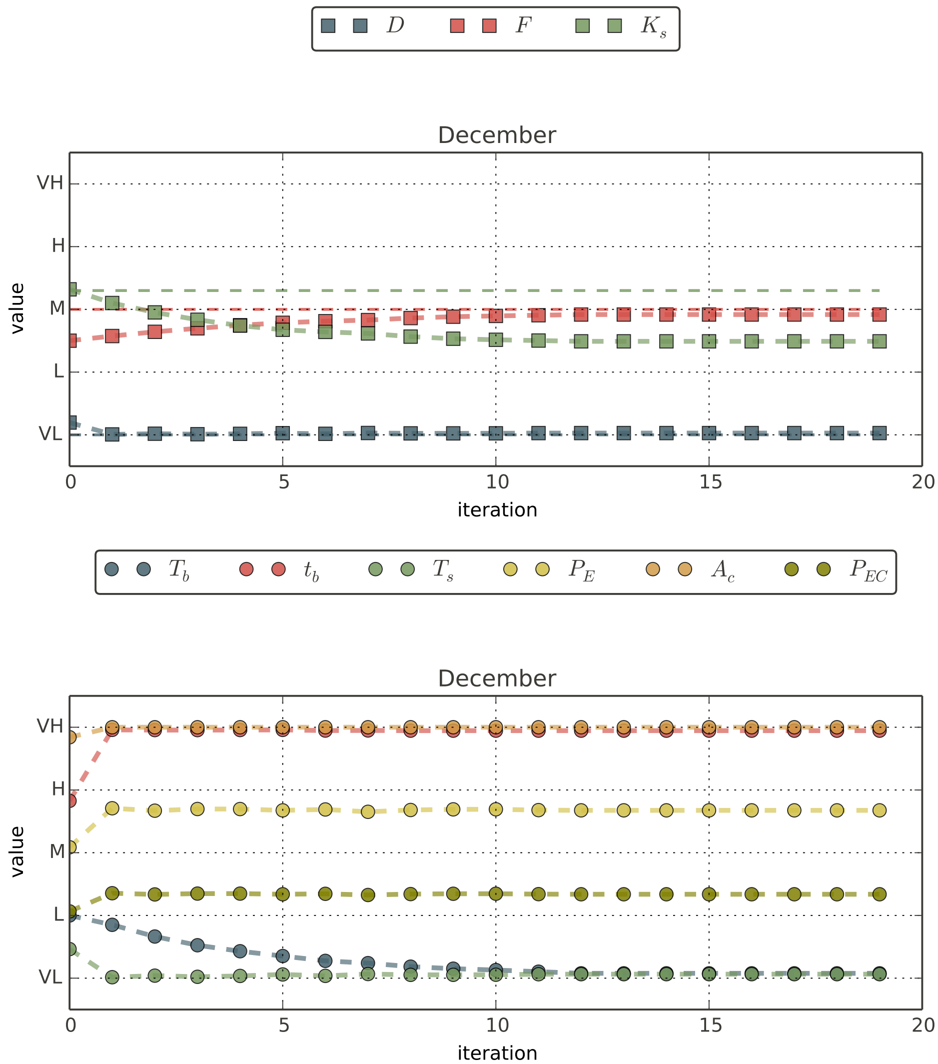


Figure 5.4: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.8$, when the priority is set to Fruity (F) and a constant disturbance is acting on Fruity (F), for the *December* scenario.

process set points end being equal, but the convergence rate in the first case is much higher than in the second.

However, choosing small values of ω yields higher convergence rate in the case of a fixed deterministic step disturbance, but the algorithm is less robust to the existence of stochastic noise, as the filtering performed by the observer is much milder. To illustrate this effect, Figures 5.5 and 5.6

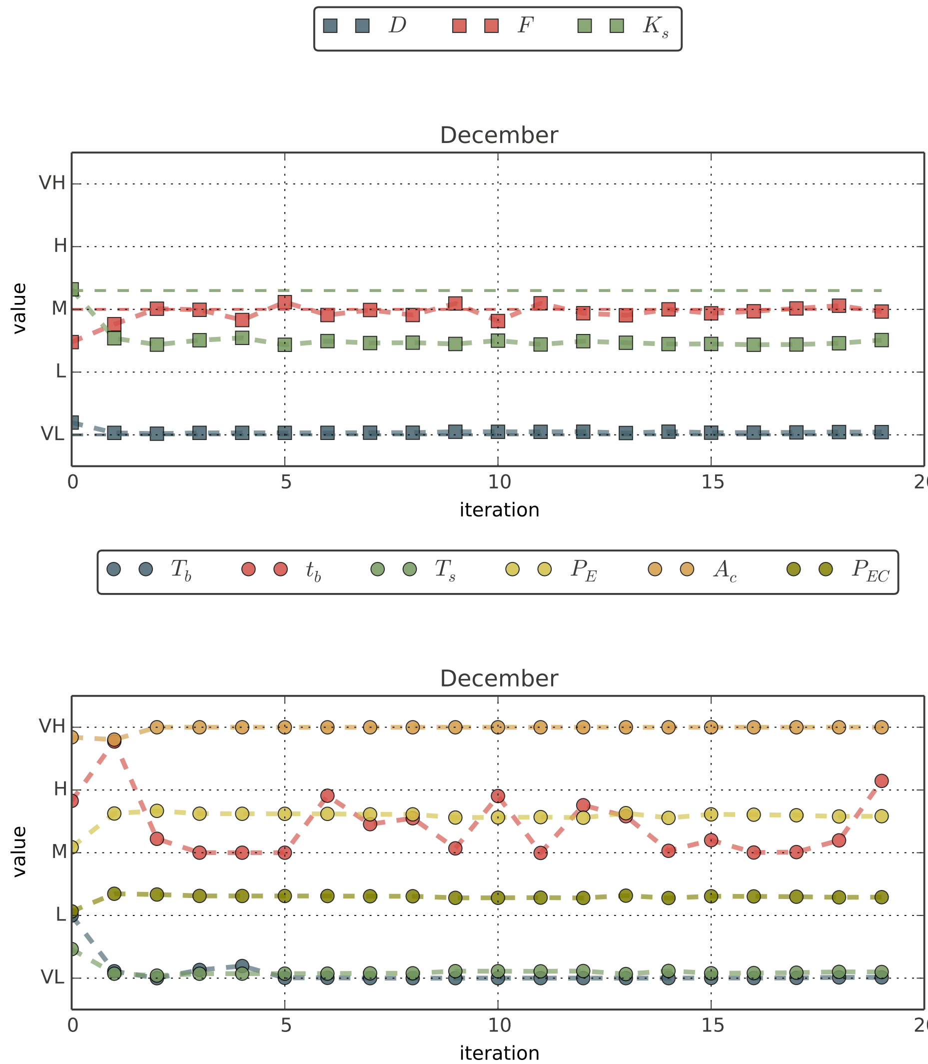


Figure 5.5: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.2$, when the priority is set to Fruity (F) and a stochastic disturbance is acting on Fruity (F), for the *December* scenario.

show the response of the system when independent random Gaussian noise of zero mean and variance 0.25 is applied. The aggressive tuning shows a much greater variability of the prescribed process set points, while the behavior is smoother for the more conservative one.

Equation 5.11 provides the condition for convergence of the algorithm for the MIMO unconstrained linear case. Using this reference, the candidate

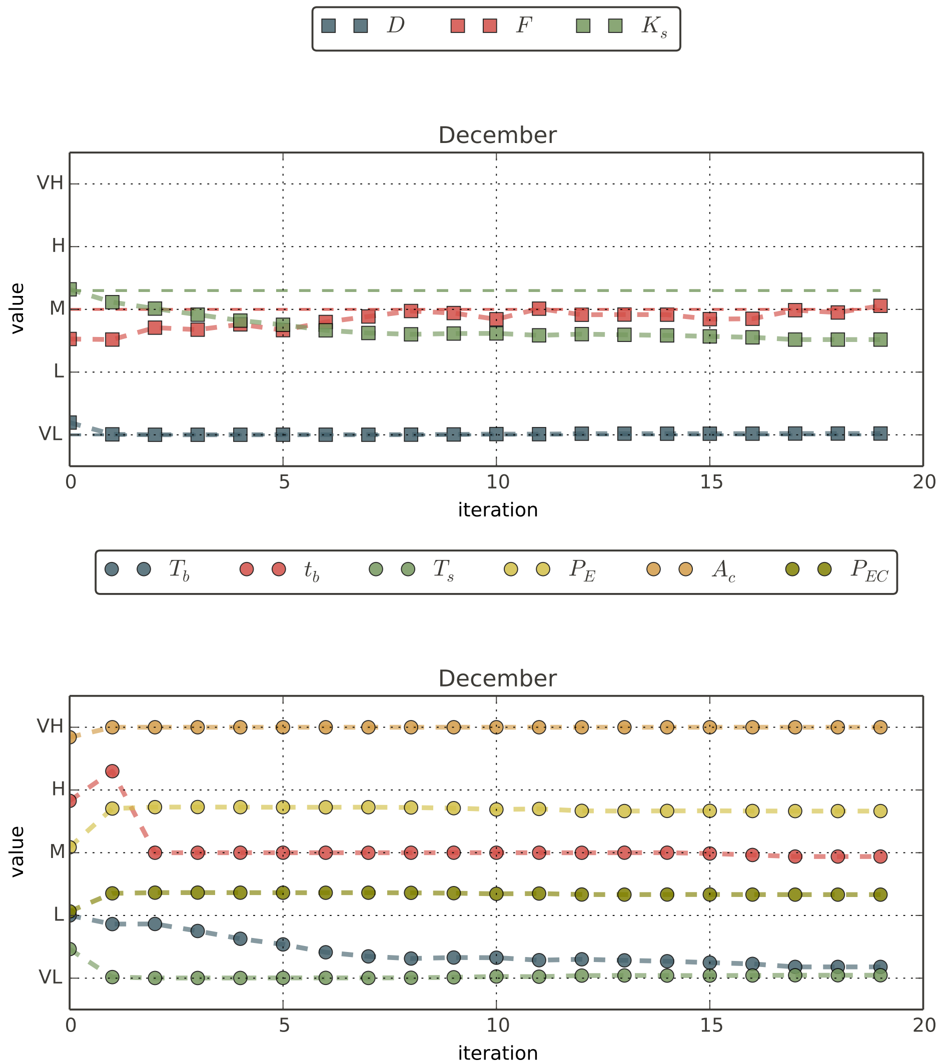


Figure 5.6: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.8$, when the priority is set to Fruity (F) and a stocastic disturbance is acting on Fruity (F), for the *December* scenario.

range of values of ω so that the system converges is the $[0, 1]$ interval. Employing a constant value of 1 for every iteration of the controller is equivalent to actually not including any feedback action at all, since we do not update the estimate of the disturbance and stick to whatever value we considered for the initial iteration.

The other extreme in the range supposes completely disregarding previous estimates of the disturbance, and select the observed mismatch in the last iteration as the estimate. In turn, simulating the system for values of ω higher than 1 effectively convey the non-convergence of the algorithm.

Finally, Figure 5.7 shows the suggested set points for a scenario where a level dependent disturbance of the form:

$$\eta_k = \alpha\, \mathrm{y}_k$$

is acting on the system. The plot shows a satisfactory behavior of the system, similar to that obtained for the constant disturbance considered before.

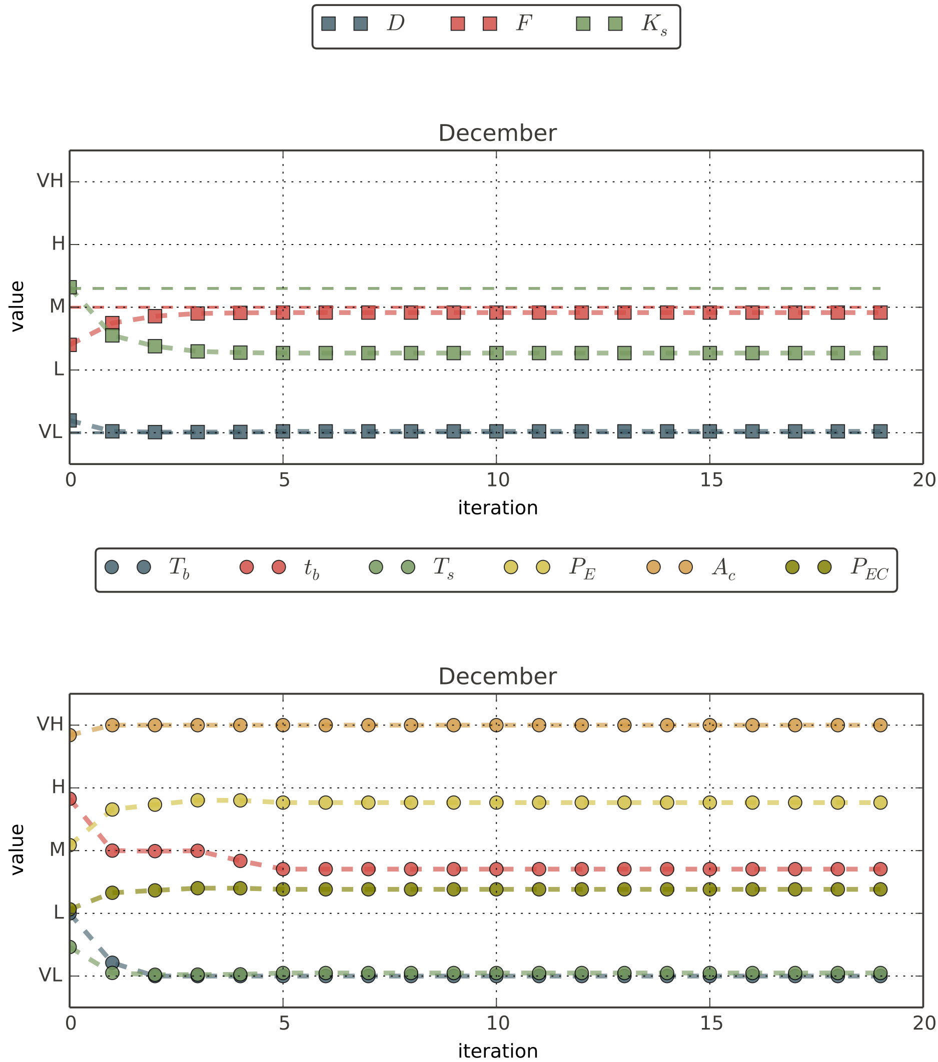


Figure 5.7: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.2$, when the priority is set to Fruity (F) and a disturbance of the form $\eta_k = \alpha\, \mathrm{y}_k$ is acting on Fruity (F), for the *December* scenario.

5.3.2.2 Analysis of set point update suggestions for different scenarios

Once that the influence of the parameters of the controller has been addressed, this Section focuses on the analysis of the proposed modifications of the process set points for the production scenarios considered in the previous Chapter.

- **November and December:** The response of the system for these scenarios, considering a constant disturbance in Fruity (F) is depicted in Figures 5.8 and 5.9. The proposed modification of the process set points are in line with the expected behavior: decrease the Kneading Temperature (T_b) and, if not enough, continue decreasing Kneading Time (t_b). In the December scenario an initial increase of Kneading Time (t_b) is prescribed to counteract the negative effect in Kneading State (K_s), suggesting a decrease in the parameter when the required level is not achieved. The gap between the objective and the final value of Fruity (F) is due to the large error required for Kneading State (K_s) and the existence of a nonzero element in the corresponding element of Q, which limits this error to be even greater.

- **January healthy and damaged:** for this production scenario, two different situations are considered for a controller where all the outputs are given the same weights. Figure 5.10 shows the case when the disturbance is acting on Fruity (F), while Figure 5.11 depicts the system for the disturbance applying on Kneading State (K_s). Again, the behavior of the system is as expected, counteracting the disturbances employing Kneading Time (t_b) and Kneading Temperature (T_b) accordingly.

  It is interesting to note that the system prescribes the same action for Figure 5.11 and for Figure 5.12, which shows the *January damaged* scenario when the same disturbance applies. The reason is that the conditions of both scenarios are equal but for Defect (D), which, as is not affected neither by Kneading Temperature (T_b) nor Kneading Time (t_b), is not relevant for the decisions to be made.

- **February and March:** these scenarios are depicted in Figures 5.13 and 5.14 respectively, when a disturbance in Kneading State (K_s) applies. Here, since Fruity (F) is not relevant, the prescribed set points were already those to provide the maximum Kneading State (K_s), so the existence of the disturbance does not change them, due to the saturation of the control action.

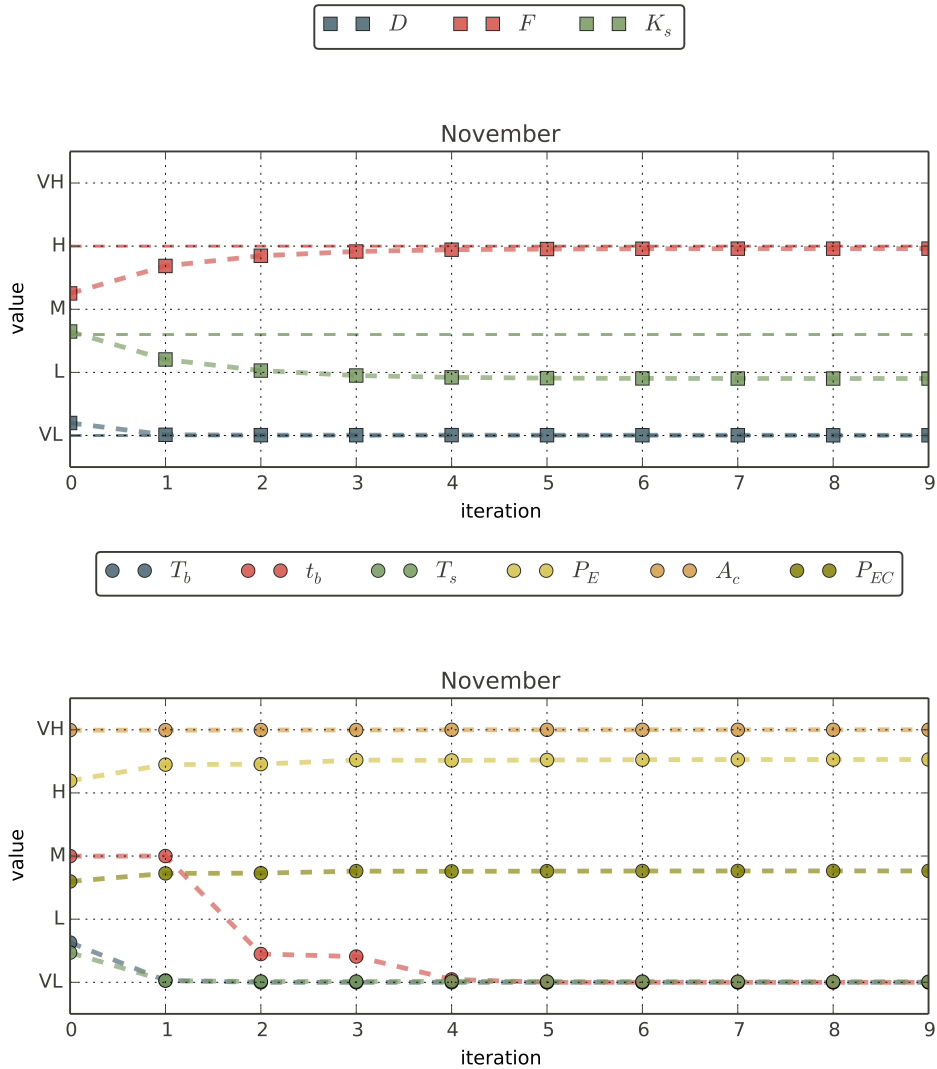


Figure 5.8: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is set to Fruity (F) and a constant disturbance is acting on Fruity (F), for the *November* scenario.

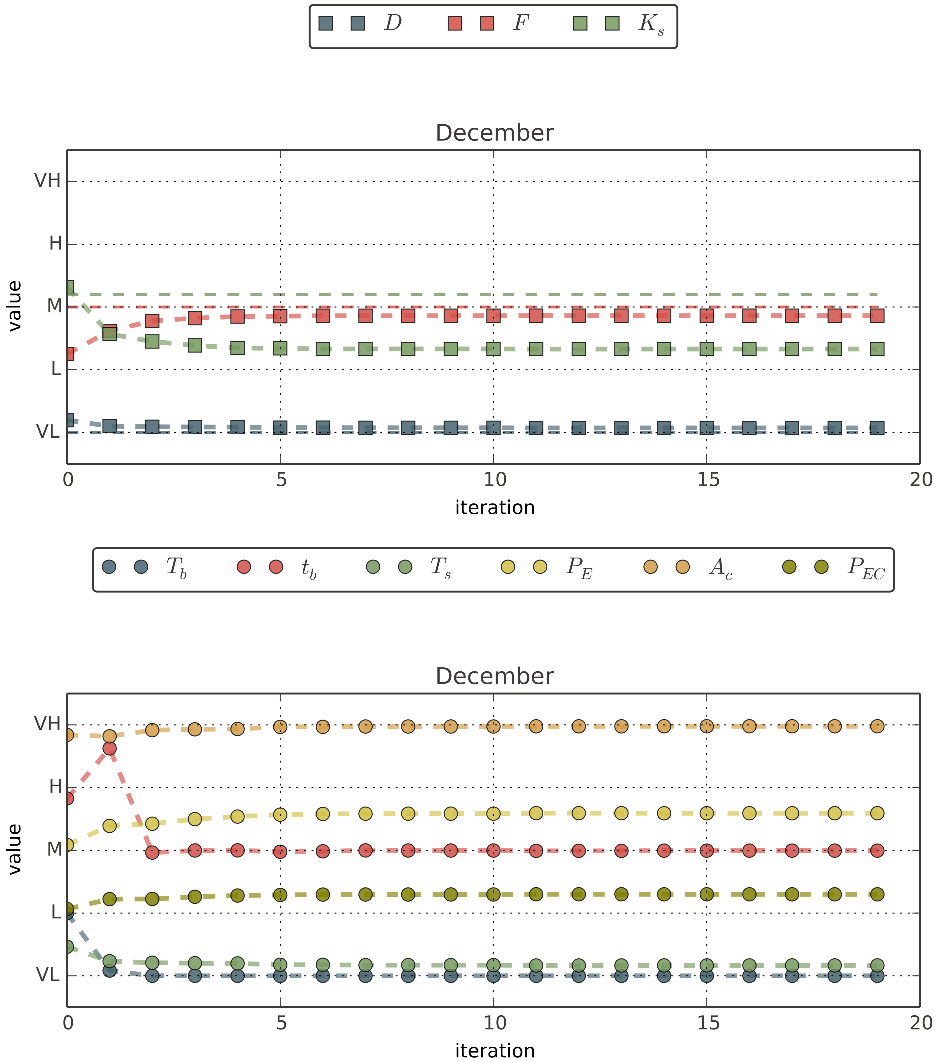


Figure 5.9: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is set to Fruity (F) and a constant disturbance is acting on Fruity (F), for the *December* scenario.

