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Autonomous Cycles of Data Analysis Tasks for the Automation of the Production Chain of MSMEs for the Agroindustrial Sector

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Abstract: In this paper, we propose autonomous cycles of data analysis tasks for the automation of the production chains aimed to improve the productivity of Micro, Small and Medium Enterprises (MSMEs) in the context of agroindustry. In the autonomous cycles of data analysis tasks, each task interacts with the others and has different functions, in order to reach the goal of the cycle. In this article, we identify three industrial-automation processes within the production chain, in which autonomous cycles can be applied. The first cycle is responsible to identify the type of input to be transformed—such as quantity, quality, time, and cost—based on information from the organization and its context. The second cycle selects the technological level used in the raw-material transformation, characterizing the platform of plant processing. The last cycle identifies the level of specialization of the generated product, such as the quality and value of the product. Finally, we apply the first autonomous cycle to define the type of input to be transformed in a coffee factory.

Keywords: production-chain; agroindustry; autonomous computing; artificial intelligence; data analysis; machine learning

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1. Introduction

One of the great current challenges of Micro, Small and Medium Enterprises (MSMEs) is to dynamically innovate to improve their supply of goods, products, and services in order to respond to the changing needs of the market [1,2]. In particular, several studies have concluded that investment in innovation has a high impact on the competitiveness of organizations, which can lead to the introduction of new products and processes. Thus, innovation is a means for companies to adapt to remain in the market, considering available resources.

Given the importance of innovation in MSMEs, and the opportunities that currently exist to exploit data from organizations and their contexts, data strategies can be defined to build models that guide the automation process in an organization. One of these strategies is the use of autonomous data analysis task cycles (ACODATS) defined in previous works [3] that allow the generation of knowledge models using different data sources for automation management. An ACODAT is composed of a set of data analysis tasks to achieve a given objective, such that each task has a specific role [4–8]: some observe the system, others analyze it, and finally, others make decisions to improve it. Thus, in ACODAT, there are interactions between the data analysis tasks in order to achieve the automation objective for which it was defined.

This paper proposes three ACODATs for the automation of the production chain of MSMEs for the agroindustrial sector to improve their competitiveness. These ACODATs allow automating the main subprocesses that have previously been determined as vital to enable the self-management of industrial automation of MSMEs in the agroindustrial sector to improve their competitiveness. The first ACODAT determines the type of input to be transformed in the agroindustrial productive chain using information from the organization and the context, the next ACODAT specifies the technological level required in the transformation process of the agroindustrial productive chain, and the last ACODAT establishes the level of production specialization. This paper also includes a detailed specification of the first autonomous cycle, which goal is the definition of the type of input to be transformed, in the context of the coffee factories. For the specification of the ACODATs, the MIDANO methodology [4] was used, which allows the development of data analysis applications and, in particular, the development of ACODATs. The main contributions of this work are the following:

- The specification of three ACODATs to manage agroindustrial automation to improve the productive chains. These three ACODATs automate the most relevant subprocesses to enable self-management of industrial automation for MSMEs in the agroindustrial sector.
- A multidimensional data model to manage industrial automation, which stores the necessary information of an organization and its context.
- A detailed description of the ACODAT to define the type of input to be transformed in a coffee factory.

In the review of the existing literature (see Section 2), it is confirmed that the great gap is that industrial automation processes have not been developed for the MSME sector based on integrated data analysis tasks, but rather isolated tasks have been developed, some using artificial intelligence techniques, to solve specific problems. The great novelty that this article proposes is that defines autonomous cycles of data analysis tasks, which integrate these tasks with the objective of allowing industrial automation of the production chain in MSMEs.

The organization of the work is the following: related work is introduced in Section 2. Afterward, in Section 3, the theoretical framework of this work is introduced. In Section 4, the identification of the agroindustrial processes of the production chains is described. After, in Section 5, the definition of the ACODATs is carried out. Section 6 presents the Multi-Dimensional Data Model for the autonomous cycles and in Section 7, the instantiation of the ACODAT to define the type of input to be transformed for the case of "Café Galavis" company is described. Section 8 presents a comparison with previous works. Finally, in Section 9, conclusions and future work directions are presented.

2. Related Work

In this section, we present the main recent works related to this paper's approach, which are the definition of schemes for the automation of agroindustrial production chains and the use of data analysis tasks in the automation of agroindustrial processes.

The concept of agroindustry refers to the establishment of links between companies and supply chains to develop, transform and distribute specific inputs and products in the agricultural sector. As an example, according to [9], in the raw sugar-cane cubes (in Spanish, panela) production chain, the following activities are intertwined: (i) agricultural production, (ii) transformation, (iii) intermediate and final commercialization; and (iv) consumption. These tasks are carried out by different production systems that are in different sectors of the economy: agriculture, manufacturing, and services. As another example, the structure of the coffee agroindustrial sector comprises five activities: (i) agricultural production, (ii) processing, (iii) roasting, (iv) marketing, and (v) export [9].

According to [10], a production chain is a relationship between companies to connect the stages of supplying inputs, manufacturing, distribution, and marketing of a specific good, where the different links make agreements that condition and subordinate their technical and productive processes. This relationship seeks to become competitive at the national and international level, by strengthening the value chain in organizations and increasing the added value of their products. Finally, in general, according to [11], a production scheme includes the following links: (i) producers of raw materials, (ii) transporters, (iii) collectors, (iv) industrial processors, (v) distributors, and (vi) final consumers.

On the other hand, in some agroindustrial sectors, smallholders have applied Machine Learning (ML) techniques for land classification to analyze climate change and monitor ecosystem service. Also, there is a work about the processing of satellite images using artificial intelligence methods (specifically, using a convolutional neural network and a genetic algorithm) to convert the images into useful data for decision making, precision agriculture and agribusiness [12]. Another example is the utilization of ML methods to estimate land-cover change [6]. Recently, computational-learning algorithms—such as Support Vector Machine (SVM) and Random Forest (RF)—have been used for automatic land classification with overall accuracy results of 86.5% [6] and 95.10%, respectively [13].

According to [14], technologies such as smart agents, Big Data, Internet of Things (IoT), Cloud Computing (CC), ML, and data mining aim to implement data and information exchange along a supply chain [15,16]. In the sugar sector, a case study using a connection-block algorithm and a multirelational data mining approach in a database of this agroindustrial sector was analyzed in [17].

In [18], the authors present an intelligent monitoring application for Industry 4.0, for a factory that operates in the agroindustrial sector. The authors present a consumption management system based on the widespread installation of sensors in production lines and the design of software to access the data [18]. On the other hand, the use of industrial robots in food manufacturing remains a challenge. Despite the significant reduction in production costs in the last decades, its adoption in food processing has been slow [19]. Finally, in [20], ML algorithms (SVM, Boosted Trees and Naïve Bayes) have been applied to predict the severity of worker injuries in industrial processes; in addition to the nature and cause thereof, with an accuracy of 92–98% [20].

