IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 24 August 2023, accepted 12 October 2023, date of publication 16 October 2023, date of current version 24 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3324813

APPLIED RESEARCH

Intelligent Data-Driven Decision Support for Agricultural Systems-ID3SAS

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This work was partially supported by the SIMShore: SIMOcean Nearshore Bathymetry Based on Low Cost Approaches. This project received funding from the EEA Grants Portugal research and innovation program under Grant agreement No PT-INNOVATION-0027; in part by GeoBioTec under Grant UIDP/04035/2020; in part by the Forest Research Centre (CEF) under Grant UIDB/00239/2020; and in part by the Associate Laboratory TERRA under Grant LA/P/0092/2020.

ABSTRACT The agricultural sector worldwide faces serious problems regarding water scarcity, which demands innovative management methods to optimise water use. In response, we propose the Intelligent Data-Driven Decision Support for Agricultural Systems (ID3SAS) methodology, which offers a scalable, flexible, and cloud-based decision support system for real-time supervision and control in agricultural environments. Aligned with the prevailing trends of Agriculture 4.0, ID3SAS integrates data acquisition, cloud-based storage, machine learning, predictive analysis, and run-time reasoning to facilitate decision-making processes, thereby assisting users in making more informed and sustainable decisions. In a case study with tomato plants, ID3SAS-irrigated plants showed 20.9% reduction in water consumption and 26.4% increase in crop production compared to traditional methods, which despite the controlled laboratory environment setting, highlights the methodology's promising potential in addressing water scarcity and enhancing agricultural productivity.

INDEX TERMS Agriculture 4.0, decision support system, fuzzy logic, Internet of Things, node-RED, wireless sensor and actuator network.

I. INTRODUCTION

Water scarcity is a growing concern in many regions around the world, due to climate change, population growth, urbanisation, industrial activities, and intensive agriculture [1], [2]. Addressing this issue requires a comprehensive approach that includes water conservation, efficient use of resources and investment in new technologies and infrastructure to improve water availability and quality. Information and Communication Technology (ICT), particularly regarding sensing technologies, robotics, Internet of Things (IoT), cloud computing, Big Data, and Artificial Intelligence (AI), are playing an increasingly important role in the digitalisation of agricultural systems. Food and Agriculture Organization (FAO) of the United Nations denominates this role as "Digital Agricultural Revolution" [3], also known as "Agriculture 4.0" [4], [5], [6], [7], [8]. It is expected that the use of such technologies will bring significant advances worldwide, improving the productivity and efficiency of agricultural sector, and enhancing the quantity, quality and availability of agricultural products. Moreover, it will aid in adapting to climate change, curbing food loss and waste, optimising the utilization of natural resources, and ultimately leading to a reduced environmental impact in the foreseeable future [8].

The associate editor coordinating the review of this manuscript and approving it for publication was Ahmed Farouk.

The research work envisioned here is focused on the design of a methodology for the development of a Decision Support System (DSS) oriented to the agricultural sector, and from this, the Intelligent Data-Driven Decision Support for Agricultural Systems (ID3SAS) methodology is born. This proposed methodology is aligned with the current Agriculture 4.0 trend and combines sensing technologies, IoT, cloud computing, data analysis based on AI methods, and decision-making support to address the issues faced by farmers/managers in agricultural environments.

For this experiment, a Wireless Sensor and Actuator Network (WSAN) was deployed to collect diverse parameters such as air temperature, humidity, soil moisture, ultraviolet (UV) radiation, infrared (IR) radiation, and visible light using sensors, with actuators (relay and water pump) enabling on-field actions. Data are transferred from the sensor nodes to a gateway via WiFi using Message Queuing Telemetry Transport (MQTT) communication protocol, which is posteriorly sent to a cloud server for storage. Machine Learning (ML) models were created for soil moisture and time-to-water estimation. Extra Trees Regression (ExtraTR) and AdaBoost provided better performance and, for this reason, were the models implemented in the system. For the DSS, we used the Fuzzy Logic theory to determine the irrigation time according to the sensors' measurements and weather forecasting. At last, an interactive and user-friendly dashboard was created for data visualisation, recommendations, and controlling actions, in real-time. Our solution was implemented and tested on tomato plants (*Lycopersicon esculentum* L.), which will be referred to as the "prototype" in this article. The case study consisted of having two crops, where one was watered according to the manufacturer's recommendations (*i.e.*, the traditional method) and the other was watered according to the recommendations of the ID3SAS system. At the end of the study, both methods were evaluated considering the number and weight of tomatoes, as well as water consumption. It is important to note that this prototype offers essential guidance for implementing the ID3SAS methodology. Its successful implementation empowers farmers/managers with data-driven insights and smart recommendations. This facilitates the optimisation of irrigation schedules, efficient resource allocation and improved crop management, leading to increased productivity, reduced water consumption and minimised environmental impact. As a result, ID3SAS provides guidance for the widespread adoption of sustainable agricultural practices.

To summarise, the contributions of the present article are as follows:

- We provide a generic methodology for the creation of a Smart Agricultural System (SAS) that can be easily adopted and adapted by the research community for additional testing and improvement. It is practical, affordable, and straightforward to implement;
- We cover a proper method for managing and preserving wireless sensor information through the utilisation of cloud computing technology and open-source software solutions;
- The experiment work collects data and takes actions in the field, which can significantly improve agricultural productivity, efficiency, and sustainability;
- The ID3SAS methodology supports decision-making in real-time, which is beneficial for farmers to address the dynamic nature of agricultural environments.

The remainder of the article is structured as follows: subsection I-A presents the background of topic under study, regarding some technologies of Agriculture 4.0, followed by an overview of related work that can be found in current literature, in subsection I-B. Section II presents the overall design of ID3SAS methodology and it is divided into three subsections: ID3SAS concept in subsection II-A, its goals and requirements in subsection II-B and system architecture in subsection II-C. ID3SAS implementation in a prototype can be found in section III. The results of the proposed system are presented and discussed in Section IV. In Section V, we conclude the research work, its limitations, and remarks regarding future work.

A. BACKGROUND

Agriculture is a complex and multi-disciplinary field that involves the collaboration of various stakeholders (including farmers, managers, producer organizations, suppliers, auditors, and researchers) for effective management, decision-making, and the successful implementation of sustainable agricultural practices. Advances in sensor technology have provided an invaluable capability to continuously monitor targeted agricultural parameters, while simultaneously, robotics has significantly enhanced the automation of farming procedures. Moreover, the rise of affordable and accessible computing power has fostered the creation of sophisticated decision support tools, which can substantially assist in the realm of improved agriculture management, leveraging data science, Big Data, and ML-based approaches. In this regard, the comprehensive exploration and analysis of Agriculture 4.0's emerging trends and core technologies were meticulously documented in the research conducted by [8]. Considering the scientific insights presented in this article, it is appropriate to briefly introduce the trends that follow.

- **Wireless Sensor and Actuator Networks:** In recent years, Wireless Sensor Network (WSN) and WSAN have been widely used in numerous agricultural applications to improve traditional farming methods. Three fundamental tasks are carried out by sensor networks: sensing, communication, and computation. The difference between WSN and WSAN is that the latter includes an additional element: an actuator. This can be any physical device (such as lamps, fans, valves, or water pumps) that interacts with the environment. These networks are distributed arrangements of several sensors and actuators "nodes" interconnected by wireless links.
- **Internet of Things:** Conceptually, IoT refers to the capacity to connect physical and digital "things" with

standard and interoperable communication protocols [9]. Since agricultural activities need to be continuously monitored and managed, agriculture is a perfect candidate for the deployment of IoT technologies. A comparison of the most used wireless communication protocols is presented in [8], featuring the basic characteristics of Bluetooth, Long Range Wide Area Network (LoRaWAN), Near Field Communication (NFC), Radio-Frequency IDentification (RFID), Sigfox, WiFi, Zigbee, and mobile communications. Within their analysis, the authors concluded that Sigfox, ZigBee, and LoRaWAN exhibit the highest suitability for IoT-based agricultural applications, due to their energy-efficient nature, cost-effectiveness, and superior communication range.

- **Cloud computing:** Nowadays, cloud computing has attracted significant interest within the agricultural sector as according to [9], it provides (a) reasonably priced data storage services that significantly lowers storage costs for agricultural enterprises; (b) intelligent large-scale computer systems that convert these agricultural data into knowledge; and (c) a secure platform for the development of diverse agricultural IoT applications.
- **Data Analytics, Big Data, and Machine Learning:** As stated in the research conducted by [10], data analytics refers to the application of computer systems to analyse large datasets to support decision-making. This field is highly interdisciplinary, incorporating elements from various scientific disciplines such as statistics, ML, pattern recognition, system theory, operations research, and AI. The phases of data analysis, as outlined by [10], include (a) data preparation (planning, data collection, feature generation, and data selection); (b) preprocessing (cleaning, filtering, completion, correction, standardisation, and transformation); (c) analysis (visualisation, correlation, regression, forecasting, classification, and clustering); (d) postprocessing (interpretation, documentation, and evaluation).
  Data analytics, through Big Data, AI/ML algorithms or statistics, has been identified as one of the main drivers behind the implementation of Agriculture 4.0 [8]. On the one hand, Big Data is defined as datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse [11]. Generally, Big Data is combined with the term "5V", representing its five dimensions [12]: (a) volume, (b) velocity, (c) variety, (d) value, and (e) veracity. On the other hand, ML can be described as a computer program or system that possesses the ability to learn specific tasks without explicit programming [13]. It is a process that involves computers or machines to make decisions or recommendations by leveraging multiple data inputs. In a review made by [14] regarding ML applications in agriculture, the authors concluded that 61% of the analysed articles used ML methods for crop management (22% disease detection, 20% yield prediction, 8% weed detection, 8% crop quality, and 3% species recognition), 19% for livestock management (12% livestock production and 7% animal welfare), 10% for soil management and 10% from water management.
- **Decision Support System:** The definition of DSS is not consensual in the literature. In the present document, we will use the definition provided by [8]: *software mechanism which aids an end-user to easily and quickly leverage complex data to improve decision-making processes*. This involves transforming both raw data and the results obtained from analytics tools into actionable knowledge, presented through a user interface in a comprehensible manner. There are several ways to classify a DSS, depending on the type to be implemented, the design, and the application [15].