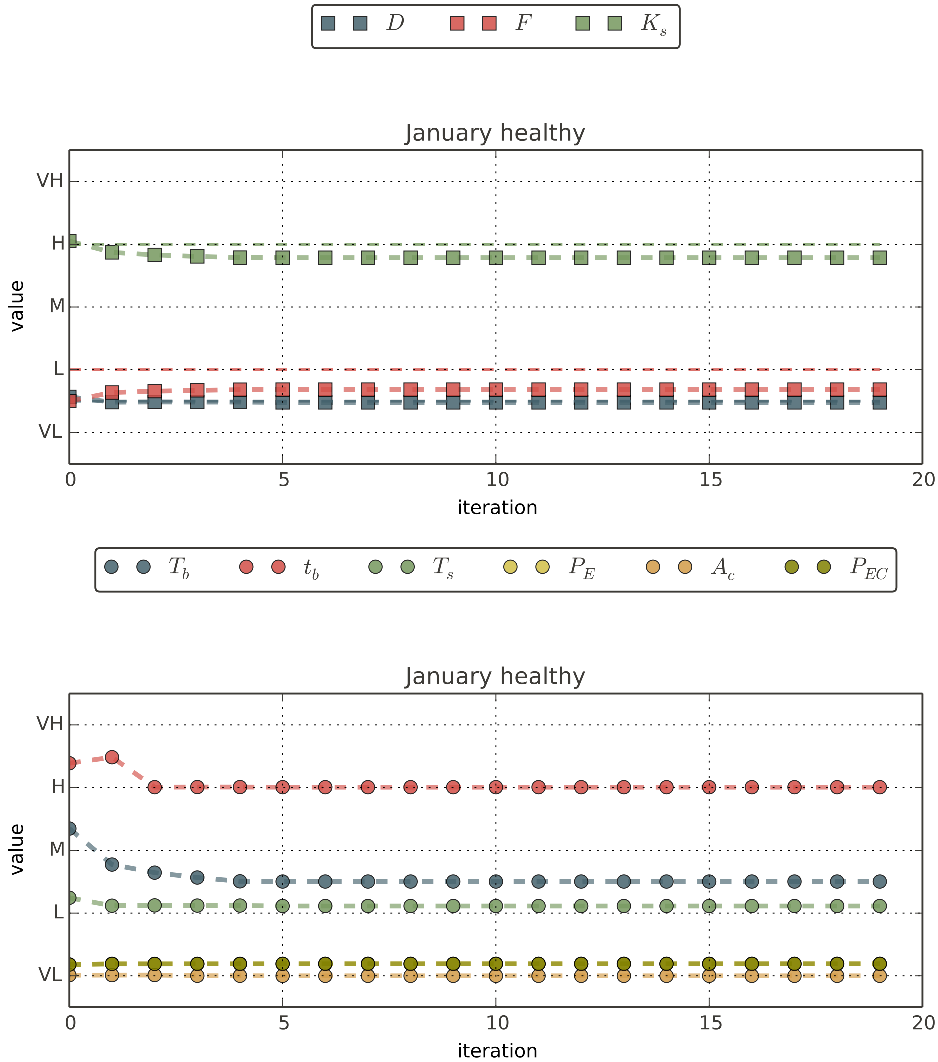


Figure 5.10: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is balanced and a constant disturbance is acting on Fruity (F), for the *January healthy* scenario.

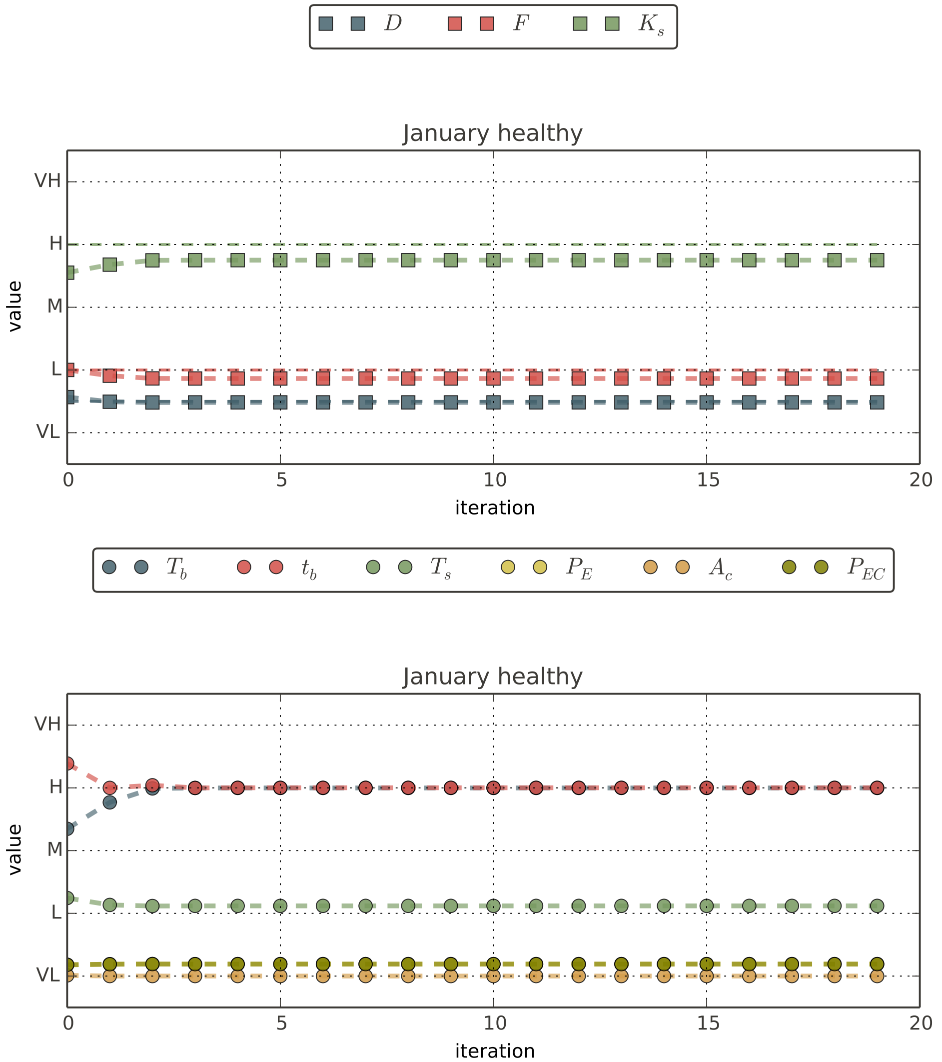


Figure 5.11: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is balanced and a constant disturbance is acting on Kneading State (K_s), for the *January healthy* scenario.

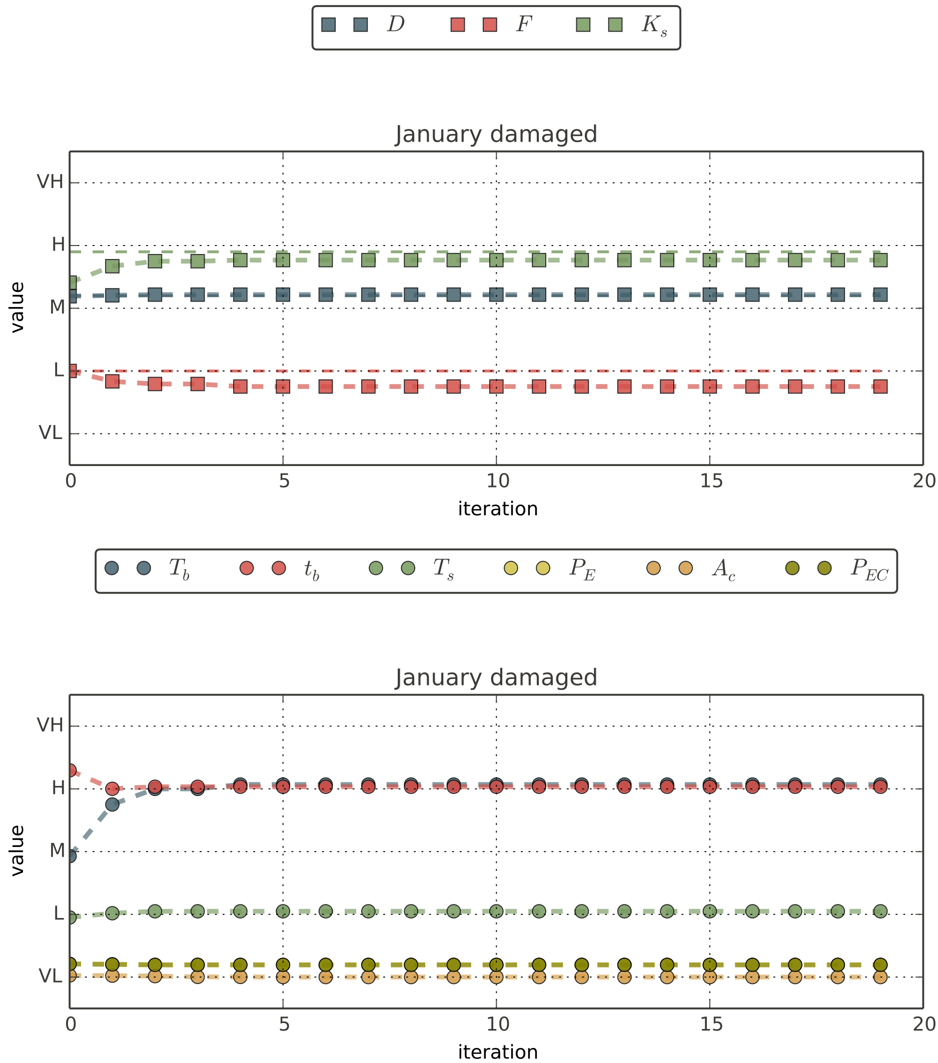


Figure 5.12: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is balanced and a constant disturbance is acting on Fruity (F), for the *January damaged* scenario.

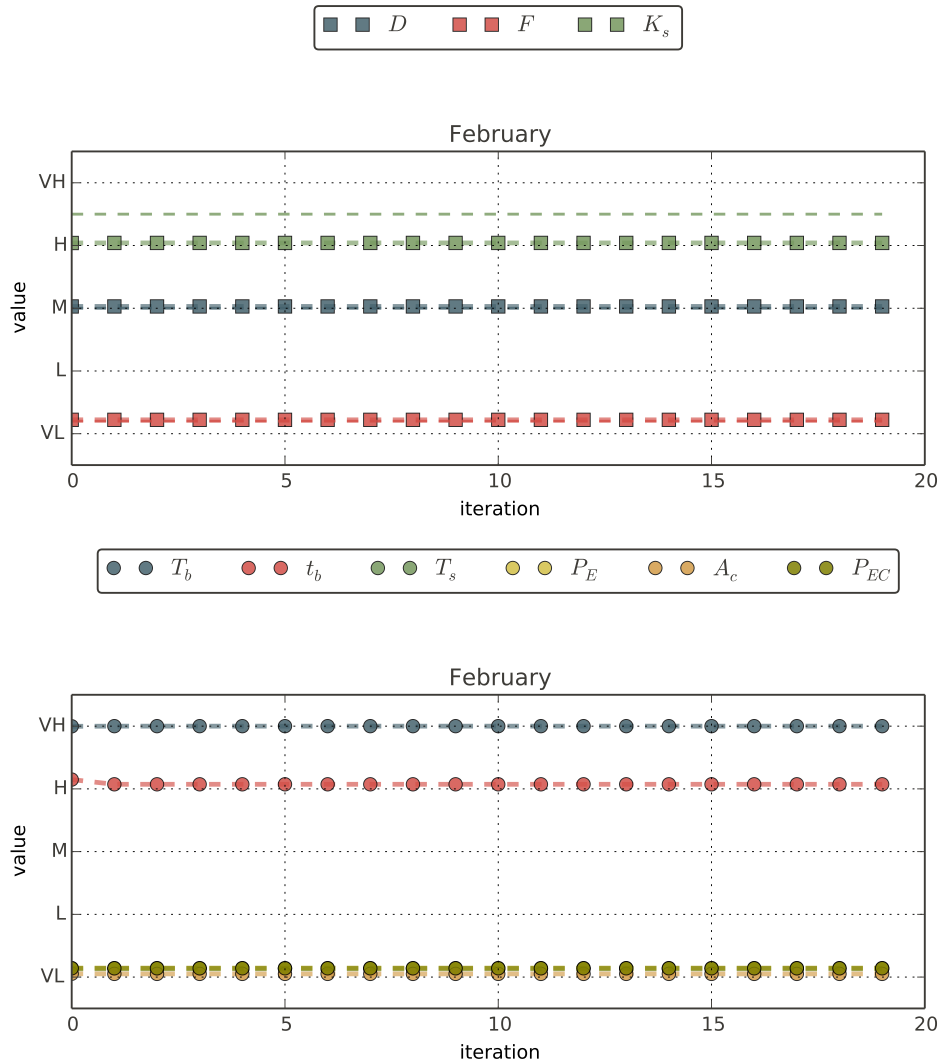


Figure 5.13: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is set to Kneading State (K_s) and a constant disturbance is acting on Kneading State (K_s), for the *February* scenario.

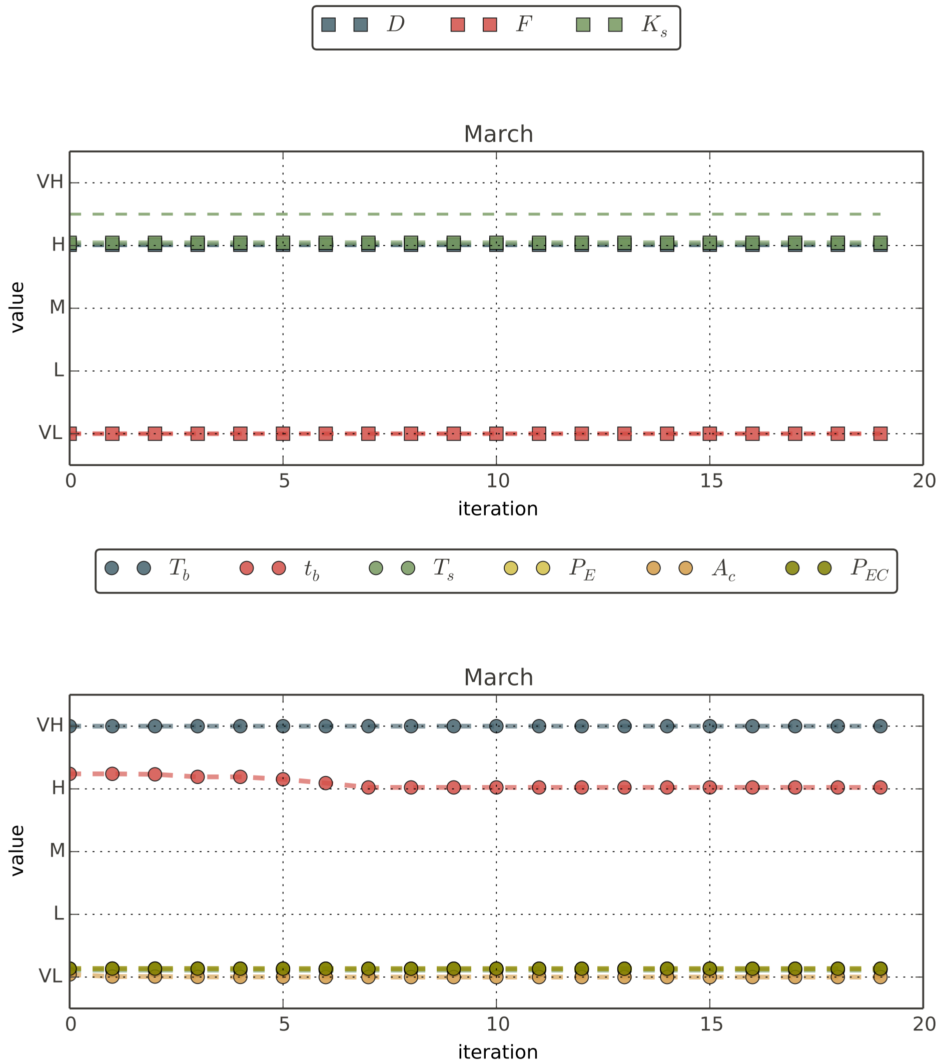


Figure 5.14: Values of the process outputs and prescribed set points by the run-to-run controller for $\omega = 0.4$, when the priority is set to Kneading State (K_s) and a constant disturbance is acting on Kneading State (K_s), for the *March* scenario.

6 Season-wide Production Planning

So far, we have dealt with the problem of finding the optimal elaboration objective and the adequate process set points to comply with them *for a given batch of olives*. That is, we suppose that the batch of olives to be processed are already in the factory, and all the decisions made are based on the properties of those olives.

As commented in Chapter D, the properties of the olives depend heavily on its ripeness, which in turn depends on the moment they are harvested [Gutiérrez et al., 1999, Jimenez Herrera et al., 2012]. So, the assumption that the olives are already harvested conveys that a key decision with fundamental influence on the properties of the elaborated VOO has already been made. In fact, the properties of the olives are the major parameters in the optimization problems used for finding the optimal objectives and set points. If these parameters change, so does the solution of the problem.

Two questions justify the interest of loosening the assumption of fixed olive properties:

- If we aim at obtaining a VOO of a given quality, it is natural to ask which are the optimal values of the olive characteristics to obtain it. This problem can be solved using the tools proposed in Chapter 4, just by including the olive properties into the decision variable set, and defining an objective function that penalizes deviations from the target quality.

- In Section 4.5, the problem of finding the most profitable production objective for a given batch of olives was briefly addressed. Looking at the overall harvesting season, a sensible question might be to ask what amounts of what quality of VOO should be produced to maximize the profit for the year, and consequently, what batches of olives should be processed to optimize this profit.

The objective of this Chapter is to obtain a method capable of determining an optimal production plan for the whole harvesting season, i.e., define what amounts of VOO of which qualities maximize the profit of the company, given pertinent restrictions.

More formally, the objective is obtaining a production plan P defined as a temporal sequence of vectors p_i:

$$P = [p_1 \, p_2 \, \cdots \, p_i]$$

where $p_i = [n_i \, q_i]^T$ and

- n_i represents the amount of oil to be produced, and
- q_i the quality objective;

as a solution of an optimization problem where the objective is maximizing the economic revenue of the company. Throughout this Chapter the subindex i indicates the considered time period.

The method employed to find this optimal production plan is based on simplified models of the relation among the process variables, along with published data of the evolution of olive properties.

The rest of the Chapter is organized as follows: Sec. 6.1 covers the theoretical part, presenting the objective function and the restrictions and models considered. Section 6.2 shows some results obtained using the proposed method for different scenarios, while Section 6.3 6.3 briefly covers the adaption of the method to employ the models and optimization approach presented in Chapters 3 and 4, which allows for a more detailed modeling of the process relations.

Table 6.1: Definition of variables involved in the optimization problem

SYMBOL	VARIABLE
P	Production plan
p	Production objective for a time period
n	Quantity of oil produced
a	Quantity of olives processed
q	Quality of oil to be produced
F^W	Fat content of the olives in wet base
F^D	Fat content of the olives in dry base
H_o	Water content of the olives
E	Extractability of the olives, defined as percentual content of oil in the pomace, expressed in dry base
R_f	Ripeness index
c^p	Elaboration cost (Euro/kg olive processed)
s	Sale price of the oil
m	Commercialization method
c^d	Commercialization cost
h	Harvesting method
c^h	Harvesting cost

6.1 Proposed Method

The method developed employs the definition of an optimization problem which includes the relations of the different variables involved in the VOO elaboration and marketing as constraints to the problem of maximizing the profit.

Table 6.1 includes the definition of the considered variables and Fig. 6.1 depicts a conceptual map of their relations. The orange blocks constitute the models providing the characteristics of the incoming olives independent of the actual VOO elaboration process, i.e., the characteristics of the olives just before being harvested. Yellow blocks include the influence of the harvesting and the VOO elaboration process; with beige blocks covering the business related aspects. In turn, the blue ellipsoidal blocks represent the costs and prices involved in the model; green blocks are intermediate variables of the model and the red ones represent the decision variables. The following subsections detail each of these components.