Borghesan et al. [21] provide an analysis of process and energy industries, considering the different mechanical, sensing, situational awareness, and decision-making tasks involved in the operation of plants. Then, they map these tasks to possible autonomous systems, and as part of autonomous system capabilities, they make a connection to the adaptation of model-based solutions. Finally, they argue that reaching higher and wider levels of autonomy requires a rethink of the design processes for both the physical plants as well as the way automation, control, and safety solutions are conceptualized. The paper [22] analyzes the effect of smart manufacturing systems on procurement processes by distinguishing between procurement tasks that will likely stay in human hands and those that will be taken over by intelligent systems. In addition, the paper presents an operational, fully automated, and manufacturing-related procurement system. For this, they begin by looking at the manufacturing-related procurement types in the era of Industry 4.0 that may be performed by machines, followed by the discussion of innovation-based procurement practices that will require human input.

All previous works focused on the use of artificial intelligence techniques in specific tasks (e.g., soil, climate, environment, and humidity monitoring); however, this analysis is not applied to the agroindustrial MSME sector. Likewise, they did not integrate into autonomic cycles of data analysis tasks for the industrial automation of the production chain. To overcome the restrictions found in previous works, this article focuses on the definition of autonomic cycles for optimal decision making on industrial automation of production chains of agroindustrial MSMEs to improve their competitiveness.

3. Background

This section presents the theoretical basis related to the field of ACODAT, which consists of a set of data analysis tasks that act together to achieve an objective in the process they supervise. The tasks interact with each other and have different roles in the cycle. Also, this section presents the methodology for the specification of data analytics tasks

(MIDANO), which is designed for the development of ACODAT for the processes of any institution/company.

3.1. ACODAT

The main goal of ACODAT is to view business problems from a data perspective [4]. The set of data analysis tasks must be performed simultaneously for the purpose of achieving a goal in the monitored process. This set of tasks is related to each other, and each task has a different role in the cycle (see Figure 1): (i) to observe the process, (ii) to analyze and interpret what happens in it, and (iii) to make decisions about the process, which allow achieving the objective for which the cycle was designed. This insertion of tasks in a closed cycle, allows complex problems to be solved. The functions of each task are described below [3,4].

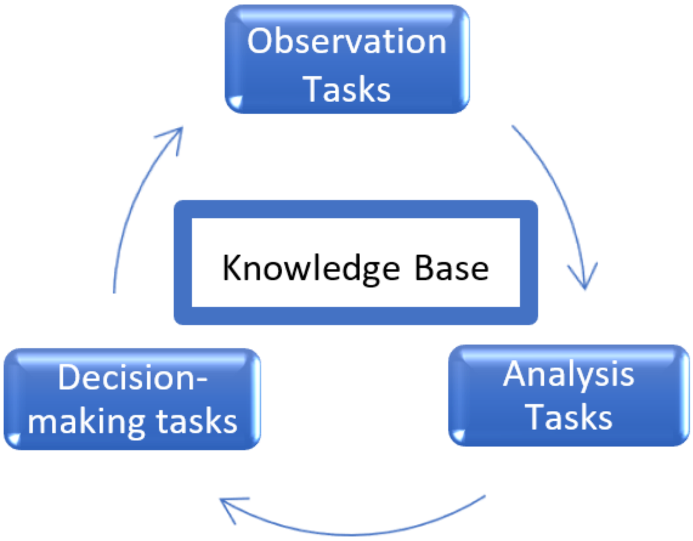

Figure 1. ACODAT task.

Observation Tasks: They correspond to tasks that monitor the process under analysis. They capture data and information that describe the behavior of the environment, and eventually, they are also responsible for their generation.

Analysis Tasks: These are a set of tasks whose purpose is to interpret, understand and diagnose, from the data, what may be happening in the context monitored by the cycle. This means that these tasks build knowledge models about the dynamics observed by the cycle.

Decision-making Tasks: This set of tasks is in charge of implementing the tasks for decision making, leading to the improvement of the process where the cycle is applied. These tasks modify the dynamics of the process to improve it, and their effects are again evaluated in the observation and analysis stages of the cycle, restarting a new one.

Observation tasks monitor and collect data and information about the monitored system or environment. This collected information is interpreted by the analysis tasks, to understand what may be happening in the system. Finally, according to the analysis carried out before, the decision-making tasks determine the activities to improve the system. Observation tasks monitor and collect data and information about the monitored system or environment. This collected information is interpreted by the analysis tasks to understand what may be happening in the system. Finally, according to the analysis carried out before, the decision-making tasks determine the activities to improve the system. It is a closed loop, where the supervision process is permanently carried out on the system under study.

ACODAT was suggested in [3], is based on concepts put forward by IBM in 2001 [23,24] and has been implemented in areas such as smart classrooms [25], telecommunications [26], Industry 4.0 [7], and smart cities [4]. ACODAT is based on the paradigm of autonomic computing [8,27,28], with the purpose of providing autonomic features to systems using smart control cycles. In general, an ACODAT requires:

- A multidimensional data model to store the data collected to characterize the behavior of the context, which will be used by the different data analysis tasks.
- A platform to integrate the technological tools required by the data analysis tasks.

The ACODAT concept has been successfully used in different fields, but it has not been applied to the processes of the agroindustrial MSME production chain. This will enable MSMEs to have autonomous management of their production processes.

3.2. MIDANO

MIDANO is a methodology for the development of applications based on data analysis for any organization [4], which is composed of three phases:

Phase 1. Identification of data sources for the extraction of knowledge about the organization: This phase performs knowledge engineering about the organizations, particularly its processes and its experts. This information is useful to define the objective of the application of data analysis in the organization. Likewise, the autonomous cycles with their data analysis tasks are designed.

Phase 2. Data preparation and processing: This phase prepares the data to be able to apply data analysis tasks to the problem under study. To do this, operations are performed on the data, such as extraction and transformation of each of the variables associated with the problem. In particular, a feature engineering process is carried out that analyzes the variables to define the variables of interest and prepare them (for example, cleaning, transforming, and reducing them). Finally, in this phase, the multidimensional data model of the autonomous cycles is designed, which is the structure of the data warehouse.

Phase 3. Development of data analytics tasks: In this phase, the data analysis tasks of the autonomous cycle are implemented. Each of them generates a knowledge model (for example, predictive, descriptive, or diagnostic models) required by the cycle. Subsequently, these tasks are integrated to form the autonomous cycle. This phase can use existing data mining methodologies for the development and validation of data analysis tasks.

