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Zero Defect Manufacturing in the Food Industry: Virgin Olive Oil Production

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Abstract: This paper provides a zero defect manufacturing (ZDM) approach designed for the virgin olive oil (VOO) industry, with the objective of producing the best possible product using sustainable methods. A deep analysis of related work for ZDM and the current state-of-the-art technology in the VOO elaboration process is presented, along with the implications of the well-known trade-off between quality and extraction yield and the importance of having the right information on the state of the fruits and the main technological variables of the process. Currently available new technologies, such as smart devices with cloud connectivity, enable having the required amount of data and information in real-time, thus making the concept of ZDM possible. Together with the proposed ZDM approach and strategies, the basic requirements and the first steps towards the implementation of ZDM in this productive sector are identified.

Keywords: zero defect manufacturing (ZDM); design for ZDM; quality assurance; virgin olive oil (VOO); food industry; process industry; smart sensors

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Citation: Satorres Martínez, S.; Illana Rico, S.; Cano Marchal, P.; Martínez Gila, D.M.; Gómez Ortega, J. Zero Defect Manufacturing in the Food Industry: Virgin Olive Oil Production. *Appl. Sci.* **2022**, *12*, 5184. https://doi.org/10.3390/app12105184

Academic Editor: Antonio Valero

Received: 21 April 2022
Accepted: 18 May 2022
Published: 20 May 2022

1. Introduction

Quality is a criterion of primary importance in each sector of the food industry, not only to ensure safe and quality food for the consumer, but also to win market shares. The number of businesses in this industry which adopt quality management systems (QMSs) in order to enhance their competitiveness on the global market is continuously rising [1]. It can be said that each company has a particular stage of maturity on the issue of QM. These stages of evolution of quality begin with the manual or automated inspection of products and its traceability, continue with the statistical quality control of products and processes, until a final stage where QMS is tightly interwoven with the company strategy is reached [2]. Lean manufacturing, six sigma, lean six sigma, total quality management and the theory of constraints are traditional quality improvement (QI) methods that have been widely used by companies for more than three decades within the framework of QMS [3].

Much work has been done in this research area, and a recent state-of-the-art paper that presented the benefits and disadvantages of using traditional QI methods concluded that alternative ones are needed [4]. The same authors have made significant contributions in QI, supporting the zero defect manufacturing (ZDM) approach as a better option with superior performance to the traditional ones. Some of these contributions are detailed hereafter.

In addition to the comparative analysis between the traditional QI and ZDM performed in [5], a clear ZDM definition was also presented to be used across the scientific community. The authors pointed out that ZDM embraces numerous ideas and concepts from traditional QI methods, such as the core concept in six sigma: to produce almost zero defective products. However, they went on to say that ZDM goes one step further because it utilises the full potential of modern data-driven technologies to achieve its goal: "making it right the first time", rather than trying to mitigate a problem at a later stage.

In addition, the concept of ZDM required defining how it can be implemented and which strategies have to be deployed at the different manufacturing stages. In [6], an intensive literature review on ZDM was presented, including the main approaches to implement it and the strategies to be used. More specifically, Ref. [7] proposed a methodology to assist manufacturers and researchers to select the most suitable approach to their specific case and Ref. [8] presented the appropriate design of strategies.

Based on the previously referenced work, in [9], a complementary analysis was performed, aiming to extensively detailing each ZDM strategy and identify the main applicable theoretical tools. The ZDM concept has also been analysed from a business perspective. Which requirements for change are necessary for achieving ZDM in a company as well as the effects desired from its implementation to make a decision on its economic viability were presented in [10]. Other recent proposals of the same authors were devoted to define a highly generalisable model for ZDM applied to the production in the manufacturing and process industries [11,12]; to date, however, it has not been applied in any industrial case.

Artificial intelligence (AI) technologies are widely present at ZDM implementations, as detailed in [9] and more specifically in [13], where a short review of AI technologies employed during product inspection and quality assessment is presented.

However, all the former approaches have little or no validity if the company does ZDM at the cost of using too many resources. Ultimately, the cost of polluting and the indiscriminate use of raw materials is going into the product and ZDM is not having the desired effects: namely, those of lower costs, lower energy consumption, lower level of wasted materials, faster production processes and improved level of output quality. For this reason, the European Union guidelines for ZDM projects (https://www.zdmp.eu/ accessed on 21 April 2022) is boosting the ZDM concept in the context of zero waste.