B. RELATED WORK

Significant work has been invested in studying the many aspects of Agriculture 4.0 during the past few years. An automatic DSS was proposed in [16] for managing irrigation in agriculture by utilising several autonomous nodes to measure soil and climatic parameters and estimate weekly irrigation needs. ML techniques are used for the reasoning engine of the system. A smart platform was proposed in [17], which aims to assist farmers in saving resources and enhancing farming productivity. This platform combines a WSN and drone imagery to gather data, allowing the tracking of soil irrigation and pest detection. The gathered data is transmitted to the cloud, where a rule-based system deduces the appropriate action based on it. In [18] the authors proposed a low-cost IoT system based on a WSN for agricultural applications. This system consists of sensor nodes (Arduino-based with a WiFi module and various sensors), a gateway (a Raspberry Pi including Mosquitto and Node-RED), and a user interface. The data are sent to the gateway via WiFi, using the MQTT protocol and posteriorly transferred to the cloud service (IBM Bluemix) for storage and visualisation in real-time. Reference [19] developed an autonomous and solar-powered IoT-based system for monitoring nitrate concentration in water bodies (lakes, streams, rivers). The collected data from sensor nodes are transferred to a gateway which, in its turn, sends data to a cloud server for storage. WiFi and LoRa protocols are used for data communication. The LoRa protocol was shown to be more efficient in terms of overall energy consumption, in addition to allowing data to travel larger distances compared to the standard WiFi protocol. Similarly, [20] developed an IoT-based sensor node to monitor a greenhouse. This node is composed of a microcontroller (ESP8266 NodeMCU), various sensors (air temperature and humidity, capacitive soil moisture, soil temperature, and light intensity), and two power units (lithium-ion batteries and a solar panel). The microcontroller is responsible for data collection and transmission to the gateway. Both Mosquitto and Node-RED are used in this implementation. In [21] an IoT-based system was proposed for smart agricultural applications. The authors designed a simulation environment (using Riverbed Modeler) with various sensors (*e.g.*, temperature, rain, light, wind, pH, acoustic, light intensity, humidity, location, and chemical properties) that collect specific cornfield data and send them to a coordinator node. This node is responsible for communicating with a drone that, in its turn, sends data to the gateway. Node-RED gathers data from the Riverbed Modeler and then stores it in InfluxDB database. Visual interfaces and graphs are provided by Grafana. Reference [22] proposed an IoT sensor simulator, using Node-RED, IBM Bluemix, and IBM IoT sensors, and was designed specifically for lettuce plants grown in greenhouses or indoor agricultural environments.

The culmination of these research efforts has played an important role in propelling the agricultural sector forward through innovative and creative approaches, consistently prioritising sustainability. These efforts encompass a diverse range of domains, including irrigation management, resource conservation, pest detection, water quality monitoring, and greenhouse monitoring. Employing cutting-edge technologies such as IoT, ML, cloud computing, and drone imagery, these initiatives seek to improve agricultural efficiency, productivity and resource optimisation.

However, these works also demonstrate general limitations including reliance on rule-based reasoning, potential lack of adaptability to dynamic conditions, limited integration of advanced data analytics and ML, and a focus on specific aspects of agricultural management rather than comprehensive DSS. In light of this, the proposed methodology, ID3SAS, bridges these gaps by combining sensing technology, advanced data analytics, and fuzzy logic reasoning within a scalable and cloud-based DSS. By addressing limitations seen in prior works and providing guidelines for seamless integration, ID3SAS presents a promising unified approach for shaping the future of agriculture – a vision that harmonises intelligence, sustainability, and global societal demands.

II. THE ID3SAS METHODOLOGY

In this section, an overview of the design and development of the proposed methodology - ID3SAS - is provided. It begins with a description of the methodology's concept, its main goals, and requirements. The methodology is then introduced, along with an overview of its individual structural components.

A. CONCEPT

ID3SAS seeks to provide researchers, and developers who want to build a SAS with a set of essential requirements, specifications, and guidelines, distilled from a comprehensive study of the latest advancements in the field [8]. Within the context of this research work, a SAS is a system that combines different technologies (IoT, sensors, actuators, AI, and cloud computing, among others) in order to give the possibility to farmers and managers to have control over the agricultural processes and make better and quicker decisions. The following services are accessible through this system:

- **Monitoring:** Several parameters are measured by sensors that are strategically placed in the agricultural field and/or greenhouses (sometimes referred to as the "physical environment" in this document) and transferred, using proper communication protocols, to a local-based or cloud-based service for storage and further processing and analysis. External sources could also provide valuable data, which could include forecasting services (*e.g.*, OpenWeatherMap API [23]) or satellite Earth observation services (*e.g.*, Copernicus-related services [24]).
- **Data transmission, storage, and processing:** IoT technology is in charge of sending the collected data from the physical environment to a gateway server, which can send to a local-based or cloud-based server for storage and further processing.
- **Data analysis and predictions:** AI-based methods, particularly in the facet of ML, can identify complex patterns, trends, and relationships in the multidimensional, heterogeneous data, making accurate predictions and providing a strong foundation for improved decision-making and operations management.
- **Decision support:** A DSS seeks to assist managers and farmers in making quicker and more effective decisions to facilitate the planning of their agricultural activities.
- **Control:** It may be necessary to act on the physical environment (automatically or under user control). For instance, activating and controlling actuators to change the environment or the condition of the process in a predefined manner. A six-level model of automated decision-making based on AI is described in [25] and [26], starting from level 0 (no autonomy) until level 5 (full autonomy).

The successful development and implementation of a SAS in the agricultural sector envisions to assist in sustainable development, by providing social, economic, and environmental benefits. These benefits could include improving crop productivity and farm profitability, optimising the management of farm inputs (*e.g.*, irrigation water), and improving both storage and marketing activities thus ensuring food security.

B. GOALS AND REQUIREMENTS

Goals have long been recognised as essential elements involved in the Requirements Engineering process as they provide the rationale for requirements [27], [28]. Considering this, Table 1 presents the goals that have been defined for ID3SAS. The description of these goals can be found in Table 7 (Appendix). These goals have as a foundation the review made by the authors in [8].

These goals can be seen as general key aspects to advance the agricultural sector towards the digitalisation and empowerment of a SAS with AI, from the integration of

TABLE 1. ID3SAS goals.

ID	Goal
G-01	Enable the digitalisation of agriculture
G-02	Enable an integrative approach for smart agriculture
G-03	Transform collected data into added-value
G-04	Support the development of an intelligent system to assist in decision-making processes
G-05	Enable a data-driven and proactive control of the physical environment
G-06	Achieve general applicability to different scenarios
G-07	Achieve robustness to dynamic environmental conditions
G-08	Facilitate the utilisation of technology

multiple sensor nodes to the adoption of data-driven and automated processes. In addition, it is important to consider a generic approach that can be adopted across diverse agricultural scenarios. Furthermore, facilitating the utilisation of technology involves providing practical solutions that are user-friendly and accessible for farmers to embrace technological advancements in agriculture.

A requirement describes the capabilities or characteristics that a product or service must provide to deal with a specific problem. According to [29], the requirements can be categorised in: (1) Functional Requirement (FR): "*1. statement that identifies what results a product or process shall produce. 2. requirement that specifies a function that a system or system component shall perform*", and (2) Non-Functional Requirement (NFR): "*1. software requirement that describes not what the software will do but how the software will do it*". Table 2 lists both FR and NFR defined for the ID3SAS. The description of each requirement can be found in Table 8 (presented in Appendix).

However, it is important to remember that these requirements should be seen as a foundation for the design and implementation of a SAS within the scope of Agriculture 4.0. Depending on the case study at hand, requirements will have to be refined or new requirements will have to be adapted, as long as they meet the particular needs and desires of the stakeholders.

C. METHODOLOGY

ID3SAS is an integrative methodology that formalises the steps that should be taken to design and implement a SAS in the context of Agriculture 4.0. It proposes valuable tools for the agricultural sector and is designed with generic applicability in mind, in order to be used in different types of crops, fields, and environmental conditions, while still offering a wide variety of features and high usability.

Figure 1 illustrates the ID3SAS methodology, its core components, data flow, and phases. This methodology has as a foundation the conceptual cloud-based IoT architecture proposed by [8]. This architecture consists of four layers (from bottom to top: physical, communication, service, and application layers). Adapting this architecture to ID3SAS, we have:

- **Physical layer**: Responsible for monitoring and actuating functions, where data are collected from the IoT devices and actions are made in the field through actuators. It includes the *Sensing* and *Control* components.
- **Communication layer:** Where adequate network allows the data communication between layers. It includes the *Gateway* component.
- **Service layer:** Responsible for data storage, processing, and analysis. It includes the *Database*, *Data Processing*, *Artificial Intelligence*, and *Decision Support* components.
- **Application layer:** For the access of agricultural information and control actions. It includes the *Human-Machine Interface* component.
- **Other sources (optional):** External dataset(s). It concludes the *External Source* component.

TABLE 2. List of Functional and Non-Functional Requirements for ID3SAS.

