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Assessment of the Digital Maturity of a Case Study in the Context of Industry 4.0

Abstract

Industry 4.0 is the new generation of industrial production systems, characterized by a high level of integration, flexibility, efficiency, and adaptability to the strategic goals. With the ever-increasing globalization, market competition, and emerging technologies, the development of Industry 4.0 became the top priority for economic growth. Hence, Industry 4.0 must be gradually introduced in industrial enterprises.

The purpose of the present work is to assess and promote the digital maturity of a company in the commodities sector. The digital maturity was assessed through a survey, followed by the application of a proposed maturity model. Through this approach, the company was determined to be at level 1, in a rank ranging from 0 to 5.

To contribute to a more intelligent and efficient production process, a revamping of three critical points was also proposed. The first proposal focused on the implementation of an online real-time monitoring and control system of the oilseed cleaning process. The second, in the implementation of an inline NIR spectrophotometer to control and rectify, in real-time, the quality of soy and rapeseed meal. The last proposal consisted of implementing a predictive maintenance strategy for a piece of equipment considered critical for the company's production process. The economic analysis of the investments showed that the second proposal is the only one that represents a profitable investment for the company. The last proposal presented conditioned profitability.

Keywords: Industry 4.0, Industry 4.0 readiness, oilseeds, process control, predictive maintenance

1. Industry 4.0

The term "Industrie 4.0" emerged for the first time at the Hannover fair (Germany) and was officially announced in 2013 as a strategic initiative to revolutionize the manufacturing industry through the integration of information and communication technologies with operational technologies [1][2]. This integration results in a smart factory - a new generation of industrial systems that are highly efficient, integrated, and flexible [3][4]. In smart factories, integrated machines and devices compose cyber-physical production systems (CPPS), which can cooperate dynamically with humans and with each other, using the internet as the main communication infrastructure. Thanks to cloud and edge computing combined with data analysis, CPPS can proactively optimize industrial production [1][5].
While the third industrial revolution focused on the automation of single machines and processes, Industry 4.0 focuses on the end-to-end digitization of all physical ecosystems with value chain partners [6].

1.1. Core Technologies

1.1.1. Big Data and Data Analysis

The increasing use of embedded sensors and networked machines results in the generation of vast amounts of data of different kinds, collected at high speed, known as *big data* [7].

Big data analysis refers to the techniques applied for knowledge discovery in databases (including deep learning, machine learning, and data mining) to extract valuable insights, hidden patterns, models, and information from these vast amounts of gathered data [8][9][10]. Therefore, big data analysis is key to the sustainable innovation and continuous optimization of industrial processes [5].

1.1.2. Cloud and Edge Computing

According to the American National Institution of Standards and Technology (NIST), cloud computing is a “model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.” One of the main advantages of cloud computing is the ability to access a wide range of remote services from everywhere [11]. With these features, cloud computing significantly contributes to the organization, management, storage, and analysis of industrial big data. On the other hand, edge computing allows for real-time data analysis that is mandatory for operational control and monitoring [12].

1.1.3.Industrial Internet of Things

The industrial internet of things (IIoT) is a system comprising networked smart objects, cyber-physical assets, associated generic information technologies and optional cloud or edge computing platforms, which enable real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information within the industrial environment [13]. Therefore, the industrial internet of things is the infrastructure that establishes the ubiquitous connection between data acquisition, storage, processing, and visualization. For this reason, it contributes to the decentralized control and self-optimization that is characteristic of smart factories [6].

1.1.4. Digital Twin

In the context of industrial production, the digital twin consists of a virtual representation of a production system that can run on different simulation disciplines and that is characterized by the synchronization between the virtual and the physical system, thanks to sensed data and connected smart devices, mathematical models and real-time data elaboration [14]. It is the digital representation of a unique asset (product, machine, service, product service system, or other intangible assets) that alters its properties, condition, and behaviour using models, information, and data [15]. The digital twin exploits these features to forecast and optimize the behaviour of the production system in real-time [14].