In view of the above, the aim of this paper was to present an approach for achieving ZDM in a specific case of the food industry: the virgin olive oil elaboration process. It is the belief of the authors that the implementation of the ZDM concept in this sector entails a qualitative leap, as QI methods have not been reported on and may have not been applied before. It is important to highlight that the scope of this work covers a ZDM proposal and the identification of the basic requirements and the problems to be solved toward its implementation. It is highly desirable to make further progress in this direction, and this proposal will represent an innovative solution for the VOO productive sector.

The structure of the paper is as follows: in Section 2, the key findings from the literature review regarding industrial use cases that implement ZDM and the current state-of-the-art technology in the VOO elaboration process are presented. Section 3 details the ZDM proposal and its basic requirements in terms of definitions, approach and strategies to be utilised, while Section 4 introduces the first steps towards ZDM implementation in the VOO production. Finally, Section 5 presents the conclusions and future works.

2. Related Work

Interest in the ZDM concept has been steadily increasing in recent years, as evidenced by the number of scientific articles that have emerged recently. Since analysing how others put into practice a ZDM approach in their productive systems can be of great support, this section first outlines ZDM works focused on industrial implementations. Then, the state-of-the-art technology of the VOO productive process is presented, along with the current practices for the quality control of the final product.

2.1. Zero Defect Manufacturing Implementations

According to the ZDM works distribution across the industrial sectors presented in [4], the dominant industry in which this approach is applied is the semiconductor one, followed by the steel and the automotive industries. With regard to the food industry, the ZDM concept is not as extended as it is in others. In a broad scope of application, successful ZDM implementations can be found, examples of which are detailed below.

In [14–16], the zero defect production of plastic-encapsulated electronic power devices was attempted, concluding that the ambitious goal to reach the zero defect frontier was achievable. The critical aspects of meeting ZDM were evaluating the influence of the major components and mechanisms involved in the productive process (root cause); selecting the appropriate materials; and keeping in mind the interdependence among the productive process components.

In [17], the authors presented intelligent manufacturing process control that aimed to achieve ZDM for the steel industry. The approach was mainly based on a thorough understanding of the production process, which comprised in-line quality control, the establishment of quality thresholds, and the process parameter effects on the output.

In [18], a framework for the consideration of customer requirements during the design phase of new manufacturing assets was designed and developed. However, the framework was tested utilising data from a real-life industrial scenario but in a laboratory-based machine shop.

Under the framework of a European Union (EU) project, the authors in [19] developed an experimental investigation of automotive rubber quality during the extrusion phase. This research was in line with the project aim: to provide tools for the monitoring, control and adjustment of production lines through simulation models running in real-time. Another successful EU project developed a ZDM solution for three different production lines, namely jet engine shafts, medical micro-catheters and railway axles. The proposal was detailed in [20] and it included the reference ZDM architecture and the different data gathering systems; however, the validation stage was proposed as future work.

There are also interesting proposals for ZDM that have not yet been validated in any industrial case study. For instance, in [21], the authors developed a multi-layer quality inspection framework for its full exploitation in the Industry 4.0 context.

Based on the examined literature, it can be safely concluded that deep knowledge about the productive process and the interdependence between its stages is of importance for effective ZDM implementation. Hence, the next subsection identifies the most important aspects of VOO production.

2.2. State-of-the-Art Technology at the VOO Elaboration Process

The VOO elaboration process can be regarded as a multistage system because it consists of multiple stages required to finish the final product. The VOO process chain consists of seven major processing stages, starting with the fruits reception in the oil mill yard and finishing with the virgin olive oil storage.

Basically, after the reception, the olives are washed to remove the leaves, stalks, earth and impurities that arrive with them. Once the fruits are cleaned, they are stored in hoppers and fed into the mill, where they are crushed to form the olive paste. The paste is kneaded in a thermomixer (malaxer) where it is slowly stirred and heated in order to improve the conditions for the oil separation. This separation is carried out in a decanter centrifuge and yields olive oil and pomace as a by-product. The humidity and impurity content of this oil is still undesirably high, so further separation is performed in a vertical centrifuge. After this operation, the oil might be filtered or directly pumped to a final tank to be stored.

In multistage systems, the quality of the final product is determined by complex interactions among the stages. That is, the quality characteristics at one stage are not only influenced by local variations at that stage, but also by variations propagated from upstream stages [22]. In the case of VOO production, the quality of the final product is deeply conditioned by the ripeness and sanitary state of the olive fruits. Process variables at the different production stages have only limited authority to influence the final features of the produced VOO, and when properly tuned, they can only preserve the potential quality offered by the fruit.