ID	Functional Requirement
FR-01	Integrate heterogeneous components
FR-02	Acquire data
FR-03	Store data
FR-04	Process the collected data and transform them into added-value
FR-05	Predict future states
FR-06	Take actions on the physical environment
FR-07	Display data
FR-08	Provide alerts and notifications
FR-09	Provide recommendations
	Non-Functional Requirement
NFR-01	Interoperability
NFR-02	Connectivity and data transmission
NFR-03	Modularity
NFR-04	Adaptability
NFR-05	Flexibility
NFR-06	Availability
NFR-07	Usability
NFR-08	Reliability
NFR-09	Predictability
NFR-10	Robustness
NFR-11	Non-invasiveness

This methodology is also divided into seven stages representing the data flow, starting from:

1) **Data Acquisition**: The first step of ID3SAS methodology and, as the name implies, is where data are collected. In this phase we have (a) *Sensing* component, responsible for acquiring the data directly from the sensors or other devices in the Physical Layer; and (b) *External Source* component (optional), an external data source could be any source in the Internet that does not belong to the local network (*e.g.*, weather forecasting services). The combination of different types of sensing devices can produce a more global informative dataset.

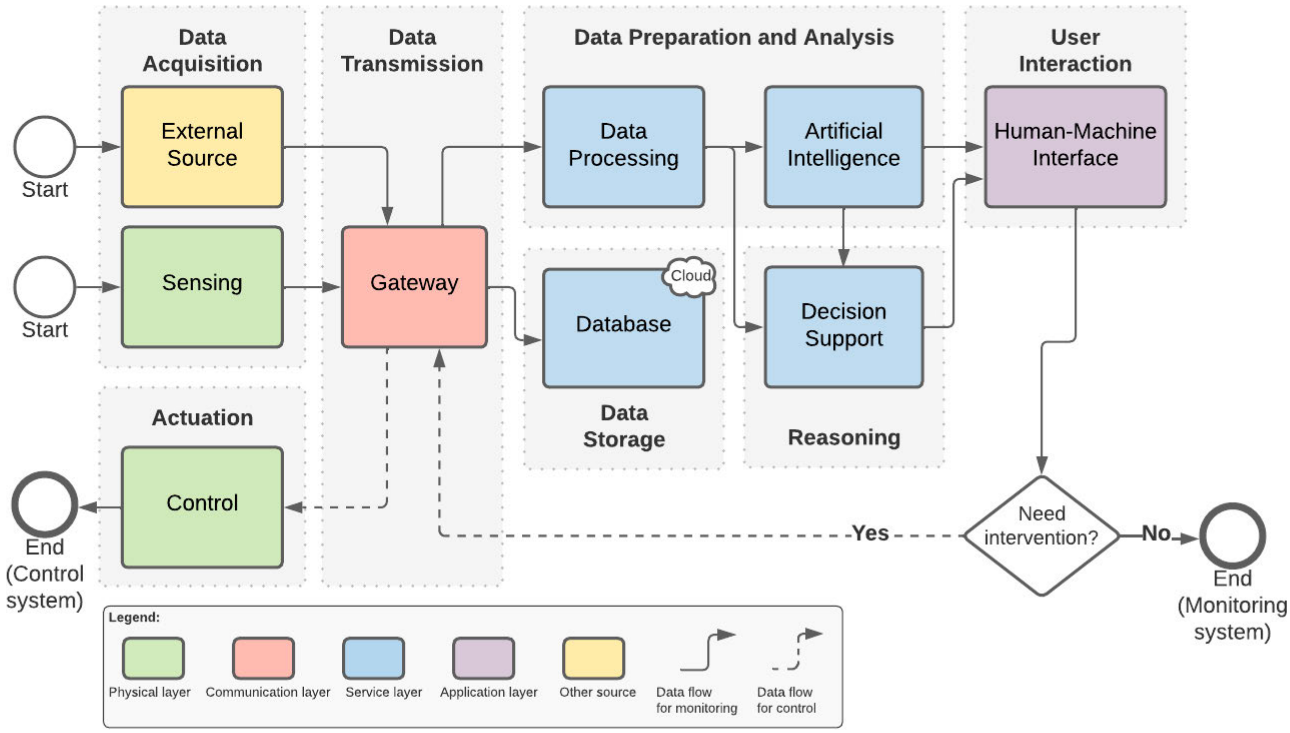

FIGURE 1. The ID3SAS Methodology, composed of nine core components: External Source, Sensing, Control, Gateway, Cloud-based Data Storage, Data Processing, Artificial Intelligence, Decision Support and Human-Machine Interface.

2) **Data Transmission:** After collecting the desired data, it is necessary to transfer it to the next phase so that it can be stored, processed, and analysed. The physical devices (sensors and/or actuators) can be connected to a *Gateway* component that plays a role as the data forwarder between different networks. The choice of the most adequate communication protocol fully depends on the requirements of the system to be designed and implemented, as well as economic, accessibility, and capacity factors.
3) **Data Storage:** Cloud computing (*e.g.*, Database-as-a-Service (DBaaS) [30] and Platform-as-a-Service (PaaS) [31]) is very convenient for applications that use a huge amount of data, as it provides inexpensive data storage services for text, image, video, and other formats, which considerably reduces storage costs for agricultural enterprises. As so, a *Cloud-based Data Storage* component can be found in this phase, where data from the *Sensing* component and external sources are virtually stored in a cloud-based server for further processing and analysis.
4) **Data Processing and Analysis:** Sometimes, data collected from sensors and/or external sources are not ready to be directly used for decision-making processes. Facing this, the *Data Processing* component is responsible for transforming these "raw" data and preparing it for the next phase. Additionally, the *Artificial Intelligence* component can be used for advanced data analysis and generating predictions.
5) **Reasoning:** In this phase, the *Decision Support* component receives inputs from the previous phases and calculates and deducts watering suggestions (*e.g.*, precise time for watering the fields). Data transformation is done by reasoning processes, *i.e.*, the component contains a Rule base and Fact base that enables the system to infer new data and make decisions. This system uses log data of the system, combined with AI-based techniques and agricultural expertise to create new appropriate rules and thus enrich the Rule base.
6) **User Interaction:** Users can easily visualise the information from the physical environment by requesting data from the *Sensing* component and/or *External Source* component. To this end, an Human-Machine Interface (HMI) should be designed to support the processes of the entire SAS. According to the user's demands, the output of this phase could be data/information for monitoring purposes, and/or physical action realised by an actuator. After the data leave the *Human-Machine Interface* component, there are two possible paths, as it is necessary to understand if there is a need to act in the physical layer: Does the agro-system "need intervention?". If NO, the data flow ends with the *HMI* component; If YES, the user sends the final command to the actuators in the *Control* component.

7) **Actuation:** In this phase, we find the *Control* component, which is responsible for controlling the actuators that are placed in the physical environment. Therefore, the level of autonomy of the system needs to be defined.

Additionally, it is possible to see in Figure 1 two input points - *Start* - indicating that the system can acquire data from both internal (sensor) and external sources. There are also two output points - *End* - indicating whether the system is a *Monitoring system* (for monitoring purposes) or a *Control system* (applicable when the physical environment needs actuator intervention).

III. ID3SAS IMPLEMENTATION

The ID3SAS methodology was deployed and tested in a lab scenario: a prototype consisting of tomato plants, located inside the UNINOVA room, at NOVA School of Science and Technology (NOVA-SST), Caparica, Portugal. The idea of this case study was to have separate tomato plants (of the same batch), where one was watered every three days according to the manufacturer's specification, and the other is watered according to the recommendations of the ID3SAS system (Figure 2). It is worth highlighting that the goal of this prototype is to provide a reference for implementing the ID3SAS methodology. As such, only two plants were used since the focus was the functionality testing of the reference implementation. Regardless, it possesses the flexibility to be customised and scaled to accommodate larger agricultural scenarios.

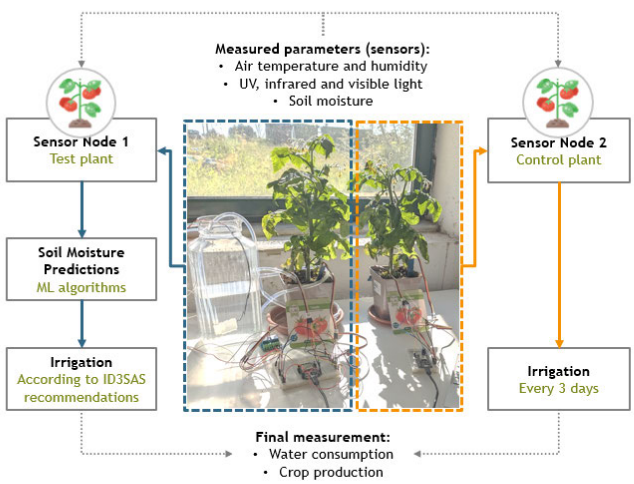

FIGURE 2. ID3SAS case study: example of two tomato pots (from the same batch), one of which received irrigation recommendations according to the manufacturer ('control plant') and the other received irrigation recommendations from the ID3SAS system ('test plant').

The material used for this case study is listed below:

- **Plants:** Tomato plants (*Lycopersicon esculentum* L.), inserted in plots with a surface area of 0,04 m^2.
- **Hardware:** (a) two microcontrollers (ESP32 NodeMCU and ESP8266 NodeMCU); (b) one single-board computer (Raspberry Pi 3 Model B); (c) six sensors (two air temperature and humidity sensors DHT11, two sunlight sensors SI1145, two capacitive soil moisture sensors); (d) two actuators (one 2-channel SPDT Relay, one submersible water pump with a flow rate of, approx., 120 $L/hour$); (e) Bresser Weather Station 7-in-1 Sensor; (f) Other relevant components (external power supply, breadboards, jumper cables, water tank).
- **Software:** (a) Arduino IDE; (b) Docker; (c) Eclipse Mosquitto; (d) Node-RED; (e) MongoDB Atlas; (f) Jupyter Notebook; (g) Weather API - OpenWeatherMap.

A. SENSING COMPONENT

In this prototype, the *Sensing* component consists of two sensor nodes, namely Sensor Node 1 and Sensor Node 2. Both of these nodes are equipped with a set of sensors, including the SHT31, SI1145, and capacitive soil moisture sensors. The primary distinction lies in the microcontroller employed by each node, as Sensor Node 1 integrates the ESP32 NodeMCU, whereas Sensor Node 2 utilises the ESP8266 NodeMCU.

