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APPLIED RESEARCH

Smart Agricultural System Using Proximal Sensing, Artificial Intelligence, and LoRa Technology: A Case Study in Vineyard Management

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ABSTRACT The agricultural sector faces significant challenges, including resource inefficiency, unpredictable weather conditions, and the need for sustainable practices. These issues necessitate the application of advanced methods introduced by Agriculture 4.0 to ensure productivity and sustainability. This paper focus on the application of the Intelligent Data-Driven Decision Support System for Agricultural Systems (ID3SAS) methodology to a proximal sensing case study aimed at improving vineyard management via monitoring and predictive modeling with Artificial Intelligence. The developed system was deployed in vineyards in Portugal, and provided a robust test-bed for real-world application.

INDEX TERMS Agriculture 4.0, decision support system, Internet of Things, LoRaWAN, machine learning, node-RED, wireless sensor network.

I. INTRODUCTION

A. BACKGROUND

Modern agriculture is confronted with numerous challenges that threaten its sustainability and productivity. These challenges include the need to produce more food with fewer resources, the impacts of climate change, resource scarcity, and the rising global demand for agricultural products [1]. Traditional farming methods often fall short in addressing these issues due to their inefficiencies and lack of adaptability to rapidly changing conditions [2]. To address these challenges, the agricultural sector is increasingly adopting advanced technologies. Agriculture 4.0 signifies a transformative shift in farming by employing state-of-the-art technologies to enhance various agricultural operations. These technologies include the Internet of Things (IoT) [3], [4], [5], Artificial Intelligence (AI) and Machine Learning (ML) [6], [7], Big Data [8], [9], cloud computing [10], [11], Decision Support System (DSS) [12], [13], [14], [15], Wireless Sensor and Actuator Network (WSAN) [2], [16], [17], [18], [19], and robotics [20], [21], [22], [23]. The role of sensors and robotics is crucial in gathering vital field data, which is subsequently transmitted to local or cloud servers using IoT technology for storage, processing,

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and analysis. By applying AI-based techniques and Big Data analytics, these data are converted into actionable insights, thus enabling more informed and efficient decision-making. Consequently, DSS tools become indispensable for optimising agricultural systems, providing users with the essential information needed to take appropriate actions and boost productivity [2], [12].

The adoption of Agriculture 4.0 technologies can help in adapting to climate change, reducing food loss and waste, and optimising the use of natural resources in the agricultural sector globally. This holistic approach ultimately minimises environmental impact, fostering sustainable farming practices. By embracing these innovations, Agriculture 4.0 not only meets the current demands of the agricultural industry but also supports long-term sustainability and resilience, making it a crucial element in the future of global food production [2], [12], [24], [25], [26].

B. MOTIVATION AND CONTRIBUTIONS

The motivation behind this research arises from the pressing need to enhance efficiency and sustainability in the agricultural sector. Traditional farming practices are typically reactive, addressing issues only after they have occurred, which can result in substantial losses in crop yield and quality and excessive use of resources like irrigation water. Consequently, there is a compelling need for systems that offer proactive, real-time information to farmers. Such systems enable informed decision-making, thereby boosting productivity and promoting sustainable agricultural practices. This research aims to bridge this gap by developing a system that provides timely insights and actionable recommendations to improve overall farm management.

The primary objective of this research is to extend the work initiated in the previous study by [27], focused on designing a methodology for developing a DSS tailored to the agricultural sector. The proposed methodology - Intelligent Data-Driven Decision Support for Agricultural Systems (ID3SAS) - is designed to align with the Agriculture 4.0 paradigm.

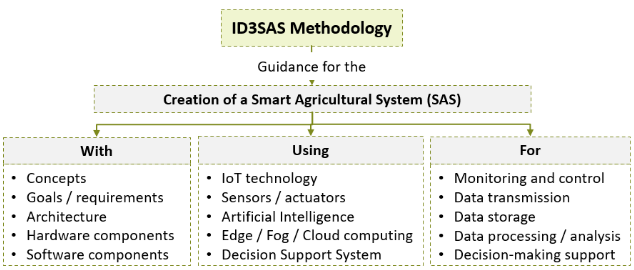


FIGURE 1. **ID3SAS concept: a guide for the integration of agriculture 4.0 technologies in smart agricultural systems.**

The developed system - ID3SAS system - integrates several advanced technologies, including IoT-based sensing, Wi-Fi and Long Range (LoRa) [28], [29], and a cloud-based database. Additionally, it employs ML for predictive analysis of soil moisture degradation and incorporates external weather forecasting services along with Fuzzy Logic [30], [31], [32] for enhanced decision-making. This system was deployed in the vineyards of the Innovation Hub of Instituto Nacional de Investigação Agrária e Veterinária (INIAV) [33] (Dois Portos, Torres Vedras, Portugal), during 20 days (from 13th June to 2nd July).

The present research has important implications for advancing precision agriculture, particularly in enhancing the use of data-driven DSS. By integrating predictive modeling with real-time environmental monitoring, this research contributes to the development of Agriculture 4.0, which seeks to make farming more efficient, sustainable, and adaptable. Specifically, this article contributes to the field of smart agriculture through:

- A detailed description of building and implementing a proximal sensing node based on ID3SAS guidelines.
- A systematic application of ML techniques to enable predictive modelling.
- A case study that validates the system's effectiveness in a real-world agricultural setting, specifically in a vineyard.

This article is organised as follows: Section I provides the background on the topic under study, in subsection I-A, focusing on key technologies of Agriculture 4.0. Subsection I-B outlines the motivations behind this research and highlights its contributions, while subsection I-C offers an overview of related work found in the current literature. Section II details the overall design of the ID3SAS methodology, focusing on its main components. Section III describes its implementation within the ID3SAS system, including its deployment in a vineyard environment. The results are presented and discussed in Section IV. Finally, section V concludes the research, addressing its limitations and providing remarks on future work.

C. RELATED WORK

The integration of advanced technologies such as IoT, proximal sensing, and AI-driven DSS into agriculture has been a growing area of research. The work developed by [34] presents a cost-efficient solar-powered smart agricultural system designed to enhance agricultural production using sensor nodes with energy harvesting capabilities. These nodes were equipped with soil moisture, temperature, and humidity sensors, along with a power converter capable of connecting a solar panel to recharge the battery and monitor its voltage level. Similar, the research presented by [35] developed a solar-powered IoT-based irrigation system. The study developed by [36] introduces an user-friendly IoT cloud platform that incorporates Message Queuing Telemetry Transport (MQTT) broker for data transmission, Node-RED for data flow design and graphical display, and InfluxDB and MongoDB for data storage. By utilising Docker containers, the platform provides a cost-effective solution for developing IoT systems without the need for developers to set up the infrastructure independently. Another relevant study is the implementation of a smart urban farming system utilising Raspberry Pi, Arduino, and the Node-RED platform [37]. This system addresses the growing need for sustainable food production in urban areas by monitoring and managing critical growth parameters such as light and soil moisture. A smart platform was developed in [38], focusing on greenhouse monitoring and control using IoT and Wireless Sensor Network (WSN) technologies. This system integrates a fuzzy logic-based decision system to optimise water and energy use while ensuring optimal growing conditions. The WSN collects environmental data like temperature, humidity, and soil moisture, which is processed by a Raspberry Pi and managed via a Node-RED interface for remote control. The data is stored in a MySQL database for monitoring and historical analysis, allowing for efficient management of the greenhouse environment and enhanced agricultural productivity. A smart agriculture monitoring and management system utilising IoT-enabled devices connected through a Long Range Wide Area Network (LoRaWAN) is proposed in [39]. This system automates the regulation of crop growth parameters by using low-power, low-cost sensors and actuators. Data are transmitted in real-time to the cloud, accessible via a customisable dashboard. The LoRaWAN network provides an extended communication range and significantly reduces power consumption compared to Wi-Fi-based systems. An automatic DSS was proposed by [40] to address issues related with water scarcity. It uses autonomous nodes to measure soil and climatic conditions. To improve decision-making, this system leverages ML techniques as its reasoning engine, enabling continuous adaptation to local conditions and providing accurate irrigation predictions similar to those made by human experts. Likewise, the DSS developed by [41] optimises irrigation management in citrus orchards by employing ML to predict weekly water requirements based on real-time data from weather stations, soil sensors, and historical irrigation patterns. Additionally, the web-based DSS introduced by [42] utilises minimal input data, such as weather forecasts and soil parameters, to simulate soil water balance and deliver irrigation recommendations through web and mobile interfaces, demonstrating its potential to support water conservation initiatives.