4. Definition of Autonomous Cycles for the Agroindustrial Sector

This section analyzes the agroindustrial production chain of MSMEs, using the MIDANO methodology, to define the processes in which the autonomous cycles will operate to improve their competitiveness. The tables used in this section are defined by MIDANO.

4.1. Application of MIDANO to the Agroindustrial Production Chain of MSMEs

Table 1 summarizes the use of the MIDANO to analyze the agroindustrial production chain of MSMEs.

Table 1. Use of MIDANO phases for Industrial Automation Processes.

Phase	Use
Phase 1	Analysis of the production chain in the agroindustrial to improve their competitiveness. To this end, this research proposes ACODAT to improve industrial production.
Phase 2	Identification of data sources (e.g., quantity, quality, time, and cost).
Phase 3	Implementation of autonomic cycles for the automation of the production chains in agroindustry.

4.2. Agroindustrial Production Chain of MSMEs

Based on an analysis of agribusiness, it is possible to establish the macro conditions under which the production chains operate. In general, there is a wide range of activities and, therefore, actors that are part of a chain. It is, therefore, necessary to clearly establish the limits of the production chain and define its operating structure by establishing a model. The work [29] proposes a production chain model (see Figure 2), the basis of our proposal.

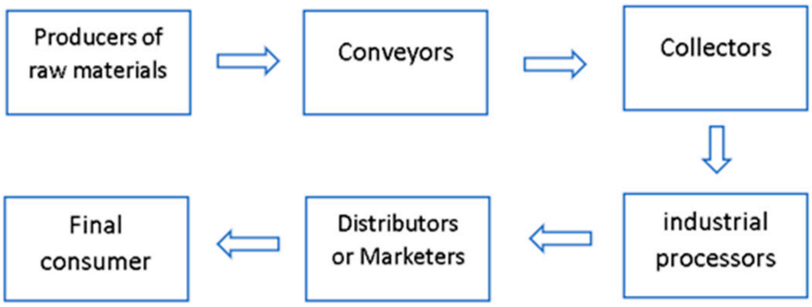

Figure 2. Production chain links (source: United Nations Industrial Development Organization).

In this context, Nonaka [30] has defined a scheme of the production chain and its main actors (see Figure 3).

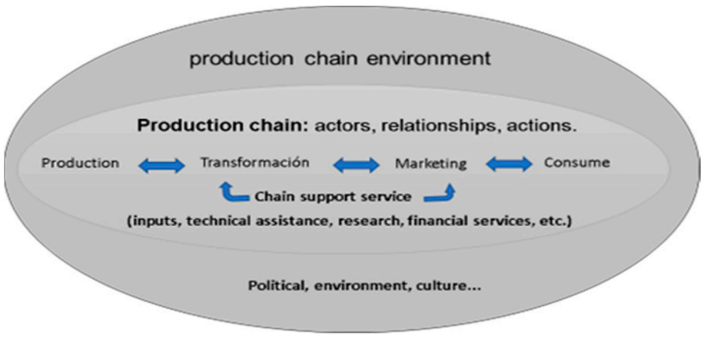

Figure 3. The production chain and its actors (source [30]).

As a starting point from such a model, it is necessary to understand the framework of production chains and establish how they are conceived, what their constituent elements are, and what characteristics they should have. The steps to follow to properly model a production chain are summarized below [31,32].

- Establish the links in the production chain (defined by the blue arrows in Figure 3).
- Determine the segments that make up each of the links in the production chain by using segmentation instruments and their corresponding variables.
- Represent the material and capital flows that take place in the chain.
- Establish the institutional and organizational environment of the chain.

The above activities must be accompanied by a validation by the chain actors. For the construction of the proposal, 15 experts from the MSME agribusiness sector validated each of the links in the production chain. Figure 4 shows our proposal of an Agroindustrial Production Chain for MSMEs.

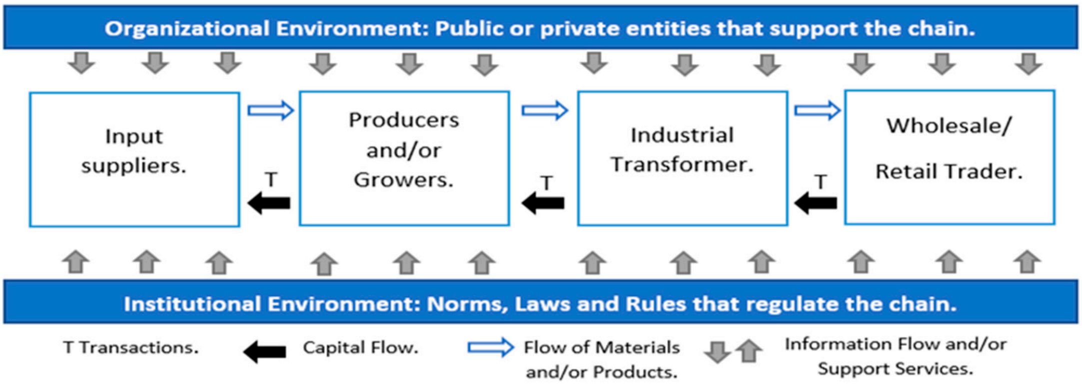

Figure 4. Our Proposal of an Agroindustrial Production Chain for MSMEs.

Our proposal has four processes (see Table 2): Input Suppliers, Producers and/or Growers, Industrial Transformer and Marketing.

Table 2. Processes in our agroindustrial production chain.

Process	Examples
Suppliers of Input Materials	Irrigation systems, organic and inorganic fertilizers, certified seeds.
Producers and/or Growers	Land tenure, area, labor force, technological level, degree of specialization, market share, working capital, forestry support services, agricultural support activities, post-harvest activities, seed processing.
Industrial Transformer	Size of the property, labor force, type of input to be processed, quality parameters, technological level, the added value of the product, market scope and coverage, level of specialization of the business.
Wholesaler/Retailer	Stockpiling and Distribution. Storage, Classification, Standardization, Packaging and Transportation.

In what follows, each process is described [9,17,29,33,34]:

- **Input Suppliers:** the entities that provide or supply certain products or services to companies for their use, for example, agrochemicals and packaging.
- **Producers and/or Growers:** this process is in charge of the harvest and post-harvest preparation. It must consider, among other things, the workmanship, the forestry support services and post-harvest activities.
- **Industrial Transformer:** this process transforms or adapts the inputs for the materialization of the intended products or services. It must consider, among other things, The type of input to be transformed, the technology required for the transformation, etc.
- **Wholesaler/Retailer Commercialization:** this process is the distribution of products or services to the market. It must consider, among other things, stockpiling and marketing.