1.1.5. Cybersecurity

Many companies still rely on management and production systems that are unconnected. With the increased connectivity and use of standard communication protocols that come with Industry 4.0, the need to protect critical industrial systems from cybersecurity threats increases dramatically. As a result, secure and reliable communications, as well as sophisticated identity and access management of machines and users, are essential [16].

1.2. Related Technologies

The utilization of other related technologies can bring additional benefits, particularly to the manufacturing industries. In the continued effort to develop Industry 4.0 capabilities, many manufacturers have recognized the adoption of new technology trends to be necessary for their businesses [17].

1.2.1. Additive Manufacturing

Additive manufacturing is a set of emerging technologies that produce three-dimensional objects directly from digital models through an additive process by joining the products with proper polymers, ceramics, or metals [18]. With Industry 4.0, these additive-manufacturing methods will be widely used to produce small batches of customized products [16].

1.2.2. Augmented Reality

Augmented reality-based systems support a variety of services, such as selecting parts in a warehouse and sending repair instructions over mobile devices. With the development of Industry 4.0 companies will make much broader use of augmented reality to provide workers with real-time information to improve decision making and work procedures [16].

1.2.3. Autonomous Robots

Manufacturers have long used robots to tackle complex assignments, but these are evolving for even greater utility. They are becoming more autonomous, flexible, and cooperative. Eventually, they will interact with one another and work safely side by side with humans and learn from them. These robots will cost less and have a greater range of capabilities than those used in manufacturing today [16].

1.3. Cyber-Physical Production Systems

Cyber-physical systems (CPS) are considered to be the key concept of Industry 4.0 because they are an essential component of a smart factory [19][20][18][21][22]. CPS are even considered a synonym of Industry 4.0 by many authors [23][20][24]. CPS are systems of collaborating computational entities that are in intensive connection with the surrounding physical world and its ongoing processes (through sensors and actuators), providing and using, at the same time, data-accessing and data-processing services available on the internet [25]. In the context of industrial production, cyber-physical production systems (CPPS) consist of autonomous and cooperative elements and sub-systems that are getting into connection with each other in situation-dependent ways, on and across all levels of production, from processes through machines up to production and logistics networks [25]. CPPS will enable and support communication between humans, machines, and products alike. The elements of a CPPS can acquire and process data, and can self-control certain tasks and interact with humans via interfaces [25]. The introduction of a CPPS allows the implementation of smart factories, aiding in various decision-making processes by predicting the future based on past and present situations [26].

1.4. Smart Factory

In a smart factory, everything is connected. Production machines, humans, products, and IT tools communicate with each other aiming to improve the overall production, not only within the physical boundaries of the company but also beyond them [4]. Therefore, the realization of a smart factory, as a concept of a highly automated and intelligent factory, presupposes three types of integration: vertical, horizontal, and end-to-end [8]. Vertical integration refers to the integration of information between the various hierarchical subsystems of the company, e.g. operational level, production control, business-level management, and corporate-level planning, making production more flexible, reconfigurable and decentralized [20]. Horizontal integration refers to integration between a resource and an information network within the value chain, to achieve the seamless cooperation between enterprises and provide a real-time product and service [20]. End-to-end integration consists of the integration of the various phases of a product's life cycle, from the development to the analysis of data generated in the use phase and recycling, through the collection and processing of data related to each phase. This type of integration allows to improve quality, to reduce the time needed from the development of a new product to its placing on the market, and to identify the characteristics that create value for the customer [20]. Intelligent production systems must therefore have the following characteristics [5][27]:

- *Interoperability* - people, machines and cyber-physical production systems exchange information transparently through IIoT;
- *Ability to operate in real-time* - acquisition and processing of data (Big Data) instantly (through edge computing), allowing decision making in real-time;
- *Virtualization* - the procedural data collected by networks of intelligent sensors are applied to virtual models of the process (digital twins), contributing to the traceability and efficient monitoring of the entire process, even remotely;
- *Decentralization* - CPPS have the autonomy and the ability to negotiate tasks with other systems, decentralizing decision-making;
- *Modularization* - the implementation of modular systems contributes to production flexibility.