Figure 3 shows the hardware structure for Sensor and Actuator Node 1. In both sensor nodes, the microcontroller is responsible for sending the collected data from sensors to the *Gateway* component (subsection III-C) via WiFi using MQTT protocol. The SHT31 (air temperature and humidity) and SI1145 (sunlight) sensors are calibrated based on the weather station readings. The soil moisture sensor is calibrated by correlating the values when the sensor is placed in the air and when it is immersed in water. Data are collected with 1 hour sampling time.

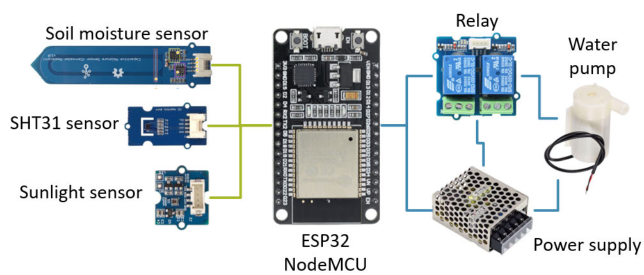

FIGURE 3. ESP32 NodeMCU connected to sensors (SHT31, SI1145, capacitive soil moisture), actuators (2-channel relay, water pump), and an external power supply.

B. EXTERNAL SOURCE COMPONENT

The *External Source* component was designed to correlate the parameters obtained by the physical sensors and by external sources (such as global and local weather stations, satellites, and radars). The developed *External Source* component relies upon the OpenWeatherMap API. This Application Programming Interface (API) is useful for retrieving both current and forecasted weather data (up to a duration of 5 days) for any given location across the globe. Subsequently, this functionality will prove valuable for the *Decision Support* component (subsection III-G), as it will require consideration of significant indicators such as precipitation patterns, including current and forecasted rainfall within the upcoming hours. Based on these indicators, the ID3SAS system will make informed decisions regarding the watering or non-watering of plants.

C. GATEWAY COMPONENT

The *Gateway* component is responsible for distributing data from the physical layer and from external sources to other components of the methodology. The communication is carried out using MQTT protocol (over WiFi network) through tools like Mosquitto and Node-RED, which serve as a communicator and integrator, respectively. MQTT is a suitable solution for this prototyping experiment, as it provides a simple and lightweight Publisher-Subscriber architecture that fits well within the scope of such IoT solutions. For monitoring purposes, the WSAN functions as a Publisher, while Node-RED assumes the role of a Subscriber. Conversely, in terms of control, Node-RED acts as a Publisher, while the WSAN as a Subscriber.

It is important to acknowledge that, despite the previous mention of Sigfox, ZigBee, and LoRa as the most suitable wireless communication protocols for IoT-based agricultural applications, this article employed WiFi for the developed case study. This choice was made due to the availability of ESP32 and ESP8266 microcontrollers equipped with built-in WiFi modules, which were readily accessible for use in the experiment.

In Figure 4 the flow was configured to get data from the Sensor Node 1 via MQTT and store it in the cloud database, using MongoDB Atlas. It also provides functionality to trigger sensor data retrieval, send commands to the ESP32, and manually refresh the sensors. The same logic was used to configure Sensor Node 2.

D. DATABASE COMPONENT

The selected database for this experiment is MongoDB Atlas,[1] a cloud-based Not Only-Structured Query Language (NoSQL) database solution provided by MongoDB. It was chosen due to its reliability, scalability, and security features, making it an ideal choice for implementing the ID3SAS system. The deployment of *Database* component was facilitated using Node-RED, by installing the "node-red-node-mongodb" package [32]. This package includes three nodes: Mongodb, Mongodb in, and Mongodb out, which enable the seamless storage and retrieval of data in/from a MongoDB instance (Figure 4).

E. DATA PROCESSING COMPONENT

The *Data Processing* component is crucial to clean, transform, and prepare the data for various purposes, such as visualisation or for training AI-based models. Figure 5 shows the processes of Artificial Intelligence and data pre-processing. The pre-processing stage was made using the Python language within Jupyter Notebook and implemented in Node-RED. It is important to note that specific pre-processing steps and techniques may vary depending on the characteristics of the data and the requirements of the intended ML models.

1) FEATURE ENGINEERING:

Feature Engineering was an important step in this process in order to improve the performance and interpretability of ML models. This involved selecting relevant features, eliminating redundancy, and creating new informative features derived from existing ones. These efforts aimed to provide additional information to the models, thereby enhancing their overall effectiveness. Table 3 provides an example of Feature Engineering applied in the prototype. In this example, the dataset was transformed to enable auto-regression modelling, such that a model can be built using the past recent values (lags) of a time series as explanatory variables (input), to predict future observations (output). As so, two engineered features were created - "Soil Moisture (t-1)" and "Soil Moisture (t+1)". These new features are derived from the original "Soil Moisture" input feature and represent the soil moisture values (from sensors) at the previous and subsequent times, respectively. By introducing these engineered features, the ML model can capture temporal dependencies and patterns in the data that might be useful for predicting future soil moisture levels. The same logic was used for the parameters "AirTemp", "AirHum", "UVLight", "VisibleLight" and "IRLight".

TABLE 3. Example of Feature Engineering used in the data pre-processing process.

Inputs (from sensors)		Engineered Input	Engineered Output
Time	Soil Moisture	Soil Moisture (t-1)	Soil Moisture (t+1)
t	60	NaN	59
t+1	59	60	58
t+2	58	59	57
t+3	57	58	NaN

2) HANDLE MISSING VALUES AND OUTLIERS:

Missing values were handled appropriately using Pandas package.[2] To remove the outliers, the techniques Z-score and Interquartile Range (IQR) were used.

3) STANDARDISATION AND NORMALISATION:

Standardisation and normalisation [33] are two common techniques used in data pre-processing to transform the features of a dataset in preparation for creating ML models. Standardisation adjusts features to have zero mean and unit variance, while normalisation scales features to a specific range, typically between 0 and 1.

[1] www.mongodb.com

[2] https://pandas.pydata.org/

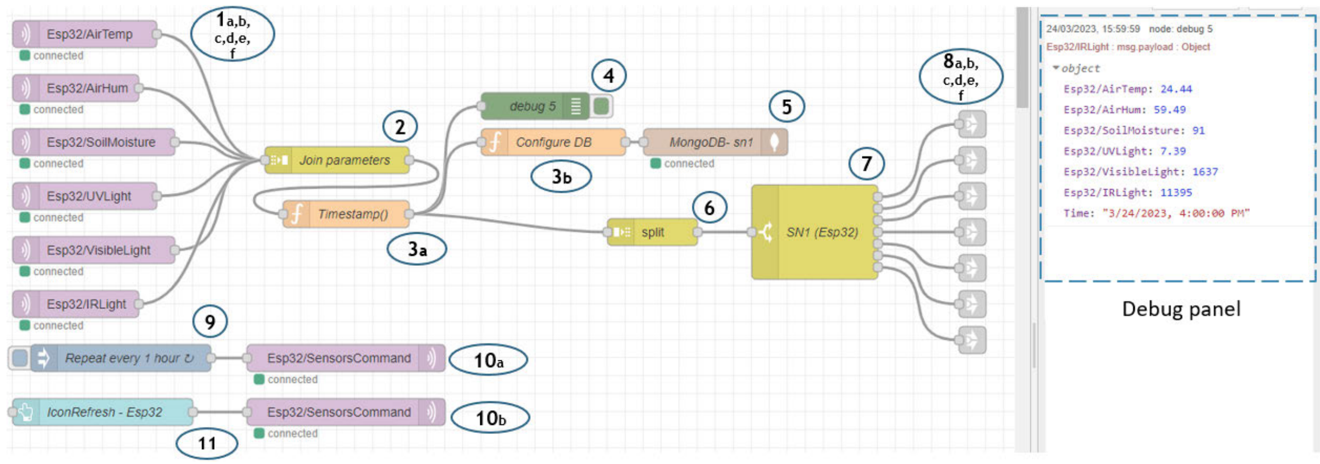

FIGURE 4. Node-RED flow configured to get data from the Sensor Node 1 (publisher) via MQTT to the Node-RED (subscriber) and store them in the MongoDB Atlas database. The nodes used are: (1a,b,c,d,e,f) MQTT in, (2) Join, (3a,b) Function, (4) Debug, (5) Mongodb out, (6) Split, (7) Switch, (8a,b,c,d,e,f) Link out, (9) Inject, (10a,b) MQTT out and (11) UI Button node.

F. ARTIFICIAL INTELLIGENCE COMPONENT

The process of creating predictive models using ML for regression tasks typically involves several key steps: data preparation, data splitting, model selection, training, evaluation, and fine-tuning. Figure 5 illustrates the steps of ID3SAS AI process:

- Data split: the dataset is divided into training and testing subsets, typically with a split of around 70-80% for training and 20-30% for testing;
- Model selection: the choice of regression models [33] includes linear regression, decision trees, random forests, etc.;
- Model training: the selected model is trained using the training data;
- Model evaluation: the trained model is assessed in terms of performance using the test dataset. Evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), or R-squared (R^2) are commonly used;
- Fine-tuning: if the model's performance is unsatisfactory, it is necessary to refine or fine-tune the model to enhance its performance. Techniques such as Grid Search Cross Validation (GridSearchCV) [33] can be used to find the best combination of hyperparameters.

1) MODEL SELECTION, TRAINING AND EVALUATION:

Five regression algorithms were selected to predict the soil moisture and the time-to-water, namely: Random Forest, ExtraTR, Gradient Boosting Regression (GradientBR), and AdaBoost (with Decision Tree) [33]. The following features were passed to the model:

- Inputs (from sensors): "AirTemp", "AirHum", "SoilMoisture", "UVLight", "VisibleLight"and "IRLight".
- Inputs (from Feature Engineering): "AirTemp(t-n)", "AirHum(t-n)", "SoilMoisture(t-n)", "UVLight(t-n)", "VisibleLight(t-n)" and "IRLight(t-n)", where n is the hour of monitoring.
- Outputs: "SoilMoisture(t+n)" (estimates soil moisture value after n hours) and "TimeToWater" (estimates the number of hours remaining until it is necessary to water the plants again).