While several studies have explored specific aspects of the integration between IoT, proximal sensing, and DSS in agriculture, the present research offers an holistic, robust, versatile, and scalable solution for the agricultural sector which has been validated in a real-world environment. By integrating ML and Fuzzy Logic System (FLS) with real-time monitoring and external data sources (*e.g.*, weather forecasting services), the ID3SAS system provides predictive insights into soil degradation (up to 24 hours ahead) and irrigation recommendations, and enabling medium-term planning and resource management. Designed to be highly durable, the system can withstand a range of environmental conditions, including warm to hot temperatures, rain, and wind, and can even handle interactions with small animals like insects and birds. Additionally, it includes a solar-powered power module, which ensures continuous operation in remote agricultural settings without relying on external power sources, thereby promoting sustainability and reducing the environmental footprint. Lastly, the system's versatility and scalability further differentiate it from existing solutions, making it adaptable to various agricultural environments, such as vineyards, orchards, and greenhouses.

II. METHODOLOGY

The ID3SAS methodology [27], depicted in Figure 2, consists of nine components, each represented by specific layers and processes within the IoT-based architecture proposed by [2]. This architecture features four distinct layers: (a) *Physical*, responsible for collecting data from IoT devices and executing actions in the field via actuators; (b) *Communication*, ensures data communication between different layers through an appropriate networks; (c) *Service*, manages data storage, processing, and analysis; and (d) *Application*, provides access to agricultural information and control actions. Additionally, there is an optional layer, named *Other sources*, which involves integrating external services, such as weather services, to enhance the system's functionality.

A. COMPONENTS

The ID3SAS methodology is composed of nine components:

1) *Sensing (Physical layer)*: This component is crucial for the data acquisition stage, providing real-time insights into the agricultural environment.
2) *External Source (Other sources layer)*: This component integrates data from external sources like weather stations, satellites, and radars. It enhances data acquisition and predictive capabilities by correlating diverse data sources for improved decision-making.
3) *Gateway (Communication layer)*: Bridges communication between IoT devices and the central server, ensuring reliable data transmission. It aggregates sensor data and handles various communication protocols, integral to the data transmission stage.
4) *Database (Service layer)*: Manages and stores vast amounts of data generated by the *Sensing* component. The database can be cloud-based or local, depending on the users' requirements.
5) *Data Processing (Service layer)*: Handles the cleansing, transformation, and preparation of data to meet various objectives.
6) *Artificial Intelligence (Service layer)*: Utilises ML algorithms to process and interpret large volumes of sensor data, identifying patterns and trends. This Service layer component is crucial for data analysis, providing insights that enable proactive agricultural management.
7) *Decision Support (Service layer)*: Based on Fuzzy Logic Theory, this component plays a vital role in the reasoning stage, offering real-time recommendations.
8) *Human-Machine Interface (Application layer)*: Facilitates user interaction by providing a clear interface

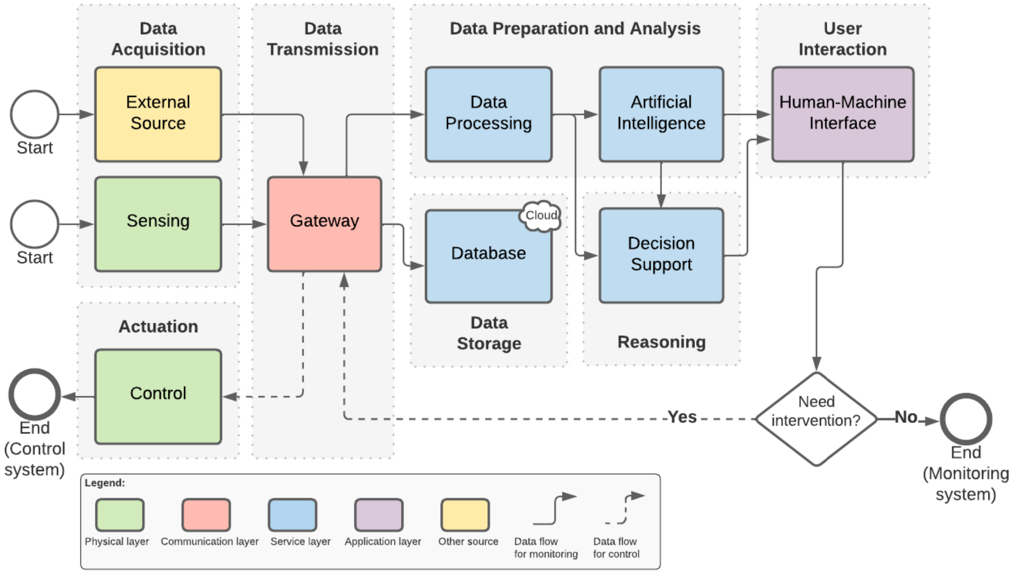


FIGURE 2. The ID3SAS methodology, composed of nine core components: External source, sensing, control, gateway, cloud-based data storage, data processing, artificial intelligence, decision support and human-machine interface. From [27].

for data visualisation and recommendations. It ensures effective engagement with the system, receiving alerts, and initiating necessary actions.

9) *Control (Physical layer)*: This component is essential for the actuation stage, translating data and recommendations into precise actions (through the use of actuators) to optimise agricultural processes.

B. MONITORING AND CONTROL SYSTEMS

The ID3SAS methodology features a dual-path structure that distinctly separates two essential processes:

- Monitoring: This path begins with the collection of data from internal sensors (the *Sensing* component) and/or external sources (the *External Source* component). The collected data are then transmitted through the *Gateway* component to a cloud-based or local database for storage. Following storage, data are processed by the *Data Processing*, the *Artificial Intelligence* and *Decision Support* components. The final destination is the *Human-Machine Interface* component, which handles data visualisation, generates alerts, provides recommendations, and supports other user interactions.
- Control: Beyond monitoring, the control path incorporates actuation capabilities through actuator nodes deployed in the field (the *Control* component). When the ID3SAS system identifies a need for intervention (such as adjusting irrigation levels based on soil moisture data), the *Control* component executes these actions either autonomously or upon user command.

This distinction is clearly illustrated in the ID3SAS methodology, which outlines these two paths following the *Human-Machine Interface* component. The decision-making process hinges on whether intervention is required in the physical environment (''Need intervention?''). If intervention is deemed necessary (''Yes''), the system directs the user to transmit commands to the actuators via the *Control* component. Conversely, if no intervention is needed (''No''), the data flow concludes at the *Human-Machine Interface* component. This structured approach ensures that actions are taken only when warranted, optimising resource use and enhancing the efficiency of agricultural management.

III. IMPLEMENTATION AND DEPLOYMENT

The implementation of ID3SAS methodology involved the deployment of ID3SAS system in a field environment. The vineyards at INIAV's Dois Portos Innovation Hub/National Viticulture Station [33] in Torres Vedras, Portugal, were selected as the test site (Figure 3). The experiment was conducted over 20 days, from June 13th to July 2nd, 2024, with the collaboration of the Smart Farm Collaborative Laboratory (SFCOLAB) team [43].

The objectives of this case study are to demonstrate the ID3SAS system's capabilities in a real-world agricultural setting. Specifically, the study aims to: (1) Validate the system's robustness by ensuring it can withstand various weather conditions, including rain, wind, cold, and heat, as well as interactions with small animals like birds and insects; (2) Assess the system's interoperability with various hardware components, solar-power module, communication protocols, and cloud-based database, highlighting its flexibility and integration capabilities essential for modern agricultural practices; (3) Use data-driven techniques to model soil moisture degradation over time, which can provide valuable insights to help optimise irrigation schedules, enhance resource management, and improve overall vineyard management.