Although new techniques and technologies and their integration play an important role in the realization of smart factories, these are not the focus, they are a means to an end - to improve efficiency, competitiveness, productivity, and create new business opportunities.

2. Case Study

The case study here presented is a chemical factory in the commodities sector, and the present work focused on the assessment and promotion of its digital maturity through revamping proposals that aim to promote the basic principles of Industry 4.0 that were described above. The company processes oilseeds (soy grain and rapeseed) to produce ingredients for animal feed, liquid biofuel, and chemical products for industrial use.

3. Assessment of Industry 4.0 Readiness

The extension of the applicability of the basic principles previously described and that preside over the implementation of Industry 4.0 must be preceded by an assessment of the company's maturity stage. The concept of maturity models has been used by companies and organizations either as a tool for continuous improvement or as a means of self or third-party assessment [28]. The purpose of maturity models is to assess qualitatively or quantitatively the ability to achieve specific targets. It is one of the most used tools to assess the maturity of a company concerning Industry 4.0, allowing its positioning in the digital transformation process and the identification of the associated potential [29][30]. In this context, "maturity" refers to a state of development of the internal and external conditions of a company, which supports the concepts of Industry 4.0 [31]. This assessment provides companies with the basis for laying out a path towards the digital transformation, allowing them to identify and prioritize projects and opportunities that add value [30].

Though there is a growth in the research trend on Industry 4.0, there is also a research gap in the use of maturity models while implementing Industry 4.0. All the maturity models found in the literature were designed for the manufacturing sector. The three main parameters of these models, namely the evaluation criteria, dimensions, and items are different for different models, and there is also no standard model well accepted for every main industrial sector [29]. Therefore, in the context of the present work, a literature review was conducted to ascertain the key dimensions to assess the readiness for implementing Industry 4.0 from a holistic perspective.

3.1. Proposed Industry 4.0 Readiness Model

In order to fit the present case study, the proposed model aims for an adaptation of the existing ones. To this end, a literature review was conducted. Four models were chosen, and their similarities analysed (Table 1). It is possible to identify a common structure that allows an effective approach to the fundamental concepts for the development of Industry 4.0. In these models, digital maturity is evaluated from 6 to 9 dimensions, classified according to 4 to 6 maturity levels and the numerical results are conveniently represented in Kiviat diagrams. In the proposed model, which consists of an adaptation of the above-analysed models, digital maturity is measured according to 5 dimensions and 6 sub-dimensions (see Figure 1). Its 5 dimensions were defined as follows:

Strategy and Culture – Assesses the state of implementation and operationalization of a strategy for Industry 4.0, as well as how the technology management within the company is made;

Production Automation – This dimension evaluates the level of integration and digital automation of the production process, through the acquisition and analysis of data and the current architecture of IT systems;

Integration of Systems – Assesses the level of vertical integration of the company as well as the horizontal integration within the company's value chain. The associated technical requirements are also evaluated,

Figure 1 - Dimensions and sub-dimensions of the proposed Industry 4.0 maturity model.

Table 1 – Reviewed Industry 4.0 maturity models.

IMPULS - *Industrie 4.0 Readiness* [32]	*Industry 4.0 Maturity Model* [31]	*Industry 4.0 / Digital Operations Self-Assessment* [33]	*Maturity and Readiness Model for Industry 4.0 Strategy* [18]
Strategy and Organization	Strategy	Organization and Culture	Strategy and Organization
	Culture		
	Leadership		
Smart Products	Products	Business Models, Product and Service Portfolio	Smart Products and Services
Employees	People	IT Architecture	Smart Business Process
Smart Factory	Customers	Compliance, Legal, Risk, Security and Tax	
Data-Driven Services	Governance	Market and Customer Access	
Smart Operations	Operations	Value Chains and Processes	

namely the cloud and data utilization, and the security of data and communications;

Data Analysis – Evaluates if the collected data is analysed through the application of data mining and machine learning algorithms.