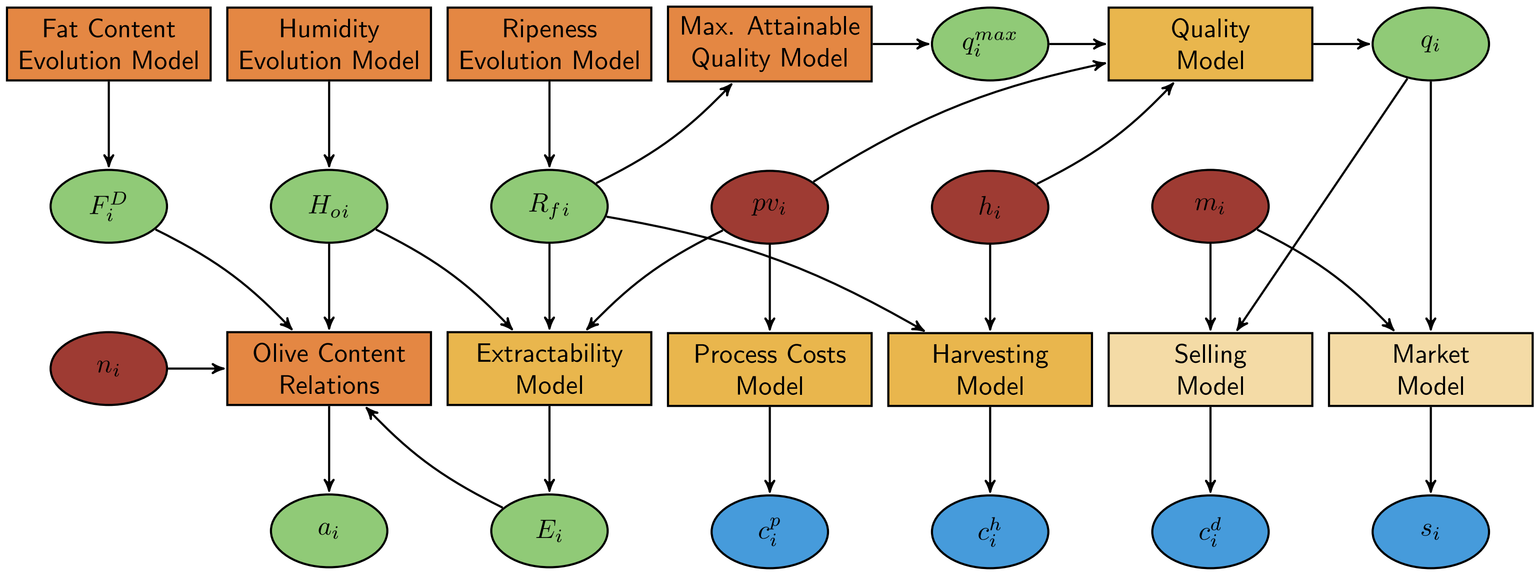


Figure 6.1: Conceptual map of the involved variables and models in the optimal production planning for VOO elaboration. The orange blocks constitute the models providing the characteristics of the incoming olives independent of the actual VOO elaboration process. Yellow blocks include the influence of the harvesting and the VOO elaboration process and beige blocks model the business related aspects. Blue ellipsoidal blocks represent the costs and prices involved in the model; green blocks are intermediate variables and the red blocks are the decision variables.

6.1.1 Olive Properties Models

The most evident restrictions to be considered in the system are those imposed by the olives. Since the characteristics of the olives evolve in time, a model of this evolution is required to provide the value of the variable exclusively as a function of the time period considered, i.e.: $x_i = f(i)$. Here, x_i denotes a generic variable and i represents the time period considered.

6.1.1.1 Ripeness, Fat Content and Humidity Evolution

The characteristics of the olives relevant to the problem are the ripeness (R_{fi}), the fat content (F_i^D) and the humidity (H_{oi}).

The ripeness of the olives (R_{fi}) is related with the maximum VOO quality attainable and the extractability (E_i) [García et al., 1996a]. The data provided in [Jimenez Herrera et al., 2012] are used for this model and implemented as a look-up table.

The fat content (F_i^D) obviously determines the total amount of oil produced, while the humidity of the olives (H_{oi}) affects also the extractability [Cert et al., 1996]. Here, the data used is extracted from [Gutiérrez et al., 1999] for F_i^D. Surprisingly, data of the evolution of H_{oi} was not included in the consulted works, so typical evolution data was provided by experts in VOO elaboration.

6.1.1.2 Olive Composition Formula

The relation between the amount of olives processed and the oil obtained depends on the composition of the olives and the amount of oil that the process is capable of extracting. Performing a mass balance on the inputs and outputs of the process, the following relation can be derived:

$$n_i = a_i(1 - \frac{H_{oi}}{100})(\frac{F_i^D - E_i}{100})(1 - \frac{E_i}{100})^{-1}, \tag{6.1}$$

where F_i^D and H_{oi} account for the composition of the olives, and E_i gathers the influence of the process in the total oil recovery.

6.1.1.3 Maximum attainable quality model

The modeling of q_i^{max} as a function of R_{fi} is an interesting problem and there are several works regarding this relation, see, for instance [Gutiérrez et al., 1999, Salvador et al., 2001]. For this initial simplified approach, the data provided by [Jimenez Herrera et al., 2012] is used and implemented as a look-up table. These data refer to olives that are on the tree.

6.1.2 Definition of Products

In order to tackle the definition of the optimization problem, it is cast as a product selection problem. Each considered product has the following distinct attributes:

- Required quality (q_k^{min})
- Commercialization method (m_k)

i.e., a product is characterized by its quality and the way it is commercialized. Note that there may be two products with the same required quality and different marketing methods, which allows to model the possible different costs and incomes due to different commercialization strategies for a single VOO quality. Throughout the Chapter, the index k references the different products considered.

6.1.2.1 Required quality implications

The definition of the required quality for the product (q_k^{min}) implies restrictions on the following variables:

- Quantity of oil produced at a given time period $n_{i,k}$: if the maximum attainable quality, as bounded by the characteristics of the incoming olives, is below the required quality, then this product cannot be produced. This requirement renders the constraint:

  $$n_{i,k} \leq \begin{cases} 0 & \text{if} \quad q_{i,k} \leq q_k^{min} \\ \overline{n}_{i,k} & \text{otherwise,} \end{cases} \tag{6.2}$$

  with $\overline{n}_{i,k}$ defining a bound based on the maximum processing capacity for the considered time period.

- Process variables: the objective of obtaining a certain quality (q_k^{min}) imposes a restriction on the possible values of the process variables:

$$pv_{k,i} \in \{pv \mid q(pv, q_i^{max}) \geq q_{i,k}^{min}\}. \quad (6.3)$$

  Here, $q(\cdot)$ stands for the model relating q_i, q_i^{max} and pv_i – this model is further treated on Sec. 6.1.3. Note that this selection of process variables affects also the extractability $E_{i,k}$ through the extractability model, as well as the process costs.

- Harvest method: analogously to the case of pv_i, a restriction is also imposed on the harvest method to be used, which, in turn, affects the harvest cost:

$$h_{k,i} \in \{h \mid q_h(h, q_i^{max}) \geq q_{i,k}^{min}\}. \quad (6.4)$$

  Again, $q_h(\cdot)$ stands for the model relating q_i, q_i^{max} and h which will be expanded in Sec. 6.1.3.

6.1.2.2 Commercialization method implications

In turn, the relations of the assigned commercialization method (m_k) comprise:

- Total quantity of product to be sold for the whole season: this quantity is bounded by the share of market of the company, thus the following constraint applies:

$$\sum_i^f n_{i,k} \leq \bar{n}_k. \quad (6.5)$$

- Commercialization cost: this cost includes the packaging, marketing and distribution costs. It will also be dependent on the company structure. This cost may depend on the total amount of product sold due to scale economies.

$$c_k^d = c^d(\bar{n}_k). \quad (6.6)$$

  Note that there is no i index in the equations, since the cost is considered to be constant for the whole season.

- Sale price: obviously, a sale price must be defined for each product. The selection of the optimum sale price and its implications on the total quantity of product sold $\bar{n}_k$, and, trough this variable, in the commercialization cost c_k^d, represents an interesting optimization problem out of scope of this work. Here, we suppose that the pricing policy of the company has already been decided.

6.1.3 Process Relations Models

The relations between quality (q), amount of oil recovered (n) and costs with the different variables and alternatives throughout the VOO elaboration process are addressed in the following subsections.

6.1.3.1 Harvesting model

The harvesting methods can be classified in two major groups:

- Methods that separate olives coming from the tree from olives already in the ground, and
- Methods that mix olives coming from the tree and the ground.

Olives that have fallen to the ground present poor quality characteristics, due to the chemical reactions that begin to take place [García and Yousfi, 2007]. Therefore, methods that mix olives cause a decrease of the potential quality that could be obtained if only olives coming from the tree were to be harvested. However, these methods tend to offer lower costs, since they require lower manual labor [Vilar Hernandez et al., 2010].

Although different non-mixing harvesting methods have been reported to show different effects on the quality of the obtained VOO [Yousfi et al., 2012], for this Chapter we focus on the difference between the two major groups. The ratio of fallen/tree olives is a parameter of importance, as determines the decrease of quality due to the mixture of qualities. The amount of fallen drupes increases as the harvesting season advances, due to the reduction of the retention force of the olives as they ripen. Meteorological phenomena, such as high intensity wind, may increment the amount of fallen olives in stages where they would normally still be on the tree. Despite the bibliographic research carried out, no published data of the typical evolution of this parameter was obtained. So, the resulting preliminary model used for the Chapter employed a linear model for the amount of fallen olives based on estimative data provided by VOO elaboration experts. However, there is published data regarding the quality evolution of harvested (or fallen) olives in [García et al., 1996a], which was included in the model. This data, together with the data available in [Jimenez Herrera et al., 2012] allows to estimate the quality of the harvested olives. Thus, the model can be expressed as:

$$r_{c,i} = f(i) \tag{6.7}$$

$$q_{c,i} = f(i, r_{c,i}, i_c) \tag{6.8}$$

$$q_{h,i} = f(r_{c,i}, q_{c,i}, q_i^{max}, h) \tag{6.9}$$

with

- $r_{c,i}$: percentage of fallen olives at time i,
- $q_{c,i}$: quality of the fallen olives at time i,
- $q_{h,i}$: quality of the harvested olives.

Another effect worth considering is the different harvest cost due to the different facility to separate the olives from the tree [Ferguson, 2006], thus influencing the productivity and, consequently, the harvesting cost. Again, the estimation of the overcost due to this effect was provided by experts. This effect may be formalized as:

$$c^h = c^h(R_f). \tag{6.10}$$

6.1.3.2 Process quality and extractability models

The influence of the different process variables on the VOO quality (q) and the extractability (E) are included in these models. As commented previously, plenty of research effort has been devoted to identify and describe these relations.

The model of the influence of the process variables on the quality and the extractability is taken from the subsystems A and B of the system proposed in [Cano Marchal et al., 2013]. In this Chapter, the relation between quality objective and expected extractability was established via a first subsystem (A). Then, a second subsystem (B) provided initial set points for the process variables as a function of the quality objective. The process variables considered were:

- T_s: the time that the olives are stored previous to their being processed (hours),
- C_s: the size of the sieve of the crushing mill (mm),
- A_c: the addition of microtalc (kg. talc / kg. paste),
- t_b: the kneading time inside the thermomixer (minutes),

- T_b: the kneading temperature in the thermomixer (°C).

Given the quality requirement fixed in the product definition, these models provide the values of extractability and process variables for each product. Note that, within this scheme, the predicted properties of the olives are not used to modify the values of these variables. The most important effect to model is the imposibility of obtaining a product if the quality of the olives is not adequate, and this is already modeled in Eq. 6.2. Some minor adjustments of the process variables might be plausible given the characteristics of the olives, but their influence in the system would be mostly through the process costs and not too relevant, so, in order to simplify the problem, the value of the process variables is supposed independent of the characteristics of the olives.

6.1.4 Process Costs Models

Once the values of the process variables are defined, the computation of approximate process costs can be performed via simple relations. The values of T_s and C_s do not have much influence in the process costs, and can be omitted. The cost associated with the use of microtalc can simply be modeled by:

$$c_{A_c} = A_c \cdot p_{talc}, \tag{6.11}$$

where p_{talc} is the price per kg. of the microtalc employed. The cost of heating the olive paste can be estimated as:

$$c_{T_b} = (T_b - T_{amb}) \cdot c_{paste} \cdot \frac{p_{fuel}}{pci_{fuel}}, \tag{6.12}$$

with c_{paste} being the heat capacity of the olive paste, pci_{fuel} and p_{fuel} the lower heating value and price of the fuel respectively.

The value of t_b does not significantly influence the total processing cost, since it is the rate of flow of paste into the decanter that determines the production rate and, consequently, the amount of time that the factory must be operating in order to process the olives. In [Cano Marchal et al., 2013], the influence of this variable was not considered, so its effect is also neglected here. Note that different t_b are achieved by simply varying the total volume of olive paste contained in the thermomixer for a given flow rate.

Lastly, the man labor cost in the factory is basically independent of the quality that is being produced, and can also be disregarded in this initial overview.

The analysis above finally renders the simple process cost estimation equation:

$$c^p = c_{A_c} + c_{T_b} \tag{6.13}$$

6.1.5 Optimization Problem Definition

In the previous subsections the different relations and constraints affecting the system have been established. In this subsection the optimization problem is formalized.

First, some additional constraints that apply to the problem must be considered:

- Bound on the total amount of olives to be harvested on the whole season, since there is an obvious natural limit on the disponibility of olives for each company:

$$\sum_{i=1}^{f} \sum_{k=1}^{k_f} a_{i,k} \leq \bar{a}. \tag{6.14}$$

- Bound on the total amount of olives to be processed per time period: this bound may be imposed by either the installed processing capacity of the factory or by the harvesting capacity:

$$\sum_{k=1}^{k_f} a_{i,k} \leq \bar{a}_i. \tag{6.15}$$

- Finally, the olives processed must be either positive or zero:

$$a_{i,k} \geq 0. \tag{6.16}$$

In Fig. 6.1, the variables $[n_i, pv_i, h_i, m_i]$ are marked as decision variables, i.e., variables whose values must be determined by the solution of the optimization problem for each time period considered. However, the introduction of the concept of product allows to change the decision variables to $n_{k,i}$, since, as commented above, the definition of (q_k^{min}) for each product fixes the values of pv_i and h_i, while the selection of m_k obviously fixes m_i. The problem, thus, is reduced to chosing the quantity of each product to be produced for each time period considered.

Since the production costs are naturally modeled as proportional to the amount of olives processed, and the commercialization costs proportional to the quantity of VOO sold, the objective function can be defined as:

$$J = \sum_{i=1}^{f} \sum_{k=1}^{k_f} n_{i,k}\,(s_k - c_k^d) - a_{i,k}\,(c_k^p + c_k^h) \tag{6.17}$$

with $i \in [1, f]$ being the index considering the different time periods and $k \in [1, k_f]$ regarding the different defined products.

Gathering the objective function with the constraints presented in the previous subsections, the optimization problem is defined as:

$$\begin{aligned}
\textbf{max} \quad & J = \sum_{i=1}^{f} \sum_{k=1}^{k_f} n_{i,k}\,(s_k - c_k^d) - a_{i,k}\,(c_k^p + c_k^h) \\
\textbf{subject to:} \quad & n_i = a_i(1 - \frac{H_{oi}}{100})(\frac{F_i^D - E_i}{100})(1 - \frac{E_i}{100})^{-1} \\
& n_{i,k} \leq \begin{cases} 0 \ \text{ if } \ q_{i,k} \leq q_k^{min} \\ \overline{n}_{i,k} \ \text{ otherwise,} \end{cases} \\
& pv_{k,i} \in \{pv \mid q(pv, q_i^{max}) \geq q_{i,k}^{min}\} \\
& h_{k,i} \in \{h \mid q_h(h, q_i^{max}) \geq q_{i,k}^{min}\} \\
& \sum_{i}^{f} n_{i,k} \leq \bar{n}_k \\
& c_k^d = c^d(\bar{n}_k) \\
& q_{h,i} = f(r_{c,i}, q_{c,i}, q_i^{max}, h) \\
& c^h = c^h(R_f) \\
& c^p = c_{A_c} + c_{T_b} \\
& \sum_{i=1}^{f} \sum_{k=1}^{k_f} a_{i,k} \leq \bar{a} \\
& \sum_{k=1}^{k_f} a_{i,k} \leq \bar{a}_i \\
& a_{i,k} \geq 0
\end{aligned}$$

Table 6.2: Sale prices in each scenario (Euros/kg)

PRODUCT	Extra Sup.	Extra	Virgin	Lampante
SCENARIOS IA-IB	4	2.71	2.51	2.36
SCENARIOS IIA-IIB	3.5	1.75	1.65	1.59

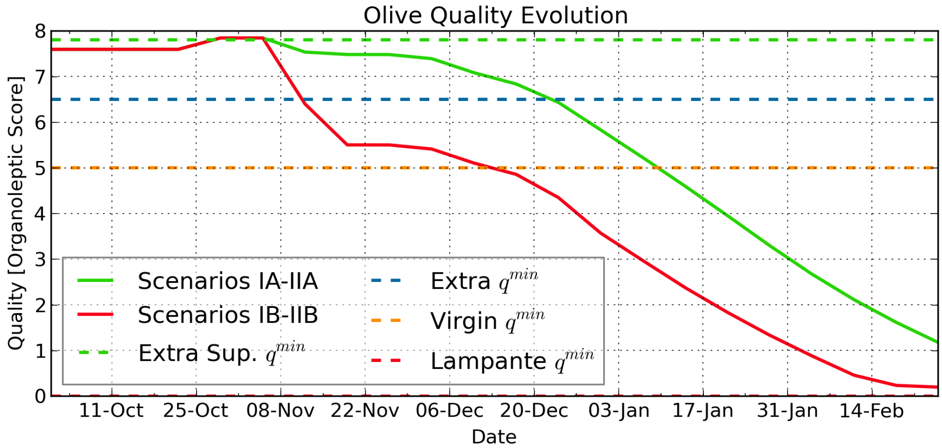


Figure 6.2: Quality evolution of the olives for the different scenarios considered.

6.2 Results

In order to illustrate the proposed method, a set of four products was defined based on the usual quality clasification of VOOs. The Extra Superior product is supposed to be sold bottled, while the rest of products are supposed to be sold in the bulk market. Consequently, a sell limit is considered for the Extra Superior, while no bound is set for the other products. The required quality for each product is plotted in Fig. 6.2 using dashed lines.

Four scenarios have been considered based on two different values for two parameters. First, two different sets of sale prices have been taken from the average bulk sale prices for the Extra, Virgin and Lampante qualities from the Poolred system [Poolred, 2014]. Data for Scenarios I are taken from the June-July period of 2013, while Scenarios II considers the same period of 2012. For the Extra Superior product, since there are no published data, the sale price has been fixed as a typical sale price for that product. The different prices are gathered in Table 6.2.

The second parameter considered is the quality evolution of the olives in the orchards. Scenarios A consider a regular evolution of the quality, while scenarios B consider the situation when some factor, such as a plague or

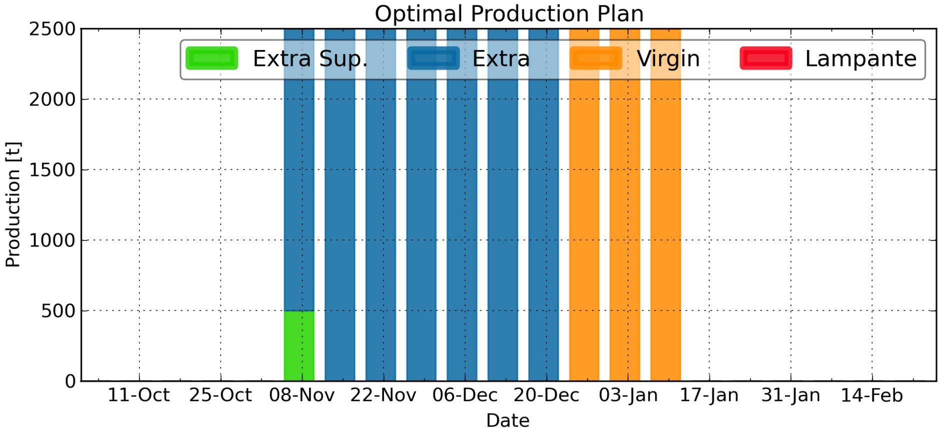


Figure 6.3: Optimal production plan for scenario IA.

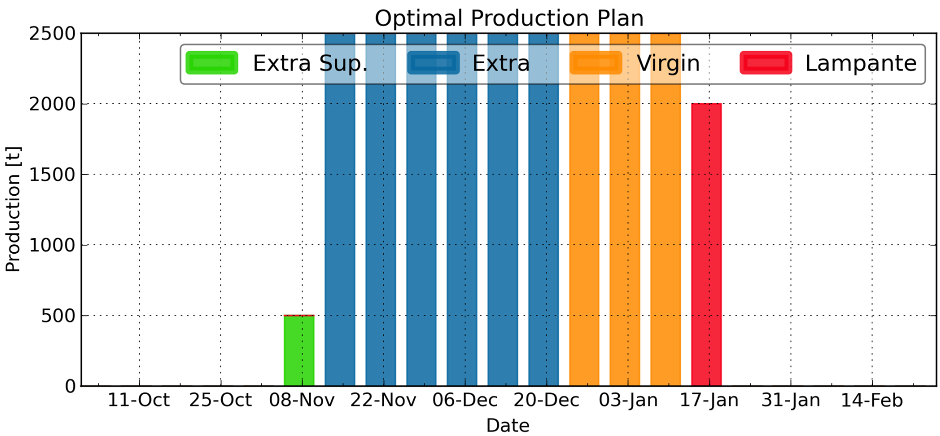


Figure 6.4: Optimal production plan for scenario IIA.

hail, supposed to occur on the first week of november, provokes a substantial decrease of the quality. Figure 6.2 depicts the evolution of the quality for the considered scenarios.

The time unit used is weeks, and 20 time instants are considered. The problem defined for each scenario was solved using OpenOpt [Kroshko, 2007] with the *glpk* solver.

Figure 6.3 plots the optimal production plan (P), for scenario IA, while Fig. 6.4 depicts scenario IIA. As can be seen, both scenarios are quite similar, just implying a small shift in production towards the final part of the harvest season for IIA. The comparison between scenarios IA and IB (Fig. 6.5) shows the convenience of starting to harvest earlier when the quality drops sharply

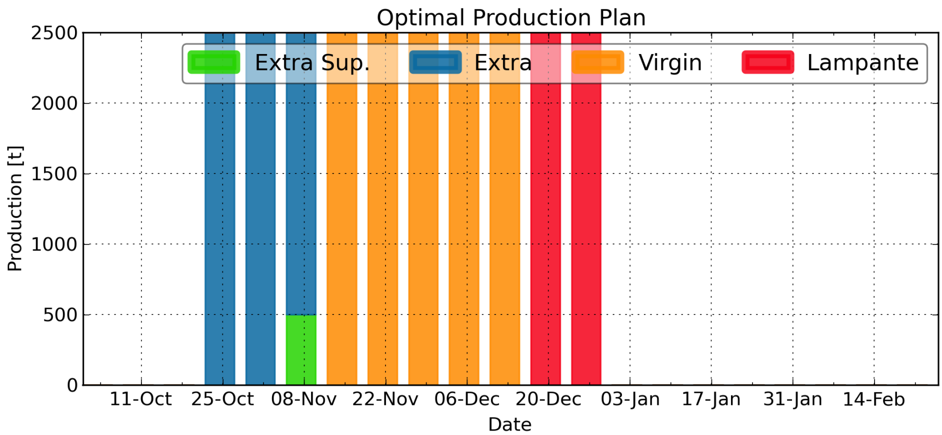


Figure 6.5: Optimal production plan for scenario IB.