As the incoming olives set an upper bound on the VOO quality, plenty of research has been devoted to the characterisation of the olives at the reception stage. In [23], the authors presented a computer vision system, composed of two devices working in the visible spectra and installed before and after the washing stage. The system automatically classified olives that were picked from the ground or from the tree. The analysis of multispectral images to discriminate olive fruits by their firmness was performed in [24] using a laboratory set-up. Infrared images were also analysed in [25,26]. In the first reference, olives were classified according the presence of defects under controlled image acquisition conditions. The image acquisition for the second reference was performed under the regular operating conditions of an olive oil mill. Moreover, the computer vision set-up was installed after the washing stage to perform the detection of defects on individual fruits.

Cameras working on the visible spectra have also been included at the kneading stage. In [27], the main indicators of the olive paste state (viscosity, granularity and presence of olive oil over the paste) were obtained from images acquired inside the thermomixer. Then, this information was used to suggest the values of the process variables according to the olive paste elaboration state.

With regard to the product quality assessment, European legislation provides classes of olive oil based on its physico–chemical and organoleptic characteristics [28]. The sensory analysis of olive oils has to be carried out by both smell and taste assessments by means of a panel test, constituted by a group of trained and selected assessors (EEC 2568/91; EC 640/08). To date, there is no methodology able to suitably replace human sensory panels but some attempts have been made to automate this process. As recently reviewed in [29], electronic noses have been widely used for the classification and quality control of edible oils. For example, in [26], this sensor was utilised to predict the level of fruity aroma and the presence of defects in virgin olive oils; in [30], this sensor was used to classify olive fruits and oils according to their fatty acid ethyl ester content, a parameter used to differentiate extra virgin olive oils from virgin olive oils.

Computer vision was also used in [31] to automatically determine the oil quality before being produced from a previous inspection of the incoming fruits. The expert assessment of the fruit conditions guided the image processing and the algorithm gave a prediction of the presence of minor compounds in the produced VOO. Finally, a more detailed description of the production steps as well as the current technologies used for the collecting process and product quality data can be found in [32].

Table 1 summarises for the currently monitored process stages which variables are susceptible to be measured and the technology used for acquiring data, as well as lists references with industrial cases of study or laboratory set-ups with potential industrial use.

Table 1. Cutting-edge technologies in the VOO elaboration process.

Process Stages	**Controlled Variables**	**Technologies**	**References**
Reception	Fruits classification (ground or tree)	CV in the visible spectra	[23]
Washing	Fruits classification	CV in the visible spectra	[23]
	Firmness of the fruits	CV (multispectral system)	[24]
	Presence of defects in the fruits	CV in the infrared spectra	[25,26]
	Oil quality prediction	CV in the visible spectra	[31]
Kneading	Olive paste state	CV in the visible spectra	[27]
Storage	Organoleptic characteristics of the VOO	Electronic nose	[26]

3. Proposal for ZDM in VOO Production

There are two main reasons for implementing the ZDM concept in the VOO sector. One is to keep the productive system at the highest level of its functionality, while the other is to more efficiently and more sustainably produce the best possible product. To achieve this, new concepts must be adapted and defined together with the approach and strategies for ZDM implementation. This section deals with these issues.

3.1. ZDM Definitions

In any manufacturing environment, what is meant by *defect* and how a product can be classified have a common understanding. Hence, it can be said that a defect is a non-conformance to product specification and in this regard, a product or a part can be defective or not. In light of this, the ZDM goal in manufacturing industries is that non-defective products leave the production site.

Extrapolating this concept to the VOO industry involves the adaptation of the ZDM goal and a new definition of some terms. The first inconsistency is the defect definition. In the VOO industry, a defect is intended as an organoleptic and a flavour feature of the produced olive oil. The final product of the elaboration process is the oil and according to the number of defects and positive attributes, analysed by a certified panel of tasters, the oil is classified into three different categories: two for edible oils and one for oil that is not suitable for human consumption.

Our view on ZDM in this sector is that it is not always required to reach zero defects in the final product, as a number of defects are allowed in function of the oil type. Hence, the ZDM objective for this approach can be defined as: "to produce the best possible product according to a predefined specifications and constrained by the quality of the incoming fruits and some of the process parameters". This conception of ZDM requires a new defect definition. Table 2 summarises the former ideas, whilst the new concepts and definitions are detailed in the subsequent subsections.

Table 2. ZDM definitions in the manufacturing and VOO industries.