Human Resources – Assesses the existence of the necessary qualifications for the implementation and development of the Industry 4.0-related technologies (namely IT, automation and data analysis).

The digital maturity was classified according to 6 maturity levels (ranging from 0 to 5), depending on the fulfilment of the established criteria, considered to be the minimum requirements for each level. The criteria were defined based on the models "IMPULS - Industrie 4.0 Readiness" and "Maturity and Readiness Model for Industry 4.0 Strategy".

3.2. Methodology

Measuring, determining, and representing the company's maturity followed a three-step procedure. The maturity was measured through a survey conducted on 11 employees from different departments of the company under study. Eight of the 21 questions on the questionnaire require quantitative answers, i.e., respondents were asked to answer using a Likert scale from 0 to 5. Since the answers to the remaining 17 questions are conditional, the results were treated so that each answer match a quantitative value from 0 to 5, where "0" corresponds to the least favourable case and "5" to the ideal situation within the scope of what the question intends to explore. The maturity of each dimension is the arithmetic mean of the scores of the corresponding questions. The level of maturity obtained in a questionnaire consists of weighting the maturities of the 5 dimensions. The company's final maturity level is the arithmetic average of the maturities obtained in all questionnaires. The weighting factors were adapted from the "IMPULS – Industrie 4.0 Readiness" model (Table 2).

Table 2 – Ponderation of different dimensions.

Dimension	Weighting Factors
Strategy and Culture	28,8%
Production Automation	17,8%
System Integration	13,8%
Data Analysis	17,8%
Human Resources	21,8%

3.3. Results and Conclusions

The Kiviat diagram in Figure 2 shows the main results obtained by the maturity model applied to the case study. The "Perception" series comprises the results of all questionnaires and were used to determine the perceived maturity. The "Responses of the speciality", on the other hand, are a subset of these results and correspond to the answers given by the respondents with greater knowledge in each of the five areas. This approach aimed to determine more accurately the company's maturity level, assumed to be the real level. The perceived maturity level was 1.7, whereas the "real" maturity level was 1.1. According to the global maturity levels obtained, and considering the requirements of each proposed level in the model in question, the company was positioned at level 1. The discrepancy between the perceived maturity levels and the "real" maturity levels, for each dimension, suggests the degree of understanding of the process (as a whole) that the respondents have. It is possible to verify a perception that there is no strategy, as detailed planning in the medium and long term, to achieve well-defined objectives in terms of Industry 4.0. After characterizing digital maturity, the definition of this strategy should be the first point of intervention. Production Automation is the dimension with the highest level of "real" maturity and is the only dimension in which the two sets (perception and responses of the speciality) overlap. The integration of information between departments was considered reasonable, while the level of information integration

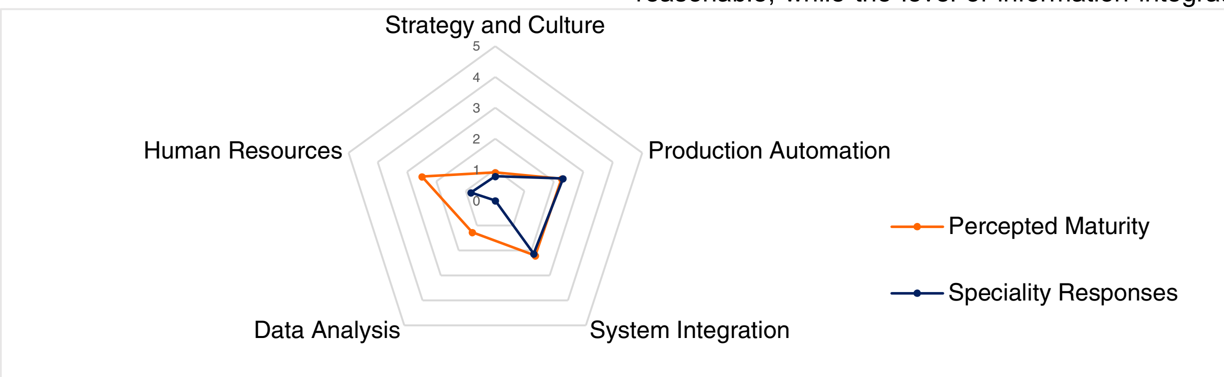

Figure 2 – Main results of the applied maturity model.

with companies in the value chain is considered to be very small, or approximately null. Data Analysis emerges as the dimension with the lowest "real" maturity since no type of data analysis is currently carried out to apply specific mathematical techniques.