(a) ID3SAS system in the vineyard (b) Soil moisture sensor placement (c) ID3SAS system exposed to rain

FIGURE 3. **Deployment of the sensor node in the vineyards.**

This approach aims to demonstrate the added value of proximal sensing and AI in enhancing vineyard management through cost-effective, weather-resilient, and solar-powered solutions. Detailed implementation of each component of the ID3SAS methodology for this case study is provided in the following subsections.

A. SENSING COMPONENT

The *Sensing* component of the ID3SAS system is centered around a sensor node, designed to collect real-time environmental data from the vineyard. The key hardware components including a XIAO ESP32-S3 microcontroller, sensors (capacitive soil moisture, BME280 for air temperature, humidity and pressure, and SI1145 for sunlight), a LoRa transceiver, a solar panel and a rechargeable battery (Figures 4 and 5).

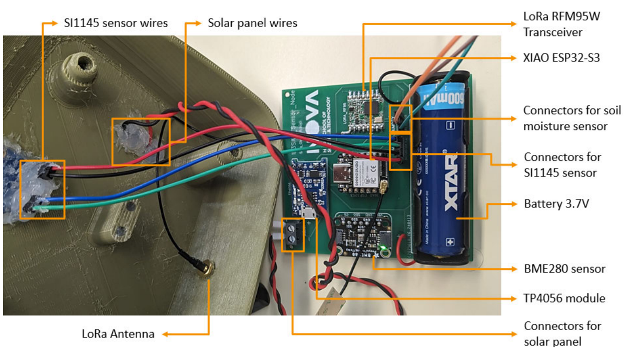


FIGURE 4. **Key hardware components of the *sensing* component.**

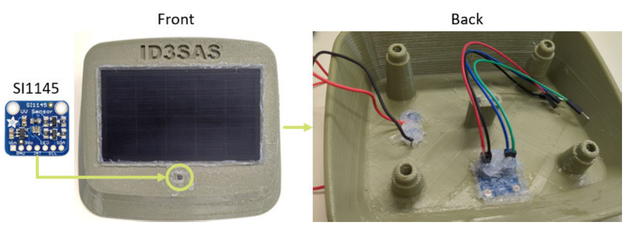


FIGURE 5. **SI1145 (sunlight) sensor and solar panel.**

For communication (subsection III-C), the ID3SAS system uses LoRa technology (LoRaWAN protocol) due to its suitability for agricultural environments where long-range and low-power consumption are essential [2], [44], [45], [46]. The power supply includes a Li-Ion battery (3.7 V, 2600 mAh), a TP4056 battery charger module, and a solar panel (5 V, 1.2 W). This setup ensures the sensor node remains operational with a sustainable power source, leveraging solar energy for recharging the battery and providing continuous monitoring capabilities in the field. The electronic components are housed in a 3D-printed weatherproof enclosure (Figure 3), based on the design developed by [47]. It is constructed in PolyEthylene Terephthalate Glycol (PETG) material to enhance durability against weather conditions, surpassing the resilience of conventional PolyLactic Acid (PLA) filament [48], [49]. The Stevenson Screen design [50] serves as a protective enclosure, shielding the sensors from precipitation and direct radiation, and this design allows for free air circulation around the enclosed sensors. Additionally, this robust assembly features a reinforced cable for the soil moisture sensor and is sealed with transparent silicone, ensuring that the enclosure remains resilient and fully operational in diverse environmental conditions.

The *Sensing* component implementation was made using Node-RED [51] (Figure 6). The system employs MQTT subscriber nodes to receive data published to different topics by the Mosquitto MQTT broker [52], obtaining environmental data from the ID3SAS sensor node and the status of the microcontroller XIAO ESP32-S3. These nodes are configured with the broker's IP address and port and send their output to a Join node that combines the payloads into a single message. A Function node then adds a timestamp to the payload, and additional Function nodes prepare the data for insertion into the database (InfluxDB or MongoDB). After the initial Function node, the data are further processed by a Split node and routed by a Switch node to different outputs. An Inject node triggers hourly messages to the MQTT publisher node, and a UI Button node triggers a command to refresh sensor data. The Text Input node is responsible for writing the geographical location on the dashboard.

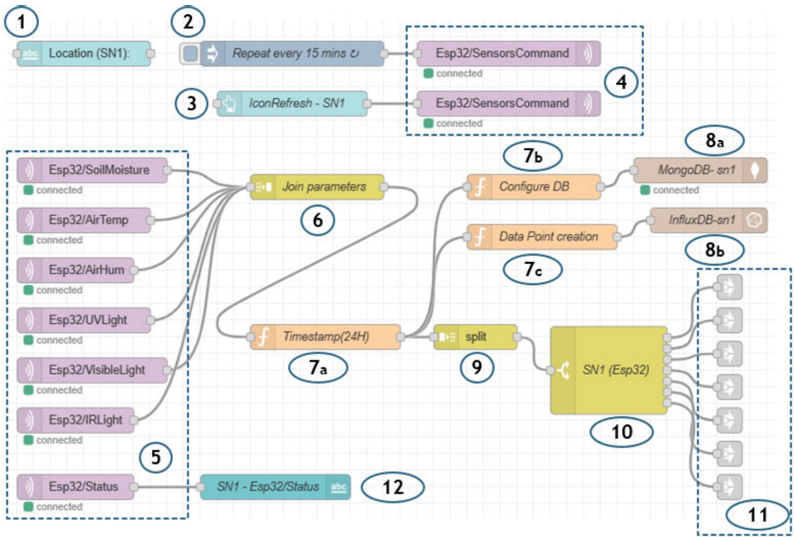


FIGURE 6. **Node-RED flow configured for the implementation of the *sensing*, *gateway* and *database* components. The nodes employed in this configuration include: (1) Text input, (2) Inject, (3) Button (dashboard), (4) MQTT-Out, (5) MQTT-In, (6) Join, (7a,b,c) Function, (8a) MongoDB-Out, (8b) InfluxDB-Out, (9) Split, (10) Switch, (11) Link-Out nodes, and (12) UI text nodes.**

B. EXTERNAL SOURCE COMPONENT

The *External Source* component was designed to integrate and correlate data from physical sensors (subsection III-A) with information from external sources, such as global weather stations, satellites, and radars. For weather data, including current conditions and forecasts up to five days ahead, the OpenWeatherMap Application Programming Interface (API) [53] was selected. This functionality is essential for the *Decision Support* component (subsection III-G), which must account for key factors like precipitation patterns, including both current conditions and forecasted rainfall for the coming hours. By analysing these indicators, the ID3SAS system will be able to make informed decisions about whether to water the plants or not.

The *External Source* component was implemented using Node-RED (Figure 7). An Inject node is used to send a trigger message every 30 minutes and a Link-In node for manual refresh. An HTTP Request node fetches weather data from the OpenWeatherMap API, with the response stored in ‘‘msg.payload’’. A UI Button can manually refresh the data by sending a ‘‘refresh’’ payload through a Link-Out node. Various Function nodes extract specific weather details from the API response, which are then displayed on the Node-RED dashboard through UI Text nodes. A Change node converts temperature values from Kelvin to Celsius. This process is also applied for weather forecasting.

C. GATEWAY COMPONENT

The *Gateway* component includes three modules: (1) Hosting module, consisting of a Raspberry Pi 3 running Mosquitto MQTT broker and Node-RED; (2) a Wi-Fi module consisting of an XIAO ESP32-S3 and an external router; and (3) a LoRa module with an RFM95W transceiver and a Heltec 32 Wi-Fi/LoRa board.