Industries	Definitions			
	Defect	**Product**	**ZDM Goal**	**New Defect Definition**
Manufacturing	Non-conformance to product specifications is detected	PART: is defective or not defective	No defective products leave the production site	–
VOO process	Organoleptic and flavour features	VOO: Varying degrees of quality	To produce the best VOO according to predefined objectives	Non-conformance to ZDM multi-objective function

3.1.1. Defects in VOO

The main causes of the generation of defects in the produced VOO are: the state of incoming fruits; post-harvest and productive process management; and how the final product is stored. The most common defects and their root causes are detailed in [33]:

- Musty—Characteristic flavour of oils obtained from fruits which have been stored under humid conditions or have been collected with earth or mud on them and have not been properly washed.
- Fusty—This occurs when harvested olives are incorrectly stored and for a longer period than advisable.
- Acid-sour—This defect appears when the olives gathered in the harvest are stored for too long before crushing them to extract the oil.
- Metallic—This is due to oil mills and their machinery whenever some component is not cleaned properly.
- Rancid—flavour of oils which have undergone an intense process of oxidation due to improper storage.

The fruity sensation, the pungency notes and the bitterness that characterise the particular taste of virgin olive oils are considered their positive attributes. According to the number of defects—or negative attributes—and positive attributes, oils are classified into the following designations [33]:

- Extra virgin olive oil (EVOO)—This is the highest quality rating for an olive oil. It contains zero defects and greater than zero positive attributes.
- Virgin olive oil (VOO)—This oil has a slightly lower quality than extra virgin olive oil. It contains defects from 0 to less than 3.5 and a free acidity of less than 2 percent.
- Lampante virgin olive oil—This type of olive is forbidden for direct sale if it is for consumption purposes. The number of defects is more than 3.5 or it has a free acidity of more than 2 percent.

3.1.2. ZDM Goal

The ZDM goal defined above requires producing the *best* possible VOO, considering the fruit characteristics and some other a priori considerations that can be related to marketing concerns or other company strategies. The key issue is how to define this *best* VOO, and a plausible approach is via an optimisation problem. Generally speaking, two objectives have to be simultaneously optimised: quality and yield; as oil mills are interested in producing the best possible oil and as much as possible. However, this problem is challenging because these are conflicting objectives, that is, the optimal solution of an objective function is different from that of the other. When an optimisation problem involves more than one objective function, the task of finding one or more optimum solutions is known as *multi-objective optimisation* [34].

Considering the two objectives that must be simultaneously optimised, a multi-objective optimisation problem can be formulated as:

$$Maximize \quad J(q,y) = w_1 \cdot q(\mathbf{x}) + w_2 \cdot y(l,k), \tag{1}$$

$$q(\mathbf{x}) = \sum_{i=1}^{N} (max_{x_{neg}} - x_{neg}(i)) - \sum_{j=1}^{M} \|x_{ref}(j) - x_{pos}(j)\|^2, \tag{2}$$

$$y(l,k) = \frac{l}{k}, \tag{3}$$

$$subject \;\; to:$$

$$\left.\begin{array}{r} 0 \le x_{neg}(i) \le max_{x_{neg}} \\ 0 \le x_{pos}(j) \le max_{x_{pos}} \\ y_{min} \le y \le y_{max} \\ f(q,y) = 0 \end{array}\right\}$$

Equation (1) represents the multi-objective cost function, where $q(\mathbf{x})$ and $y(l,k)$ are the quality and yield, respectively. As stated before, these are contradictory objectives, as the oil quality increases its yield decreases. It is represented as a weighted sum approach and the weights w_1 and w_2 establish the importance of each objective in the context of the problem.

The VOO quality, determined in Equation (2), can be expressed as a sum of the positive and negative attributes assessed to classify the oil. To maximise the whole expression, the value of the negative attributes is normalised considering the maximum value of this type of attributes, $max_{x_{neg}}$. Positive attributes are also normalised with a reference value, x_{ref}, as a very high value in some positive attributes such as pungency can be detrimental for the oil quality perceived by the consumer. This relates to the broader topic of customer-perceived quality and marketing strategies for the VOOs. Finally, Equation (3) defines the oil yield that measures the quantity of the obtained oil, l, per kilograms of fruit k.

The former equations are subjected to restrictions. The maximum value for the negative attributes, $max_{x_{neg}}$, has to be 3.5 in order to avoid producing Lampante oil. In a test panel, positive attributes range from 0 to 10, therefore, $max_{x_{pos}}$ has to be 10. The yield range is mostly conditioned by the state of the incoming fruits and the kneading stage in the productive process. Usually, this value is between 10 and 30.

Finally, in order to have a well-posed optimisation problem, a constraint that explicitly models the trade-off between quality and yield is required, and that is generically denoted

$f(q, y) = 0$. This constraint can be thought of as a model of the VOO production process itself, in the sense that it needs to explicitly state what is achievable in terms of quality and yield for the given batch of olives to be processed [35]. Furthermore, it also provides the relations between x_pos and x_neg and the different process variables and characteristics of the olives. This model could be obtained via complex modelling approaches, such as that proposed in [36], or simply stated using the historical data of a company.