Table 4 compares the selected models according to their evaluation metrics - RMSE and R^2 (equations 1 and 2, respectively). These metrics were used to assess the accuracy and performance of the predictive models:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

where, n represents the number of data points, yi the observed values, $\hat{y}_i$ the predicted values, and $\bar{y}$ the mean of the observed values.

The two best models were selected for optimisation using GridSearchCV [33].

2) DEPLOYMENT:

The *Artificial Intelligence* component was deployed in Node-RED. Thus, five Predictor nodes were created, namely: "AdaBoost_SoilMoisture_t+1", "AdaBoost_SoilMoisture_t+12", "AdaBoost_SoilMoisture_ t+24", "ExtraTR_SoilMoisture_t+6" and "ExtraTR_ Timetowater". These models were chosen according to Table 4.

G. DECISION SUPPORT COMPONENT

The *Decision Support* component aims to aid managers and farmers in expediting and enhancing the decision-making process, thereby facilitating the strategic planning of their agricultural endeavors. Figure 6 illustrates its process. The first step is to retrieve the current data (air temperature and

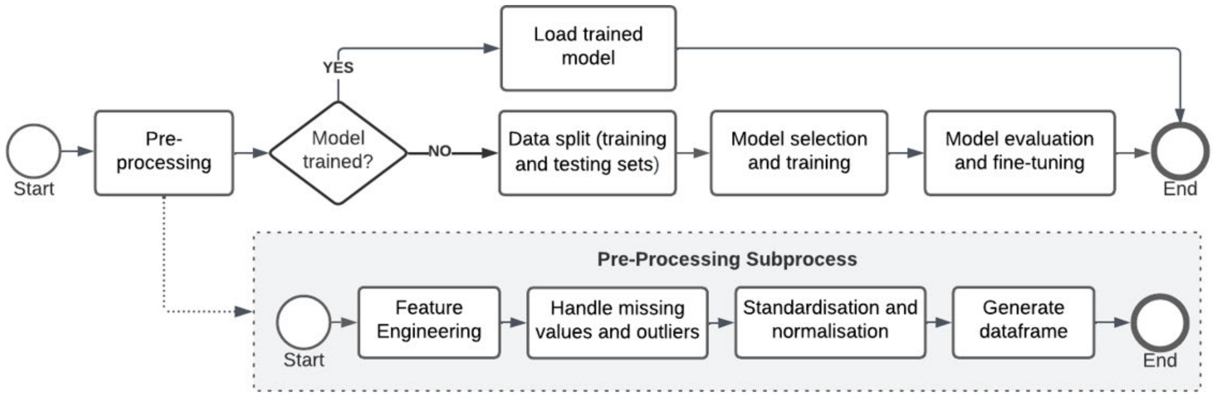

FIGURE 5. ID3SAS Artificial Intelligence process and data pre-processing subprocess.

TABLE 4. Performance evaluation (RMSE and R^2) of the predictive models for "SoilMoisture(t+n)" and "TimeToWater" estimations.

	SoilMoisture(t+n)								TimeToWater	
	t+1		t+6		t+12		t+24			
Model	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Random Forest	3.84	0.91	6.93	0.67	7.46	0.67	9.40	0.47	9.06	0.82
ExtraTR	3.94	0.90	5.88	0.77	7.00	0.71	9.00	0.52	7.48	0.88
GradientBR	4.14	0.89	6.68	0.70	7.69	0.65	9.88	0.42	8.52	0.85
AdaBoost	3.91	0.90	6.29	0.73	8.28	0.59	8.98	0.52	8.92	0.83
After GridSearchCV										
ExtraTR	4.46	0.87	$\boxed{5.57}$	$\boxed{0.79}$	7.13	0.70	8.47	0.57	$\boxed{7.26}$	$\boxed{0.89}$
AdaBoost	$\boxed{3.81}$	$\boxed{0.91}$	7.50	0.62	$\boxed{6.73}$	$\boxed{0.73}$	$\boxed{8.11}$	$\boxed{0.61}$	8.68	0.84

humidity, soil moisture, UV, visible light and infrared light) from sensors (*Sensing* component, subsection III-A). If the soil moisture value is higher than the threshold (in this case study the limit value is 60%), then the system does not take actions. On the other hand, if the value is lower, then the system checks the weather forecasting (*External Source* component, subsection III-B). If it is expected to rain in the next 6 hours, the system does not irrigate the plants. Otherwise, if it is not expected to rain, the Fuzzy Logic System (FLS) calculates the irrigation time in accordance with data retrieved from the sensors. We used Fuzzy Logic to determinate irrigation time, as it is useful to handle uncertain and imprecise inputs rather than relying on binary classifications (*e.g.*, soil moisture is "dry" or "not dry"), allowing for more accurate and flexible irrigation scheduling.

1) DEFINING PARAMETERS

The crop's water needs are influenced by weather parameters. Table 5 shows the general relation between tomato water needs and air temperature and humidity, cloudiness, UV index [34], and wind speed. It is important to note that this Table provides a general indication of the relations between the crop water needs and climatic factors, as the actual water needs required may vary based on the crop type, soil type, and other environmental factors.

From Table 5, it is possible to take into consideration the following general principles:

TABLE 5. General relation between crop water needs and climatic factors (air temperature and humidity, cloudiness, UV index, and wind speed). "+", "++", "−" and "−−" represent strong, very strong, weak, and very weak relations, respectively. Information based on [35] and [36] for tomato plants.

Parameters		**Crop water needs**
Air temperature	Very cold (<10°C)	- -
	Cold (10-15°C)	-
	Normal (16-30°C)	+
	Hot (>30°C)	++
Air humidity	Low (<40%)	++
	Medium-low (40-55%)	+
	Medium-high (56-70%)	-
	High (>70%)	- -
Cloudiness	Overcast (<39%)	- -
	Mostly cloudy (40-69%)	-
	Partly cloudy (70-89%)	+
	Clear sky (90-100%)	++
UV Index	Low (0-2)	- -
	Moderate (3-5)	-
	High (6-7)	+
	Very high (>8)	++
Wind speed	Light (<2 ms^{-1})	-
	Moderate (2-5 ms^{-1})	+
	Strong (5-8 ms^{-1})	++
	Very strong (>8 ms^{-1})	++

- Air temperature: higher temperatures increase water evaporation, leading to greater water requirements for plants;

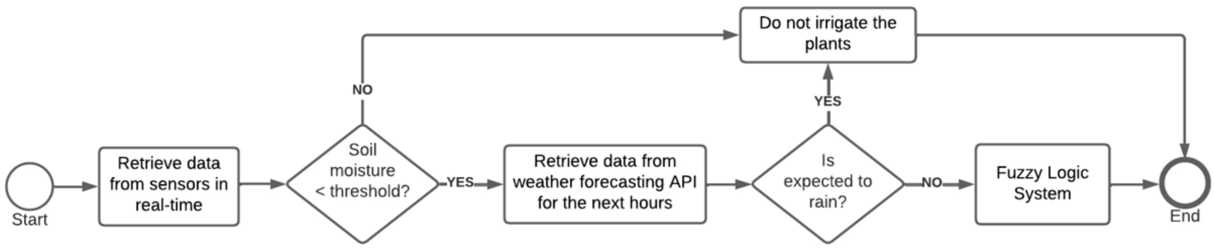

FIGURE 6. ID3SAS Decision Support process.

- Air humidity: lower humidity levels enhance water evaporation, necessitating more water for plants in low humidity conditions;
- Cloudiness: clear sky conditions result in elevated evaporation rates and higher water needs, while cloudy conditions reduce evaporation and decrease water requirements;
- UV Index: higher UV radiation levels stimulate increased evaporation and transpiration in plants, increasing their water needs;
- Wind speed: strong winds accelerate evaporation and can dry out plants, requiring additional irrigation to compensate for the enhanced water loss.

In this article, the water crop needs are translated to "Irrigation Time", and so was considered the output of the FLS. It has four subparameters, namely: "Short" (2 secs), "Medium-short" (3 secs), "Medium-long" (4 secs), and "Long" (5 secs). Remembering that the submersible water pump used has a flow rate of 120 L/hour (approx.), it implies that the pump irrigates 33.3 mL/second (approx.) of water.

2) FUZZY SETS AND MEMBERSHIP FUNCTIONS

The FLS sets and their associated membership functions are represented in Figure 7. All three inputs "Air Temperature", "Air Humidity" and "UV Index" and the output "Irrigation Time" have four fuzzy sets. The "Cloudiness" and "Wind speed" parameters were not considered, as the experiment was performed inside a room.

3) FUZZY RULES

Given the fuzzy sets, there are 64 possible rules that can be generated based on Mamdani Fuzzy Inference System [37]. These rules were described using the "IF - THEN" condition. Examples: Rule 1: "IF Air Temperature is Very Cold AND Air Humidity is Low AND UV Index is Low THEN Irrigation Time is Short"; Rule 2: "IF Air Temperature is Normal AND Air Humidity is Medium-high AND UV Index is High THEN Irrigation Time is Medium-Long"; Rule 3: "IF Air Temperature is Hot AND Air Humidity is Low AND UV Index is Low THEN Irrigation Time is Long". These rules were decided based on Table 5 and the professional knowledge of the authors of this article.