Figure 8 schematise how data are transmitted wirelessly from the sensor node to the LoRa board (Heltec 32 Wi-Fi/LoRa) using LoRa technology (LoRaWAN protocol). Serving as an intermediary, this LoRa board receives data and forwards them the Raspberry Pi (Host). The Raspberry Pi, hosting Docker containers with Mosquitto and Node-RED, communicates with the LoRa board via Wi-Fi using the MQTT protocol [54], [55]. Finally, data are sent from the Raspberry Pi to the InfluxDB database (subsection III-D) via HTTP over Wi-Fi. Figure 9 shows the *Gateway* component of the third case study, which is comprised of a LoRa Board (Heltec 32 Wi-Fi/LoRa) and a Raspberry Pi 3, which runs Docker containers (Mosquitto MQTT broker and Node-RED). The distance between the sensor node installation site and the LoRa board (Gateway) is approximately 188 meters (Figure 10).

The *Gateway* component was implemented using Node-RED, and Figure 6 represents a flow that collects sensor data from the ID3SAS sensor node and stores it in the database. It also provides functionality to trigger sensor data retrieval, send commands to the XIAO ESP32-S3, and manually refresh the sensors.

D. DATABASE COMPONENT

The *Database* component was implemented using Node-RED, as shown in Figure 6, which illustrates the flow for receiving sensor data from ID3SAS sensor node and storing it in the database. The implementation involved creating a free InfluxDB account [56], setting up a bucket, and obtaining an API token for access. The ‘‘node-red-contrib-influxdb’’

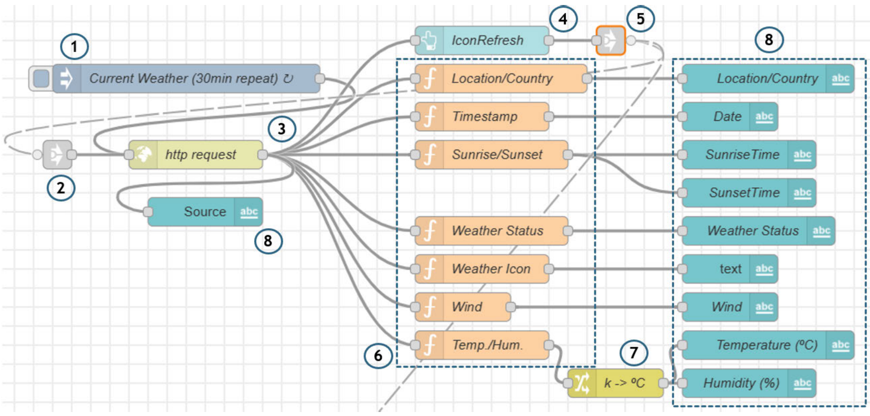


FIGURE 7. Node-RED flow configured for the implementation of the *external source* component using OpenWeatherMap API. The nodes employed in this configuration include: (1) Inject, (2) Link-In, (3) HTTP request, (4) UI Button, (5) Link-Out, (6) Function, (7) Change, and (8) UI Text nodes.

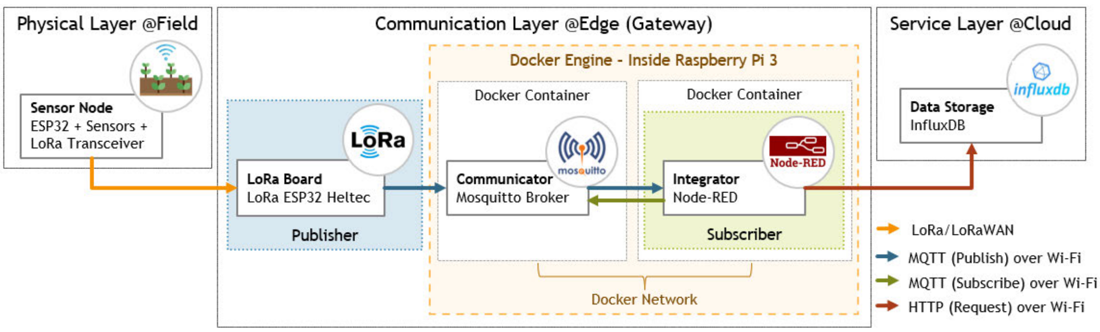


FIGURE 8. Gateway component, using a LoRa board, Mosquitto MQTT broker and Node-RED to communicate with the sensor node and the cloud-based database (InfluxDB). Both Mosquitto and Node-RED run under docker, inside a Raspberry Pi 3.

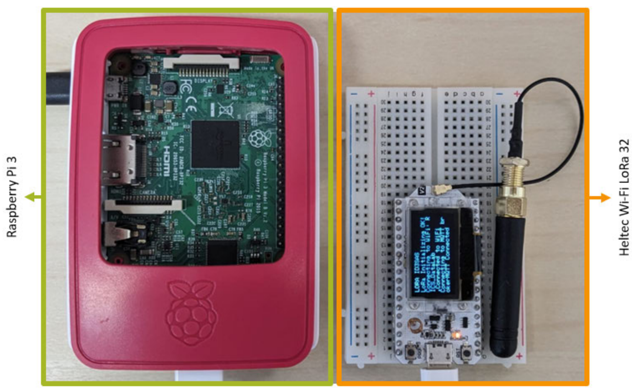


FIGURE 9. ***Gateway*** **component, consisting of a raspberry Pi 3 (with Mosquito MQTT broker and Node-RED) and a Heltec 32 Wi-Fi/LoRa (LoRa board).**

package [57] was then installed in Node-RED, enabling the use of specialised nodes for writing and querying data. Finally, a Node-RED flow was created to facilitate the seamless storage and retrieval of sensor data from InfluxDB.

E. DATA PROCESSING COMPONENT

The *Data Processing* component is crucial for cleaning, transforming, and preparing data for visualisation or training predictive ML models. This process, illustrated in Figure 4.16, was accomplished using Python within Jupyter Notebook [58], and implemented in Node-RED. The specific pre-processing steps and techniques used vary depending on the data characteristics and requirements.

1) Handle missing values: Techniques such as eliminating rows or columns with the "dropna()" function [59], imputing missing values with the mean or median using the "fillna()" function [60], and interpolating missing values using the "interpolate()" function [61] were utilised.
2) Handle outliers: Outliers were identified and removed using statistical measures like the Z-score and Interquartile Range (IQR) [62].
3) Feature Engineering: Focused on selecting relevant features, and creating new features from existing data. This process enriches the dataset for developing predictive ML models within the *Artificial Intelligence* component. For example, new features, such as "Soil Moisture $(t - n)$" and "Soil Moisture $(t + n)$," were derived from the original "Soil Moisture $(t = n)$" input [27]. These engineered features represent the soil moisture values at the previous and subsequent time steps, helping ML models capture temporal

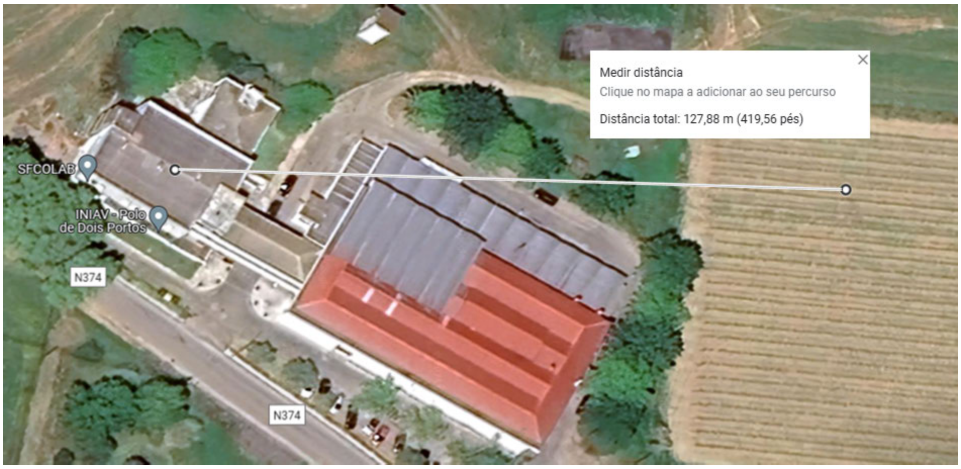


FIGURE 10. Distance between the sensor node placement and the LoRa gateway at SFCOLAB facilities, Dois Portos.

dependencies and patterns for more accurate predictions of future soil moisture levels.