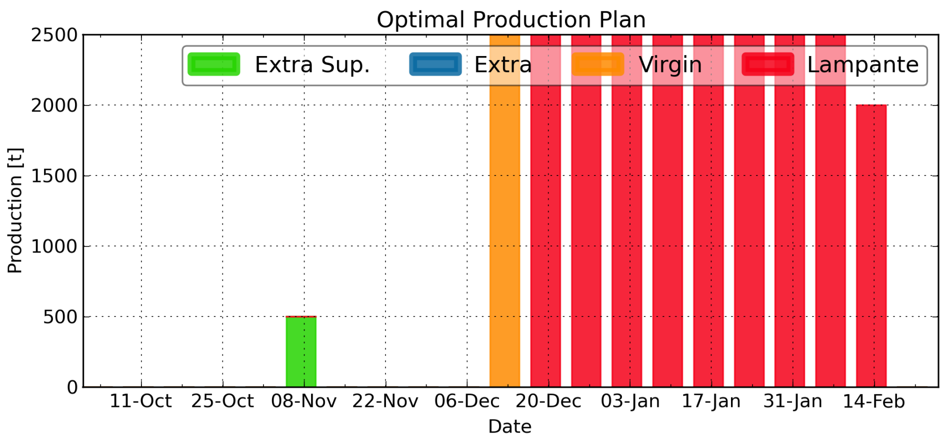


Figure 6.6: Optimal production plan for scenario IIB.

and the spread between prices for the products is high.

The remarkably different plans provided for scenarios IB and IIB (Fig. 6.6) highlight the fact that if the spread of prices is not high enough, and the base quality is low, it is better to plan the production just aiming to maximize the amount of obtained oil. Finally, it is worth noting that the production of Extra Superior remains constant between scenarios, and limited by the selling capacity considered. The fact that it is produced as late as possible is justified by the increasing fat content and extractability due to the evolution of the ripeness of the olives.

6.3 Inclusion of detailed VOOEP models

The models derived in Chapter 3 and the optimization approach to finding the achievable production objective and its corresponding set points presented in Chapter 4 can be used as underlying models for the season-wide production planning. In particular, they provide a unified replacement for the maximum attainable quality, quality, process cost and extractability models included in Figure 6.1.

Indeed, the objective of these models is to define:

- how much VOO,
- of what quality, and
- at what production cost

can be obtained for each time period considered. When fed with the properties of the olives, the optimization approach of Chapter 4 also provides these data.

The quality characteristics of each considered product can be included as constraints in an optimization problem whose objective is to maximize the industrial yield, which, as commented in Section 4.5, is equivalent to maximizing Kneading State (K_s).

The optimization problem presented in that Section is slightly different from the optimization problem required for the product based optimization approach presented above. In the optimization problem of Section 4.5, we intend to maximize the profit for a given batch of olives, and we take into account the bulk market price and the production costs, to find which alternative yields the best result.

In this optimization problem, what we seek is the maximum yield we could obtain *for a given commercial VOO quality*. Thus, the solution of the following optimization problem:

$$\begin{aligned} \underset{\mathrm{x}}{\text{maximize}} \quad & J = K_s \\ \text{subject to} \quad & F \geq F_{min} \\ & D \leq D_{min} \\ & \mathrm{p} = \mathrm{p}_i \\ & \mathrm{y} = f(\mathrm{x}, \mathrm{p}) \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \end{aligned}$$

for each p_i provides the required data. Here p_i represents the properties of the olives at time instant i. If the problem is unfeasible, that means that the required quality is not achievable for the olive properties at hand. If the problem is feasible, then there may be more than one set of process variable capable of obtaining the desired outcomes. Then, following a lexicographic approach, an optimization problem minimizing the production costs can be solved, introducing the quality and Kneading State (K_s) values as restrictions.

This approach allows to take into account the small differences of process cost that might exist depending on the properties of the olives when aiming at an specific quality, which in the approach presented before were disregarded.

It also allows to consider different values of the extractability for each considered product depending on the characteristics of the olives, which again, were not included in the previous approach. Figure 6.7 shows a diagram of the updated scheme of variables and models in the new approach.

The solution of the season-wide production planning problem employing this approach, and the comparison of the obtained results with those provided by the former approach, is left for future research.

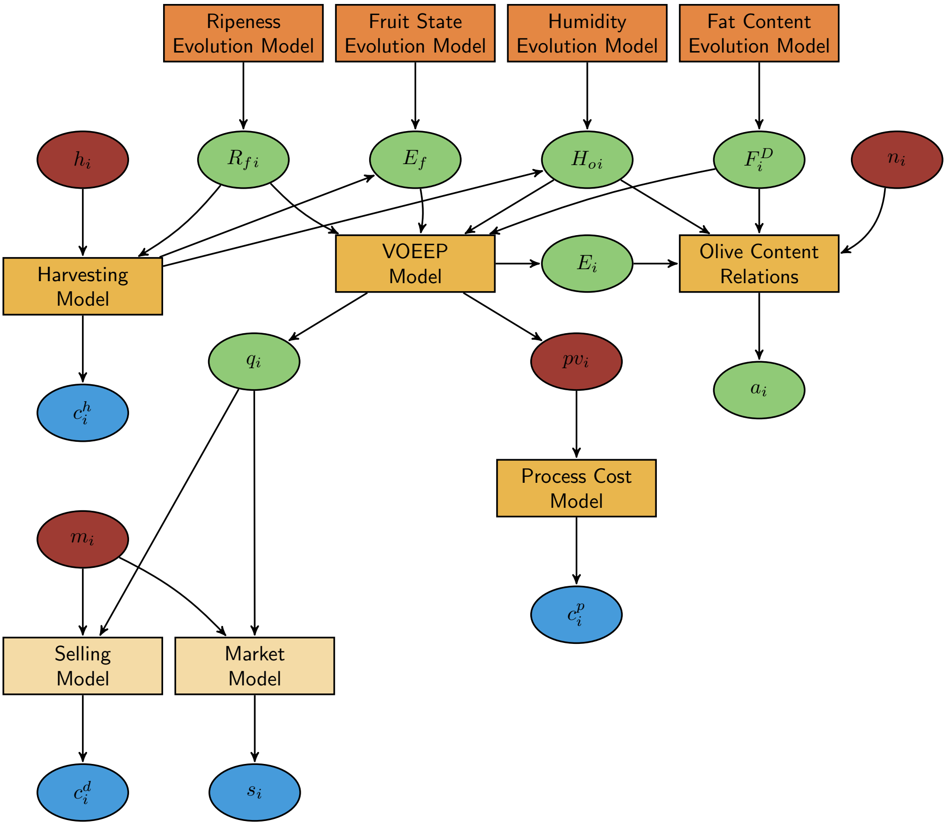


Figure 6.7: Conceptual map of the involved variables and models in the optimal production planning for VOO elaboration using the models derived in Chapter 3. The orange blocks constitute the models providing the characteristics of the incoming olives independent of the actual VOO elaboration process. Yellow blocks include the influence of the harvesting and the VOO elaboration process and beige blocks model the business related aspects. Blue ellipsoidal blocks represent the costs and prices involved in the model; green blocks are intermediate variables and the red blocks are the decision variables.

7

Conclusion and Contributions

This Chapter presents the conclusions of this Thesis, lists the contributions made during its development, and discusses the future research lines relevant to the topics at hand.

7.1 Conclusion

The Virgin Olive Oil Elaboration Process (VOOEP) is a fairly complex industrial process whose objective is the extraction of the oil contained in the olives using exclusively mechanical means, which entitles virgin olive oil to be regarded as *olive juice*. The characteristics of this natural juice depend on both the properties of the incoming olives and the values of the different technological parameters of the VOOEP. These olive properties set an upper bound on the quality of the VOO that can be obtained, and also influence what values of the process parameters must be employed to obtain an acceptable industrial yield, or oil recovery rate. Moreover, preserving the olive quality and obtaining high industrial yield are conflicting goals, with improvements in one objective usually requiring a toll to be paid in the decrease of the other.

The VOOEP can be broken into two layers of relations among variables:

- Higher-level: concerning the relations existing between the obtained VOO properties and the set points of the technological variables.
- Lower-level: dealing with the dynamics governing the transformation from set point to actual value of the process variables.

Assuring that the process variables effectively match their defined set points is obviously desirable and important for the VOOEP, and can be dealt with using mostly standard automatic control techniques. However, assuring that a process variable effectively remains at its prescribed value despite disturbances acting on the system, does not guarantee that the output characteristics of the VOO equal the desired objectives. For that to be so, these set point values must also be defined and adjusted properly, considering the relations of the higher-level layer of the VOOEP. Moreover, the definition of a plausible and adequate production objective based on the properties of the incoming olives constitutes itself a non-trivial and important issue to be addressed in the VOOEP.

The core topic of this Thesis aimed at assisting the decision maker of the VOOEP when addressing the following questions:

1. What production objective should be chosen for the particular batch of olives at hand?
2. What values of the process variables enable the fulfillment of the objective?
3. If the objective is not exactly obtained, how should the values of the process variables be modified, so that the objective is reached?
4. When should the harvesting of the olives be carried out to optimize the economical return for the whole production season?

The first step to answer the above questions was to obtain a sufficiently detailed model of the relations and influence of the different variables of the VOOEP. A main obstacle when facing the problem is that, currently, there are no sensors capable of providing reliable on-line measurements of the relevant output process variables. This major constraint rendered it non-viable to employ a classical system identification approach to model the system, which led to resorting to the expert knowledge of operators to obtain the required models.

Given the non-trivial complexity of the VOOEP, due to the number of relevant process variables and the relations among them, fuzzy cognitive maps were the proposed technique to construct the model of the system. This technique provides a graphical description of the system which makes it very intuitive to analyze and interpret the relations between the nodes. Moreover, it is a highly modular technique, and it allows to easily increase the level of detail of some parts of the model by the introduction of further nodes and relations, without requiring the modification of the satisfactory areas.

The particular fuzzy cognitive map technique employed to construct the model was a modified version of the Simplified Dynamic Cognitive Networks [Miao et al., 2010], employing matrices to encode the relations among the labels defined in the universe of discourse of each node. Using this technique, a model of the paste preparation stage of the VOOEP and the solid-liquid separation performed in the decanter were constructed. The outputs of the models for different combinations of the inputs scenarios were studied and validated with experts in the VOOEP.

These models constitute the base of the whole decision support system, as they already contain the information and knowledge about the system relations required to answer the target questions. All that was left was to propose a method to obtain the answers to the questions employing these models.

The approach taken was to translate the questions to objective functions for an optimization problem, using the already available models as constraints. The answer to the first question *What production objective should be chosen for the particular batch of olives at hand?* was answered in a two step process: first the whole set of Pareto optimal points was sought, which allowed to visualize the trade-offs in the objectives. Then, a specific criterion, namely, the maximization of the profit, was considered, and a single production objective of the Pareto frontier was found. Different conditions of the incoming olives were considered as production scenarios, and the objectives prescribed by the approach were studied and validated with the help of experts.

The answer to the second question was found to be already provided by the solution of the previous optimization problems, as it comprised of the values of the decision variables specified by the optimization problem. A small precaution was pointed out, as it is required to slightly modify the objective function to account for the fact that multiple sets of process variables may lead to the same production objective, thus being convenient to impose extra conditions to select the most advantageous one out of them. The previously defined production scenarios were again considered, and set point values provided by the system were studied and their congruence assessed.

Regarding the question of including some feedback from the process to correct the prescribed process set points in case of mismatch between the desired objective and the actual process outputs, the unavailability of on-line sensors again imposed severe constraints on the viable approaches. Given this lack of on-line sensors and the static nature of the available models, run-to-run control emerged as the natural alternative. In this context, following the traditional configuration of this type of controllers, we proposed to augment the already derived system with an observer to estimate the disturbances or errors affecting the plant, and use this estimate to include the feedback from the process into the system. Although no proof of convergence of the scheme was granted, the simulations performed illustrated the good behavior of the approach. In particular, quite good robustness was observed when different types of disturbances were applied.

In all these previous points, the hypothesis that the olives to be processed were already in the *almazara* was assumed. However, the harvesting of the olives greatly determines the properties of the olives, which in turn influence the whole VOOEP. The relaxation of this hypothesis required asking when should the olives be harvested so that the properties of the olives allow to maximize the profit for the whole season. In this context, the use of models providing the evolution of the olives in the orchards and the consideration of the harvesting influence was considered, and an optimization problem including the production for the whole season was proposed. Using this model, simulations considering different scenarios were performed, and their results assessed.

Finally, it is worth emphasizing that, considered as a whole, the proposed methods allow to address the different question posed above *just* requiring the construction of a model of the influence of the process variables. More specifically, the knowledge required to be elicited from the experts is that of how one variable affects another, or what is the expected value of one variable when the other has a specific level, and how strong is that relation. No elicitation of typical control actions when facing particular situations are required, as the control actions are *deduced* by the system from the relations embedded in the models. With the proposed modular modeling approach, these models may be constructed in successive efforts to increase its accuracy and completeness, with the possibility of employing data coming from the process to refine the model performance.

7.2 Contributions

Below can be found the contributions made during the development of this Thesis, both those directly related to the main topic of this Thesis and others that, although not directly addressing this core topic, are considered to be relevant, as they address related issues of the VOOEP modeling and control or particular techniques closely related to those employed in the work.

- Contribution to journals:

  1. *Expert system based on computer vision to estimate the content of impurities in olive oil samples*. P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. Journal of Food Engineering 119, n. 2 (November 2013).
  2. *Situación actual y perspectivas futuras del control del proceso de elaboración del aceite de oliva virgen*. P. Cano Marchal, J. Gómez Ortega, D. Aguilera Puerto, y J. Gámez García. Revista Iberoamericana de Automática e Informática Industrial RIAI 8, n. 3 (July 2011).

- Contributions to international conferences:

  1. *Optimal Production Planning for the Virgin Olive Oil Elaboration Process.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 19th IFAC World Congress. August 24-29, 2014, Cape Town, South Africa.
  2. *Iterative Learning Control for Machining with Industrial Robots.* P. Cano Marchal, O. Sörnmo, B. Olofsson, A. Robertsson, J. Gómez Ortega, R. Johansson. 19th IFAC World Congress. August 24-29, 2014, Cape Town, South Africa.
  3. *Fuzzy Decision Support System for the Determination of the Set Points of Relevant Variables in the Virgin Olive Oil Elaboration Process*. P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 2013 IEEE International Conference on Systems, Man, and Cybernetics (SMC). Manchester, UK.
  4. *Control System of the Malaxing State for the Olive Paste Based on Computer Vision and Fuzzy Logic*. D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. 2013 IEEE International Conference on Systems, Man, and Cybernetics (SMC). Manchester, UK.

5. *Application of computer vision and Support Vector Machines to estimate the content of impurities in olive oil samples.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 18th International Conference on Automation & Computing. Loughborough, UK, 2012.
6. Título de la aportación: *Hyperspectral imaging for determination of some quality parameters for olive oil*. D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. 18th International Conference on Automation & Computing. Loughborough, UK, 2012.

- Contributions to national conferences:

1. *Sistema experto para la determinación de referencias en el proceso de elaboración de aceite de oliva virgen.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. XXXIV Jornadas de Automática. Tarrasa (Barcelona), 2013.
2. *Determinación del estado de batido de la pasta de aceituna empleando visión por computador.* D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. XXXIV Jornadas de Automática. Tarrasa (Barcelona), 2013.
3. *Aplicación del control repetitivo para el rechazo de perturbaciones periódicas en la temperatura de la pasta en la batidora del proceso de elaboración de aceite de oliva virgen* P. Cano Marchal, J. Gámez García, D. Santamaría García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.
4. *Propuesta de modelo y estrategia de control para el decánter del proceso de elaboración de aceite de oliva virgen* P. Cano Marchal, J. Gámez García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.
5. *Clasificador automático de aceitunas según su variedad utilizando información hiperespectral* J.P. Aranda Carmona, P. Cano Marchal, E. Estevez Estevez, S. Satorres Martínez, J. M. López Paniza, J. Gámez García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.
6. *Grado actual de automatización del proceso de elaboración de aceite de oliva virgen en España.* D. Aguilera Puerto, P. Cano Marchal, J. Gómez Ortega, J. Gámez García. XXXI Jornadas de Automática, Jaén, 2010.
7. *Aplicación del control automático al proceso de elaboración de aceite de oliva virgen. Situación actual y perspectivas futuras.* P. Cano

Marchal, J. Gómez Ortega D. Aguilera Puerto y J. Gámez García. XXXI Jornadas de Automática, Jaén, 2010.

- Book chapters:

  1. *La automatización en el proceso de extracción de aceite de oliva virgen. Situación actual y líneas de mejora.* Juan Gómez Ortega, Javier Gámez García, Pablo Cano Marchal and Diego Martínez Gila. In *El Sector de elaboración de aceite de oliva: un estudio multidisciplinar*. Edited by GEA-Westfalia. 2013.

- National patents:

  1. *Sistema de regulación automático de la salida de la interfase entre agua y aceite de un decantador centrífugo horizontal en el proceso de elaboración de aceite de oliva.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega.
  2. *Sistema de control de trazabilidad en el proceso de elaboración de aceite de oliva mediante la identificación e lotes de aceitunas por radiofrecuencia RFID, y procedimiento asociado al mismo.* D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega.

Besides these already published works, a paper dealing with the modeling of the paste preparation stage employing the approach presented in Chapter 3, and another regarding the solid-liquid separation are scheduled to be submitted to *Engineering Applications of Artificial Intelligence*.

A paper presenting the optimization approach for suggesting the process set points covered in Chapter 4 is to be submitted to *IEEE Transactions on Systems, Man and Cybernetics*, and another dealing with the application of run-to-run control to update the prescriptions of the system, as presented in Chapter 5, to *Expert Systems and Applications*.

Finally, a paper covering the season-wide production planning approach, based on the work presented in Chapter 6, is to be submitted to *Journal of Food Engineering*.

The submission of the papers to their corresponding journals will be made before the defense of this Thesis takes place.

7.3 Future Research Lines

A first interesting research line is the extension of the process models to incorporate other VOO characteristics. Particularly interesting is the inclusion of the influence of the process variables on the content of polyphenols and other minority compounds of the VOO, given their relation to the healthy properties of the VOOEP and the current active research on the topic. From a transference to the industry point of view, this line is compelling, as it is the subjective impression of the author that knowledge of the influence of the process parameters on these health-related VOO properties is not widespread in the industry.

Currently, the non-convexity of the models and existence of local minima makes it problematic to find the global optimum, forcing to resort to global optimization techniques to find the solutions. Increasing the size of the models would undoubtedly aggravate these problems, which encourages analyzing further the mathematical structure of the proposed process models. In particular, the possibility of analytically computing the derivatives of the relations defined by them might ease the solution of the optimization problems where these models are employed.

In addition, the analysis of the mathematical properties of the models would also be of interest for the study of the convergence of the run-to-run approach, which is an important topic, particularly if a more autonomous control system is sought.

Continuing with the run-to-run control, it is worth noting that the employed objective function penalizes both positive and negative deviations from the process objective. If the prescribed production objective is effectively a Pareto efficient point, then there is no major drawback to employing this type of function. However, if there is some error in the models used to define the optimal production objective, it might be case that extra achievements in one variable might not suppose a decrease in the others, that is, it might be that the prescribed process objective is not really a Pareto efficient point. If this is the case, it might be of interest to just penalize one sign of the error, allowing deviations of the opposite sign. This discussion suggest the interest of looking into the application of different objective functions, particularly goal-programming-like functions, for the run-to-run controller.

Regarding the season-wide production planning, the corresponding Chapter already mentioned the interest of studying the problem using more detailed VOOEP models. Another interesting extension would be to explore the implications and difference in the obtained solutions when the unpredictability of the weather conditions is considered, including stochastic components in the olive evolution models.

Besides these points, the research on the development of sensors capable of providing reliable on-line measurements or estimations of the relevant process output variables, line on which our research group is already investing some effort, is also of great interest. The possibility of obtaining data at a higher sampling rate and lower acquisition cost would eventually enable the construction of dynamic models of the relations, leading to the possibility of applying better control schemes.

Furthermore, the availability of sensors capable of providing the required information from the process without human intervention may turn the applicability of the proposed methods from a decision support system to a more autonomous higher-level controller of the VOOEP. For this transition, of particular relevance are the issues concerning the stability of the proposed run-to-run approach, and the influence of noise in its performance.

Finally, the packaging of the proposed methods along with a user interface to implement the approach in an industrial *almazara* and exploit the data-driven adjust of the models is considered as a high priority research line.