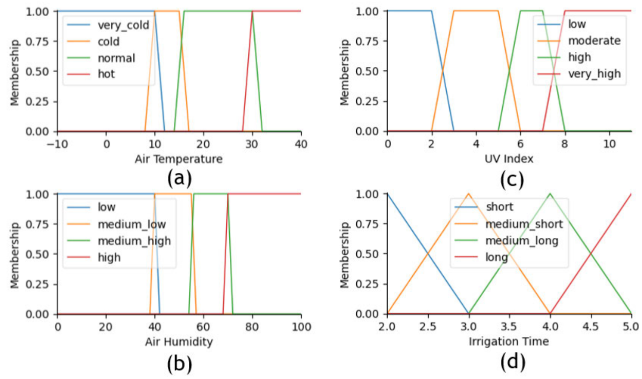

FIGURE 7. Membership functions of Fuzzy Logic System: (a) Air Temperature (fuzzy sets: 'very_cold', 'cold', 'normal' and 'hot'), (b) Air Humidity (fuzzy sets: 'low', 'medium_low', 'medium_high' and 'high'), (c) UV Index (fuzzy sets: 'low', 'moderate', 'high' and 'very_high') and (d) Irrigation Time (fuzzy sets: 'short', 'medium-short', 'medium-long' and 'long').

4) DEPLOYMENT

The *Decision Support* component was deployed using Node-RED. As illustrated in Figure 6, the first step is to set the soil moisture value. In this case study, the value is 60%. The second step is to retrieve information from the *External Source* component (subsection III-B), where it is possible to understand if it is predicted to rain in the next few hours. However, as the experiment was performed indoors, this functionality was not considered for the recommendations.

The result of this process is the "Irrigation Time", which maps it to the corresponding irrigation label: "Short" (2 secs), "Medium-short" (3 secs), "Medium-long" (4 secs) or "Long" (5 secs). These outputs will subsequently serve the purpose of controlling the duration of the water pump's operation (subsection III-H), thereby regulating the amount of water utilised for watering the respective plant.

H. CONTROL COMPONENT

The *Control* component of the prototype consists of one Actuator Node, composed of a microcontroller (ESP32 NodeMCU), a relay (2-channel SPDT Relay), and an actuator (submersible water pump) (Figure 3). The relay is used to control the water pump. Given that the ESP32/ESP8266 was not sufficient to power both the sensors and the water pump, an external power supply was incorporated into the system. Depending on the system requirements, the actuators can be controlled in two ways: manually or automatically.

Figure 8 illustrates the *Control* component process. The outputs generated by the FLS regulate the duration of the water pump's operation, thereby directly controlling the quantity of water utilised for the irrigation processes.

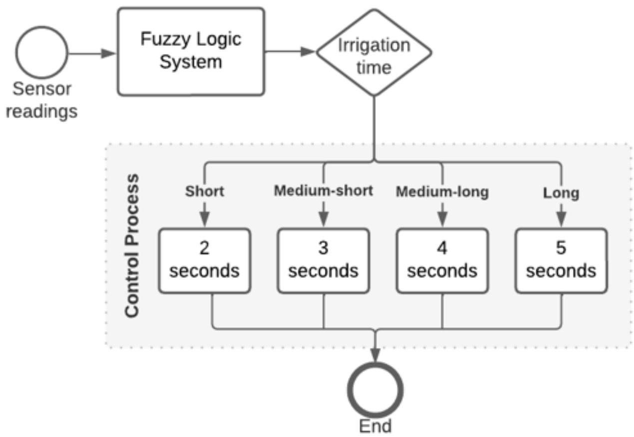

FIGURE 8. ID3SAS Control process.

I. HUMAN-MACHINE INTERFACE COMPONENT

The ID3SAS dashboard has six tabs offering various features:

- **Home tab:** Provides real-time data visualisation from sensors, actuators, and weather. It also offers recommendations based on the data. (Figure 9).
- **Weather forecasting tab:** Displays weather forecasts for up to 5 days, using OpenWeatherMap's API.
- **Plant's Info tab:** Contains a dataset with information on various plants, including vegetables (beetroot, broccoli, carrot, cucumber, eggplant, garlic, green pea, lettuce, onion, pepper, potato, and sweet potato) and fruits (apple, lemon, melon, strawberry, tomato, and watermelon). (Figure 10).
- **Historical Data tab:** Stores weekly data collected from sensors.
- **Predictions tab:** Stores weekly data generated by predictive ML models.
- **Files tab:** Enables users to download data from the database (specifically, MongoDB Atlas) in.csv format.

The user-friendly dashboard provided an intuitive interface that allowed users to access real-time data and information effortlessly. Moreover, predictions and recommendations are visualised in the dashboard, and were based on the analysis of historical data, current conditions, and crop-specific requirements. By leveraging this intelligent guidance, users could optimise resource allocation, mitigate risks, and maximise crop yield. Beyond data visualisation and recommendations, the dashboard also facilitated control actions. Users can remotely monitor and adjust irrigation systems, activate or deactivate equipment, and implement automated processes for timely interventions.

IV. RESULTS AND DISCUSSION

A. GOALS AND REQUIREMENTS

The current article highlights the implementation of ID3SAS methodology in a laboratory scenario (*i.e.*, the prototype). The aim is to assess the functionality and efficacy of the methodology and if it successfully achieves the initially proposed goals (Table 1) and fulfills the established requirements (Table 2). Table 6 provides information on the extent to which the ID3SAS prototype meets the intended goals and satisfies both FR and NFR.

TABLE 6. Goals and (functional and non-functional) requirements validation for ID3SAS implementation in the prototype.

ID/Goals		ID/FR		ID/NFR	
G-01	✓	FR-01	✓	NFR-01	✓
G-02	✓	FR-02	✓	NFR-02	✓
G-03	✓	FR-03	✓	NFR-03	✓
G-04	✓	FR-04	✓	NFR-04	✓
G-05	✓	FR-05	✓	NFR-05	✓
G-06	✓*	FR-06	✓	NFR-06	✓
G-07	—	FR-07	✓	NFR-07	✓
G-08	✓	FR-08	✓	NFR-08	✓
		FR-09	✓	NFR-09	✓
				NFR-10	—
				NFR-11	✓

While the authors duly recognise the importance of plant physiology, crop production, and water consumption in irrigation processes, it asserts that, within the scope of this study, the primary focus is placed on evaluating the performance of the ID3SAS methodology itself. According to this Table, all goals were successfully accomplished for the prototype, with the exception of goal 7 - *Achieve robustness to dynamic environmental conditions*. The outcome can be attributed to the controlled laboratory setting in which the experiment was conducted, where dynamic environmental factors such as rainfall and wind were absent. Consequently, the corresponding requirement NFR-10, which relates to robustness, could not be fulfilled. In order to address this, the acquisition of more resilient and outdoor-ready hardware, including sensors and actuators, will be necessary. The authors are fully aware of this and have plans to incorporate it into a future outdoor case study in the near future.

Regarding goal 6 - *Achieve general applicability to different scenarios* - and despite the fact that ID3SAS methodology was implemented and tested exclusively in tomato plants, a notable feature has been integrated into the HMI dashboard (Figure 10). This feature incorporates information pertaining to various vegetables and fruits, encompassing essential parameters such as the minimum, maximum, and optimum temperature for vegetative growth, relative humidity, and photoperiodism. Consequently, users can conveniently navigate the dashboard and select the specific plant of interest. By doing so, the system will provide the corresponding requirements tailored to the selected plant, enabling effective decision-making and facilitating the implementation of relevant strategies.

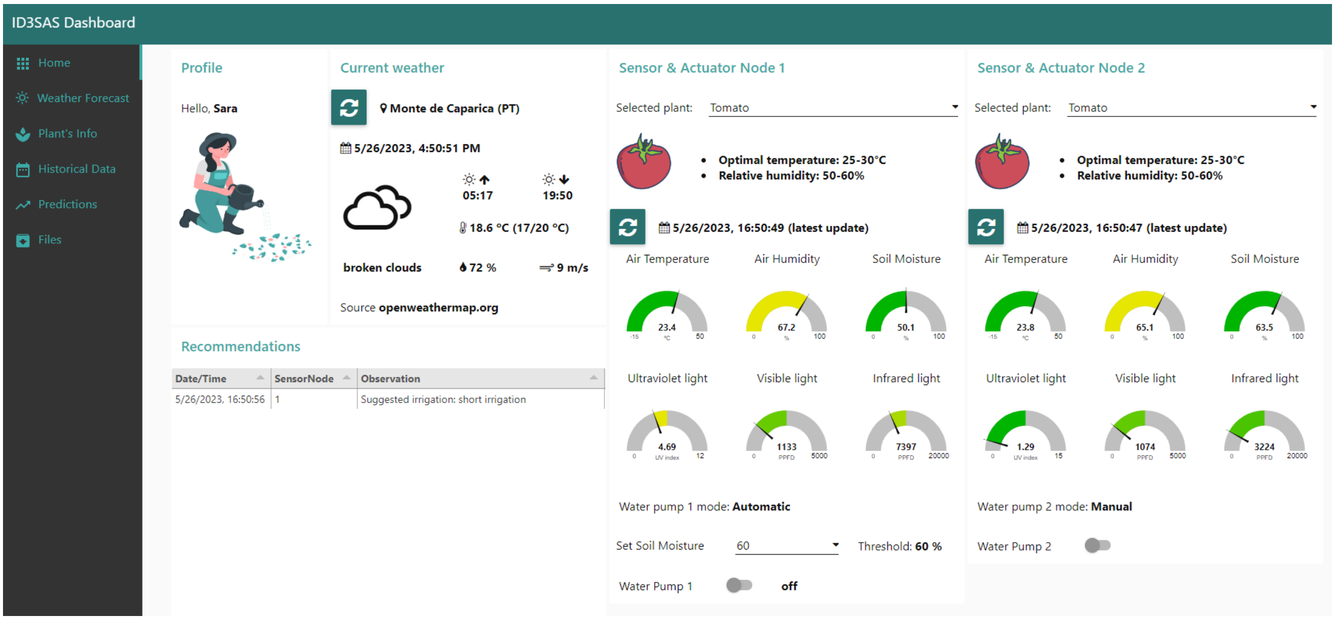

FIGURE 9. ID3SAS Human-Machine Interface (HMI) dashboard, composed of six tabs: Home, Weather Forecasting, Plant's Info, Historical Data, Predictions, and Files.