The implementation of the *Data Processing* component was made in Node-RED. For this, it was necessary to install the packages "node-red-contrib-pythonshell" [63], "node-red-contrib-python-function-ps" [64] and "node-red-contrib-python-function" [64], in order to run Python scripts from Node-RED. The scripts for handling missing values and outliers, and for Feature Engineering process were created using Jupyter Notebook platform.

Figure 11 illustrates the flow that collects data from sensors, processes them and constructs features that can be used for the creation of predictive ML models. The result of this process is an array ("input") containing the values from current sensor measurements and from the *Data Processing* component.

The first Link-In node collects data from the soil moisture sensor of the ID3SAS sensor node. These data are processed by a Function node that converts the numeric soil moisture value to a binary value (1 or 0) based on a global threshold. If the soil moisture is below the threshold, the payload is set to "1" (indicating the need for irrigation); otherwise, it is set to "0". This result is then sent to a Change node to update a global variable "irrigationcolumn". Other Link-In nodes gather data from various sensors, including air temperature, humidity, soil moisture and ultraviolet (UV) index. These inputs are checked for "NaN" values by Change nodes, which set a "hasNaN" property in the message to indicate the presence of such values. Based on this, Switch nodes route the message either to a PythonShell node for imputation or continue processing if no "NaN" values are detected. The PythonShell node executes a script to fill missing values using the mean of the dataset. Additionally, Function nodes handle Feature Engineering for different parameters, incorporating real-time data and data from the previous three hours. These processed messages are sent to a Join node, which accumulates 16 messages before forwarding them. These 16 messages represent four measurements (at current and previous three hours) for each of the seven parameters (air temperature, humidity, soil moisture, and UV). Finally, a Function node arranges these sensor values into an array for use in the Predictor node, part of the *Artificial Intelligence* component (subsection III-F), for further analysis and decision-making.

F. ARTIFICIAL INTELLIGENCE COMPONENT

The *Artificial Intelligence* component enhances the system by utilising ML algorithms to analyse and interpret sensor data, thereby identifying patterns and trends for informed decision-making. The development of predictive models for soil moisture prediction ("SoilMoisture($t + n$)", where $t + n$ means the time in hours) involved a structured process comprising the following steps (Figure 12):

1) Data split: the dataset was divided into a training subset (70%) and a testing subset (30%) to ensure representativeness of the overall data distribution.
2) Model selection: four regression algorithms were selected as baselines to predict the soil moisture: Random Forest (RF), Gradient Boosting Regression (GradientBR), Adaptive Boosting (AdaBoost) (with Decision Tree (DT)) [65], and Extra Trees Regression (ExtraTR) [66]. The development process was executed using Python 3.9 [67], along with the "scikit-learn" Python library [68], known for its extensive support for implementing ML models and statistical modeling. The parameters used to train these models include:
   a) Inputs (from sensors): "AirTemp", "AirHum", "SoilMoisture", and "UVLight".
   b) Engineered inputs (from Feature Engineering): "AirTemp(t$-n$)", "AirHum(t$-n$)", "SoilMoisture (t$-n$)", and "UVLight (t$-n$)".
   c) Engineered outputs (from Feature Engineering): "AirTemp(t+n)", "AirHum(t+n)", "SoilMoisture (t+n)", and "UVLight (t+n)".

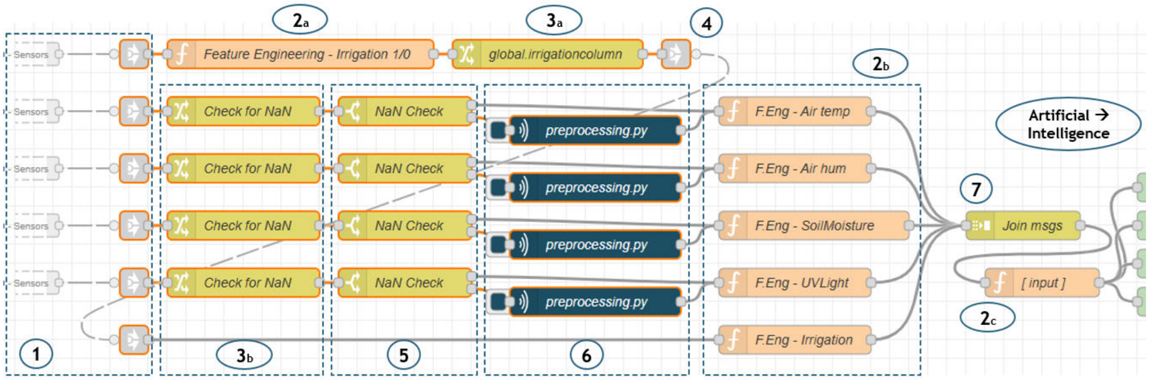


FIGURE 11. Node-RED flow configured for the implementation of the *data processing* component. The nodes employed in this configuration include: (1) Link-In, (2a,b,c) Function, (3a,b) Change, (4) Link-Out, (5) Switch, (6) Pythonshell, and (7) Join nodes.

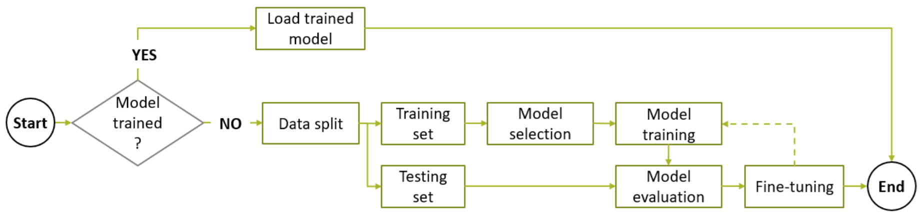


FIGURE 12. ID3SAS artificial intelligence process.

   d) Output (previsions): "SoilMoisture(t+n)" (estimates soil moisture value after n hours).
3) Model training: the selected models were trained on the training subset.
4) Model evaluation: post-training, the models' predictive capabilities were evaluated on the test dataset using Root Mean Squared Error (RMSE) (Equation 1) and R-squared (R^2) (Equation 2) metrics to quantify prediction accuracy and the proportion of variance explained by the model, respectively. Table 2 compares the selected models according to their evaluation metrics.

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

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

   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.
5) Fine-tuning: hyperparameter tuning was performed using Grid Search Cross Validation (GridSearchCV) [69] to optimise the model parameters for improved performance [70]. The parameters include "n_estimators", "random_state", "max_depth", "min_samples_split", "learning_rate", "subsample", and "tree_reg".

The *Artificial Intelligence* component was implemented in Node-RED using the "node-red-contrib-machine-learning-v2" package [71], as illustrated in Figure 13, facilitating the integration of the predictive models within the ID3SAS system.

The processed data from the Function node (Figure 11)) are sent to five different Predictor nodes, each representing a distinct ML model that generates predictions based on the input. After each prediction, a Function node formats the results and prepares them for display in a table on the dashboard. This table, rendered by a Table (dashboard) node, includes columns for the timestamp, sensor node ID, and the prediction value (Figure 22, in subsection III-H).

G. DECISION SUPPORT COMPONENT

The *Decision Support* component aims to enhance the decision-making process, thereby aiding in the strategic planning of agricultural activities. The process of this component is illustrated in Figure 14. Initially, the system retrieves current sensor data, including air temperature, humidity, soil moisture, and UV index. If the soil moisture level is above a predefined threshold, no action is taken. However, if the soil moisture is below this threshold, the system checks the weather forecast. If rain is expected within the next 12 hours, the system does not irrigate the plants (sub-subsection III-G1). Otherwise, the FLS calculates the necessary irrigation time based on the sensor data (sub-subsection III-G2).