The number of respondents was limited by the time available to assess the company's digital maturity. A more accurate evaluation of the company's digital maturity using this method would involve extending the questionnaire to a larger number of respondents. Even so, given that there was a reasonable level of agreement between the responses of the various respondents in most dimensions, it is considered that the sample (12%) would have been representative.

4. Examples of Critical Points

The collection of process data is a fundamental prerequisite to unlock the potential of Industry 4.0 [32]. Taking into account the digital maturity of the company under study, the first step will be to guarantee the collection and visualization of procedural data necessary for traceability, control, and quality of operations [11]. In the following points, revamping proposals are presented, for identified critical points which currently constitute barriers to the referred traceability and control of the production processes of vegetable oils and soybean and rapeseed meal in the chemical industry under study.

4.1. Oilseed Cleaning Process

The oilseed cleaning process is the first step in the production of vegetable oils. In a combi cleaner sieve (see Figure 3), the oilseeds are separated from the entrained impurities, which are mostly hulls, skins, and pods. The coarse impurities are separated through sieving in perforated plates and the fine ones through the sieve's aspiration system.

Figure 3 - Operation of a combi cleaner sieve.

Currently, the sieve operation cannot be monitored or optimized remotely in an automated way, despite the importance that its operation has for the smooth functioning of the entire downstream process. On the one hand, the entrainment of impurities in a stream of clean oilseeds contributes to a reduction in the oil extraction yield (with solvent), since it causes a decrease in the porosity of the cake in the extractor (disfavouring solvent permeation). On the other hand, the amount of oilseed that is dragged with the impurities corresponds to a direct loss of yield from the extraction process and corresponds to a significant economic loss, since the oil not extracted is sold at the price (per ton) of meal. Figure 4 shows the amount of oilseeds dragged by the impurities stream. The mass percentage of impurities and oilseeds was determined by sieving in 57 samples (collected in 57 shifts), 27 of soybeans, and 30 of rapeseed, from the inlet and outlet streams of the cleaning process.

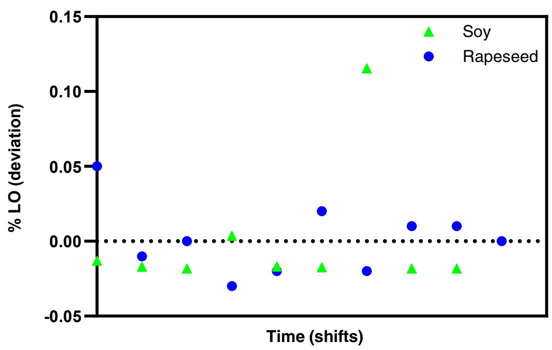

Figure 4- Mass percentage of loss of oilseeds (LO) to the stream of separated impurities. Deviation from the average.

4.1.1.Proposed Revamping

A reconditioning to this process should focus on automatic and real-time control and monitoring of the critical variables of the cleaning process. These are (i) the amount of impurities in the input stream, to be able to monitor the efficiency of the process, (ii) the amount of impurities in the clean oilseed stream, and (iii) the amount of oilseed in the impurities' stream. Through the automatic acquisition of this data, it is possible to increase the traceability of the cleaning process. The monitoring of the referred variables implies the distinction and quantification of particles of a process stream of oilseeds and impurities, in a representative way. In turn, the distinction of particles requires their classification according to distinctive characteristics. In this case, the processed oilseeds (both soybeans and rapeseed seeds) have a range of characteristic sizes, as well as high sphericity, therefore it is through these two particularities that they will be differentiated from the particles of impurities, which are mostly husks, skins, and pods, with more irregular geometries. Thus, the reconditioning of the oilseed cleaning process will require the implementation of particle analysis technologies in the current process. Besides, the automatic acquisition of data for purposes of control, optimization, and traceability of the process imply that the analysis is done inline or online.