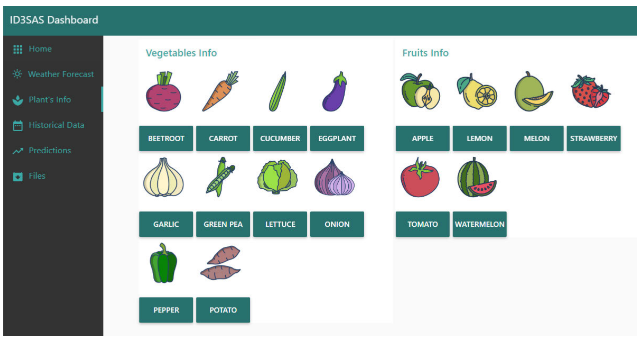

FIGURE 10. ID3SAS Human-Machine Interface (HMI) dashboard: Plant's Info tab.

B. CASE STUDY - PROTOTYPE

ID3SAS methodology was tested on a case study that consisted of having tomato plants in separated pots, where one was watered according to the manufacturer (*i.e.*, every three days) and the other is watered according to the recommendations of the ID3SAS system (Figure 2). After conducting the experiment (from March to April 2023), measurements were taken to assess water consumption and tomato production in both plants. The results indicate that the plant watered in accordance with ID3SAS recommendations had a water consumption of 2190 mL and a crop production of 148 g. In contrast, the plant irrigated according to conventional methods had a water consumption of 2770 mL and a crop production of 109 g. The findings demonstrate a reduction in water consumption of 20.9% and an increase in crop production of 26.4% when using the ID3SAS recommended irrigation technique in comparison to traditional methods. Nevertheless, the authors are aware of the limited representativeness of the case study, as two tomato plants are not representative of the agricultural reality. Consequently, it becomes imperative to undertake a comprehensive implementation on a medium-large scale scenario, in order to validate the efficacy of the ID3SAS system in terms of both production yield and the water consumption used for irrigation purposes. The authors hold the expectation that, upon conducting a case study of a larger scale, the outcomes pertaining to water consumption and crop production will exhibit similarly promising results.

C. HARDWARE AND SOFTWARE

The entirety of the setup depicted in this case study exemplifies a low-cost approach to implementing a SAS, with a total cost of less than 300€. This expense consists of ± 200euro allocated to sensors, actuators, and weather station (which functioned as the reference point for accurate measurements), and ± 70euro to computing equipment. From all the material used in the experiment, some conclusions can be drawn: (1) we chose the ESP32 and ESP8266 microcontrollers instead of Arduino due to their built-in WiFi and Bluetooth modules; (2) we did not notice any difference in performance between the ESP32 and the ESP8266, thereby we suggest that the more cost-effective option can be pursued; (3) a high disparity exists between a resistive soil moisture sensor and a capacitive and corrosion-resistant soil moisture sensor. Initially, the resistive sensor was employed, but after a week of operation, the sensor was corroded, leading to inaccurate measurements. Consequently, it is recommended to employ a capacitive and corrosion-resistant soil moisture sensor; (4) the 7-in-1 Weather Station was exclusively used to calibrate the sensors, specially in terms of air temperature,

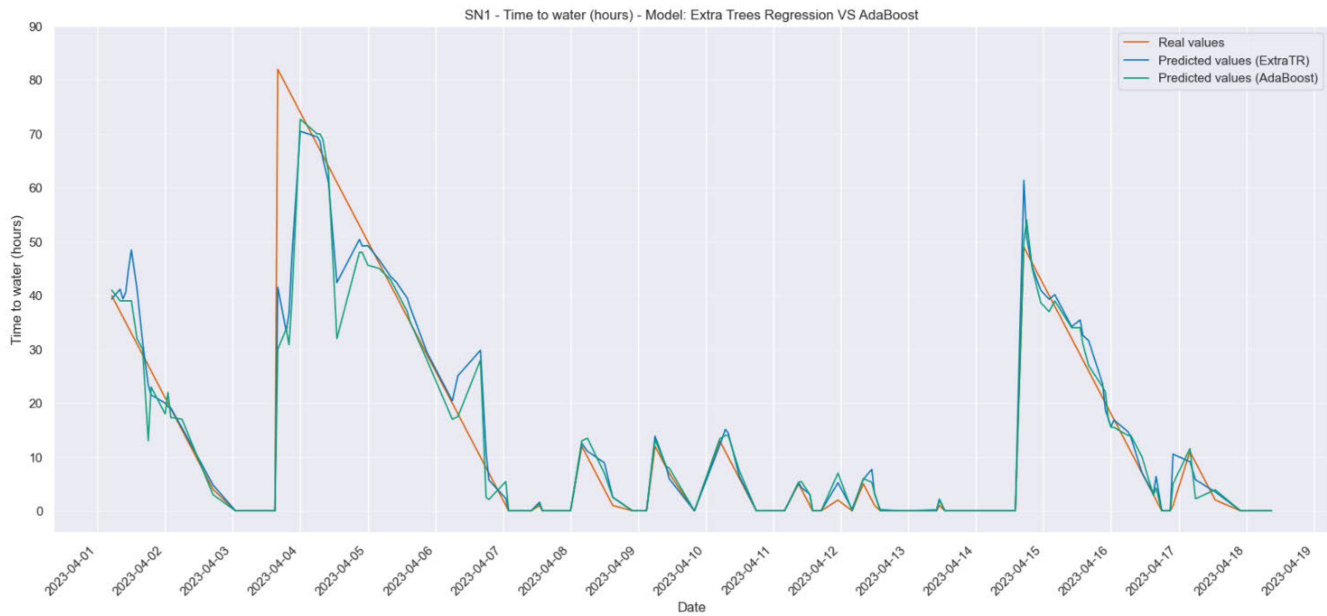

FIGURE 11. Comparison of real values and predicted values (ExtraTR and AdaBoost models) for "TimeToWater" parameter.

humidity and UV measurements; (5) the utilisation of a 2-Channel SPDT (Single Pole Double Throw) Relay was determined based on the availability of resources at hand. However, it should be noted that, for the experiment, only one actuator was employed (submersible water pump), connected to a single relay. As so, if there is only one actuator connected to the WSAN, it is recommended to purchased a non-2-channel relay module instead, as this would allow cost savings without compromising the intended functionality; (6) an external power supply (12VDC/2.1A/25W) was used to facilitate the seamless operation of the ESP modules, sensors and actuators. It was observed that in cases where a node solely consists of sensors without any actuators, the requirement for an external power supply is rendered unnecessary.

However, when designing a SAS based on ID3SAS methodology, it is imperative to consider the adaptation of the equipment to the specific scenario and budgetary constraints. For instance, the selection of appropriate sensors that are outdoor-ready might entail higher costs.

Regarding the software, the selection of open-source software was motivated by its widespread availability, enabling researchers/developers interested in developing a SAS based on the ID3SAS methodology to access and utilise such software freely.

D. ID3SAS COMPONENTS

In the present experiment, by implementing the *Sensing* component (subsection III-A), the prototype was able to gather important agricultural data such as air temperature, humidity, sunlight, and soil moisture. These data served as inputs for subsequent components in the system, enabling informed decision-making and efficient control of irrigation actions.

The *Database* component (subsection III-D) was implemented involving a cloud-based storage, namely MongoDB Atlas. This approach should be the most appropriated choice for storing agricultural information, as it requires a good storage capability for huge volumes of data. However, in situations where enterprise networks restrict access to cloud services, storing the data locally becomes a viable alternative.

The *Data Processing* component (subsection III-E) was important to pre-process data. Feature Engineering was used to generate engineered features based on existing sensor inputs, allowing the predictive ML models to capture temporal dependencies and patterns in data. Missing values and outliers were also handled appropriately.

With regard to the *Artificial Intelligence* component (subsection III-F), the evaluation results of the predictive ML models presented in Table 4 indicate that ExtraTR and AdaBoost exhibited superior performance in estimating soil moisture levels and predicting time-to-water, respectively. The ExtraTR model achieved a RMSE of 5.57 for "SoilMoisture(t+6)" estimation and a R^2 of 0.79. For "TimeToWater" estimation, it achieved a RMSE of 7.26 and a R^2 of 0.89. On the other hand, the AdaBoost model outperformed the ExtraTR model in terms of RMSE and R^2 for "SoilMoisture(t+1)" (3.81 and 0.91, respectively), "SoilMoisture(t+12)" (6.73 and 0.73, respectively), and "SoilMoisture(t+24)" (8.11 and 0.61, respectively) estimations. Furthermore, the output generated by the "TimeToWater" model (Figure 11) was found to be more accurate when compared to the "SoilMoisture(t+*n*)" model. While it is observed that the "SoilMoisture(t+1)" model

TABLE 7. ID3SAS goals and description.