1) RAIN FORECAST

A Node-RED flow (Figure 15) retrieves up to 12 hours of weather forecast data from the OpenWeatherMap API for a specified location and displays various weather parameters

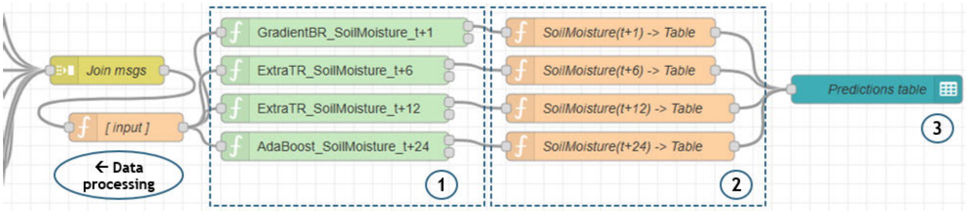


FIGURE 13. Node-RED flow configured for the implementation of the *artificial intelligence* component, more precisely, the predictive ML models. The nodes employed in this configuration include: (1) Predictor, (2) Function, and (3) Table (dashboard) nodes.

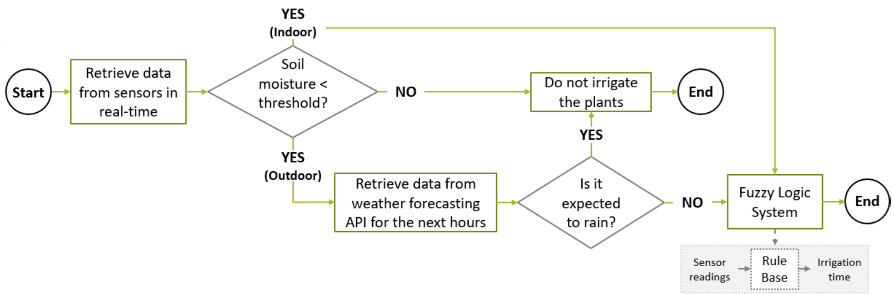


FIGURE 14. ID3SAS decision support process.

on the dashboard (subsection III-H)). This flow is similar to the one presented in Figure 7 (subsection III-B), except for a new Function node "Check Rain t + 1", which checks the weather status for the presence of critical keywords and sets a flag accordingly. These keywords are "shower", "rain" and "drizzle" [72]. The data are then sent to a Function node, which checks whether the flag is true or false. If it is true, data are forwarded to the "Recommendations" table (Figure 19, in subsection III-H) via a Link-Out node, and prints a message with the state of the weather (*e.g.*, "light rain") and the respective time for which the weather is forecast. This process is repeated for each forecast time step up to 12 hours ahead. The results of this flow are displayed in Figure 16, showing weather status information and the flag results. For example, if the weather status is "scattered clouds", the flag is set to "false", indicating no rain. Conversely, if the status is "light rain", the flag is set to "true", indicating rain.

2) FUZZY LOGIC SYSTEM

In the present case study, the FLS was not used due to the specific characteristics of the vineyard, which lacked manual or artificial irrigation systems. The vineyard was only irrigated naturally through rainfall, making the application of the FLS unnecessary. However, in scenarios where manual or artificial irrigation is possible, the FLS feature would play an important role. This system is designed to optimise irrigation schedules by analysing environmental factors and determining the appropriate irrigation time, thus enhancing water management efficiency. The following steps outlines the implementation and operational details of the FLS in the ID3SAS system.

1) Defining parameters: weather parameters significantly impact crop water requirements. Higher temperatures and lower humidity levels increase water evaporation, necessitating more water for plants, while clear skies and higher UV levels also contribute to greater water needs. Conversely, cold temperatures, high humidity, and overcast conditions reduce the need for irrigation. The parameters used for this system provide a general indication but can vary depending on crop type, soil type, and environmental conditions.
2) Fuzzy sets and membership functions: The FLS sets and their associated membership functions for inputs such as "Air Temperature", "Air Humidity", and "UV Index", and the output "Irrigation Time," each had four fuzzy sets. These inputs were used to create the membership functions, represented in Figure 17. In this article, the water crop needs are translated to "Irrigation Time", and so was considered the output of the FLS.
3) Fuzzy rules: The fuzzy sets allowed for the creation of 64 possible rules based on the Mamdani Fuzzy Inference System [32], [32], [73]. These rules, described using "IF - AND - THEN" conditions, were determined based on the relationships outlined in the parameter definitions. For example, if the air temperature is very cold, air humidity is low, and UV index is low, then the irrigation time is short. Conversely, if the air temperature is hot, air humidity is low, and UV index is low, the irrigation time is long. These rules enable the system to adjust irrigation time based on the current environmental conditions effectively.

The FLS feature was implemented using Node-RED, as shown in Figure 18. The flow starts with Link-In nodes collecting air temperature, humidity, and UV radiation data from ID3SAS sensor node, which are combined into a single message by the Join node. A Function node uses the "skfuzzy"

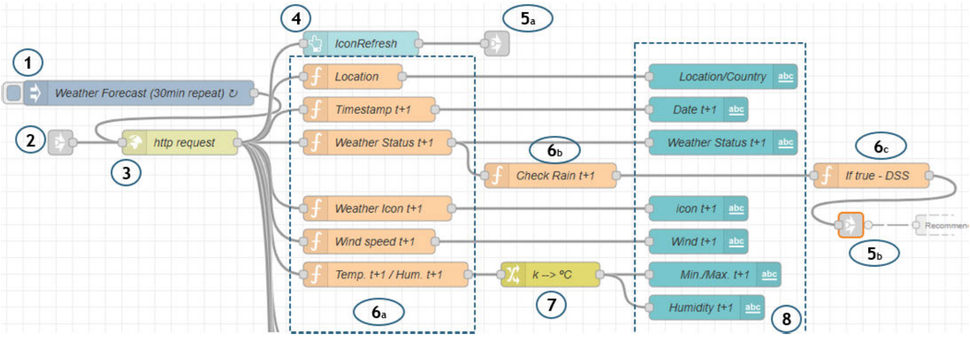
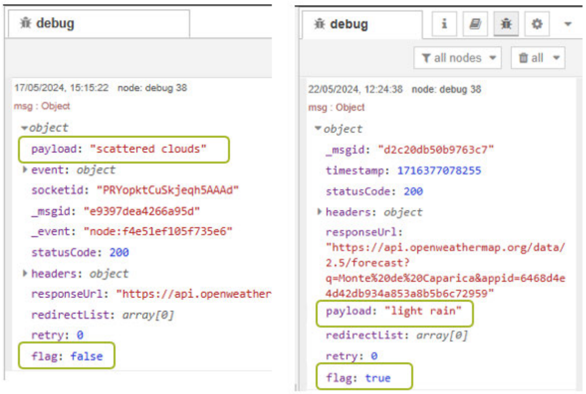


FIGURE 15. Node-RED flow configured for the rain forecast verification process, via the *external source* component using the OpenWeatherMap API. The nodes used in this configuration include: (1) Inject, (2) Link-In, (3) HTTP request, (4) UI button, (5a,b) Link-Out, (6a,b,c) Function, (7) Change, and (8) UI text nodes.



(a) "scattered clouds" = false (b) "light rain" = true

FIGURE 16. Results of the Node-RED flow for rain forecast verification in the debug panel. (a) displays the "msg.payload" as "scattered clouds" with "msg.flag" set to "false", indicating no rain; (b) displays "light rain" in the "msg.payload" with "msg.flag" set to "true", indicating the presence of rain.