A

Table of Variables

Variable Name	Symbol
Oil Content of Olives	X_o
Paste Oil Content	X_o
Acidity	A
Thermomixer Water Addition	A_B
Water Addition to Decanter	F_W
Mill Water Addition	M_W
Coadjuvant Addition	A_c
Yield	X
Storage Time in Hopper	T_s
Bitter	B
Interphase width	W_{wo}
Decanter Blocking	B_d
Mill Blocking	B_m
Oil Income Flow	F_o
Water income flow	F_w
Solid income flow	F_s
Economic Aspects	C_e
Sieve Size	C_s
Sieve Size	C_{se}
Defect	D
Sieve Worn	D_c

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VARIABLE NAME	SYMBOL
Hammer Worn	D_h
Paste Emulsion	P_E
Corrected Paste Emulsion	P_{EC}
Uncorrected Paste Emulsion	P_{EU}
Olive Illnes	O_I
Kneading State	K_s
Fruit State	E_f
Incoming Fruit State	E_f^I
Fluid movement ease	E
Total phenols	C_F
Pulp Firmness	P_F
Paste Fluidity	F_p
Milling Production Rate	M_R
Fruity	F
Crushing Degree	G_m
Olive Moisture	H_o
Incoming Olive Moisture	H_o^I
Paste Moisture Content	P_H
Milling Temperature Increase	Δ_{Tm}
Dirtiness	D_t
Oil Cleannes	O_c
Separation Interphase	r_s
Ripeness	R_f
Oil Pool Width	h_o
Water Pool Width	h_w
Solid Width	h_s
Elaboration Objective	O_E
Weirs-Separation Interphase Offset	Δr
Decanter Torque	d
Pungent	P
Overflow Weirs Position	r_1
Pit-Flesh Ratio	R_p
Production Rate	F
Cells Breakage	R_c
Paste Solid Content	P_S
Drop Size	D_s
Kneading Temperature	T_b
Kneading Time	t_b
Residence Time	t_r

Continued on next page

Variable Name	Symbol
Sieve Type	S_t
Variety	V
Differential Speed	$\Delta\omega$
Mill Speed	V_m
Main velocity	Ω
Paste Viscosity	mu_p
Volatile Content	V_c

B

Paste Preparation Model Relations

Predecessor	Sucessor	R_{ij}	ω_{ij}
Sieve Size (C_{se})	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Sieve Worn (D_c)	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5
Hammer Worn (D_h)	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5
Mill Speed (V_m)	Paste Emulsion (P_E)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.25

Olive Moisture (H_o)	Paste Emulsion (P_E)	$\begin{bmatrix} 20 & 20 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 2 \end{bmatrix}$	1
Pit-Flesh Ratio (R_p)	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.75
Ripeness (R_f)	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Fruit State (E_f)	Paste Emulsion (P_E)	$\begin{bmatrix} 20 & 1.75 & 1.0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Olive Illnes (O_I)	Paste Emulsion (P_E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5
Kneading Temperature (T_b)	Fruity (F)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 1.0 & 3.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Kneading Time (t_b)	Fruity (F)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 1.0 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.25
Ripeness (R_f)	Fruity (F)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75

Milling Temperature Increase (Δ_{Tm})	Fruity (F)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Fruit State (E_f)	Fruity (F)	$\begin{bmatrix} 3.0 & 1.0 & 0.5 & 0.25 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Kneading Temperature (T_b)	Kneading State (K_s)	$\begin{bmatrix} 2.0 & 0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0 & 0 & 0 & 0 & 0.75 \end{bmatrix}$	0.75
Kneading Time (t_b)	Kneading State (K_s)	$\begin{bmatrix} 1.0 & 0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0.75 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Corrected Paste Emulsion (P_{EC})	Kneading State (K_s)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 20 \\ 0 & 0 & 0 & 20 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Paste Moisture Content (P_H)	Kneading State (K_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Crushing Degree (G_m)	Kneading State (K_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Sieve Worn (D_c)	Milling Temperature Increase (Δ_{Tm})	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.75

Hammer Worn (D_h)	Milling Temperature Increase (Δ_{Tm})	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.75
Mill Speed (V_m)	Milling Temperature Increase (Δ_{Tm})	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Sieve Size (C_{se})	Mill Speed (V_m)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Olive Moisture (H_o)	Mill Speed (V_m)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Pit-Flesh Ratio (R_p)	Mill Speed (V_m)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Pulp Firmness (P_F)	Mill Speed (V_m)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Milling Production Rate (M_R)	Mill Speed (V_m)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Sieve Size (C_s)	Sieve Size (C_{se})	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75

Sieve Type (S_t)	Sieve Size (C_{se})	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.2 & 0.4 & 0.6 & 0.8 \end{bmatrix}$	0.75
Incoming Olive Moisture (H_o^I)	Olive Moisture (H_o)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Olive Moisture (H_o)	Paste Moisture Content (P_H)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Mill Water Addition (M_W)	Olive Moisture (H_o)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.75
Thermomixer Water Addition (A_B)	Paste Moisture Content (P_H)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.75
Coadjuvant Addition (A_c)	Paste Moisture Content (P_H)	$\begin{bmatrix} 0 & 0 & 0 & 0.5 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Coadjuvant Addition (A_c)	Corrected Paste Emulsion (P_{EC})	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Paste Emulsion (P_E)	Corrected Paste Emulsion (P_{EC})	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75

Sieve Size (C_{se})	Crushing Degree (G_m)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Pulp Firmness (P_F)	Crushing Degree (G_m)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Pit-Flesh Ratio (R_p)	Crushing Degree (G_m)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Storage Time in Hopper (T_s)	Olive Moisture (H_o)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.75
Storage Time in Hopper (T_s)	Fruit State (E_f)	$\begin{bmatrix} 0 & 0.25 & 0.75 & 1.0 & 2.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Incoming Fruit State (E_f^I)	Fruit State (E_f)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.75
Fruit State (E_f)	Defect (D)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	1
Olive Illnes (O_I)	Defect (D)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5

Dirtiness (D_t)	Defect (D)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5
Fruit State (E_f)	Pulp Firmness (P_F)	$\begin{bmatrix} 0 & 0.25 & 0.5 & 0.75 & 1.0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Ripeness (R_f)	Pulp Firmness (P_F)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5

C

Solid-Liquid Separation Model Relations

Predecessor	Sucessor	R_{ij}	ω_{ij}
Production Rate (F)	Residence Time (t_r)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Production Rate (F)	Oil Income Flow (F_o)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Production Rate (F)	Water income flow (F_w)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Production Rate (F)	Solid income flow (F_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5

Paste Oil Content (X_o)	Oil Income Flow (F_o)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Paste Oil Content (X_o)	Solid income flow (F_s)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Paste Moisture Content (P_H)	Water income flow (F_w)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Paste Moisture Content (P_H)	Solid income flow (F_s)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Water Addition to Decanter (F_W)	Water income flow (F_w)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.25 & 0.5 & 0.75 & 1.0 \end{bmatrix}$	0.5
Differential Speed $(\Delta\omega)$	Solid Width (h_s)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Differential Speed $(\Delta\omega)$	Water Pool Width (h_w)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Water income flow (F_w)	Water Pool Width (h_w)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5

Solid income flow (F_s)	Solid Width (h_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Weirs-Separation Interphase Offset (Δr)	Yield (X)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \end{bmatrix}$	0.75
Weirs-Separation Interphase Offset (Δr)	Oil Cleannes (O_c)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}$	0.75
Solid Width (h_s)	Separation Interphase (r_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Water Pool Width (h_w)	Separation Interphase (r_s)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Solid Width (h_s)	Decanter Blocking (B_d)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Residence Time (t_r)	Oil Cleannes (O_c)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Residence Time (t_r)	Yield (X)	$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5

Fluid movement ease (E)	Oil Cleannes (O_c)	$\begin{bmatrix} 2 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Kneading State (K_s)	Fluid movement ease (E)	$\begin{bmatrix} 2 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	0.5
Kneading Temperature (T_b)	Paste Viscosity (mu_p)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Paste Viscosity (mu_p)	Fluid movement ease (E)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Main velocity (Ω)	Interphase width (W_{wo})	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Fluid movement ease (E)	Interphase width (W_{wo})	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Interphase width (W_{wo})	Yield (X)	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5
Main velocity (Ω)	Decanter Torque $(_d)$	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5

Water Pool Width (h_w)	Decanter Torque $(_d)$	$\begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$	0.5

D
Motivación

D.1 Introducción

La producción de aceite de oliva virgen (AOV) es una importante actividad económica llevada a cabo en más de 20 países. La media mundial de producción del período 2008–2013 fue de 2.843.000 t, lo que supone un incremento del 1.5% sobre la media del período 2001–2007 [Council, 2014], y se espera que esta tendencia continúe, puesto que las plantaciones creadas durante la última década continúan incrementando su producción. Esta producción, valorada a los precios medios de venta a granel del periodo 2008–2013, 2100 € por tonelada, posiciona a la producción de AOV como una actividad económica mundial de 5970 millones € [Poolred, 2014].

La calidad del AOV está acotada por las aceitunas que se procesan, y determinada por la influencia de las variables de proceso durante la elaboración. Obviamente, la cantidad de AOV producido depende críticamente de las características de las aceitunas de entrada y de los valores de las variables de proceso. Calidad y cantidad son objetivos contrapuestos, dado que los valores de proceso que preservan la calidad tienden a reducir la cantidad de AOV producido, y viceversa [Di Giovacchino et al., 2002].

Dada esta relación de compromiso entre cantidad y calidad, más allá del interés evidente en el control de bajo de los diferentes estadios del proceso de elaboración de aceite de oliva virgen (PEAOV), un nivel superior,

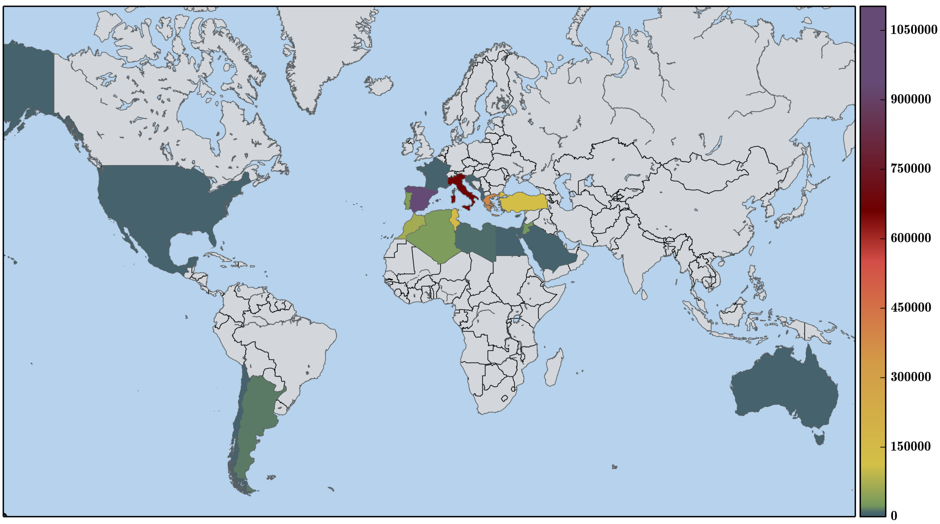

Figure D.1: Distribución geográfica de la producción media mundial para el periodo 2008–2013.

relacionado con el manejo de las implicaciones de estas relaciones globales del PEAOV, aparece como un candidato prometedor a contribuir a la mejora del proceso.

El objetivo de este capítulo es presentar el contexto y la motivación de esta tesis. La próxima sección presenta algunos datos sobre la importancia la producción de AOV, con la sección D.3 describiendo brevemente el PEAOV. La sección D.4 introduce las ideas principales y la motivación de esta tesis, mientras que la sección D.5 avanza su estructura.

D.2 Datos de Producción del Aceite de Oliva Virgen

La distribución geográfica mundial de la producción de AOV se puede ver en la Figura D.1 y en la Tabla D.1. Como se muestra, la principal zona de producción es la cuenca mediterránea, que representa casi el 98% de la producción mundial total. Menores niveles de producción se puede encontrar en países fuera de esta zona que presentan clima mediterráneo, tales como Argentina, Chile y Australia.

Los países fuera del área mediterránea muestran un incremento muy rápido de producción. Chile y Australia triplicaron su producción entre

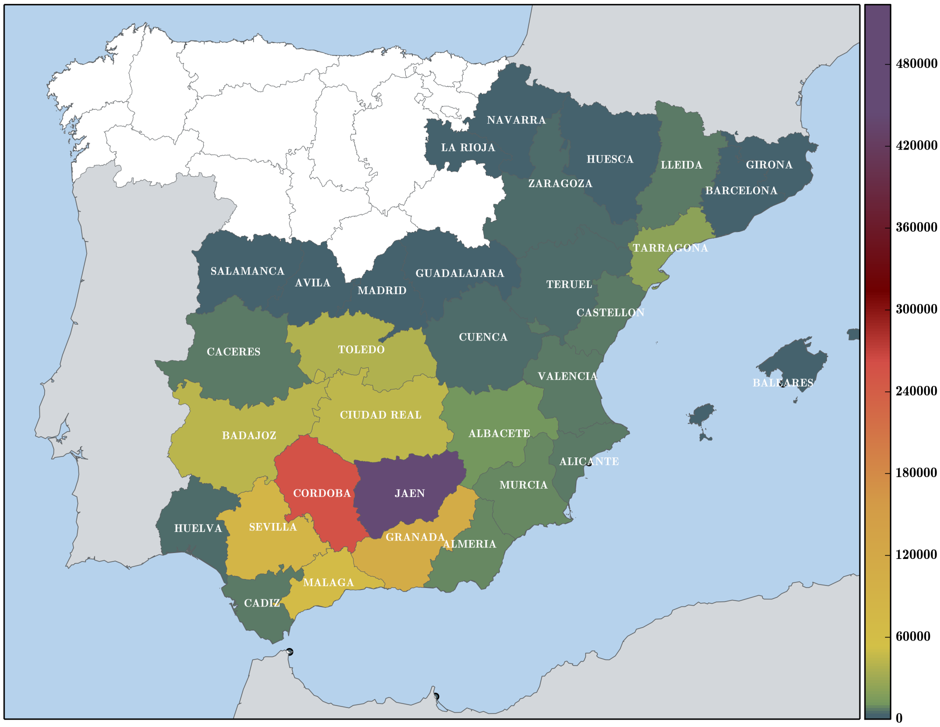

Figure D.2: Distribución geográfica de la producción media española para el periodo 2008–2013.

los períodos 2001–2007 y 2008-2013. A pesar de estas tasas, el peso de la producción de estos países en la producción mundial es aún pequeño.

Dentro de la cuenca mediterránea, la Unión Europea es el mayor productor de AOV, representado más del 70% del total mundial. España, Italia, Grecia y Portugal son, en orden decreciente, los cuatro mayores productores. Fuera de la Unión Europea, Túnez, Turquía y Siria son los mayores productores.

Como se pone de relieve en la Figura D.1, España es el mayor productor mundial, representando el 42% del total de la producción. La distribución geográfica de la producción dentro de España se incluye en la Figura D.2, con la Tabla D.2 mostrando las cifras concretas. Como se observa en la Figura, la producción se extiende por prácticamente todo el país, salvo la zona noroeste.

Sin embargo, la producción no presenta una distribución homogénea en el país, sino que existen pocas áreas donde la producción está muy concen-

Table D.1: Producción Mundial de AOV (t).

Country	Avg. Prod. 2001-2007	% 2001-2007	Avg. Prod. 2008-2013	% 2008-2013
Albania	0	0.00	7,300	0.26
Algeria	32,800	1.17	47,400	1.67
Argentina	15,100	0.54	22,700	0.80
Australia	4,800	0.17	14,600	0.51
Chile	5,000	0.18	15,400	0.54
Croatia	4,800	0.17	4,800	0.17
Cyprus	6,800	0.24	0	0.00
Egypt	4,000	0.14	5,800	0.20
France	4,200	0.15	5,300	0.19
Greece	384,900	13.73	317,600	11.17
Iran	3,200	0.11	4,800	0.17
Israel	6,000	0.21	9,200	0.32
Italy	663,500	23.67	455,800	16.03
Jordan	25,800	0.92	20,800	0.73
Lebanon	6,000	0.21	14,800	0.52
Libya	9,800	0.35	14,700	0.52
Mexico	1,900	0.07	0	0.00
Montenegro	500	0.02	500	0.02
Morocco	67,500	2.41	110,000	3.87
Palestine	17,700	0.63	14,900	0.52
Portugal	35,300	1.26	58,400	2.05
Saudi Arabia	0	0.00	3,000	0.11
Slovenia	300	0.01	500	0.02
Spain	1,102,100	39.32	1,215,100	42.74
Syria	132,700	4.73	159,300	5.60
Tunisia	149,500	5.33	167,000	5.87
Turkey	117,700	4.20	149,200	5.25
USA	1,000	0.04	4,300	0.15

trada. Andalucía y Castilla-La Mancha son las Comunidades Autónomas con mayor producción, con Córdoba y, particularmente, Jaén, como las provincias más destacadas. La producción de Jaén representa alrededor del 40% de la producción española y casi la quinta parte de la producción mundial.

Con más de 300 almazaras en Jaén, el sector del aceite de oliva es una actividad económica importante en la región, siendo la principal en las zonas rurales. Con un 55% de sus 664.916 habitantes residiendo en municipios de menos de 20000 habitantes, la importancia del PEAOV en la economía de Jaén es indiscutible [{Instituto Nacional de Estadística}, 2014]. Considerando la media de 2100 € por tonelada, la producción de Jaén equivale

Table D.2: Producción Española de AOV (t).

Region	Avg. Prod. 2001-2007	% 2001-2007	Avg. Prod. 2008-2013	% 2008-2013
Albacete	6,725	0.61	10,281	0.79
Alicante	7,618	0.69	7,891	0.61
Almeria	6,976	0.63	9,464	0.73
Avila	1,003	0.09	1,053	0.08
Badajoz	34,268	3.11	41,134	3.17
Baleares	199	0.02	430	0.03
Barcelona	586	0.05	800	0.06
Caceres	9,283	0.84	7,687	0.59
Cadiz	6,240	0.57	7,632	0.59
Castellon	7,950	0.72	7,837	0.60
Ciudad real	27,807	2.52	44,371	3.42
Cordoba	222,386	20.16	256,342	19.78
Cuenca	5,799	0.53	5,165	0.40
Girona	726	0.07	811	0.06
Granada	83,635	7.58	108,576	8.38
Guadalajara	2,021	0.18	1,943	0.15
Huelva	4,321	0.39	5,503	0.42
Huesca	1,786	0.16	1,840	0.14
Jaen	465,844	42.23	523,818	40.42
La rioja	699	0.06	1,288	0.10
Lleida	5,880	0.53	8,097	0.62
Madrid	3,457	0.31	3,850	0.30
Malaga	56,358	5.11	65,926	5.09
Murcia	6,205	0.56	8,597	0.66
Navarra	2,250	0.20	3,642	0.28
Salamanca	265	0.02	208	0.02
Sevilla	65,704	5.96	85,329	6.58
Tarragona	22,329	2.02	22,104	1.71
Teruel	5,442	0.49	4,270	0.33
Toledo	27,078	2.45	38,175	2.95
Valencia	7,747	0.70	7,125	0.55
Zaragoza	4,526	0.41	4,755	0.37

a un volumen anual de 1100 millones de euros.

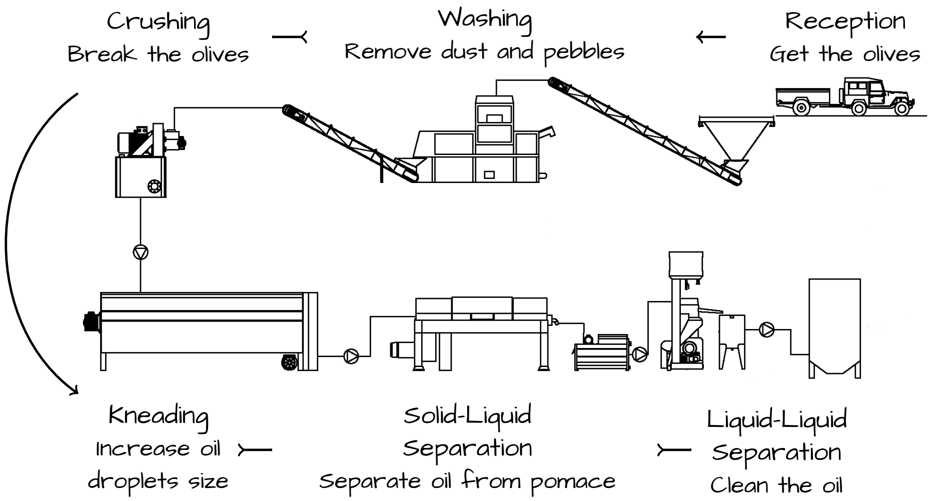

Figure D.3: Diagrama el Proceso de Elaboración de Aceite de Oliva Virgen

D.3 Breve Descripción del Proceso de Elaboración de Aceite de Oliva Virgen

El PEAOV comienza con la recepción de las aceitunas en la almazara. Estas aceitunas son lavadas para eliminar el polvo, pequeñas piedras y hojas que suelen acarrear. Tras esta fase previa, los frutos se almacenan en tolvas y se alimentan a un molino, donde se machacan para formar la pasta de aceituna. La pasta en este estado no permite una adecuada separación del aceite, por lo que se bombea hasta una batidora donde se calienta y remueve para mejorar sus condiciones de cara a la separación. Esta separación se lleva a cabo en el decánter, produciendo *orujo* como subproducto. El contenido de humedad e impurezas del aceite a la salida del decánter es aún excesivamente alto, por lo que una separación adicional se produce bien en centrífugas verticales, bien en tanques decantadores. Tras esta operación, el aceite puede ser filtrado o bombeado directamente a los depósitos de almacenamiento. La Figura D.4 muestra una fotografía de una fábrica, y la Figura D.3 incluye un diagrama de bloques del proceso.

Este proceso de elaboración se puede dividir en tres etapas principales: la preparación de la pasta, la separación del aceite del resto de componentes de la pasta, y la eliminación de humedad e impurezas posterior. La preparación de la pasta comprende el almacenamiento del fruto, la molienda y el batido en la batidora. La separación del aceite incluye la operación del

Figure D.4: Fotografía del cuerpo de fábrica de una almazara.

decánter, con el resto de operaciones constituyendo la fase de retirada de humedad e impurezas.

Las dos principales variables globales de salida del proceso son la calidad del aceite obtenido y el agotamiento. Estas dos variables tienen una cota superior impuesta por las propiedades de las aceitunas que se procesan, y su valor final obtenido depende de las diferentes variables de proceso. La preparación de la pasta determina en gran medida la calidad del aceite obtenido, e impone una cota superior al agotamiento alcanzable. Por su parte, la fase de separación afecta al agotamiento, alcanzando valores inferiores al óptimo si el proceso no se lleva a cabo adecuadamente. El proceso de eliminación de humedad e impurezas tiene una influencia menor en la calidad y agotamiento del aceite elaborado [Civantos, 1998a].

La siguientes secciones detallan algo más cada estadio del proceso y destacan las variables importantes y sus relaciones.