3.1.3. New Defect Definition for ZDM

Based on the former ZDM proposal, a defect can be defined as a non-conformance to the multi-objective function that models the ZDM goal. Figure 1 shows the space of solutions for the multi-objective problem. It can be observed that one solution is better than others in one objective, but it is worse in the second one. Since no one solution can be termed as an optimal solution to multiple conflicting objectives, the resulting multi-objective optimisation problem resorts to a number of trade-off optimal solutions lying on the Pareto-front. Not optimal but feasible solutions are included in the optimal space and those correspond to what has been defined as defect for ZDM.

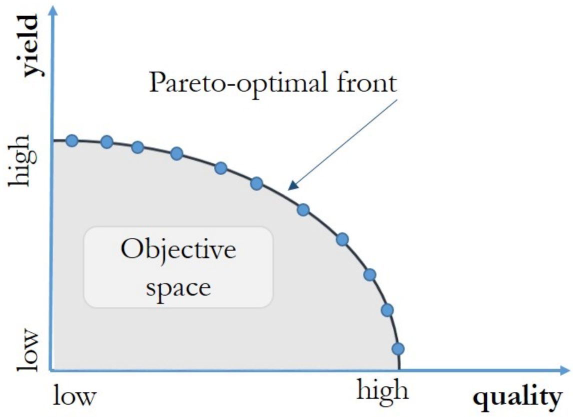

Figure 1. Optimal solutions of the function J for different weights (w_1 and w_2).

3.2. ZDM Approach

We present in Figure 2 the ZDM concept designed for the VOO elaboration process. As it is shown, it can be implemented in two different approaches but both under the ZDM thinking: obtaining the best possible product minimising the generation of waste. First, the green arrow follows a product-oriented approach while the yellow one can be defined as a process-oriented approach.

The product-oriented approach estimates the main features of the produced VOO; therefore, the cost of the product inspection is a key factor in order to implement it. When a non-conformance according to the multi-objective function is detected, the process data are analysed to identify the causes and correct them.

The process-oriented approach analyses the main process data for the oil being produced. If abnormalities are detected to the process data, the inspection is only performed to the oil produced since the abnormality detection.

The major drawback of the current VOO elaboration process is that the product quality is evaluated offline. As a result, the manufacturing process parameters cannot be quickly reconfigured and the quantity of produced oil that does not fit the quality or yield expectations is increased.

Because of this current limitation, our proposal is a process-oriented approach. As schematically represented in Figure 2, data on the state of the incoming fruits and the main process variables are analysed and correlated with an estimation of the product quality. This estimation allows the better and faster tuning of the process parameters for obtaining a product according to the specifications, mathematically defined as the solution to the multi-objective problem.

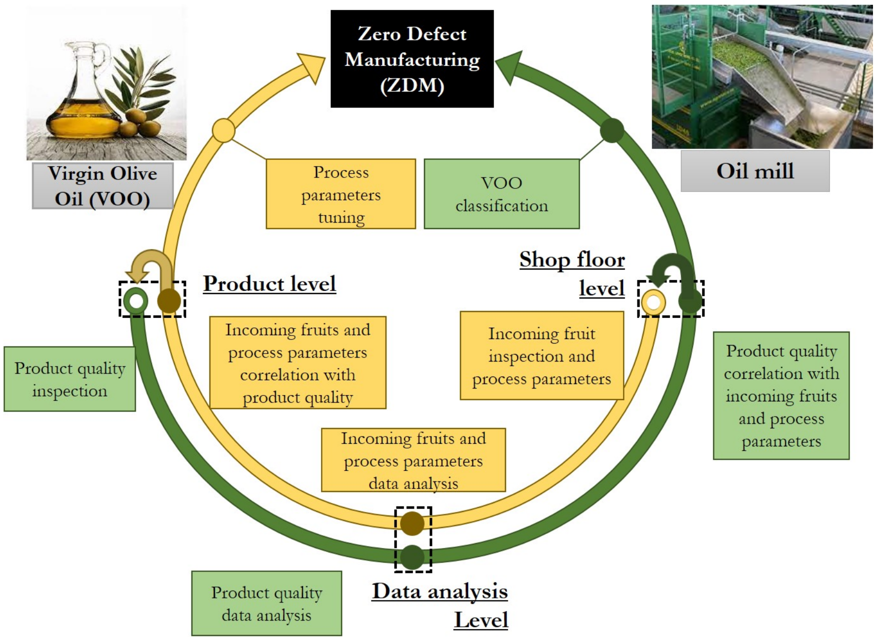

Figure 2. Zero defect manufacturing strategy designed for the virgin olive oil industry.