For this purpose, the implementation of an online dynamic image analysis (DIA) system was proposed. DIA operates in a similar way to a modern microscope: a digital camera with special optics captures the particles within the frame. Physical information about particle properties is transmitted to a computer. For every single particle in the image size and shape descriptors are determined by evaluation software [34]. The result of DIA is the numerical distribution of one or more morphological parameters of the analysed particles. The monitoring of the oilseed cleaning process and the acquisition of data related to the variables involved, in an automated way, also requires the integration of the DIA system in the company's supervision and data acquisition system (SCADA). The data collected by the analyser can, therefore, be processed on the server by image analysis software and the results transmitted, through an appropriate communication protocol, to a programmable logic controller (PLC). The latter, after comparing the controlled variables with the set-point values, returns, if necessary, commands for handling the airflow rates and airspeed in the sieve aspiration systems. Simultaneously, the data resulting from the image analysis can be stored in the company's database for analysis and optimization purposes. The characterization of streams in the cleaning process can also contribute to the optimization of operating conditions in downstream equipment, through the correlation of process variables.

4.1.2. Economic Analysis

Different suppliers were consulted to obtain technical proposals and their estimates. Results showed in Figure 4 were used to estimate the economic losses associated with the dragging of oilseeds by impurities, based on the difference of economic values of meals and vegetable oils produced. Thus, an investment profitability analysis was carried out based on cash flows. The main indicators of economic profitability for 8 years were inferred: net updated value (NPV); internal rate of return (IRR) and; payback period (PP).

Table 3 - Summary of the DIA investment profitability analysis.

Rubric	Supplier A
Profitability Indicators	
NPV	- 163.057 €
IRR	- 23 %
PP	>8 years

Table 3 presents a summary of the profitability analysis, from which it is possible to verify that the net updated value is negative after 8 years and, consequently, the payback period is greater than 8 years. Based on the results for these indicators, the project is not profitable, although its contribution to greater control and traceability of the entire process.

4.2. Quality Control of Soybean and Rapeseed Meal

Currently, in the industry understudy, a significant amount of process data is still collected and processed manually or semi-automatically. One essential data set for the traceability and optimization of the process, as well as for the control of the final quality, is the analytical composition of the produced meal: the content of water, protein, fibre, and residual oil. These variables are very important: on one hand, because they measure the quality of the final product and, therefore, its monitoring contributes to production within specifications; on the other hand, they are fundamental to establish correlations between procedural variables. These correlations are relevant for understanding the dynamics of the oilseed preparation and vegetable oil production processes so that later on, these variables can be optimized in an efficient and automated way. Currently, offline analysis of the produced meal, through NIR spectroscopy, and manual processing of data greatly limit the control and optimization of the process. Figure 5 shows the water content of soy and rapeseed meals that are currently produced. These values were obtained by offline NIR analysis of samples collected hourly, between 01/01/2019 and 01/15/2019. The significant variability of the water content of soybean and rapeseed cake suggests that there is a significant margin to increase the water and fibre content of the cake produced and reduce the dispersion of values around a set point.

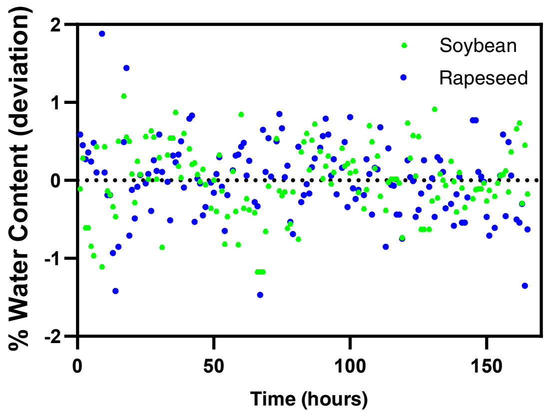

Figure 5 – The water content of soy and rapeseed meals currently produced. Mass percentage. Deviation from the mean value.