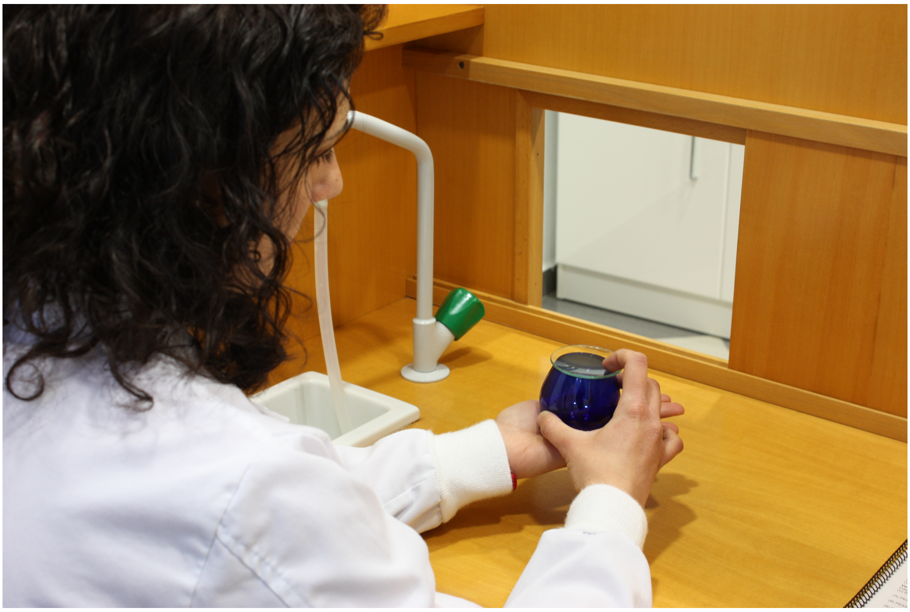

Figure D.5: Catador realizando una evaluación organoléptica de un AOV.

D.3.1 Definición de Calidad del Aceite de Oliva Virgen

El aceite de oliva virgen es el aceite obtenido de las aceitunas empleando únicamente medios mecánicos para su extracción [Vilar, 2013]. Esto es, ningún proceso químico ni de refinado tienen lugar durante su producción. Consecuentemente, el AOV es en realidad zumo de aceituna.

El diccionario Collins define *calidad* como *una característica distintiva, propiedad o atributo* [Dictionaries, 2012]. Existen distintas características relevantes del AOV, y una aclaración es conveniente.

La primera noción de calidad de un AOV es la calidad técnica reglamentada. Los parámetros técnicos clásicos, así como sus valores para cada una de las categorías de calidad de aceite de oliva virgen – aceite de oliva virgen extra, aceite de oliva virgen y aceite de oliva virgen lampante –, se pueden encontrar en el reglamento europeo 2568/91. Los parámetros incluidos aquí se pueden clasificar en dos grupos principales: físico-químicos y organolépticos. Los parámetros físico-químicos se determinan por medios químicos, mientras que la evaluación de las características organolépticas es llevada a cabo por un panel de catadores expertos. La Figura D.5 muestra a un catador realizando la evaluación organoléptica de un AOV.

Los parámetros físico-químicos se pueden clasificar, a su vez, en parámetros de calidad y parámetros de pureza. Los parámetros de calidad están orientados principalmente a la clasificación de los AOV en sus distintas calidades, mientras que el principal objetivo de los parámetros de pureza es evitar el fraude debido a mezclas del relativamente caro AOV con otros aceites vegetales de menor precio. Ejemplos de parámetros de calidad son la acidez, el índice de peróxidos y el K270, mientras que el contenido de ceras y esteroles son parámetros de pureza.

Los parámetros organolépticos se dividen en atributos positivos y negativos, estos últimos también llamados *defectos*. Únicamente existen tres atributos positivos: frutado, amargo y picante. Estos atributos están considerados como positivos porque aparecen de forma natural en aceites elaborados de aceitunas sanas [Civantos, 1998a]. Por su parte, existen muchos más atributos negativos, siendo los más comunes atrojado-borras, moho-humedad y rancio. Los atributos negativos aparecen cuando el fruto no está en perfecto estado o el proceso de elaboración no se ha llevado a cabo con el cuidado necesario. Dependiendo de la anomalía en el fruto o el proceso, aparece un defecto u otro.

Un grupo de características del AOV cuya relevancia en el sector se ha incrementado en los últimos tiempos, son aquellas características relacionadas con las propiedades saludables del AOV. Polifenoles, tocoferoles y otros componentes minoritarios han sido encontrados responsables de muchos de los efectos beneficiosos para la salud provocados por el AOV [Covas et al., 2006], por lo que altas concentraciones de estos componentes son deseables. Sin embargo, estos parámetros no se consideran para la clasificación del AOV en sus diferentes calidades.

Una distinción sutil se puede realizar entre *calidad técnica* y *calidad orientada al consumidor,* ya que características deseables desde un punto de vista técnico pueden no siempre estar alineadas con las preferencias del consumidor [Delgado and Guinard, 2011, Predieri et al., 2013], y características valoradas por el consumidor pueden no ser un criterio técnico. Un ejemplo típico es la reacción media de los consumidores frente a valores elevados de los atributos *amargo* y *picante.* Desde un punto de vista técnico, son considerados atributos positivos, pero investigación sobre el tema [Delgado and Guinard, 2011] y experiencia personal sugieren que los consumidores no siempre los encuentran características atractivas en un AOV. Otro ejemplo es el color: no es un parámetro de calidad regulado, pero los consumidores sí muestran actitudes diferentes dependiendo de él.

Como se deduce de los párrafos anteriores, se puede aludir a varios parámetros al referirse genéricamente a *calidad* del AOV. Para la variedad Picual,

Figure D.6: Aceitunas en distintos estados de madurez.

que es la principal en Andalucía, los factores más limitantes para la calidad son los organolépticos. Consecuentemente, cada vez que se haga una referencia genérica a la *calidad* del AOV, se está refiriendo a los atributos organolépticos, y principalmente al atributo *frutado*. Cuando nos refiramos a algún otro parámetro de calidad, se hará mención expresa a él.

Por último, como nota al pie, se podría mencionar que *Virgen* y *Virgen Extra* no son los únicos tipos de aceite que un consumidor puede encontrar en una tienda. Aceite de oliva, sin más adjetivos, también está disponible en el mercado. El aceite de oliva es una mezcla de AOV o AOV extra con *aceite refinado de oliva*. Este aceite refinado de oliva es AOV lampante que ha pasado por un proceso de refinado que ha eliminado los sabores y olores no deseables del mismo.

D.3.2 Propiedades de las Aceitunas y su Evolución en Campo

Aunque el PEAOV en sí mismo se puede considerar que comienza con la recepción en la almazara de las aceitunas, las características de estas aceitunas ejercen una influencia tan fundamental en el proceso, que es adecuado definir estas propiedades y comentar brevemente su evolución en el campo.

La madurez es la característica que indica el estado de desarrollo del fruto. La evolución de la madurez del fruto comienza cuando éste ha alcanzado su tamaño final, típicamente unas 25 semanas después de la floración. Este estadio es conocido como *estadio verde*, ya que el fruto presenta color verde. Conforme avanza la temporada, los pigmentos de clorofila de la piel son reemplazados por antocianinas [Beltrán et al., 2004], lo que hace visible la evolución de la madurez del fruto a través del cambio en el color de la piel. El fruto pasa secuencialmente por los estados *moteada*, *morada* y finalmente alcanza el estado *negra* [Beltrán et al., 2004]. Aunque algunos otros métodos se han propuesto para la evaluación de la madurez [Mickelbart and James, 2003, Garcia and Yousfi, 2005, Cherubini et al., 2009], el método principalmente usado es el método del índice de color [Hermoso et al., 1997]. La Figura D.6 muestra aceitunas en distintos estados de madurez.

La madurez de la aceituna es un parámetro principal en la determinación de la calidad de las aceitunas y la influencia de este parámetro en diferentes aspectos de la calidad de los aceites obtenidos ha sido estudiado en diferentes trabajos [García et al., 1996b, Gutiérrez et al., 1999, Salvador et al., 2001, Jiménez Herrera et al., 2012].

El nivel de acidez aumenta con la madurez, mientras que el contenido total de polifenoles y pigmentos decrece [García et al., 1996b, Gutiérrez et al., 1999, Salvador et al., 2001, Jiménez Herrera et al., 2012]. Es más, la firmeza de las aceitunas decrece con el avance de la campaña, lo que facilita el daño mecánico y la infección por patógenos de los frutos, y por tanto favorece el decremento del nivel general de calidad de las aceitunas [García et al., 1996b]. Este deterioro de la calidad resulta usualmente en un incremento de la acidez y en la aparición de defectos organolépticos.

Respecto a los parámetros organolépticos, el atributo frutado alcanza su máximo durante las primeras etapas del proceso de maduración, y permanece prácticamente constante hasta un índice de madurez del entorno de 3.5, cuando comienza un declive de los valores observados. Existen variaciones menores entre variedades, pero el comportamiento es básicamente equivalente [Jiménez Herrera et al., 2012]. El amargo y el picante decrecen con el índice de madurez, lo que es coherente con la bien conocida correlación entre estos parámetros y contenido total de polifenoles [Gutiérrez et al., 1999].

Estudios publicados indican que la evolución del contenido en aceite expresada como porcentaje en base seca se mantiene bastante plana una vez que el fruto ha alcanzado un grado de madurez del entorno de 3.5 [García et al., 1996b, Beltrán et al., 2004]. Otros trabajos, sin embargo, muestran un incremento continuo hasta que un nivel mayor se ha alcanzado [Gutiérrez et al., 1999, Salvador et al., 2001]. En cualquier caso, el contenido graso expresado en base húmeda sí aumenta junto a la madurez debido al descenso de humedad que acontece [Beltrán et al., 2004].

Finalmente, cabe destacar que la fuerza de retención de las aceitunas se reduce conforme maduran, por lo que con el avance de la campaña se pueden encontrar mayores cantidades de fruto en el suelo [García et al., 1996a]. Estas aceitunas caídas están expuestas a procesos que degradan su calidad, y sufren un incremento de acidez y la aparición de defectos organolépticos [García and Yousfi, 2007].

D.3.3 Recolección y Recepción

Como principio general, cuanto mayor es el tiempo pasado entre que la aceituna se separa del árbol y es procesada, peor será la calidad esperada del AOV obtenido [García and Yousfi, 2007]. Esta tasa de deterioro se ve incrementada si la piel del fruto se rompe, lo que está favorecido por dos factores:

- Baja firmeza del fruto, debido a un estado de madurez avanzado,
- Transporte y almacenamiento en contenedores de alta capacidad, que suponen elevadas presiones para las aceitunas que están en la base.

Los métodos de recolección se pueden clasificar en dos grupos principales:

- Métodos que separan las aceites provenientes del árbol de las aceitunas del suelo, y
- Métodos que mezclan aceitunas de vuelo y suelo.

Como se ha comentado en la sección anterior, las aceitunas que han caído al suelo presentan pobres características de calidad, debido a las reacciones químicas que comienzan a tener lugar [García and Yousfi, 2007]. Por tanto, métodos que mezclan los distintos tipos de aceitunas provocan una disminución de la calidad potencial que se podría obtener si sólo se recolectara las aceitunas provenientes del árbol. Sin embargo, estos métodos tienden a presentar menores costos, al requerir menor mano de obra [Vilar Hernandez et al., 2010].

Aunque algunos estudios presentan resultados mostrando que diferentes métodos de recolección de aceituna exclusivamente de vuelo, presentan efectos distintos sobre la calidad del AOV obtenido [Yousfi et al., 2012], el efecto debido a la mezcla de aceitunas es mucho mayor.

Una vez que las aceitunas llegan a la fábrica, las hojas son retiradas por medio de corrientes de aire forzadas en las llamadas *limpiadoras*, mientras que la tierra y los guijarros se eliminan empleando agua en las *lavadoras*.

Trabajos publicados indican que dejar algunas hojas para ser procesadas junto a las aceitunas ayuda a conferir un color más verde a los AOV, pero no influye en el contenido total de polifenoles [Di Giovacchino et al., 2002].

Tradicionalmente, debido a las bajas capacidades de molturación en relación a la entrada de aceituna, las aceitunas se han almacenado por largos períodos de tiempo, incluso meses, en grandes montones llamados *trojes*. García, bastante gráficamente, escribe: *'Tradicionalmente, las aceitunas se han tratado desde el momento de su recolección hasta su procesado con la misma sensibilidad que materiales de construcción como arena o grava podrían recibir.'* [García and Yousfi, 2007].

Actualmente, las aceitunas no se almacenan en trojes, sino que se almacenan en tolvas. Adicionalmente, la capacidad de producción de las almazaras modernas hace que sea muy poco frecuente tener que recurrir al almacenamiento de aceituna debido a falta de capacidad de molturación. Aún así, el tiempo que las aceitunas permanecen almacenadas en la tolva es un parámetro importante en el PEAOV.

Durante su almacenamiento, las aceitunas pierden humedad y firmeza, debido a los procesos que tienen lugar. Este efecto es negativo para la calidad del AOV, puesto que se incrementa la acidez, la intensidad de frutado decae y pueden aparecer defectos organolépticos [Vichi et al., 2009, Clodoveo et al., 2007]. Sin embargo, la extractabilidad de las aceitunas mejora con el almacenamiento [Uceda and Hermoso, 1997]. Este comportamiento hace que el tiempo de almacenamiento sea un parámetro interesante a tener en cuenta en el compromiso entre calidad y cantidad.

D.3.4 Molienda

El objetivo de la molienda es romper las células de las aceitunas y liberar el aceite. Existen distintos tipos de molinos usados en la industria, si embargo, el molino de martillos es, con gran diferencia, el más usado actualmente en España.

Los principales parámetros que determinan el comportamiento de la molienda para este tipo de molinos son la geometría y el tamaño de la criba, y la velocidad de rotación del molino.

Trabajos publicados han reportado que variaciones en la velocidad de rotación no afectan a la acidez, índice de peróxidos, K y composición en ácidos grasos. Sin embargo, tamaños de criba más pequeños y mayores velocidades de rotación tienden a acentuar el incremento de temperatura experimentado por la pasta y a incrementar el contenido total de polifenoles [Di Giovacchino et al., 2002, Inarejos-García et al., 2011]. En línea con la buena correlación entre contenido en polifenoles e intensidad del atributo *amargo*, este parámetro organoléptico también aumenta en estas condiciones. La parte negativa es el descenso en componentes volátiles que experimenta el aceite.

El tamaño de la criba y la firmeza del fruto determinan el tamaño medio de las partículas que constituyen la pasta de aceituna, junto con el grado de ruptura de las células. Este parámetro ejerce una influencia directa en el rendimiento industrial obtenido, y es importante seleccionarlo bien. Tamaños de criba más pequeños y aceitunas con menor nivel de firmeza tienden a producir un mayor grado de ruptura de celdas, contribuyendo a obtener un mejor agotamiento. Sin embargo, tamaños de criba menores requieren un mayor consumo de energía por parte del proceso, y contribuyen a la formación de emulsiones si el contenido de humedad en las aceitunas es elevado.

La humedad de las aceitunas es importante en la fase de molienda. Niveles muy bajos de humedad pueden provocar un descenso en la capacidad de molturación del molino, e incluso provocar su bloqueo. Niveles elevados de humedad provocan la formación de emulsiones [Civantos, 1998a], lo que se su vez redunda en un marcado descenso del agotamiento si no son contrarrestadas durante la fase de preparación de la pasta.

D.3.5 Batido

El objetivo del batido es aumentar el tamaño de las gotas de aceite y romper las emulsiones que pueden haber sido provocadas en la molienda, con el objetivo de facilitar la separación del aceite del resto de componentes de la pasta.

Esta operación es clave tanto para el agotamiento como para la calidad del AOV. Los bioprocesos que tienen lugar en este estadio del PEAOV influyen decisivamente en la calidad final del aceite. Dos efectos principales influyen en esta operación: el efecto de partición de componentes entre agua y aceite, y la actividad catalítica de las enzimas liberadas en la molienda [Clodoveo, 2012].

Las principales variables tecnológicas en el proceso de batido son la temperatura de batido, la duración del proceso y la adición de coadyuvantes.

El rango habitual de temperaturas de batido en el PEAOV está entre los 25 y los 40 °C. Temperaturas más altas tienden a incrementar el agotamiento obtenido, mientras que disminuyen el contenido de volátiles [Inarejos-García et al., 2009]. Existen resultados contradictorios sobre el signo de la influencia de la temperatura en el contenido total en polifenoles y los atributos amargo y picante [Clodoveo, 2012]. Para algunas variedades, acidez, peróxidos y K se incrementan cuando la temperatura sube de 30 a 35 °Cs [Ranalli et al., 2001], sin embargo, para otras variedades la influencia de la temperatura en el resto de características de calidad se han encontrado despreciables, salvo por la tendencia de las mayores temperaturas de incrementar los valores de las variables relacionadas con la pureza [Clodoveo, 2012].

Los tiempos de batido típicos abarcan de los 45 a los 120 minutos. Valores altos tienden a incrementar el rendimiento industrial, mostrando efectos de saturación en torno a los 75 minutos, o incluso un ligero decremento en el agotamiento [Ranalli et al., 2003]. Según algunos trabajos, valores altos también tienden a incrementar el contenido de volátiles, tanto para atributos positivos como negativos, y a reducir el contenido en polifenoles [Inarejos-García et al., 2009, Ranalli et al., 2003]. Sin embargo, otros trabajos reportan que el tiempo de batido no altera significativamente las características organolépticas del aceite [Di Giovacchino et al., 2002].

La adición de microtalco como coadyuvante es útil en la ruptura de emulsiones, mientras que no afecta a la calidad del AOV [Cert et al., 1996]. La dosis de adición depende del nivel de emulsiones de la pasta y del tamaño de partícula del producto, con valores nominales alrededor del 0.5% para talcos con tamaños de partícula menores, y 1% para los de mayor granulometría. El uso de carbonato de calcio como coadyuvante también ha sido investigado y se han mostrado buenos resultados en su utilización [Moya et al., 2010], sin embargo, actualmente su uso no está aprobado por la normativa europea, puesto que aún está en discusión si existe o no actividad química de esta substancia con el AOV.

Cuando la humedad de la pasta es baja, es habitual añadir pequeñas cantidades de agua para compensarla, puesto que el batido de pastas muy secas es menos efectivo que aquellas que presentan un nivel de humedad óptimo. Además, la resistencia opuesta por la pasta es también mayor cuando la humedad es baja, lo que resulta en mayores consumos de energía de la planta.

Finalmente, existen publicaciones que muestran que la atmósfera en contacto con la pasta también tiene influencia en la calidad final de aceite producido. El uso de nitrógeno incrementa la concentración de componentes fenólicos y produce una mejora de las características organolépticas del aceite [Clodoveo, 2012]. Sin embargo, esta línea de investigación es relativamente reciente, y algún tiempo debe pasar antes de que sea un parámetro habitualmente considerado en el sector.

D.3.6 Separación

La separación sólido-líquido que tiene lugar en el decánter es muy importante en el agotamiento obtenido, pero no tiene un papel fundamental en la calidad del AOV obtenido [Civantos, 1998a].

Distintos factores influyen en la eficacia del proceso de separación, siendo el *estado de batido* de la pasta uno de los más importantes. El estado de batido se refiere a la forma en que la pasta ha sido preparada en la batidora. Tiene en cuenta aspectos tales como un buena distribución del tamaño de gotas, la no existencia de emulsiones y un contenido de humedad adecuado.

Si aún existen emulsiones después del batido, no hay mucho margen para contrarrestar la contribución negativa al agotamiento, más allá de reducir ligeramente el caudal de entrada de pasta al decánter [Civantos, 1998a].

El caudal de entrada al decánter es un parámetro que influye en la operación del decánter, puesto que determina el tiempo de residencia de la pasta dentro de la máquina, y por tanto, el tiempo disponible para que el aceite se separe del orujo.

La velocidad teórica de sedimentación de una esfera en un fluido en el que únicamente actúan fuerzas centrífugas, suponiendo una esfera de diámetro suficientemente pequeño y flujo está dada por la Ley de Stokes:

$$v_c = \frac{D^2 \omega^2 r(\rho_2 - \rho_1)}{18\mu}, \tag{D.1}$$

donde:

- D: Diámetro de la esfera.

- ω: Velocidad de rotación.
- r: Distancia de la esfera al eje de rotación.
- ρ_1 and ρ_2: Densidades del líquido y de la esfera.
- μ: viscosidad del líquido.

Esta fórmula incluye la mayoría de los parámetros que influyen en la operación:

- Viscosidad: valores más bajos de viscosidad tanto del agua como del aceite permiten mayores velocidades de sedimentación dentro del decánter, y por tanto favorecen teóricamente la obtención de mejores agotamiento para un tiempo de sedimentación dado.
- Tamaño de gota: gotas de mayor tamaño permiten obtener mayores velocidades de sedimentación, favoreciendo el agotamiento.
- Velocidad de rotación: la velocidad de rotación incrementa la fuerza ejercida sobre las gotas, incrementando por tanto la velocidad de sedimentación y el agotamiento.

Un parámetro muy importante es el proceso de separación es la posición relativa de la interfase teórica entre agua y aceite y la posición de las presillas de salida de aceite. Este parámetro influye tanto en el agotamiento como en la limpieza del aceite. La posición de la interfase está determinada por la composición de la pasta, el ritmo de producción y la velocidad diferencial tornillo-bol [Leung, 1998].

Tener una interfase sustancialmente más alejada del eje de rotación de la máquina que las presillas supone tener un aceite limpio, pero menores agotamientos. Una posición de la interfase teórica más cercana al eje de rotación supone obtener un aceite con mayor cantidad de humedad, pero alcanzar mejores agotamientos. La posición óptima teórica de la interfase es la coincidente con las presillas.

El proceso de separación líquido-líquido se puede llevar a cabo en una centrífuga vertical o en depósitos de sedimentación. Los parámetros que influyen en la operación de la centrífuga vertical son la temperatura de agua de adición, que debe ser ligeramente mayor que la del aceite para no dañarlo y evitar pérdidas. La frecuencia de descarga de los sólidos es también un parámetro importante para la operación de la máquina, para evitar dañar la calidad del aceite por no eliminar de forma eficiente las impurezas.