3.3. ZDM Strategies

As described in [6], ZDM is composed of four main strategies: detect (Dt); predict (Pd); prevent (Pv); and repair (Rp), which are generally used in pairs according to the following combinations: Dt–Rp; Dt–Pv; and Pd–Pv. The first two pairs (Dt–Rp and Dt–Pv) are not new, having existed in the manufacturing domain for decades. The Dt–Rp pair is applied when something is already faulty and corrections are required, while the Dt–Pv pair is appropriate when data are used from the production to avoid future defects. The Pd–Pv pair is a fairly new concept that relies on advanced data-driven approaches for predicting when in the future a fault will be created, thus enabling it to be prevented before it occurs [9].

In our ZDM approach for the olive oil sector, we propose the following strategies with the purposes detailed hereafter:

- Pd–Pv–A prediction of the olive oil quality and an estimation of the oil litres that can be obtained from a predefined fruit quantity are used to establish the importance of quality versus yield. In other words, the Pd–Pv pair defines the weights in the multi-objective fitness function. As such, the oil mill productivity and future profitability are better suited to the characteristics of the incoming fruits. These strategies have to be applied several times during the productive campaign, as the state of the fruit changes over the time. During the first months of the productive campaign, fruits are healthier and have a higher content of minor compounds which are responsible for relevant health properties as well as for increasing their shelf life [31]. These fruits are ideal for obtaining EVOO; therefore, in this case, the quality objective should be weighed against yield. However, as time passes, the fruit ripens and could be damaged because of adverse meteorological conditions. In this scenario, the second objective, yield, gains more significance.
- Dt–Pv. The detection of olive oils that do not fulfil the expected quality standard and/or yield is used to produce oil according to the specifications. For this, the oil quality estimation is based on the historical data of the panel test assessments and in-line information of the productive process. The yield can also be estimated by analysing the quantity of oil in the separation phase that remains in the pomace. On the basis of these data, the corresponding process parameters can be tuned to achieve the intended objectives.

We discarded the Dt–Rp pair as it is inapplicable in this particular case. Once the oil has been produced, it is classified by the panel test into an specific designation (EVOO, VOO or Lampante), and at this point, its quality or yield cannot be improved.

4. First Steps towards ZDM Implementation

The integration of sensory systems and how the acquired data are transformed into information are key factors in implementing the ZDM in a productive process. This section particularises the former issues for VOO production and summarises the general functional requirements that are needed to implement ZDM.

4.1. How to Obtain Data

The first challenge for ZDM implementation is that of collecting the data gathered from different and heterogeneous sources distributed in the production line. The relevant data for VOO production include: the state of incoming fruits, the main process variables, operator impressions and an estimation of the product quality and quantity. The sensory technologies to be integrated at the different productive stages are detailed below:

- State of the incoming fruits—Computer vision is viable technology to classify fruits according their ripening and sanitary state before the oil extraction process. Two types of image acquisition set-ups based on cameras working in the visible and infrared (IR) spectra, have to be installed before and after the washing stage. First, cameras working in the visible spectra and installed at the reception yard before the washing stage acquire images that will be used to differentiate between the fruits picked from the ground or from the tree. Second, two different technologies of cameras must be installed after the washing stage. Images from a camera working in the visible spectra will be later processed to detect the ripening index of the fruits; while images from the other set-up working in the IR spectra will be used to classify fruits according to their internal and external damage.
- Process parameters—In this regard, it has to be considered those manipulated and controlled variables of the process having an influence on the product quality or yield. Among the decisive process variables, there are the storage time and storage conditions of the fruits before their processing (e.g., humidity, cooling or pressure); kneading stage parameters (e.g., paste temperature, water or talc addition); and olive paste state and the storage conditions of the final product (e.g., temperature, exposure to oxygen and exposure to light). The acquisition of the process data, except for the paste state, is supported by an HMI to allow the operator to gather the remaining data. Finally, a computer vision set-up working in the visible spectra and installed inside the thermomixer provides images, which will later be used to extract information about the olive paste state (e.g., viscosity, granularity, and the presence of olive oil over the paste).
- Product quality—Since there is no in-line systems for oil mills to provide the VOO organoleptic and flavour features, the product quality has to be estimated. Based on previous studies [24,29,31,37], it is possible to offer an estimation of the VOO quality supported by different sensory technologies and historical data. The information obtained from the images acquired with the set-ups installed after the washing stage are used to predict the maximum level of quality. If fruits are properly processed, the predicted quality can be reached. Data obtained from electronic nose technology can also be used to classify the obtained oil into its proper designation. This technology has to be installed after the centrifugation stage and before the oil storage. In addition, the historical data of the panel test assessments together with real-time data from the operator view and impressions are used for the quality estimation.
- Productivity—The quantity of VOO litres obtained from a predefined quantity of fruits can be inferred from the oil that remains in the pomace. New intelligent devices based on NIR technology enable the extraction of information on fat yield and moisture. This device has to be installed after the separation stage.