Each process of the Agroindustrial Production Chain of MSMEs has different subprocesses, which should be prioritized according to whether data analysis tasks can be used and what its relevance is to improve the competitiveness of an MSME in the agroindustrial sector. We identify 15 subprocesses, listed in Table 3.

Table 3. Subprocesses in the Agroindustrial Production Chain of MSMEs.

Process	Subprocess	ACRONYM
Input suppliers	Certified seeds	SCS
	Organic and inorganic fertilizers	AOEI
	Primary, secondary and tertiary packaging	EPST
	Applications of agrochemicals in particular and fertilizers.	AAPF
Producers and/or growers	Workmanship	MOEP
	Forestry support services	SAAF
	Post-harvest activities	APAC
	Technological level	NTAP
Industrial transformer	Type of input to be processed	TIAT
	Transformer technology level	NTAT
	Market reach and coverage.	ACDM
	Level of business specialization.	NEDN
Wholesaler/retailer commercialization	Stockpiling	ACOP
	Leveling	NIVE
	Distribution	DIST

4.3. Prioritization of Subprocesses of the Agroindustrial Production Chain of MSMEs

A prioritization table has been used to select the subprocesses. The criteria to evaluate the relevance of the subprocesses were defined according to the importance of each subprocess in the MSME Agroindustrial Production Chain, and the possibility of performing data analysis tasks. Thus, these values determine the level of importance of each subprocess (see Table 4).

Table 4. Evaluation metrics.

Meaning	Weight
Subprocess is not important	1
Subprocess is slightly important	2
Subprocess is important	3
Subprocess is very important	4

For the construction of the prioritization table, 15 experts in the MSME Agroindustrial sector, and 10 research professors rated each of the criteria. In the result, each of the answers provided by them was averaged. The results are shown in Table 5, where the columns with the numbers in red represent the subprocesses with the highest priority (they represent the highest scores), for which the ACODATs are proposed in this work.

Table 5. Prioritized subprocesses by experts.

Weight	Evaluation Criteria	Processes														
		Input Suppliers				Producers and/or Growers				Industrial Transformer				Wholesaler/Retailer		
		SCS	AOEI	EPST	AAPF	MOEP	SAAF	APAC	NTAP	TIAT	NTAT	ACDM	NEDN	ACOP	NIVE	DIST
Relevance to Production Management																
4	the factors that intervene in the process are characterized.	4	3	2	4	3	3	4	4	4	4	4	4	3	3	4
4	the uses and functions of the materials and tools used are distinguished	3	4	3	4	2	2	4	4	4	4	4	3	2	3	3
4	information and knowledge management is identified	2	3	3	4	2	3	3	4	4	4	4	4	2	3	4
4	Production, service and support processes are identified.	2	4	3	4	3	4	4	4	4	4	4	3	2	3	4
4	Environmental responsibility, good use and conservation of biodiversity.	3	4	4	4	2	4	4	3	4	4	4	4	2	3	3
4	Machinery capacity	2	3	4	4	2	3	3	3	4	4	3	4	3	3	2
4	Accessibility to technology.	3	3	4	2	2	3	3	4	4	4	4	4	3	3	4
4	Skilled Labor (Requirement and Availability)	4	3	3	2	4	2	3	4	4	4	4	4	3	3	4
4	Identification of suppliers of raw materials and inputs (domestic, international origin)	4	4	4	3	2	3	3	2	4	4	4	4	4	3	4
Relevance for performing data analysis tasks																
4	How many internal or external sources of information exist: databases, Excel sheets, reports, etc.	3	3	4	3	3	3	3	4	3	4	4	4	4	3	4
4	What level of access do you have to the information	4	3	3	4	3	2	4	4	3	4	4	4	4	3	4
4	Level of use of computer tools (Words, excel, power point, etc.).	2	3	3	3	3	2	3	4	3	3	4	3	4	3	4
4	Frequency of information gathering at this stage of the process	3	3	3	3	3	3	3	4	3	3	4	4	4	3	4
	Total unweighted	39	43	43	44	34	37	44	48	48	50	51	49	40	39	48
	Weighted total	36	36	37	39	37	33	38	39	42	41	38	41	37	36	38

From the above table, the subprocesses "Type of Input to Transform", "Transforming Technological Level" and "Business Specialization Level" were the highest prioritized.

5. Definition of Autonomous Cycles of Data Analysis

Figure 5 presents the ACODATs of the prioritized subprocesses, to allow an autonomous coordination of the industrial-automation process of MSMEs (ACPCPA-000).

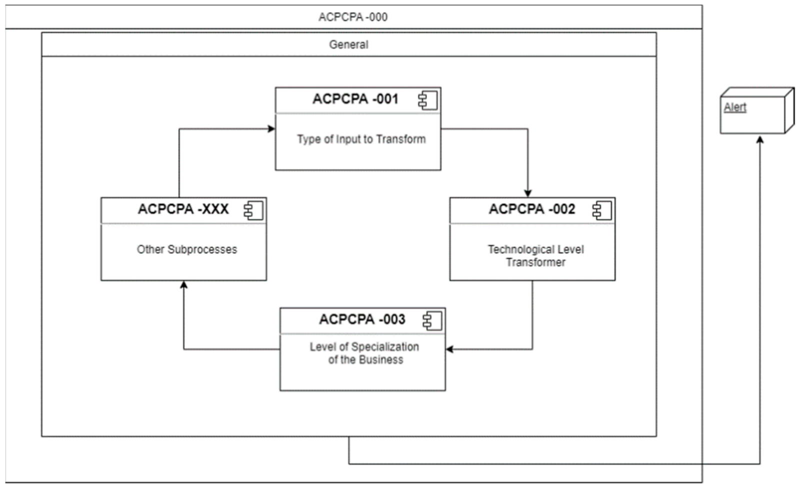

Figure 5. ACPCPA-000: Autonomous cycles of the prioritized processes of MSMEs.

The objective of ACPCPA-000 is the self-management of the industrial-automation of MSMEs within the agroindustrial sector to improve their competitiveness. To achieve this objective, we propose three ACODATs:

ACPCPA-001 (Type of Input to Transform): This cycle is responsible for obtaining useful information to identify the type of input to transform in the agroindustrial production chain, such as quantity, quality, time (seasonality and durability), cost, etc., based on information from the organization and the context.

ACPCPA-002 (Transforming Technological Level): This cycle is responsible for obtaining useful information to identify the technological level required in the transformation process of the agroindustrial production chain, such as identifying the raw material transformation processes and selecting the technology for processing.

ACPCPA-003 (Business-Specialization Level): This cycle is responsible for obtaining useful information to identify the Business-Specialization Level of the production, such as the specific customer sector to cover (target market), the quality of the product, etc.