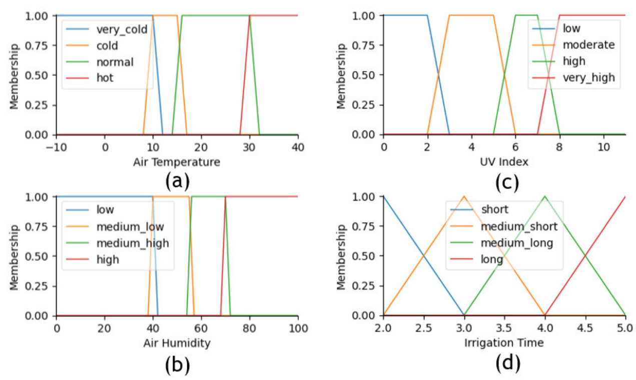


FIGURE 17. Membership functions of the fuzzy logic system: (a) Air temperature (fuzzy sets: "very_cold", "cold", "normal" and "hot"), (b) Air humidity (fuzzy sets: "low", "medium_low", "medium_high" and "high"), (c) UV Index (fuzzy sets: "low", "moderate", "high" and "very_high") and (d) Irrigation time (fuzzy sets: "short", "medium-short", "medium-long" and "long").

library [74] to calculate irrigation time based on these inputs, and the result is stored in ''payload.irrigationtime.'' Another Function node assigns an irrigation label (''short irrigation'', ''medium-short irrigation'', ''medium-long irrigation'' or ''long irrigation''). The Change node saves this label globally. The final Link-Out node makes the irrigation label available for other flows.

H. HUMAN-MACHINE INTERFACE COMPONENT

1) DASHBOARD

The ID3SAS dashboard has seven tabs offering the features below. For the development of this dashboard, it was necessary to install the ''node-red-dashboard'' package [75] in Node-RED, which provides a set of nodes to quickly create a live data dashboard.

1) ''Home'' tab (Figure 19): Displays the user profile, real-time data from sensors, actuators, and current weather. It also offers a ''Recommendations'' table based on the data from *Decision Support* component. While the graphs for visible light and infrared (IR) light appear on the dashboard, they remain inactive, as the SI1145 sensor was exclusively used for UV index measurements
2) ''Calibration Sensors'' tab (Figure 20): Allows users to easily update the soil moisture sensor readings for calibration purposes. When the sensor is placed in air, the calibration can be set to 0% soil moisture, and when immersed in water, it can be set to 100% soil moisture.
3) ''Weather Forecast'' tab: Displays weather forecasting, using the OpenWeatherMap API.
4) ''Plant's Info'' tab (Figure 21): Contains a dataset with information of some vegetables (beans, beetroot, broccoli, carrot, cucumber, eggplant, garlic, green pea, lettuce, onion, pepper, potato, and sweet potato), and fruits (apple, blueberry, grape, lemon, melon, strawberry, tomato, watermelon). This feature encompasses essential parameters such as the minimum, maximum and optimal temperature, relative humidity, and photoperiodism for vegetative growth. Consequently, users can conveniently navigate the dashboard and select the specific plant of interest.
5) ''Historical Data'' tab: Displays data in graphical format with user-defined granularity (*e.g.*, daily, weekly, monthly).

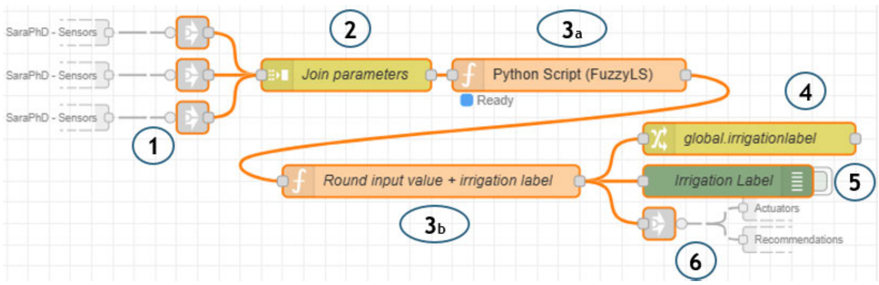


FIGURE 18. **Node-RED flow configured for the implementation of the fuzzy logic feature on the *decision support* component. The nodes employed in this configuration include: (1) Link-In, (2) Join, (3a,b) Function, (4) Change, (5) Debug, and (6) Link-Out nodes.**

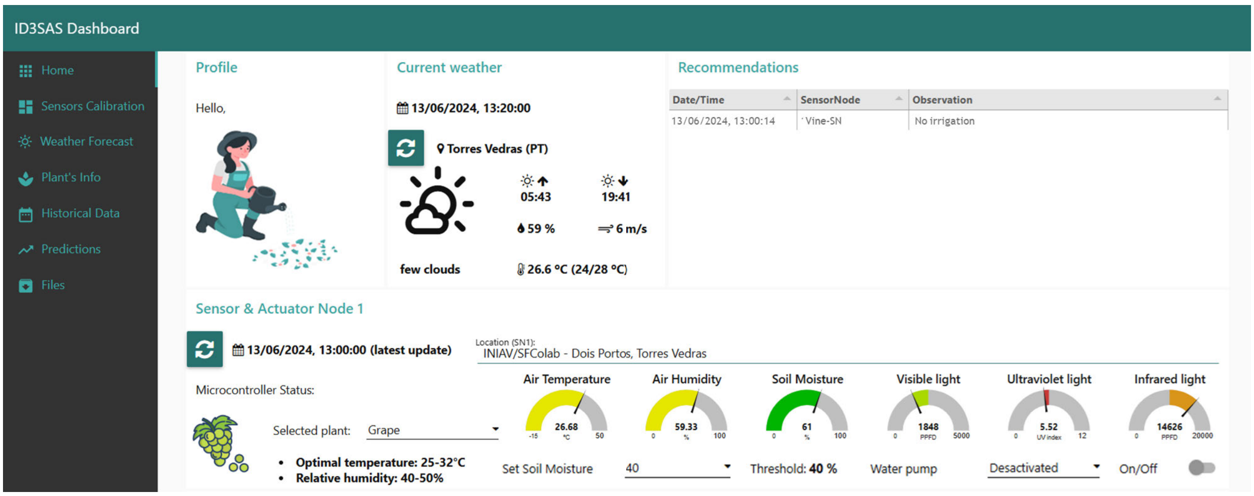


FIGURE 19. **ID3SAS HMI dashboard: "Home" tab, featuring the user profile, current weather, data from sensors, and recommendations table.**

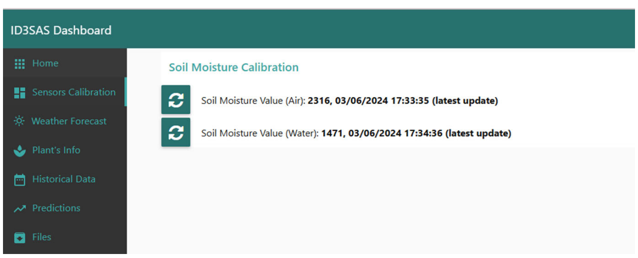


FIGURE 20. **ID3SAS HMI dashboard: "sensors calibration" tab, displaying measurements of the soil moisture sensor when placed in air and in water.**

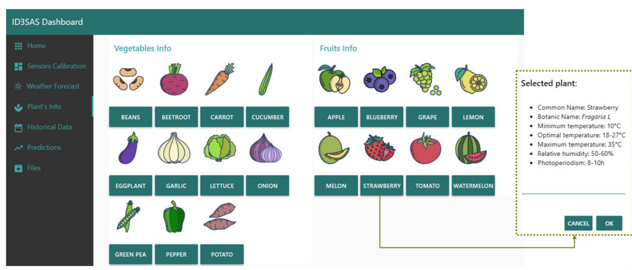


FIGURE 21. **ID3SAS HMI dashboard: "Plant's Info" tab, providing detailed insights into the environmental preferences of various vegetables and fruits, with an example focus on the details of the strawberry fruit.**

6) "Predictions" tab (Figure 22): Presents data generated by predictive ML models, from the *Artificial Intelligence* component.
7) "Files" tab: Enables users to download data from the database in csv format.

2) ALERT SYSTEM

Additionally, the alert system of the ID3SAS system was implemented using Node-RED. To enable email alerts, the "node-red-node-email" package [76] was installed. This flow monitors soil moisture levels from ID3SAS sensor node, sending an email alert if levels drop below a predefined threshold, along with an irrigation recommendation from the *Decision Support* component.