Nr.	Goal	Description
1	Enable the digitalisation of agriculture	ID3SAS aims to digitally transform agriculture by leveraging low-cost and advanced technologies such as sensors, actuators, microprocessors and platforms like satellites and UAV. This digitalisation is enabled through improved wireless communication protocols, IoT deployment, cloud-based ICT systems, AI-based techniques, and Big Data analysis. By converting agricultural data into digital formats and utilising these technologies, ID3SAS empowers farmers and stakeholders to make informed decisions, optimise processes, and maximise productivity in the agricultural sector.
2	Enable an integrative approach for smart agriculture	Smart agriculture is a highly disciplinary domain that involves the combination of different competences and technologies from various areas, such as agronomy, IoT, sensing technologies, cloud computing, data science. An integrative approach is necessary to facilitate the collaboration and integration of heterogeneous actors from these disciplines, enabling effective cooperation and knowledge sharing in the pursuit of sustainable and efficient smart agriculture solutions.
3	Transform collected data into added-value	A reasoning process will be adopted in the ID3SAS Methodology, whose purpose is to transform data that exist in a raw stage into information or/and knowledge deemed useful, through the use of AI and ML techniques. This process is crucial as it facilitates data interpretation and enhances decision-making processes for users. Examples of this transformation include analysing data patterns, predicting future trends, and providing actionable insights to improve agricultural practices and resource utilisation.
4	Support the development of an intelligent system to assist in decision-making processes	By combining the data transformation process with advanced AI techniques, ID3SAS creates an Intelligent DSS that enhances decision-making processes. The intelligent DSS employs a variety of AI-based techniques to support decision-makers, providing assistance in solving complex problems that occur in real-time and involve large amounts of data. This results in improved decision quality and enables more efficient and sustainable agricultural practices.
5	Enable a data-driven and proactive control of the physical environment	The SAS must be capable (autonomously or not) of taking appropriate actions in the physical environment based on data collected from sensors and predictive analysis. For example, the system can activate the irrigation system based on sensor data and predictive models, ensuring optimised resource usage and proactive control of the agricultural environment.
6	Achieve general applicability to different scenarios	The ID3SAS methodology is designed with generic applicability in mind, allowing it to be adapted to different agricultural scenarios, including diverse crops, regions, and seasons. This flexibility enables its widespread adoption and utilisation across various agricultural contexts, facilitating the development of specialised and customised smart agricultural systems.
7	Achieve robustness to dynamic environmental conditions	ID3SAS must be designed to be robust and adaptable to withstand various dynamic environmental conditions, such as high/low temperatures, precipitation, and other environmental factors. The system should incorporate resilience and adaptability features to ensure its reliable operation in diverse and challenging agricultural environments.
8	Facilitate the utilisation of technology	The ID3SAS system is designed to interact with users in an intuitive and user-friendly manner. An efficient HMI allows users to visualise relevant data obtained from the fields, receive recommendations and make informed decisions. The user-friendly interface ensures that the system can be easily utilised by individuals with varying technological expertise, promoting widespread adoption and accessibility.

has the lowest RMSE and highest R^2 (Table 4), its practical usefulness is limited for short-term predictions. In turn, the "TimeToWater" model offers enhanced planning capabilities over significantly longer time horizons. Additionally, although auto-regression models typically exhibit strong performance over short time spans, in this specific scenario, a decline in performance can be observed after 24 hours, whereas the "TimeToWater" model demonstrates success beyond 70 hours and with a smaller dataset. Moreover, in terms of interpretability, from an end-user perspective, the scheduling of irrigation events is easier to comprehend than the degradation of soil moisture levels.

The *Decision Support* component (subsection III-G) assists users in making informed decisions and effectively planning their agricultural activities. Its process involves retrieving current data from sensors, checking weather forecasts, and utilising Fuzzy Logic approach for irrigation time calculations. The result is the determination of irrigation time, categorised as "Short", "Medium-short", "Medium-long", or "Long". These categories are then used to control the duration of the water pump's operation, regulating the amount of water used for irrigation. By adjusting the "Irrigation Time", the system effectively manages and optimises the irrigation process, ensuring appropriate and efficient utilisation of water resources.

The *Control* component plays an important role in managing the actuators within the physical environment. As a result, it becomes imperative to define the level of autonomy the system should possess. In the context of this prototype, the decision to control the actuators manually or automatically will affect the overall functionality, performance, and application of the system.

Lastly, the *HMI* component (subsection III-I), served as a powerful tool, empowering users with real-time information,

TABLE 8. List of Functional and Non-Functional Requirements for ID3SAS Methodology.

ID	Requirement	Description
FR-01	Integrate heterogeneous components	The system should measure several parameters. Therefore, there is a need to ensure interoperability between the physical components and the system. The adoption of a shared data model and common standard interfaces can to facilitate the exchange of data and communications between the different actors in the system.
FR-02	Acquire data	The system must be able to collect data from internal (physical environment) and/or external sources (*e.g.*, weather forecasting services). Specifying the protocols or mechanisms through which the data will be acquired, such as WSN or API integration with external services, should be considered.
FR-03	Store data	The system must be able to store data from internal (physical environment) and external sources (*e.g.*, weather forecasting services) on local or cloud-based servers. The volume of data, retention period and security measures for data storage should be taken into consideration.
FR-04	Process the collected data and transform them into added-value	Data acquired directly from the physical environment and/or external sources are sometimes inconclusive and difficult to interpret. Through AI-based data analysis techniques, it is possible to transform these data into knowledge to make the decision process easier and more effective.
FR-05	Predict future states	With the aid of AI-based data analysis, it is expected to generate predictions of the agricultural environment based on incoming data.
FR-06	Take actions on the physical environment	The system should automatically and/or by user's command activate and control actuators to modify the state of the process or the environment in a predefined manner.
FR-07	Display data	The design of a dashboard for the visual presentation of data will be considered. This will provide visual interfaces, so that data can be easily interpretable by non-technical personnel, through visual graphs, charts, tables or even maps.
FR-08	Provide alerts and notifications	The system must periodically inform the user about the status of the physical environment through notifications to the computer or smartphone, and alert when certain values go over the threshold.
FR-09	Provide recommendations	The system should provide recommendations based on the collected sensor data, historical patterns, and data analysis based on AI. Additionally, external sources (such as forecasting services) can be used to support these recommendations.
NFR-01	Interoperability	The system must communicate, execute programs, and transfer data among various functional units through the use of common interfaces and data representations.
NFR-02	Connectivity and data transmission	The system must establish reliable connections between its components and provide wired and/or wireless transmission capabilities to enable real-time data collection and exchange between the physical environment and the system.
NFR-03	Modularity	The system should be designed in a modular manner, allowing for the addition, removal, or modification of elements/modules (*e.g.*, sensors, actuators) without disrupting the overall system functionality. Well-defined interfaces between modules ensure smooth integration and flexibility.
NFR-04	Adaptability	The system should be built on a cloud computing infrastructure, allowing for easy adaptation and scalability by adding resources such as data storage, processing power, and visualisation capabilities as needed for efficient service delivery.
NFR-05	Flexibility	The system should be easily modified for use in various applications and environments beyond its initial design. Thanks to its generic nature, ID3SAS can be implemented in different case studies, accommodating diverse plant types, soil compositions, regions, and seasonal variations. This versatility allows the system to cater to a wide range of agricultural scenarios and adapt to specific needs. Moreover, the flexibility of the ID3SAS methodology extends beyond agricultural environments, offering potential applicability in other domains.
NFR-06	Availability	The system should ensure high availability of its services and components, making them accessible and usable when requested.
NFR-07	Usability	The system must be functional, easy to use, efficient, and capable of providing an effective and satisfying user experience in achieving specified goals within the context of its use.
NFR-08	Reliability	The system must ensure the accuracy and reliability of acquired data, as well as the reliable execution of processes and integrity of functions. This includes robust data acquisition, transmission and processing mechanisms to maintain the trustworthiness of the system.
NFR-09	Predictability	The system should possess the capability to predict future events by leveraging data correlation, historical data, and external sources such as forecasting services. This prediction ability aids in better planning of agricultural activities, such as irrigation scheduling, and early detection of potential anomalies in the physical environment.
NFR-10	Robustness	The system should be designed to withstand various adverse environmental conditions, such as high/low temperatures, precipitation, and snow. This requires the use of resilient hardware components, environmental sensors, and appropriate protection measures to maintain system functionality in challenging environments.
NFR-11	Non-invasiveness	The system should interact with the physical environment in a non-intrusive manner, minimising any negative impacts. This involves employing non-invasive sensing techniques, using low-power devices and adhering to environmentally friendly practices.

personalised recommendations, and control actions. It improved decision-making capabilities, contributing to more sustainable and successful farming practices.

V. CONCLUSION, LIMITATIONS AND FUTURE WORK

This article focuses on the implementation of the ID3SAS methodology, which represents a major breakthrough for the agricultural sector. By integrating wireless sensor data, field actuators, IoT, cloud computing, advanced data analytics, predictive models, and decision support tools, it offers significant contributions to creating a cutting-edge SAS, providing farmers with real-time decision-making capabilities that can lead to increased productivity and reduced water consumption. Embracing the transformative potential of Agriculture 4.0 technologies, the ID3SAS methodology paves the way for more sustainable and efficient agricultural practices.

ID3SAS was implemented and tested in a laboratory scenario, referred to as the prototype. The primary objective is to evaluate the functionality and effectiveness of the methodology in achieving the proposed objectives and fulfilling the established requirements. While the study acknowledges the significance of plant physiology, crop production, and water consumption in irrigation processes, it primarily emphasises assessing the performance of the ID3SAS methodology itself.

However, it is imperative to consider the limitations of the current study. The experiment was conducted in a controlled laboratory setting, lacking dynamic environmental factors such as rainfall and wind, which limits the generability of the findings to real-world agricultural conditions. To address this, future research should focus on conducting outdoor case studies to evaluate the robustness and performance of the ID3SAS methodology under varying environmental conditions. Moreover, further research is needed to expand the applicability of ID3SAS to different crops and agricultural contexts. This could involve refining the predictive models to accommodate crop-specific requirements and optimising the decision-making algorithms for diverse farming practices. Additionally, the acquisition of more resilient and outdoor-ready hardware, including sensors and actuators, will be crucial for the successful implementation of the system in real-world agricultural settings. Continued research and development efforts in these areas will contribute to the advancement and widespread adoption of intelligent data-driven DSS in agriculture, ultimately promoting sustainable and efficient agricultural practices.

While the ID3SAS methodology may demonstrate success within the parameters of the study, further research, tests, and validations in relation to plant physiology and its impact on crop performance could be vital for its real-world applicability and practical effectiveness.

APPENDIX

See Tables 7 and 8.

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