5.1. Specification of the Autonomous Cycles for the Type of Input to Transform

In this section, we detail ACPCPA-001, which obtained the highest score in the prioritization. This autonomous cycle determines the type of input to transform. Mainly, this cycle is composed of four tasks (see Figure 6). Table 6 shows the general description of each task of this autonomous cycle.

Task 1. Quantity of Input to be transformed: This task identifies the raw materials required to produce the product to satisfy customer demands. Its objective is to identify the historical evolution, yields and alternative uses of the product, etc. This task uses a predictive model to determine the amount of input to be transformed.

Task 2. Quality of Input to be processed: This task identifies the quality of the inputs. Its quality affects the quality of the products and depends on the cultural practices and storage and transport services used, among other things. This task uses a diagnostic model.

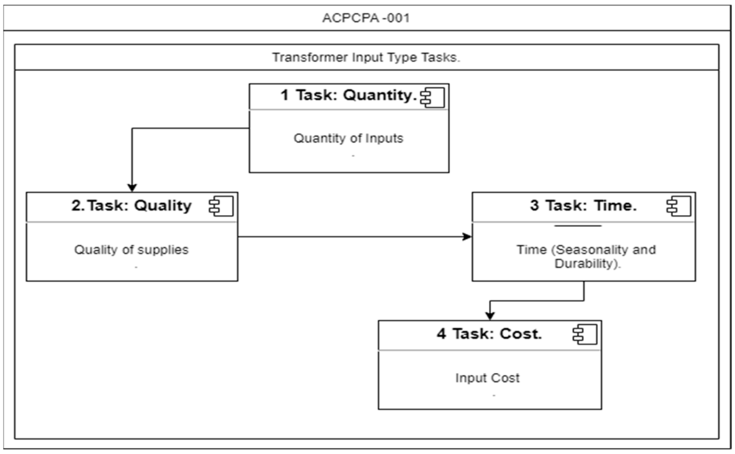

Figure 6. Tasks of ACPCPA-001.

Table 6. Description of ACPCPA-001 tasks.

	Task Name	Knowledge Models	Data Sources
1.	Determine the amount of input to transform.	Predictive Model	Production demand, customers.
2.	Determine the quality of the input to be processed.	Diagnostic Model	Inputs used on the farm, cultural practices, storage, and transport services.
3.	Determine the time (Seasonality and Durability) of the input to be transformed.	Predictive Model	Annual demand.
4.	Determine the cost of input to be transformed.	Predictive Model	Operating Costs.

Task 3. Timing (Seasonality and Durability) of the Input to be processed: This task identifies the factors related to timing. For example, seasonality because many raw materials or inputs are only produced during certain times of the year. Also, the durability of the raw materials and inputs used because some are perishable. For this task, a predictive model can be used.

Task 4. Cost of the Input to transform: This task determines the cost of raw materials or inputs, to determine if it is low enough to contribute to the production profitability.

The first task predicts the quantity of raw material to be transformed, which is the input of the second task to diagnose its quality. The next task uses the result of the previous task to predict its durability, as it can be perishable or seasonal. Finally, the last task predicts the cost of that raw material.

5.2. Specification of the Autonomous Cycles for the Transformer Technology Level

The Autonomous Cycle for the Transforming Technology Level (ACPCPA-002) has as its main objective the characterization of the technology to be used to transform the raw material or input. In general, this autonomous cycle is composed of three tasks (see Figure 7). Table 7 shows the description of each task.

Task 1. Characterize Processing Plant: This task identifies and classifies how the MSMEs work through the identification of essential elements that allow the management and control of the production, such as location, edification, access roads, structure and finishes, lighting, and ventilation. This task uses classification models.

Task 2. Identify raw-material transformation process: This task identifies the raw material or input transformation process (collection and production). This process is related to distances to input, location of the different processing plants, ease of transportation, availability of labor, availability of infrastructure, and cost of land, among other things.

It also manages inventories, due to the seasonal and perishable nature of certain raw materials, storage capacity, inventory financing, for which it can use a prescriptive model.

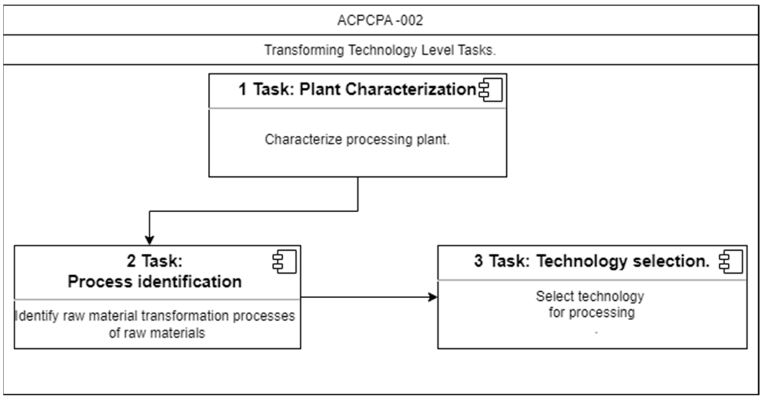

Figure 7. Structure of the ACPCPA -002- Transforming Technology Level.

Table 7. Description of ACPCPA-002 tasks.

Name Task		Knowledge Models	Data Sources
1.	Characterize the processing plant.	Classification Model	Location, the exclusivity of the premises, access roads, structure and finishes, lighting, ventilation.
2.	Identify raw material transformation processes.	Prescription Model	Phases (collection and production), transportation and storage, sources of supplies, availability of labor, availability of infrastructure, cost of land and raw material, quality standards.
3.	Select technology for processing.	Classification or identification Model	Type of production process (made-to-order or job, batch, mass, and continuous flow).

Task 3. Select technology for processing: This task identifies the technology for processing raw materials or inputs to satisfy the demand. Its objective is to identify the technology dedicated to production. For that, it must select the type of production process, such as on-demand, batch, mass, and continuous flow. This task uses a classification or identification model to select the type of technology for the production processes to be transformed.

The first task identifies the production process to be carried out in the MSME using a classification model; from there, the next task prescribes the transformation process of the raw material. Finally, the last task selects the processing technology for that raw material using a classification or identification model.

5.3. Specification of the Autonomous Cycles for the "Business-Specialization Level"

The Autonomous Cycle for the Business-Specialization Level (ACPCPA-003) has as its main objective the characterization of the final product (target market, quality, and value of the product). This cycle is composed of two tasks (see Figure 8). Table 8 shows the description of each task.