Figure 3 shows examples of sensory technologies that are used to monitor and save data. They were installed by the ISR company in the Picualia oil mill.

Figure 3. Example of sensory technologies: (**a**) Image acquisition set-up installed at the reception yard; (**b**) NIR device installed after the separation stage; (**c**) Electronic nose installed after the centrifugation stage; and (**d**) HMI to gather operator impressions.

4.2. Transforming Data into Relevant Information

Having identified the sensory technologies to acquire relevant data for VOO production, the reference architecture designed to implement the ZDM approach must be detailed. Figure 4 shows the reference architecture and it grounds on the four following major pillars:

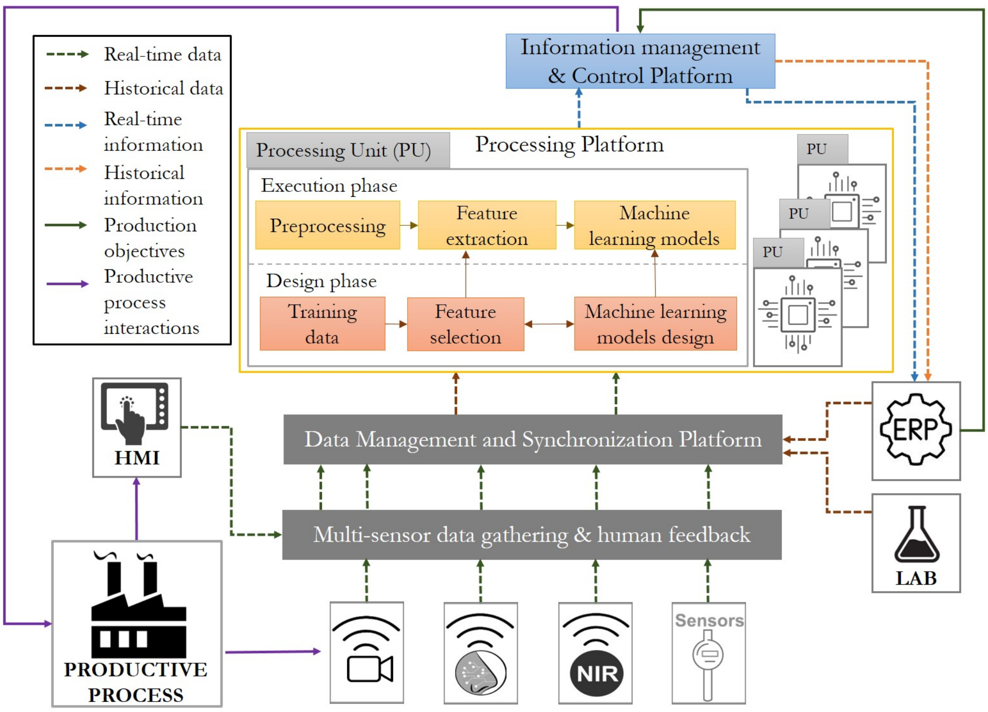

Figure 4. Reference architecture for the implementation of ZDM in VOO production.

- Multi-sensor gathering and human feedback layer—This enables to collect data gathered from different sources distributed across the different stages of the productive process. These data include: images in the visible and IR spectra, gathered from smart cameras; data to further predict the fruity aroma and defect level in the produced VOO, gathered from the smart e-nose; data to estimate the quantity of oil that remains in the pomace, gathered from the smart NIR; process data, gathered from in-process sensors; operator impressions and feedback, gathered from HMI. Each of the former devices interfaces with a software component in charge of encapsulating the acquired data. These software components share a common structure and send the received data in a unified format to the data management and synchronisation platform.