Los principales parámetros de proceso para la separación en tanques de decantación son el tiempo de residencia y la frecuencia de purgado. Ambos parámetros se deben ajustar para permitir una eliminación suficiente de las impurezas, al tiempo que se asegure que la calidad del aceite no se deteriora por el tiempo en contacto con la humedad y las impurezas.

D.4 Motivación de la Tesis

Como se ha destacado en la sección anterior, el PEAOV es un proceso industrial complejo, con diferentes variables involucradas y objetivos de producción contrapuestos [Civantos, 1998a]. La calidad del AOV elaborado depende de las características del fruto de entrada y de las distintas variables de proceso. Usualmente, los valores de las variables de proceso que favorecen la calidad tienden a penalizar la cantidad de aceite obtenido. Adicionalmente, conforme avanza la campaña de recolección, la máxima calidad potencial del aceite decrece, por lo que la relevancia de las restricciones impuestas por el objetivo de obtener alta calidad también disminuye.

Teniendo esto en cuenta, la primera cuestión relevante que afrontar al elaborar AOV es, por tanto, establecer un buen objetivo de elaboración basado en las características de las aceitunas de entrada. Dos problemas se desprenden de éste: determinar qué objetivos se pueden alcanzar dado el lote de aceitunas a procesar, y cuáles de ellos son considerados *buenos*.

Una vez que se ha definido el objetivo de elaboración, el siguiente paso es definir cómo obtenerlo. Más concretamente, es necesario determinar los valores de referencia de las variables tecnológicas que permiten alcanzar dicho objetivo de elaboración. Este problema, de nuevo, se puede descomponer entre hallar todos los valores que permiten alcanzar el objetivo, y cuáles de ellos son considerados *buenos*.

En este punto, ya se habría definido qué se pretende elaborar, e incluso cuáles son los valores de las variables tecnológicas que permitirían alcanzar este objetivo. Sin embargo, frecuentemente, los valores de las variables de salida no serán exactamente los deseados, debido al efecto de pequeños errores de modelado y las perturbaciones que actúan sobre el proceso. Aquí, la aplicación de realimentación es la clave para modificar los valores de las variables de proceso de manera que las salidas eventualmente alcancen los objetivos deseados.

Dado un lote de aceitunas en el patio de recepción de la almazara, sabríamos qué producir, cómo hacerlo y cómo modificar los valores de las variables para asegurar que efectivamente alcanzamos el objetivo. Pero aún hay un consideración adicional sobre el PEAOV: una vez que el lote de aceitunas llega a la almazara, ya se ha fijado una cota superior a la calidad del AOV por la decisión de cuándo se ha recolectado estas aceitunas [Gutiérrez et al., 1999, Jimenez Herrera et al., 2012]. Puesto que la calidad de las aceitunas evoluciona a lo largo de la campaña, una cuestión relevante es considerar cuándo recolectar las aceitunas para maximizar el beneficio de toda la campaña.

Actualmente, la decisión de cuándo recolectar la toman los dueños de los olivares, estando limitada la influencia de los dueños de las almazaras al precio pagado por las diferentes calidades de aceitunas.

Las decisiones que hay que tomar en la almazara son habitualmente tomadas por el maestro, como se conoce al jefe de producción de la almazara, basándose en su experiencia.

El objetivo de elaboración se establece atendiendo al aspecto de las aceitunas, la relación entre capacidad de molturación y entrada de aceitunas, y quizás alguna directiva por parte de la dirección de la entidad, especialmente durante el inicio de la campaña.

La selección de los valores de referencia de las variables de proceso, junto con sus modificaciones en caso de no coincidir los valores deseados de las variables de salida con los obtenidos, es realizada enteramente por el maestro de almazara basándose en su experiencia.

En todos los casos, el proceso actual de toma de decisiones es principalmente manual y basado en la experiencia de uno o varios operarios expertos.

El problema al que esta tesis contribuye es al desarrollo de un **sistema de apoyo a la decisión** para asistir al operador de la almazara en cada una de las decisiones que hay que tomar en el PEAOV:

1. ¿Qué objetivo de elaboración se debe fijar, dadas las características de las aceitunas de entrada?
2. ¿Qué valores de referencia de las variables de proceso permiten alcanzar este objetivo?

3. ¿Cómo se deben modificar estos valores de referencia para rechazar las perturbaciones y asegurar que se alcanza el objetivo propuesto?
4. ¿Cuándo se deben recolectar las aceitunas para maximizar el beneficio de la campaña?

Aunque la última cuestión no concierne directamente al operador de la almazara, es una cuestión relevante en el conjunto del PEAOV, y la aproximación al problema no sería completa sin incluirla.

Como casi cualquier proceso industrial, en el PEAOV se puede distinguir dos niveles de relaciones:

- Alto nivel: concierne a las relaciones existentes entre las propiedades del AOV obtenido y los valores de referencia de las variables tecnológicas.
- Bajo nivel: trata las dinámicas que relacionan los valores de referencia con los valores reales de las variables de proceso.

Como ejemplo se puede considerar la temperatura en batidora y el nivel de frutado del AOV obtenido. Que la temperatura de batido tenga un valor determinado no es un objetivo global del PEAOV, pero es necesario para obtener el valor de frutado objetivo. Además, la temperatura no es una variable directamente manipulable, sino que requiere seleccionar valores de apertura de válvulas y temperatura de agua de calefacción adecuada que permitan obtener los valores deseados. Aquí, el sistema de bajo nivel es el que relaciona la apertura de la válvula y la temperatura del agua de calefacción con la temperatura de la pasta, mientras que la relación entre esta temperatura de la pasta y el nivel de frutado constituye la capa de alto nivel.

La Figura D.7 muestra un diagrama de bloques conceptual para el control global del PEAOV. En este esquema, el control de bajo nivel se puede afrontar empleando técnicas estándar o relativamente sofisticadas de control realimentado, y aunque hay ciertamente espacio para la mejora, este problema se puede considerar como esencialmente resuelto.

Sin embargo, asegurar que una variable de proceso alcanza su nivel definido a pesar de la existencia de perturbaciones no responde a las cuestiones planteadas. Las relaciones de la capa de alto nivel son obviamente determinantes para tratar el problema globalmente, y por tanto se deben considerar e incluir en el sistema.

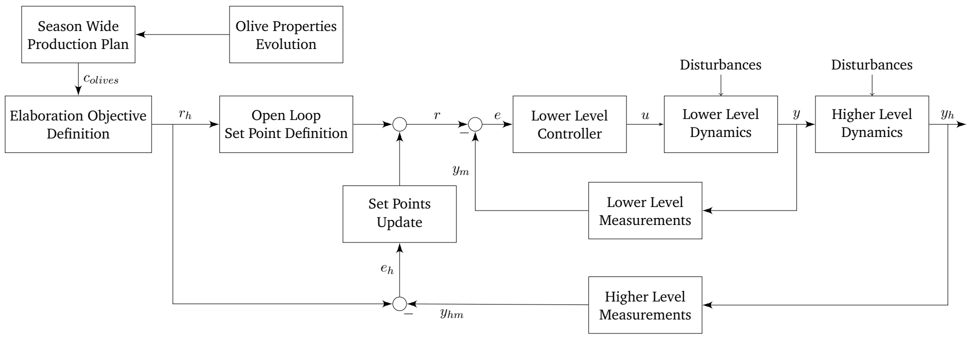

Figure D.7: Diagrama de bloques del enfoque propuesto al control global del PEAOV.

Una dificultad importante es que, actualmente, no existen sensores fiables capaces de proporcionar medidas en línea precisas para las variables de interés del PEAOV. Este hecho, aparte de resaltar la necesidad de desarrollar este tipo de sensores, hace inviable la utilización de técnicas de identificación de sistemas y de control tradicionales en la capa superior del PEAOV. Sin embargo, existen sensores a pie de línea y operadores expertos pueden proporcionar información sobre las salidas basándose en una inspección visual de algunos puntos del proceso y probando el aceite elaborado. Por tanto, alguna información sobre el proceso está disponible, pero con tiempos de muestreo muy limitados.

En estas circunstancias, la utilización de lógica borrosa y conocimiento experto aparecen como un candidato natural para construir los modelos de la capa superior del PEAOV. En particular, la técnica empleada son los Mapas Cognitivos Borrosos [Kosko, 1986].

Después, basándose en estos modelos, se plantean y resuelven distintos problemas de optimización para determinar el objetivo de elaboración óptimo para un lote de aceitunas, y los valores de referencia óptimos que permiten alcanzar este objetivo.

Como se ha comentado anteriormente, la aplicación de técnicas de control estándar a la capa superior del PEAOV es difícil debido a la no disponibilidad de sensores en línea adecuados. Sin embargo, la existencia de equipamiento a pie de línea y las estimaciones proporcionadas por expertos permiten tener información sobre el comportamiento del sistema que puede ser utilizada para realimentar el proceso. Aunque el PEAOV no es completamente un proceso por lotes, el control run-to-run se propone como candidato para este fin.

Finalmente, el enfoque empleado para el plan de producción anual es la definición de un problema de optimización donde el modelo del PEAOV se amplía con modelos simples de evolución de las propiedades de las aceitunas en el olivar, y algunas características empresariales de la entidad llevando a cabo la actividad.

D.5 Esquema de la Tesis

Esta Tesis está organizada de la siguiente forma: el Capítulo 2 presenta el estado del arte de la aplicación del control automático al PEAOV, junto con los resultados de una encuesta realizada para obtener una imagen de la tasa de adopción de las diferentes técnicas de automatización y control en la industria oleícola española.

El Capítulo 3 trata del modelado del PEAOV. Primero, se trata la estructura de modelo seleccionada, junto con las elecciones específicas y detalles relacionadas con la construcción de los modelos. Posteriormente, se incluyen los modelos obtenidos junto con gráficas y comentarios de las salidas obtenidas.

El Capítulo 4 se centra en la formulación y solución de los problemas de optimización para determinar el objetivo de elaboración óptimo y los valores de referencia de las variables de proceso óptimas que permiten alcanzar estos objetivos. Los diferentes problemas considerados son presentados y se incluyen y comentan las soluciones particulares a diferentes escenarios de elaboración.

El Capítulo 5 trata la aplicación del control run-to-run para incluir realimentación a la capa de alto nivel del PEAOV, y se presenta la aplicación de esta propuesta a distintos escenarios de elaboración.

El Capítulo 6 versa sobre la planificación anual de la producción del PEAOV. Se presentan los modelos adicionales requeridos, junto con las consideraciones desde el punto de vista empresarial relevantes. A continuación, se formula el problema de optimización y se presentan distintos escenarios.

Finalmente, el Capítulo 7 introduce las conclusiones de esta Tesis, resume las contribuciones y las líneas futuras de trabajo.

E

Resumen

El proceso de elaboración de aceite de oliva virgen (PEAOV) es un proceso industrial complejo, con distintas variables implicadas y objetivos de producción contrapuestos. La calidad del aceite elaborado depende de las características de las aceitunas de entrada y de los valores de las diferentes variables de proceso. Usualmente, los valores de las variables de proceso que favorecen la calidad del AOV penalizan la cantidad de aceite producido. Adicionalmente, conforme avanza la campaña de recolección, la máxima calidad potencial del aceite decrece, con lo que la relevancia que estas restricciones impuestas por el objetivo de obtener alta calidad también decrecen.

Teniendo esto en cuenta, la primera cuestión relevante que se ha de afrontar al elaborar AOV es, por tanto, establecer un objetivo de elaboración adecuado, basado en las condiciones de las aceitunas de entrada. Una vez que este objetivo está fijado, el siguiente paso es definir cómo alcanzarlo. Concretamente, se deben establecer los valores de las variables de proceso que permiten obtener dicho objetivo. Sin embargo, con frecuencia, los valores de las variables de salida no coincidirán exactamente con los fijados como objetivo, debido al efecto de pequeños errores de modelado y perturbaciones que afecten al proceso. Aquí, la aplicación de realimentación es la clave para modificar los valores de las variables de proceso de forma que las salidas alcancen los valores deseados.

El problema al que esta tesis contribuye es a desarrollar un sistema de

apoyo a la decisión para asistir al operador de la almazara en cada una de las decisiones a tomar en el PEAOV:

1. ¿Qué objetivo de elaboración se debe fijar, dadas las características de las aceitunas de entrada?

2. ¿Qué valores de referencia de las variables de proceso permiten alcanzar este objetivo?

3. ¿Cómo se deben modificar estos valores de referencia para rechazar las perturbaciones y asegurar que se alcanza el objetivo propuesto?

4. ¿Cuándo se deben recolectar las aceitunas para maximizar el beneficio de la campaña?

En esta tesis se utilizan lógica borrosa y conocimiento experto para modelar el PEAOV desde un punto de vista global. Posteriormente, basados en estos modelos, se plantean distintos problemas de optimización para determinar el objetivo óptimo de elaboración para un lote de aceitunas dado, y los valores de referencia de las variables de proceso que permiten alcanzar este objetivo.

La aplicación de técnicas de control automático al nivel superior del PEAOV es difícil debido a la no disponibilidad de sensores en línea fiables. Sin embargo, la existencia de equipos a pie de línea y las estimaciones proporcionadas por operadores expertos permiten disponer de alguna información del comportamiento del proceso que podría ser utilizada para la aplicación de algún tipo de realimentación. Aunque el PEAOV no es completamente un proceso por lotes, la propuesta para realizar esta realimentación es el control run-to-run.

Finalmente, la planificación anual de la producción se trata por medio de la definición de un problema de optimización donde el modelo del PEAOV se amplía con modelos simples de la evolución de las propiedades de la aceituna en las plantaciones y algunas características empresariales de las organizaciones que llevan a cabo la actividad.

A continuación se incluye un resumen de cada uno de los temas tratados en esta Tesis.

E.1 Modelado

El modelado global del PEAOV es un problema complejo debido principalmente a tres factores:

- El número de variables implicadas en el sistema no es pequeño, existen interacciones entre ellas, y la misma variable puede influir sobre el mismo objetivo a través de distintos efectos.
- La falta de sensores en línea capaces de medir de forma fiable las variables de salida relevantes del proceso de elaboración.
- El limitado período de disponibilidad de aceitunas durante el año, siendo incluso más limitada la disponibilidad de aceitunas con características específicas.

La técnica empleada para la construcción del modelo del PEAOV es una modificación de los sDCM. De forma análoga a esta técnica, el modelo se compone de una colección de nodos y arcos que representan las relaciones entre los nodos.

Para cada nodo v_i del sistema se definen las siguientes propiedades:

- U_{v_i}: universo del discurso del nodo, definido como el conjunto de todos los valores nítidos que puede tomar v_i. Los nodos tienen valores reales, por lo que $U_{v_i} \subseteq \mathbb{R}$.
- H_{v_i}: el conjunto de términos (conjuntos borrosos) $L^j_{v_i}$ definidos en U_{v_i}, junto con las funciones de pertenencia a cada término:

$$L^j_{v_i} = \{\langle x, \mu_{L^j_{v_i}}(x)\rangle \; : \; x \in U_{v_i}\}, \tag{E.1}$$

$$H_{v_i} = \{L^j_{v_i}, \; j = 1, 2, \cdots, n_{v_i}\}. \tag{E.2}$$

- $S_f(v_i)$: el estado del nodo, definido como un vector que contiene el grado de pertenencia de v_i a cada conjunto borroso L_{v_i} definido en H_{v_i}:

$$S_f(v_i) = [\mu_{L^1_{v_i}}, \cdots, \mu_{L^{n_{v_i}}_{v_i}}]^T. \tag{E.3}$$

- $S_c(v_i)$: el valor nítido del estado del nodo, calculado empleando una función de defuzzificación sobre S_f, de acuerdo con la definición de los elementos en H_{v_i}.

Por su parte, para cada arco a_{ij} se definen las siguientes propiedades:

- R_{ij}: matriz de relación causal. Se define como la matriz que transforma el grado de pertenencia a cada el grado de pertenencia a cada etiqueta del antecesor en contribuciones al grado de pertenencia del sucesor a sus etiquetas correspondientes. El tamaño de la matriz es $n_i \times n_j$, con n_i y n_j siendo el número de etiquetas en H_{v_i} y H_{v_j} respectivamente. Los elementos de estas matrices deben ser no negativos.

- ω_{ij}: valor absoluto de la intensidad de la relación entre los nodos conectados por el arco.

La definición del parámetro ω_{ij} no es estrictamente necesaria, pero clarifica la importancia relativa de cada antecesor.

La utilización de las matrices de relación permiten mayor flexibilidad en la definición de las relaciones entre nodos que la encontrada en sDCMs. Estas matrices matrices permiten introducir relaciones asimétricas entre los nodos [Koulouriotis et al., 2005].

El modelado del proceso se ha llevado a cabo estudiando de forma independiente las fases de preparación de la pasta y separación en decánter, desarrollando un modelo distinto para cada una de ellas, haciendo uso de la modularidad de la técnica de modelado empleada.

E.2 Definición de Objetivo Óptimo de Elaboración y los Valores de Referencia de las Variables de Proceso

Las variables del PEAOV se pueden clasificar atendiendo a su rol en el proceso como:

- Propiedades del fruto de entrada: este grupo incluye a aquellas variables que caracterizan a las aceitunas y cuyo valor ya está fijado cuando llegan a la almazara.

- Parámetros tecnológicos: todas las variables cuyo valor es susceptible de ser asignado por el operador de la fábrica.

- Parámetros auxiliares: aquellas variables cuyo valor depende de otras variables aguas arriba del proceso y, por tanto, su valor no puede ser elegido arbitrariamente, pero no representan una variable de salida del proceso.

- Variables de salida: las variables de interés del proceso que normalmente se incluyen en los objetivos de elaboración.

Por otra parte, las variables del PEAOV se pueden clasificar, de acuerdo con su rol en los problemas de optimización que se van plantear, en:

- Parámetros (p): estas variables del PEAOV se considera que tienen valor fijo en el problema de optimización. Normalmente incluirán las propiedades de las aceitunas de entrada junto con aquellas variables tecnológicas del proceso cuyo valor esté justificado que se considere como fijo.

- Variables de decisión (x): estas son las variables del PEAOV cuyo valore debe ser fijado por el problema de optimización.

- Variables objetivo (y): aquellas variables del PEAOV cuyo valor se considere una salida del proceso y estén incluidas en el vector de objetivos.

Los problemas planteados para contestar las preguntas planteadas tienen la estructura general:

$$\begin{aligned} \text{"min"} \quad & F(\mathrm{x} \mid \mathrm{p}) \\ \text{s.t.} \quad & \mathrm{y} = f(\mathrm{x},\ \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \end{aligned}$$

donde el significado de "min" se debe definir en cada problema estudiado en particular.

El carácter multiobjetivo del PEAOV se puede formalizar matemáticamente con la definición de un vector que incluya como elementos cada uno de estos objetivos. La existencia de objetivos contrapuestos hace que, en general, no exista un único conjunto de valores de variables de proceso que optimice a la vez todos los elementos de este vector objetivo, sino que existan un conjunto de puntos no dominados pertenecientes a la frontera de Pareto. Estos puntos en la frontera de Pareto representan situaciones en las que una mejora en uno de los elementos del vector objetivo supone empeorar al menos otro de los elementos del vector.

Para hallar estos puntos de la frontera de Pareto, se ha empleado el método de escalarización por suma ponderada, que requiere hallar la solución al siguiente problema:

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & J = \sum_{k=1}^{c} \omega_k f_k(\mathrm{y}, \mathrm{x}) \\ \text{subject to} \quad & \mathrm{y} = f(\mathrm{x}, \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \end{aligned}$$

para distintas combinaciones de valores de los pesos ω_k.

Una vez que se han hallado los objetivos de elaboración óptimos, la siguiente cuestión es hallar los valores de referencia de las variables de proceso que permiten alcanzarlos. Debido al planteamiento del problema anterior, la respuesta a esta cuestión se corresponde con los valores de las variables de decisión. Ahora bien, puesto que pueden existir más de un conjunto de valores de las variables de proceso que permitan alcanzar un objetivo concreto, es conveniente modificar el problema para incluir un criterio que permita seleccionar el conjunto más adecuado.

De esta forma, se plantea un segundo problema de optimización:

$$\begin{aligned} \underset{\mathrm{x}}{\text{minimize}} \quad & J = H f_1(\mathrm{y}, \mathrm{x} \mid \mathrm{p}) + f_2(\mathrm{y}, \mathrm{x} \mid \mathrm{p}) \\ \text{subject to} \quad & \mathrm{y} = f(\mathrm{x}, \mathrm{p}) \\ & \mathrm{p} = \mathrm{p}^0 \\ & \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \end{aligned}$$

con H representando una constante tal que $H >> 1$, y $f_2(\mathrm{y}, \mathrm{x} \mid \mathrm{p})$ representando la función que implementa el costo de las variables de proceso. Los valores de las variables de decisión de la solución de este problema proporcionan los valores de referencia de las variables de proceso óptimas para el objetivo de elaboración asociado.

Para seleccionar un único objetivo de elaboración perteneciente a esta frontera de Pareto es necesario establecer un criterio. Suponiendo que el criterio elegido es maximizar el beneficio económico, la función objetivo asociada sería:

$$J = X\ p(q(F, D)) - \sum_j c_j x_j, \tag{E.4}$$

donde $p(\cdot)$ denota la función que transforma la calidad comercial del AOV a su precio de mercado, y c_j se corresponde con el costo unitario de la variable de proceso x_j, siendo j el índice que recorre todas las variables de proceso relevantes. La solución de este problema de optimización proporciona tanto el objetivo óptimo de elaboración como el valor de las variables de proceso que permiten alcanzarlo para el criterio de optimización fijado.

E.3 Actualización de los Valores de Referencia de las Variables de Proceso

La estructura general de un controlador run-to-run se basa en un modelo del sistema, un observador y un método para calcular la acción de control en base a este modelo y observador. Con anterioridad ya se han propuesto modelos del PEAOV y un método para calcular los valores de las variables de proceso para alcanzar los objetivos propuestos. La propuesta para realizar el control run-to-run es aumentar este sistema con un observador del error o perturbaciones que actúan sobre el sistema, y continuar empleando el enfoque de optimización para calcular la acción de control, dado el carácter MIMO del sistema.