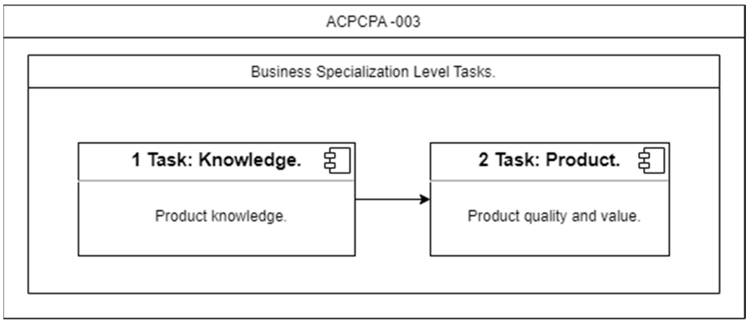

Figure 8. Structure of the ACPCPA-003 Business Specialization Level.

Table 8. Description of ACPCPA-003 tasks.

	Name Task	Knowledge Models	Data Sources
1.	Identify product knowledge.	Classification or identification Model	Demand needs, access to markets.
2.	Determine the quality and value of the product.	Diagnostic Model	Hygienic-sanitary quality and bromatological quality management in production.

Task 1. Identify product knowledge: This task identifies knowledge of the target market of the product. It defines the needs of demand and is the means to access sophisticated international markets with greater value added. Its objective is to acquire knowledge of the relationship of the product with a target market. This task uses a classification model to identify knowledge of the product.

Task 2. Determine the quality and value of the product: This task identifies the quality and value of the product in terms of hygienic-sanitary quality management in production and quality management in production. This task uses a diagnostic model.

In this ACODAT, the first task identifies the target market of the product using a classification model; and from that identification, the next task determines the quality and value of the product using a diagnostic model.

6. Multidimensional Data Model for the Autonomous Cycles

This section defines the multidimensional data model for the above autonomous cycles. The multidimensional data model is defined in Figure 9.

The model in Figure 9 includes different data sources (e.g., about the raw materials, the production process, the context (market, etc.)). Data are grouped in different dimensions of the data model, depending on their characteristics. The multidimensional data model is a star model that has a fact table (Planning–Input–Converting) and three main dimensions (product, organization, and person). In turn, the product dimension is composed of the dimensions of quantity, quality, time and cost. Finally, the person dimension is made up of the client, seller and employee dimensions. Each dimension is described below. The dimensions are as follows:

- **Product Dimension:** Stores product data (e.g., location, selling price, production cost).
- **Quantity Dimension:** Stores data on the quantity of raw materials required to satisfy demand, for example, historical evolution, yield, and alternative uses.
- **Quality Dimension:** Stores data on the quality of raw materials or products, and the information related; for example, inputs used on the farm, cultural practices, storage and transportation services, and quality controls established.
- **Time Dimension:** Stores time data of raw materials or inputs identifying the various factors related to time, for example, seasonality, durability, and storage time.

- **Cost Dimension:** Stores data on the cost of raw materials or inputs; for example, supply and demands, opportunity cost, logistic services, government interventions, alliances with producers and contracting standards in the area.
- **Organization Dimension:** Stores company or organization data; for example, name, address, and type of organization such as producers, suppliers, processors, transporters, warehousing, financial, marketing and distributors.
- **Person Dimension:** Stores individual data; address, phone, and email.
- **Client Dimension:** Stores client data (e.g., type and frequency of demand).
- **Seller Dimension:** Stores seller data (e.g., type of product to sell).
- **Employee Dimension:** Stores Employee data; for example, the type of employees such as producers, coordinators, or operators.

Thus, the Planning–Input–Converting is the fact table of the multidimensional model, which stores the information generated by the ACODATs (the measures that are being analyzed) and the keys to join each dimension table.

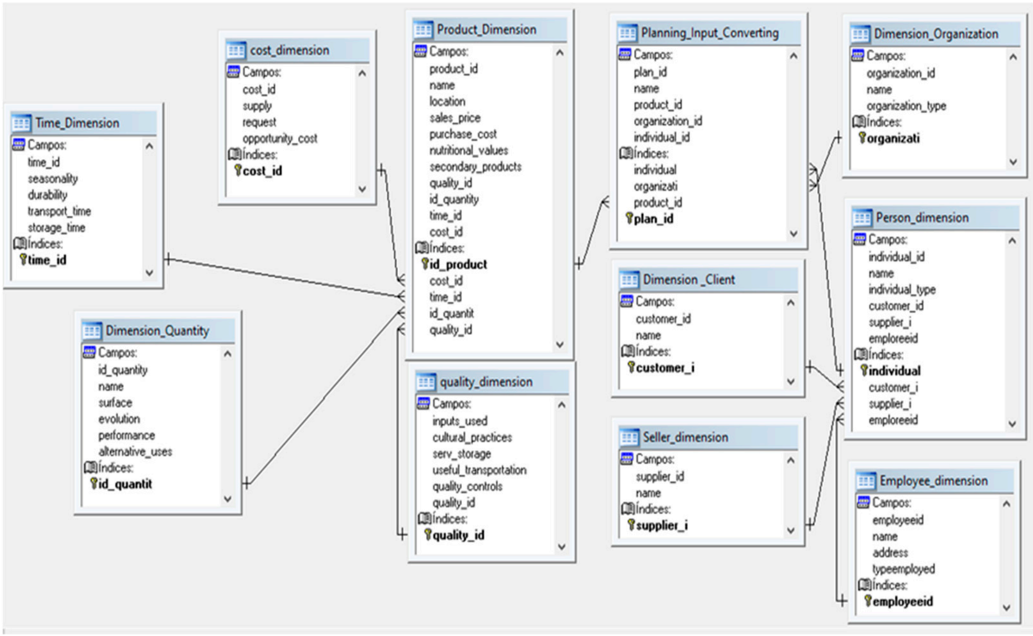

Figure 9. Multidimensional Model.

7. Case Study of Café Galavis

For this case study, this section presents the experimental context and the instantiation of ACPCPA-001 (Type of input to be processed).

7.1. Experimental Context

The raw material to be processed is a key element in the agroindustrial sector. The processing must deliver to the market a product that has an acceptable quality, in an adequate and sufficient quantity for the chosen market, in a time that allows covering the needs of the demand, and at a reasonable and competitive price.

In this case study, we use data from the company "Café Galavis", located in the industrial zone of the city of Cúcuta, Colombia. This operation is dedicated to the roasting and distribution of coffee.

To illustrate the functionality of ACPCPA-000, this case study analyzes ACPCPA-001 according to the following scenario. The coffee beans enter the factory in a process called "reception of the beans" with 70 kg bags and are stored in optimal conditions complying with the quality standards of the market to which the product is directed (ambient temperature between 20 °C and 25 °C and humidity between 10% and 12%). The coffee is stored in the warehouse, in green beans, and classified according to various criteria, mainly size and density.

The beans are measured by passing them through a sieve to classify the size, a process called "storage and weighing", which is a large and adequate place to protect the raw material from the sun, wind, water, animals, odors, dust and dirt. Once the coffee has been processed and classified into qualities, it is packaged into 60 kg sacks, which is an international standard.