4.2.1. Proposed Revamping

The implementation of an inline NIR spectrophotometer was proposed. The transposition of the current monitoring method (offline) to inline quality control in real-time will allow, in the first place, to automate the rectification of meal parameters, through the implementation of a control loop. It is intended that the inline control of the parameters will contribute to the production of meal with more constant water content and to minimize the risk of producing meal outside specifications. In this way, greater control over the production process and consequently greater quality of the final product is possible. Secondly, the implementation of inline analysis allows the automatic collection and processing of process data, contributing to the increase in the traceability of operations so that later, data analysis can be applied efficiently, aiming to achieve a more intelligent, autonomous, and efficient production. The principle of inline NIR analysis is fundamentally the same as that of offline NIR analysis (outside the production line, on a benchtop spectrophotometer). In the first, the product in motion is analysed inside the production line by a spectrophotometer installed outside the transport system. In the proposed control loop, water and fibre contents are controlled variables while the manipulated variables are the flows of water and impurities (mostly hulls, skins, and pods separated in the cleaning process which have high fibre content) that are introduced upstream.

4.2.2. Economic Analysis

Different suppliers were consulted to obtain technical proposals and respective quotes for NIR spectrophotometers. Economic profitability is, in this case, related to the sale of meal with the highest possible water and fibre content, within the limits of the product's sales specifications. An investment profitability analysis was carried out based on cash flows. The main indicators of economic profitability (for 8 years) were inferred: NPV, IRR, and PP. The profitability analysis of the investment showed that increasing the setpoint by 0.2 percentage points for soybeans and 0.3 percentage points for rapeseed, an average NPV of 561.209 €, an average IRR of 160% and an average PRI of seven months was obtained. These are good indicators of profitability, taking into account the associated investment risk.

4.3. Predictive Maintenance

Although it is not a new concept, predictive maintenance was fostered by the emergence of technologies such as CPS, IIoT, big data, and data analysis, which allowed its optimized application in modern production systems [35][17][36]. Predictive maintenance is a strategy that can be disintegrated into two sub-categories: statistical predictive maintenance, in which the information generated about breakdowns is used to develop statistical models that aim to predict new failures and thus develop preventive maintenance strategies; and in conditioned predictive maintenance, in which maintenance activities are scheduled only when symptoms of failure are detected [35]. The main advantage of this methodology is the increase in equipment uptime and remaining useful life, which leads to an increase in process productivity. Also, the ability to allocate maintenance periods in a planned and organized manner allows for more efficient management of inventory parts [37]. Compared to corrective and preventive strategies, predictive maintenance, currently the most used in modern industries, ensures the maximum interval between maintenance tasks and thus minimizes the number and cost of unplanned stops that affect productivity, product quality, and efficiency of the overall production process [35]. In the case study, it was verified, in a collaborative way with the maintenance team, which equipment was considered critical for production and which maintenance strategy is currently used: an industrial gearbox responsible for the rotation of the central axis of a desolventizer toaster and dryer to which the maintenance carried out based on a conditioned preventive strategy. Periodic inspections are made by a third party, in which measurements of the equipment's vibrations are made, as well as visual inspections. These inspections result in reports of vibration analysis, in which the assessment of vibratory severity is carried out according to ISO 10816–1: 1995. Given the capital cost of the gear unit and its maintenance and the criticality of this equipment for the plant's operation, it is justifiable to explore the implementation of a strategy of continuous predictive maintenance that mitigates the risk of unexpected breakdowns. The consequent unscheduled stops, already experienced in the past, result in very damaging economic losses for the companies.