El principal punto débil de esta propuesta es que no se dispone de resultados que garanticen la convergencia del controlador, pero dado que la aplicación del sistema es un sistema de apoyo a la decisión, y existe una supervisión por parte del operador de la planta de los resultados suministrados por el sistema, desde un punto de vista práctico no es imprescindible disponer de este resultado.

Empleando una función objetivo cuadrática, el controlador propuesto es:

$$
\begin{aligned}
\underset{\mathrm{x}_k}{\text{minimize}} \quad & J = (\hat{\mathrm{y}}_k - T)^T \, Q \, (\hat{\mathrm{y}}_k - T)^T + \mathrm{x}_k^T \, R \, \mathrm{x}_k \\
\text{subject to} \quad & \hat{\mathrm{y}}_k = f(\mathrm{x}_k, \mathrm{p}) + \hat{\nu}_k \\
& \mathrm{p} = \mathrm{p}^0 \\
& \mathrm{x}_{min} \leq \mathrm{x} \leq \mathrm{x}_{max} \\
& \hat{\nu}_k = \omega \, \hat{\nu}_{k-1} + (1-\omega) \, (\mathrm{y}_{k-1} - f(\mathrm{x}_{k-1}, \mathrm{p}^0)),
\end{aligned}
$$

donde Q, R y ω son los parámetros de sintonización.

Los primeros dos parámetros determinan el peso relativo de los errores de cada una de las variables de salida y de la acción de control, mientras que ω determina la forma en que el observador estima la perturbación que afecta al sistema, y por tanto influye en la convergencia del controlador.

El rango de valores de ω esperado que permita la convergencia del método es el intervalo $[0, 1]$. Emplear un valor de 1 en todas las iteraciones supone no aplicar ninguna realimentación al proceso, mientras que un valor de 0 es equivalente a considerar como valor de perturbación el valor observado en la última iteración.

La utilización de valores en el rango superior del intervalo permite alcanzar tasas de convergencia más elevadas, pero produce mayores variaciones de la acción de control ante la existencia de ruido. Por su parte, valores en el rango inferior del intervalo presentan una disminución del error más lenta.

Los resultados de simulación obtenidos muestran el buen funcionamiento del método y su robustez frente a perturbaciones.

E.4 Planificación Anual de la Producción

El objetivo de esta sección es la propuesta de un método que permita definir la cantidad y calidad de AOV que hay que producir a lo largo de la campaña para maximizar el beneficio total, teniendo en cuenta la evolución de las propiedades de las aceitunas y condiciones de mercado.

De manera formal, lo que se busca es un plan de producción definido como una secuencia temporal de vectores s p_i:

$$P = [p_1\, p_2\, \cdots\, p_i]$$

donde $p_i = [n_i\; q_i]^T$ y

- n_i representa la cantidad de aceite que se ha de producir y
- q_i denota el objetivo de calidad;

como la solución de un problema de optimización donde el objetivo es maximizar el beneficio económico de la compañía.

Para el planteamiento del problema se ha recurrido a la definición de *productos*, de forma que el problema se transforma en un problema de selección de qué producto producir en cada instante de tiempo. Las características que definen un producto son:

- Calidad requerida (q_k^{min})

- Método de comercialización (m_k)

De esta forma, el problema de optimización propuesto se expresa como:

$$
\begin{aligned}
\textbf{max} \quad & J = \sum_{i=1}^{f}\sum_{k=1}^{k_f} n_{i,k}\,(s_k - c_k^d) - a_{i,k}\,(c_k^p + c_k^h) \\
\textbf{sujeto a:} \quad & n_i = a_i(1-\frac{H_{oi}}{100})(\frac{F_i^D - E_i}{100})(1-\frac{E_i}{100})^{-1} \\
& n_{i,k} \leq \begin{cases} 0 \;\; \text{if} \;\; q_{i,k} \leq q_k^{min} \\ \overline{n}_{i,k} \;\; \text{otherwise,} \end{cases} \\
& pv_{k,i} \in \{pv \mid q(pv, q_i^{max}) \geq q_{i,k}^{min}\} \\
& h_{k,i} \in \{h \mid q_h(h, q_i^{max}) \geq q_{i,k}^{min}\} \\
& \sum_{i}^{f} n_{i,k} \leq \bar{n}_k \\
& c_k^d = c^d(\bar{n}_k) \\
& q_{h,i} = f(r_{c,i}, q_{c,i}, q_i^{max}, h) \\
& c^h = c^h(R_f) \\
& c^p = c_{A_c} + c_{T_b} \\
& \sum_{i=1}^{f}\sum_{k=1}^{k_f} a_{i,k} \leq \bar{a} \\
& \sum_{k=1}^{k_f} a_{i,k} \leq \bar{a}_i \\
& a_{i,k} \geq 0
\end{aligned}
$$

donde las restricciones incluyen consideraciones sobre la evolución de las propiedades del fruto en el campo, la influencia del método de recolección y su costo asociado, la influencia de las variables de proceso y límites tanto en la disponibilidad del fruto, como de capacidad de proceso y de venta.

F

Conclusiones y Contribuciones

Este capítulo presenta la conclusiones de esta tesis, enumera las contribuciones realizadas en el marco de su desarrollo, y plantea las líneas futuras de trabajo.

F.1 Conclusiones

El proceso de elaboración de aceite de oliva (PEAOV) es un proceso industrial complejo cuyo objetivo es la extracción del aceite contenido en las aceitunas empleando exclusivamente medios mecánicos, lo que permite al AOV ser considerado *zumo de aceituna*. Las características de este zumo natural depende tanto de las propiedades de la aceituna de entrada como de los valores de las diferentes variables tecnológicas del proceso. Las propiedades de las aceitunas establecen una cota superior sobre la calidad de AOV que se puede obtener, y también influencian qué valores de las variables de proceso se deben emplear para conseguir rendimientos industriales aceptables. Es más, la preservación de la calidad del aceite elaborado y la obtención de un rendimiento industrial elevado son objetivos contrapuestos, y mejoras en uno de ellos se traducen, usualmente, en decrementos del otro.

En el PEAOV se pueden distinguir dos niveles de relaciones entre las variables:

- Alto nivel: concierne a las relaciones existentes entre las propiedades del AOV obtenido y los valores de referencia de las variables tecnológicas.
- Bajo nivel: trata las dinámicas que relacionan los valores de referencia con los valores reales de las variables de proceso.

Asegurar que las variables de proceso efectivamente alcanzan los valores de referencia definidos es obviamente deseable e importante para el PEAOV, y se puede tratar empleando principalmente técnicas estándar de control automático. Sin embargo, asegurar que una variable de proceso efectivamente se mantiene en su valor prescrito a pesar de las perturbaciones que actúan sobre el sistema, no garantiza que las características del AOV producido son las deseadas. Para alcanzar ese objetivo, los valores de referencias de las variables de proceso también deben ser definidos y ajustados adecuadamente, teniendo en cuenta las relaciones de la capa de alto nivel del proceso. Es más, la definición de objetivos de elaboración alcanzables y adecuados basados en las características de las aceitunas de entrada constituye en sí misma una cuestión importante y no trivial.

El tema principal de esta tesis es la asistencia al operador de almazara al enfrentarse a las siguientes cuestiones:

1. ¿Qué objetivo de elaboración se debe seleccionar para el lote de aceitunas del que se dispone?
2. ¿Qué valores de las variables de proceso permiten alcanzar este objetivo?
3. Si no el objetivo no se alcanza exactamente, ¿cómo se deben modificar los valores de referencia de las variables de proceso para que efectivamente se alcance este objetivo?
4. ¿Cuándo se deben recolectar las aceitunas para maximizar el retorno económico de la actividad para toda la campaña?

El primer paso para responder a las preguntas anteriores ha sido obtener un modelo suficientemente detallado de las relaciones e influencia de las distintas variables del PEAOV. Un obstáculo fundamental al afrontar este problema es que, actualmente, no se dispone de sensores capaces de aportar información fiable en línea. Esta restricción fundamental provoca que la aplicación de técnicas de identificación de sistemas estándar no sean viables, lo que ha llevado a utilizar técnicas de modelado basadas en conocimiento experto para la construcción de los modelos.

Dada la complejidad no trivial del PEAOV debida al elevado número de variables de proceso relevantes y a sus interacciones, los mapas cognitivos borrosos han sido la técnica propuesta para la construcción del modelo del sistema. Esta técnica provee una descripción gráfica del sistema que hacen muy intuitivo el análisis y la interpretación de las relaciones entre los nodos. Además, es una técnica muy modular, que permite fácilmente incrementar el nivel de detalle de algunas partes del modelo mediante la introducción de nuevos nodos y relaciones, sin requerir la modificación de las zonas que presentan un comportamiento aceptable.

La técnica concreta de mapas cognitivos borrosos empleada para la construcción del modelo ha sido una versión modificada de las redes dinámicas cognitivas simplificadas [Miao et al., 2010], utilizando matrices para codificar las relaciones definidas entre las etiquetas definidas en el universo de discurso de cada nodo. Empleando esta técnica se ha construido un modelo de la preparación de la pasta y de la separación sólido líquido en el decánter. Las salidas de los modelos para diferentes combinaciones de variables de entrada se han estudiado y validado con expertos en el PEAOV.

Estos modelos constituyen la base para el sistema de apoyo a la decisión, ya que contienen la información y el conocimiento sobre el sistema necesario para responder las preguntas propuestas. Todo lo que quedaba por hacer era desarrollar un método que permitiera obtener estas respuestas utilizando los modelos.

El enfoque propuesto es la traducción de las preguntas a funciones objetivo para un problema de optimización que emplea estos modelos como restricciones. La respuesta a la primera pregunta *¿Qué objetivo de elaboración se debe seleccionar para el lote de aceitunas del que se dispone?* se ha contestado en un proceso de dos pasos: en el primero se buscan todos los puntos de la frontera de Pareto, lo que permite la visualización de las soluciones de compromiso entre objetivos. Posteriormente, se ha considerado un criterio específico, particularmente, la maximización del beneficio, y se ha hallado el punto de la frontera de Pareto correspondiente a dicho objetivo. Diferentes condiciones de las aceitunas de entrada se han considerado como escenarios de producción, y los objetivos prescritos por el sistema han sido estudiados y validados con la ayuda de expertos.

La respuesta a la segunda pregunta ha sido obtenida a partir de la solución del problema de optimización anterior, puesto que los valores de las variables de decisión son justamente los valores de referencia de las variables de proceso que permiten alcanzar el objetivo. Una pequeña precaución hay que tener en cuenta, puesto que la existencia de múltiples combinaciones de variables de proceso que pueden proveer el mismo objetivo de elaboración hace conveniente modificar ligeramente la función objetivo del problema de optimización para imponer las condiciones que permiten seleccionar la combinación de variables considerada más ventajosa. Los escenarios de producción definidos anteriormente fueron de nuevo estudiados.

Respecto a la aplicación de realimentación para corregir los valores de referencia de las variables de proceso en el caso de desviación de los objetivos establecidos y el valor real de las variables de proceso, la no disponibilidad de sensores en línea impone, de nuevo, severas restricciones sobre las soluciones viables al problema. Dada esta falta de sensores en línea y la naturaleza estática de los modelos disponibles, el control run-to-run aparece como la alternativa natural. En este contexto, y siguiendo la configuración tradicional de este tipo de controladores, se ha propuesto aumentar el sistema propuesto hasta ahora con un observador para estimar las perturbaciones y errores que afectan a la planta, y emplear estas estimaciones para incluir la realimentación del proceso. A pesar de que no se ha probado la convergencia del método, las simulaciones realizadas ilustran el buen funcionamiento de la propuesta. En particular se ha observado una robustez bastante elevada cuando se han aplicado distintos tipos de perturbaciones.

En cada una de las cuestiones anteriores se ha asumido la hipótesis de que las aceitunas para procesar estaban ya disponibles en la almazara. Sin embargo, la recolección de las aceitunas determina en gran medida sus propiedades, lo que a su vez influye sobre todo el PEAOV. La relajación de esta hipótesis requiere considerar cuándo se deben recolectar las aceitunas para que sus propiedades permitan maximizar el beneficio para toda la campaña. En este contexto, se ha considerado la utilización de los modelos que proveen la evolución de las propiedades del fruto en el campo y la influencia del método de recolección. Diferentes escenarios de simulación han sido considerados y los resultados obtenidos validados.

Finalmente, es conveniente remarcar que, considerado en su conjunto, los métodos propuestos permiten afrontar las distintas cuestiones planteadas requiriendo únicamente la construcción de un modelo de la influencia de las variables de proceso. Más específicamente, el conocimiento que se requiere del experto es cómo cada variable afecta a otra, o cuál es el valor esperado de una variable cuando otra presenta un determinado nivel, y la intensidad de la relación. No es necesario que el experto suministre acciones de control típicas cuando se enfrenta a un objetivo de elaboración determinado, puesto que estas acciones de control son *deducidas* por el sistema a partir de las relaciones de las que constan los modelos. Con el procedimiento modular de modelado propuesto, la construcción de los modelos se puede realizar mediante esfuerzos sucesivos para incrementar su precisión, con la posibilidad de utilizar datos provenientes del proceso para refinar el comportamiento del modelo.

F.2 Contribuciones

A continuación se incluyen las contribuciones realizadas durante el desarrollo de esta Tesis, tanto las que están directamente relacionadas con su tema principal, como otras que, si bien no tratan directamente este tema, sí son consideradas relevantes al tratar cuestiones relacionadas sobre el control y modelado del PEAOV o sobre técnicas concretas estrechamente relacionadas con las utilizadas en este trabajo.

- Contribuciones a revistas:

  1. *Expert system based on computer vision to estimate the content of impurities in olive oil samples*. P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. Journal of Food Engineering 119, n. 2 (November 2013).
  2. *Situación actual y perspectivas futuras del control del proceso de elaboración del aceite de oliva virgen*. P. Cano Marchal, J. Gómez Ortega, D. Aguilera Puerto, y J. Gámez García. Revista Iberoamericana de Automática e Informática Industrial RIAI 8, n. 3 (July 2011).

- Contribuciones a congresos internacionales:

  1. *Optimal Production Planning for the Virgin Olive Oil Elaboration Process.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 19th IFAC World Congress. August 24-29, 2014, Cape Town, South Africa.
  2. *Iterative Learning Control for Machining with Industrial Robots.* P. Cano Marchal, O. Sörnmo, B. Olofsson, A. Robertsson, J. Gómez Ortega, R. Johansson. 19th IFAC World Congress. August 24-29, 2014, Cape Town, South Africa.

3. *Fuzzy Decision Support System for the Determination of the Set Points of Relevant Variables in the Virgin Olive Oil Elaboration Process*. P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 2013 IEEE International Conference on Systems, Man, and Cybernetics (SMC). Manchester, UK.
4. *Control System of the Malaxing State for the Olive Paste Based on Computer Vision and Fuzzy Logic*. D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. 2013 IEEE International Conference on Systems, Man, and Cybernetics (SMC). Manchester, UK.
5. *Application of computer vision and Support Vector Machines to estimate the content of impurities in olive oil samples.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. 18th International Conference on Automation & Computing. Loughborough, UK, 2012.
6. *Hyperspectral imaging for determination of some quality parameters for olive oil*. D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. 18th International Conference on Automation & Computing. Loughborough, UK, 2012.

- Contribuciones a congresos nacionales:

1. *Sistema experto para la determinación de referencias en el proceso de elaboración de aceite de oliva virgen.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega. XXXIV Jornadas de Automática. Tarrasa (Barcelona), 2013.
2. *Determinación del estado de batido de la pasta de aceituna empleando visión por computador.* D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega. XXXIV Jornadas de Automática. Tarrasa (Barcelona), 2013.
3. *Aplicación del control repetitivo para el rechazo de perturbaciones periódicas en la temperatura de la pasta en la batidora del proceso de elaboración de aceite de oliva virgen* P. Cano Marchal, J. Gámez García, D. Santamaría García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.
4. *Propuesta de modelo y estrategia de control para el decánter del proceso de elaboración de aceite de oliva virgen* P. Cano Marchal, J. Gámez García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.
5. *Clasificador automático de aceitunas según su variedad utilizando información hiperespectral* J.P. Aranda Carmona, P. Cano Mar-

chal, E. Estevez Estevez, S. Satorres Martínez, J. M. López Paniza, J. Gámez García, J. Gómez Ortega. XXXII Jornadas de Automática, Sevilla, 2011.

6. *Grado actual de automatización del proceso de elaboración de aceite de oliva virgen en España.* D. Aguilera Puerto, P. Cano Marchal, J. Gómez Ortega, J. Gámez García. XXXI Jornadas de Automática, Jaén, 2010.
7. *Aplicación del control automático al proceso de elaboración de aceite de oliva virgen. Situación actual y perspectivas futuras.* P. Cano Marchal, J. Gómez Ortega D. Aguilera Puerto y J. Gámez García. XXXI Jornadas de Automática, Jaén, 2010.

- Capítulos de libro:

  1. *La automatización en el proceso de extracción de aceite de oliva virgen. Situación actual y líneas de mejora.* Juan Gómez Ortega, Javier Gámez García, Pablo Cano Marchal and Diego Martínez Gila. In *El Sector de elaboración de aceite de oliva: un estudio multidisciplinar*. Edited by GEA-Westfalia. 2013.

- Patentes nacionales:

  1. *Sistema de regulación automático de la salida de la interfase entre agua y aceite de un decantador centrífugo horizontal en el proceso de elaboración de aceite de oliva.* P. Cano Marchal, D. Martínez Gila, J. Gámez García, y J. Gómez Ortega.
  2. *Sistema de control de trazabilidad en el proceso de elaboración de aceite de oliva mediante la identificación e lotes de aceitunas por radiofrecuencia RFID, y procedimiento asociado al mismo.* D. Martínez Gila, P. Cano Marchal, J. Gámez García, y J. Gómez Ortega.

Además de estos trabajos ya publicados, un artículo sobre el modelado del proceso de preparación de la pasta basado en el capítulo 3, y otro sobre el proceso de separación sólido-líquido van a ser enviados a la revista *Engineering Applications of Artificial Intelligence*.

Un artículo presentando la propuesta de técnicas de optimización para la determinación de las referencias de proceso incluida en el capítulo 4 va a ser enviado a *IEEE Transactions on Systems, Man and Cybernetics*, y otro tratando la aplicación del control run-to-run a la actualización de dichas referencias como se ha presentado en el capítulo 5, a *Expert Systems and Applications*.

Finalmente, un trabajo sobre la planificación de la producción anual basada en el enfoque propuesto en el capítulo 6, va a ser enviado al *Journal of Food Engineering*.

El envío de los artículos a las revistas correspondientes se va a realizar antes del acto de defensa de esta Tesis.

F.3 Líneas de Trabajo Futuras

Una primera línea de investigación interesante en la extensión de los modelos de proceso con la incorporación de otras características del AOV. Particularmente interesante es la inclusión de la influencia de las variables de proceso en el contenido en polifenoles y otros componentes minoritarios, dada su relación con las características saludables del AOV. Desde un punto de vista de transferencia al sector es una línea interesante, puesto que la impresión subjetiva del autor es que el conocimiento sobre la influencia de los parámetros del proceso sobre estas características de los AOV no es muy amplio en el sector.

Actualmente, la no convexidad de los modelos y la existencia de mínimos locales hace problemática la búsqueda del óptimo global, y supone tener que emplear técnicas de optimización global para hallar las soluciones. Un aumento del tamaño de los modelos conllevaría un agravamiento de estos problemas, lo que motiva un análisis más detallado de la estructura matemática de los modelos propuestos. En particular, la posibilidad de calcular analíticamente las derivadas de las relaciones definidas puede facilitar la solución de los problemas de optimización en los que se utilizan estos modelos.

Adicionalmente, el análisis de las propiedades matemáticas de los modelos puede ser de interés para el estudio de la convergencia del controlador run-to-run, que es un tema importante, particularmente si se busca un sistema de control más autónomo.

Continuando con el control run-to-run, es relevante remarcar que la función objetivo utilizada penaliza desviaciones tanto positivas como negativas respecto del objetivo de proceso. Si el objetivo de elaboración fijado es efectivamente un punto perteneciente a la frontera de Pareto, este comportamiento no supone ninguna desventaja apreciable. Por contra, si existe error en los modelos utilizados para hallar este objetivo de elaboración, puede ser que este objetivo prescrito no sea realmente un punto de la frontera de Pareto. En este caso, puede ser de interés penalizar únicamente las desviaciones en un sentido, permitiendo las de signo opuesto. Esta discusión sugiere el interés de utilizar distintas funciones objetivo, en particular, funciones del tipo empleadas en la programación de objetivos, para el control run-to-run.

Respecto a la planificación anual de la producción, el capítulo correspondiente ya menciona el interés de estudiar el problema empleando modelos del PEAOV más detallados. Otra extensión interesante puede ser explorar la implicaciones y las diferencias en las soluciones obtenidas cuando se considera la impredecibilidad de las condiciones meteorológicas incluyendo componentes estocásticas en los modelos de evolución de propiedades de las aceitunas.

Además de estos puntos, la investigación en el desarrollo de sensores capaces de proporcionar medidas en línea fiables o estimaciones de las variables de proceso relevantes, línea en la que nuestro grupo de investigación ya está realizando esfuerzos, es también de gran interés. La posibilidad de la obtención de datos con tiempos de muestreo más reducidos y menor costo de adquisición permitiría la construcción modelos dinámicos de las relaciones, conduciendo a la posibilidad de aplicar mejores esquemas de control.

Es más, la disponibilidad de sensores capaces de proporcionar la información requerida del proceso sin intervención humana puede convertir la aplicabilidad de los métodos propuestos de un sistema de apoyo a la decisión a un sistema de control de alto nivel con mayor autonomía. Para esta transición es particularmente relevante los aspectos relacionados con la estabilidad del control run-to-run, y la influencia del ruido en el mismo.

Finalmente, el inclusión de los métodos propuestos en sistema software con una interfaz de comunicación con el usuario para implementar la propuesta en una almazara industrial y hacer uso de la posibilidad de emplear datos de proceso para ajustar los modelos se considera una línea de trabajo de alta prioridad.

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