Depending on the orders or demand, the quantity for the production order of the day is then weighed. Once the above is fulfilled, the beans are dehydrated until they reach the required point, through the application of heat, which causes several physical changes and chemical reactions that develop the aroma and flavor. During the roasting process, the temperatures that the coffee beans reach are around 193 °C for a light roast, close to 200 °C for a medium roast, and close to 218 °C for a dark roast. This allows processing 280 kg in 20 min, that is to say, a production capacity of 60,000 pounds per month.

The coffee then goes through the cooling process that consists of activating the system for a period of approximately 5 min; through an air-suction system, coffee is elevated to three meters high, producing the first cleaning of the pure grain. Next is the milling process, which is carried out through two types of mills, in which one part is processed in 75% in the granulating mills and the other in the fractional mills in 25%. The milled grain is then mechanically conveyed through special ducts. A second cleaning of the coffee is carried out by means of a vibration system, separating it from the remaining particles.

The milled grain enters the hoppers of the packing machines dosing the product according to its presentation, according to its weight previously selected, and programmed by portions of 2500, 500, 250, 125, 50 and 25 g. Thus the process is finished in perfect conditions.

The finished product is placed on plastic pallets where the process of control, coding and sealing of the packaging is carried out. Once the coffee is in inventory, it is taken by carts to the finished product warehouse. It is then delivered to the team of distributors who are in charge of delivering it to the final consumer.

7.2. Instantiation of ACPCPA-001 (Type of Input to Transform)

The instantiation of ACPCPA-001 should consider, for example, the quantity, quality, time, and cost of coffee beans used in production. The following steps describe how ACPCPA-001 has been instantiated for this case study.

Task 1. Input quantity task: The first task consists of automatically determining the quantity of coffee beans, for which a prediction model is used. The prediction model is built with historical data found in the company's software. The prediction model uses variables such as surface area, evolution, yield, ambient temperature, and humidity. An example of the results of the prediction model is shown in Table 9. Two cases of this task are described below.

Table 9. Predictions generated by the first task.

Winery	Week	Quantity (Bags)	Ambient Temperature °C	Humidity %
Bod_01	Week 1	100	20	12
Bod_01	Week 2	120	22	13
Bod_01	Week 3	150	18	15
Bod_01	Week 4	110	25	14

Case 1: For storage of 110 bags of green coffee beans, the model estimates that it should have a temperature of 25 °C and humidity of 14%. The recommendation is that green beans be stored between 20 °C and 25 °C. In this case, Task 2 can be carried out because storage is maintained at the desired levels.

Case 2: For 150 bags stored, the model estimates the ambient temperature of 18 °C and humidity of 15%. As the recommendation is a temperature between 20 °C and 25 °C and humidity between 12 and 14%. Given that the temperature and humidity conditions for storage are not favorable, in this case, a warning is generated to the warehouseman to take the appropriate decisions.

The first task predicts the amount of coffee to be transformed according to the contextual conditions. For the first case, it is expected that 110 bags of green coffee beans can be processed/transformed, and for the second case, 150 bags can be processed.

Task 2. Input-quality task: The second task uses a diagnostic model based on historical data from raw-material sale websites. The diagnostic model uses variables such as inputs used, acidity, aroma, cultural practices, storage, and transportation services used and quality controls. An example of the results of the diagnostic model is shown in Table 10. Two cases of this task are described below.

Table 10. Diagnostics generated by the second task.

Winery	Week	Quantity (Bags)	Acidity (4.9–5.2)	Category (0–5)
Bod_01	Week 1	100	4.9	0
Bod_01	Week 2	120	5.0	2
Bod_01	Week 3	150	5.5	6
Bod_01	Week 4	110	5.2	4

Case 1: It is recommended that green beans have a pH of acidity between 4.9 and 5.2. This is an important factor in determining the quality of coffee in terms of flavor. When the coffee has a pH lower than 4.9, it acquires a flavor that is too acidic and above 5.2 it is bitterer. Another factor is the size and density of the bean. For a coffee to be a specialty coffee, it must have zero defects (category 1) and a maximum of five defects is category 2. Table 9 shows that the model diagnoses a storage of 120 bags of green coffee beans, with an acidity of 5.0 and a category of 2. In this case, Task 3 would be carried out since the quality of the beans is maintained at the desired levels.

Case 2: For 150 bags, the model diagnoses an acidity of 5.5 with a category of 6, as presented in Table 9 (see Week 3). Given that the conditions for storage (the inputs used: coffee body and aroma) are not favorable, in this case, a warning is generated to the warehouse personnel so they can make the appropriate decisions.

Thus, this task diagnoses the quality characteristics of the coffee determined to be processed in the first task. For the first case (120 bags of green coffee beans), it diagnoses an acidity of 5.0 and a category 2, and for the second case (150 bags), the model diagnoses an acidity of 5.5 and a category 6.

Task 3. Input-Time Task: In the third task, the system will use a predictive model to identify the various time-related factors such as seasonality and durability of the input. The predictive model uses variables such as surface area, evolution, yield, roasting temperature, and time. An example of the results of the prediction model is shown in Table 11. Two cases of this task are described below.

Table 11. Predictions generated by the third task.

Toaster	Week	Quantity (Bags)	Temperature (°C)	Time (Minutes)
Tost_01	Week 1	100	193	12
Tost_01	Week 2	120	200	13
Tost_01	Week 3	150	218	14
Tost_01	Week 4	110	300	20

Case 1: It is recommended that the roasting temperature in the industrial machines start with the oven preheated to 200 °C. After loading the coffee, the temperature drops to half, and then, gradually rises again at a rate of 10 °C per minute. If it rises faster, the coffee beans are roasted externally but remain raw and hollow on the inside. The model estimates that the roasting of 120 bags of green coffee beans has a temperature of 200 °C and a time of 13 min. In this case, Task 4 can be carried out, as the roasting and cooling process is maintained at the desired levels.

Case 2: For 110 bags, the model estimates a roasting temperature of 300 °C and a time of 20 min, as presented in Table 11 (see Week 4). Since the temperature conditions in the roasting machine are not favorable, in this case, a warning is generated to the roasting machine operator to make the appropriate decisions.

Specifically, this task estimates the durability characteristics of the production process of the coffee. For the first case (120 bags of green coffee beans), the model estimates that roasting must have a temperature of 200 °C and a time of 13 min, and for the second case, it estimates a roasting temperature of 300 °C and a time of 20 min.

Task 4. Input Cost Task: In the fourth task, the system will use a predictive model to estimate the cost of raw materials or inputs. These costs should be low enough to contribute to the processing plant's profitability. This model uses variables such as supplies, demand, and quality and time of inputs. Two cases of this task are presented below.