4.3.1. Proposed Revamping

The proposed revamping consisted of implementing a condition-based predictive maintenance strategy in the industrial gearbox above mentioned.

The proposed predictive maintenance system comprises: (i) the collection of vibrational data from the machine to be monitored, through the permanent installation of vibration sensors in adequate locations (see Figure 6);

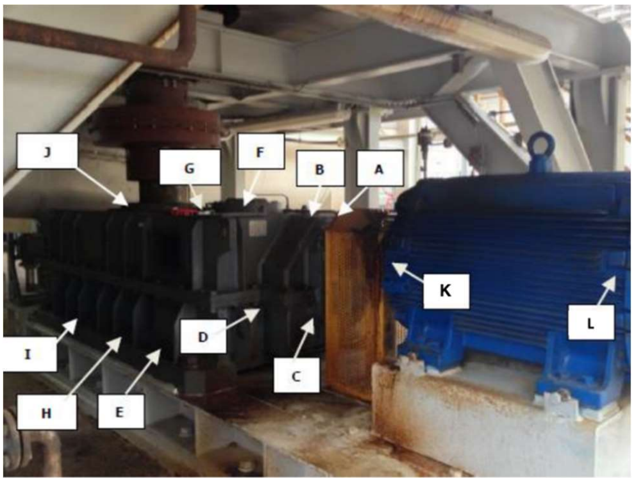

Figure 6 – Proposed vibration monitoring locations.

(ii) the integration of the data collected in the company's SCADA system; (iii) data storage and data analysis software and; (iv) the visualization of information about the condition of the equipment in real-time to support the maintenance activities of the machine.

4.3.2. Economic Analysis

Different suppliers were consulted to obtain technical proposals and respective estimates for the installation of a predictive maintenance system. The investment's profitability was estimated based on (i) the costs of the inspections that are part of the current strategy of conditional preventive maintenance; (ii) possible economic losses resulting from an unscheduled stop for some time sufficient to repair the gearbox and; (iii) the cost of repairing the gearbox. The profits will vary according to the occurrence, or not, of a malfunction during the time considered for the project (8 years) and according to the repair cost that the malfunction entails. The profitability corresponding to the non-occurrence of a malfunction corresponds only to the cost of periodic inspections of the gearbox. The profitability analysis showed that the investment is profitable only if it allows, at a minimum, to mitigate the probability of an unscheduled stop, a scenario for which an average NPV of 113,976 €, an average IRR of 1124% and an average PRI of one month were obtained, being very positive profitability indicators.

5. Conclusions

This work aimed to evaluate the digital maturity of a case study, to identify the main measures necessary for a transition to Industry 4.0. According to the proposed maturity model, it was possible to infer that the industry understudy has an estimated digital maturity level of 1 (from 0 to 5). The results allowed to conclude that the lack of a strategy for the implementation of Industry 4.0, as well as the current lack of qualifications to deal with its implementation, are critical points for the development of the company's digital maturity. It was also concluded that collection and analysis of data are aspects that currently lack development, considering the significant amount of data that is collected and processed manually and do not undergo any type of analysis. To promote the digital maturity of the case study, three reconditions were proposed in examples of current critical points. The economic analysis of the investments allowed to conclude that the implementation of an inline NIR spectrophotometer was the only proposal that resulted in a profitable investment for the company. The implementation of a conditioned predictive maintenance strategy to an industrial gearbox presented conditioned profitability.

6. Future Work

Taking into account the results and conclusions that the present work allowed to draw, some measures of future action are proposed. First, it is proposed to formulate a strategy (and a set of KPIs) for the transition to Industry 4.0, which must be supported by the existence of the necessary qualifications for its implementation. The future collection and automatic processing of all data fundamental to the characterization of the company's operations must also be guaranteed. In this sense, the importance of installing a process scale is highlighted, namely at the beginning of the production line, to allow greater traceability and control of all downstream processes. This equipment will also allow to improve the performance of a control loop for the automation of the rectification of the parameters of the soy and rapeseed meals.

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