- Data management and synchronisation platform—Data from the former layer are stored (historical data) and updated in a structured and formalised way. In addition, this platform is enriched with data from the production planning system (ERP) and from the VOO analyses conducted by accredited laboratories. This platform integrates web services in API format (application programming interface) which receive the formatted data from the multi-sensor gathering and human feedback layer and transmit the synchronised real-time and historical data to the processing platform. The platform also offers persistence to the received data.
- Processing platform—Data gathered from the data management platform represent a relevant source of knowledge and are key elements for implementing ZDM. However, this knowledge has to be extracted and structured in order to be taken advantage of, and this is performed in the processing platform. This platform is composed of a set of processing units (PUs) where machine learning models are first designed and then executed to transform data into information. In the design phase, historical data from the multi-sensor data gathering and human feedback platform conveniently correlated with data from the ERP and laboratories are used as the training dataset to extract features and design the data processing models. Once the models were designed and validated, real time data are preprocessed to extract the features needed for the machine learning models. Although PUs share a common design, data processing algorithms are particularised for each type of data source.
- Information management and control platform—This platform stores and distributes the information extracted from the processing platform. Historical and real-time information feed the ERP and this in turn defines the production targets through a predict and prevent ZDM strategy. The control systems at the different stages of the productive process are also included in this platform. Using real-time information, it is possible to establish the set-points or references at the critical process stages, and proactively adjust the manipulated variables enabling the controlled variables to reach the reference. Detection and prevention ZDM strategies are implemented in the control platform to define references. Systems integrating computation and physical actuation capabilities also run in this platform to control every process stage.

4.3. General Functional Requirements

In view of the above, the general functional requirements of ZDM can be summarised by the productive process possessing the following capabilities:

- Automatic capture and formatting of relevant data using an intelligent sensors system.
- Automatic data processing, filtering and feature extraction.
- Data mining and knowledge algorithms for inferring information from data.
- Self-adaptation and optimisation control.
- Provision of clear and concise defect information and advice supplied to the user.

At this time, intelligent sensory systems are becoming increasingly integrated in the productive process together with advanced data analysis and artificial intelligent techniques to extract valuable information for decision making. The next steps to be undertaken for ZDM implementation should reinforce the former capabilities.

5. Conclusions and Future Works

This work focused on an emerging concept in quality control and the improvement of production processes named ZDM. The goal was to present an approach for a specific case of the food industry: the virgin olive oil elaboration process. Based on the content analysis performed for recent state-of-the-art and research articles on ZDM, published in a variety of academic journals and conference proceedings, the design and the steps required to implement the ZDM concept in VOO production were presented.

First, it was necessary to adapt and define some terms which significantly differed between the manufacturing and process industries. What is meant by defect, the state of the final product and the final goal of the productive system are examples of such nonconformities. In this respect, the main targets of the VOO productive process were mathematically modelled as a multi-objective optimisation problem and a non-optimal solution was defined as a defect.

Then, the two possible approaches to address the problem of ZDM implementation were presented. Due to the current technological constraints to assess the product quality in-line, a process-oriented approach was proposed. With this approach, the main process data for the oil being produced are analysed, and if abnormalities are detected, the process parameters are tuned in order to produce according to the predefined specifications. This approach also needs to inspect the product and for the time being, this inspection has to be supported by different sensory technologies and historical data.

Strategies for ZDM performance were presented and a combination of two pairs to be applied with different purposes were proposed. The study concluded with the first steps to put ZDM into practice in the VOO productive sector. The main sensory technologies already included in the productive process were described, and their area of application at the different process stages were detailed. A reference software architecture to promote ZDM implementation and the required productive process capabilities were finally summarised.

The authors consider that the implementation of the ZDM concept in this sector could lead to substantial benefits in line with new European Union policies for making a green transition. These potential benefits include the improvement of oil mill's sustainability, competitiveness, efficiency and profitability. Future research steps will be directed towards the full implementation of this concept in a pilot plant, and in this regard, a highly automated VOO producer has indicated his interest in and support of this approach.

Author Contributions: Conceptualisation, S.S.M., S.I.R., P.C.M. and J.G.O.; formal analysis, S.S.M., P.C.M. and D.M.M.G.; funding acquisition, S.S.M. and J.G.O.; investigation, S.S.M., P.C.M. and D.M.M.G.; writing—original draft, S.S.M. and P.C.M.; writing—review and editing, S.S.M., S.I.R., P.C.M., D.M.M.G. and J.G.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Spanish Ministry of Science and Innovation under the project PID2019-110291RB-I00 and the I+D+i project within the cooperative frame FEDER-Andalucía with the FEDER code A1123060E00010 and the reference 1380776.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The study did not report any data.

Acknowledgments: The authors would like to thank Almazara Picualia, S.L. and the Integración Sensorial y Robótica (ISR) S.A. company for their collaboration in this work.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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