Case 1: If the tasks of quantity, quality, and time of inputs to be transformed are kept at the desired levels, it could be predicted that costs will remain stable in production.

Case 2: If one or all of the tasks of quantity, quality, and time of inputs to be transformed are not maintained at the desired levels, it can be predicted that costs will increase in production. In this case, a warning is generated to the operators or managers to make the appropriate decisions.

Finally, the last task predicts the cost of the coffee. For the first case, due to the quantity and quality of the coffee, it predicts a stable cost in production. In the second case, because the quantity and quality are not maintained at the desired levels, it predicts that costs will increase in production.

8. General Discussion

8.1. Comparison with Previous Works

In this section, we propose several criteria to analyze the automation of the production chain of MSMEs for the agroindustrial sector to improve their competitiveness. This is followed by a qualitative comparison of this work with related works, based on the above criteria (see Table 12) [35].

Table 12. Comparison with previous work.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4
[12]	X	√	√	X
[17]	X	√	√	X
[18]	X	X	X	X
[19]	X	X	X	X
[32]	X	X	X	X
[36]	X	√	√	X
This work	√	√	√	√

- **Criterion 1:** Automation of the entire industrial production chain of MSMEs.
- **Criterion 2:** Use of data mining techniques in the industrial automation of the production chain.
- **Criterion 3:** Quantity, quality, time, and cost are jointly analyzed in the industrial-automation process.
- **Criterion 4:** Consider efficient and environmentally friendly production.

Table shows whether the analyzed works meet the criteria indicated above, indicating √ that it does and X that it does not. As shown in Table 12, the related articles did not meet all the criteria. Specifically, in criterion 1, our research enables, through autonomic cycles, the automation of the entire production process. For this automation, it is necessary to use paradigms such as multi-agent systems together with ACODAT architecture to model the whole production process [7,30].

For criterion 2, García et al. [17] analyzed a case study of multirelational data mining, using the Connection-Block algorithm, applied to the database in this agroindustrial sugar sector. The basis of our proposal is data-driven autonomous decision making, with knowledge extracted from the industrial transformation of the production chain.

For criterion 3, Roukh et al. [36] focused on the acquisition, processing, and visualization of massive amounts of data, both batch and real time. Sen et al. [12] and Garcia et al. [17] focused on converting data useful for decision making, especially for precision agriculture and agribusiness, to estimate land-cover change. Meyer et al. [18] showed how consumption management problems can be solved by the widespread installation of sensors on production lines. Bader et al. [19] stated that the adoption of industrial robots, in food processing, has been slow. This proposal considers the quantity, quality, time, and cost of the inputs to be transformed, in the industrial automation of the production chain of MSMEs.

Finally, regarding criterion 4, this proposal meets the criterion of efficient and environmentally friendly production because the operator (warehouseman, processor) and manager can know the quantity, quality, time, and cost of the raw material. This can be used to reduce greenhouse gases, manage the hygienic-sanitary quality in production, make agroindustrial production more sustainable, etc.

8.2. Quality of the Knowledge Models

In this section, we carry out a quantitative analysis of the behavior of the knowledge models used in each task (see Table 13). To do this, we have used R^2 and MAPE (Mean Absolute Percentage Error) as metrics for the predictive models, and, in the case of the diagnostic model, the silhouette index. R^2, MAPE, and the silhouette index are self-contained metrics, so a value close to 1 indicates a very good quality of the models. In addition, we have used as machine learning techniques to build the models to RF in the case of the prediction models, and K-means in the case of the diagnostic model. We see that the results obtained are very good in general. For example, in the first task, it gives us a fairly good R^2 and MAPE (95 and 89%, respectively). Likewise, the quality of the diagnostic model is very good, with a Silhouette index value of 0.87.

Table 13. Quality of the Knowledge Models for each task.

Task Number	Knowledge Models	Quality Metrics
1	Predictive Model	R^2 = 0.95 MAPE = 89%
2	Diagnostic Model	Silhouette index = 0.87
3	Predictive Model	R^2 = 0.92 MAPE = 88%
4	Predictive Model	R^2 = 0.97 MAPE = 95%

9. Conclusions and Direction of Future Work

This paper presents an architecture for the industrial automation of the production chains of MSMEs. The architecture combines multiple variables (e.g., temperature, humidity, acidity, quantity, quality, and time) and allows the integration and interoperability of actors in the context of production. The proposed architecture is based on the ACODAT concept and proposes several autonomous cycles to give autonomy to the industrial production chains of MSMEs. Furthermore, this article shows the instantiation of the autonomous cycle for the characterization of the inputs to be transformed as the first step toward an efficient and effective industrial automation process of the production chain.

At the level of industrial automation, our main contribution is the specification of the three main ACODATs to manage the most relevant subprocesses for the agroindustrial automation of the production chains of MSMEs. The main benefit of our approach is that it allows an industrial automation process to be carried out based on the data of the organization and its environment, which allows MSMEs to exploit their data without increasing their operational costs. Observing the case study in a coffee factory, our first ACODAT determines the characteristics of the coffee to be processed (both in terms of quantity, quality, and the characteristics of its production process), to later estimate the cost of production, according to the target market aspired to reach. Thus, we see, in this specific case, the comprehensive behavior of ACODAT to carry out an exhaustive analysis of coffee production using its organizational and context data.

Other results of this research are (i) the use of environmental variables to make decisions on optimal industrial automation, (ii) the ability to use mining techniques to improve system knowledge and decision-making processes (e.g., data mining, text mining and web mining techniques), and (iii) real-time analysis for production in the industrial automation process. In particular, the case study shows that extraction techniques of knowledge are necessary to address self-management in industrial automation. This case study serves as a guide for incorporating self-management in industrial-automation of the production chain of the coffee industry, based on the paradigm of autonomic computing and data mining techniques.

The main limitations of this study are the following. The first is that only one of the autonomous cycles was instantiated in a very specific case study, so its scalability in other contexts must be evaluated. The second major limitation is that the integration of the different autonomous cycles that automate the different processes present in the automation of the production chain has not been evaluated. A third limitation is the lack of evaluation of the operational costs involved in maintaining the data repository and models based on data in real-time.

Future work is aimed at implementing this framework in a real-time context to verify the functionalities of this solution. In this sense, we plan to use historical data of the company "Café Galavis" to develop the different data analysis tasks (e.g., to determine the quality of the coffee bean). Finally, one of the biggest challenges to implement this type of system is the cost associated with the sensors for data acquisition. In addition, other challenges are the optimal distribution of these sensors, and the Internet connectivity in the industrial installation. Thus, future studies should analyze these aspects and how to consider them in the proposed architecture.

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