I. CONTROL COMPONENT

In the present case study, the *Control* component was not developed due to logistical and resource constraints. Integrating actuator nodes requires additional hardware and power management, which were not feasible in the vineyards.

IV. RESULTS AND DISCUSSION

This section provides an in-depth exploration of the components of the ID3SAS methodology, detailing their

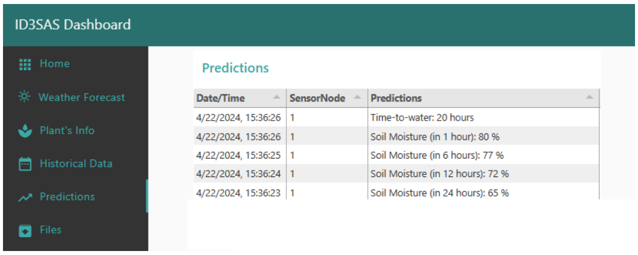


FIGURE 22. **ID3SAS HMI dashboard: "predictions" tab, featuring an example of predictions, including "time-to-water", and "soil moisture" for 1, 6, 12 and 24 hours ahead.**

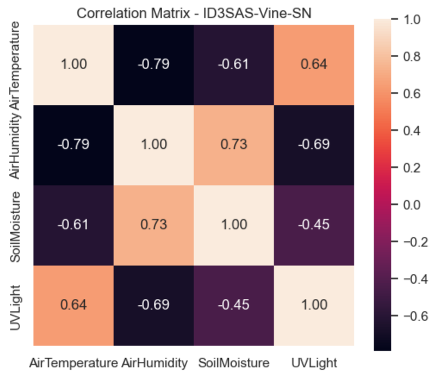


FIGURE 23. **Correlation matrix of the measured parameters for the ID3SAS sensor node, from june 13th to 2nd july, 2024.**

implementation specifically for the Vineyards case study. Each component plays a critical role in the overall functionality and performance of the ID3SAS system in this context.

A. SENSING COMPONENT

According to Table 1, all measurements appear satisfactory except for the soil moisture parameter. This discrepancy can be attributed to several factors related to sensor technology and environmental conditions. Calibration issues are a primary concern, as improper calibration can lead to inaccurate readings. Environmental conditions such as temperature fluctuations and humidity levels can affect sensor performance. Sensor placement within the soil profile is also crucial, as incorrect insertion depths may not capture the true variability of moisture content across different soil layers. Additionally, sensor characteristics like drift over time and sensitivity to soil type variations can contribute to inaccuracies in soil moisture measurements. To validate the performance of the ID3SAS system, the measurements from its sensors were compared with data collected by the weather station operated by SFCOLAB [77], which was also situated within the same vineyard.

TABLE 1. **Raw statistical data of the ID3SAS sensor node, from june 13th to 2nd july, 2024, prior to data processing.**

Parameters	Mean	Standard dev.	Min.	Max.
Air Temperature (°C)	19.0	3.7	10.8	29.7
Air Humidity (%)	81.00	16.9	43.9	100.0
Soil Moisture (%)	28.4	32.0	0.2	99.8
UV Index	1.5	2.5	0.0	9.6

Figure 23 shows the correlation matrix for sensor measurements of the ID3SAS Sensor Node. There is a strong negative correlation between air temperature and air humidity (−0.79), indicating that higher temperatures correspond with lower humidity, typical of hotter and drier days. Air temperature also has a moderate negative correlation with soil moisture (−0.61), suggesting that warmer days lead to decreased soil moisture due to higher evaporation rates. Conversely, there is a moderate positive correlation between air temperature and UV radiation (0.64), implying that higher temperatures are associated with increased UV radiation, likely due to clearer skies. Air humidity has a strong positive correlation with soil moisture (0.73), indicating that more humid conditions help retain soil moisture by reducing evaporation. There is also a strong negative correlation between air humidity and UV radiation (−0.69), suggesting that more humid, cloudier conditions lead to lower UV radiation levels. Lastly, soil moisture shows a moderate negative correlation with UV radiation (-0.45), indicating that higher soil moisture levels are generally found under conditions with lower UV radiation, likely due to cloudier weather.

The solar-powered power supply module of the ID3SAS system operated with no interruptions during the 20-day experiment (June 13th to July 2nd, 2024), eliminating the need for external power sources. This ensured continuous, autonomous operation of the sensor node in field conditions, thereby promoting sustainable agricultural practices.

The use of deep-sleep mode in the system results in a significant reduction in power consumption, decreasing the daily energy usage from 20661.6 mWh to just 286.81 mWh. This represents an impressive reduction of approximately 98.6%. Such a drastic decrease in power consumption is crucial for extending the battery life and ensuring the sustainability of the system, particularly in remote or off-grid agricultural environments where energy efficiency is paramount. However, the system currently lacks battery charge level monitoring, posing a risk of unexpected energy depletion, which highlights an area for future improvement.

The ID3SAS enclosure, inspired by the Stevenson screen design [50], was crucial for protecting electronic components and ensuring optimal sensor performance of the system. Positioned on a vineyard fence under direct sunlight to maximise solar panel efficiency, the enclosure demonstrated exceptional durability against various environmental conditions (*e.g.*, heavy rain, thunderstorms, hail, strong winds, direct sun exposure) and insects during the 20-day experiment. This robust design contributed significantly to the system's reliability and functionality in harsh outdoor settings.

The custom-designed Printed Circuit Board (PCB) offered significant advantages over traditional breadboards, including space-saving, easier assembly, and faster implementation in the ID3SAS system. It also ensures high reproducibility and low-cost manufacturing, making it ideal for integrating electronics with sensors [78].

B. EXTERNAL SOURCE COMPONENT

The *External Source* component was developed to correlate local sensor data with broader weather trends, enhancing the reliability and utility of the ID3SAS system by providing a more comprehensive environmental overview. By integrating the OpenWeatherMap API, this component allows for the inclusion of real-time and forecasted weather data, improving the functionality of the ID3SAS system and demonstrating its potential for scalable and flexible environmental monitoring solutions.

C. GATEWAY COMPONENT

The *Gateway* component in the ID3SAS system facilitates crucial data exchange between the Physical Layer (sensors and actuators) and the Service Layer. In the present case study, LoRa technology was essential for communication due to its long-range capabilities and low energy consumption, which made the deployment feasible at the INIAV's Dois Portos Centre vineyards, where Wi-Fi coverage is unavailable.

Currently, the communication between the ID3SAS Sensor Node and the LoRa board (gateway) is unidirectional: the sensor node transmits data to the gateway, but no data is sent back. This unidirectional setup simplifies communication and conserves battery power, critical for the sensor node, which relies on solar-supplemented battery power. While LoRa supports bidirectional communication, implementing it would increase power consumption and complexity, necessitating reliable message delivery and handling signal interference. Despite these limitations, LoRa proved highly effective for long-range, low-power remote monitoring and data collection in this case study. However, for future implementations that include control or action systems, exploring LoRa's bidirectional communication capabilities is essential.

D. DATABASE COMPONENT

In the present case study, the ID3SAS system used InfluxDB Cloud [56] for its *Database* component, leveraging its scalable cloud-based storage for efficient time-series data management. It was implemented using Node-RED and the "Node-RED-contrib-influxdb" package [57].

E. DATA PROCESSING COMPONENT

The *Data Processing* component was implemented using Python scripts and Node-RED, and ensured the quality and usability of data. It effectively handled missing values and outliers, which could result from sensor malfunctions or data transmission issues. Feature Engineering was another critical aspect, involving the creation of new features from existing data to enhance the performance of predictive ML models. In this case, this process included creating features like "Soil Moisture (t-n)" and "Soil Moisture (t + n)" to capture temporal dependencies and patterns, thus improving predictive accuracy.

F. ARTIFICIAL INTELLIGENCE COMPONENT

According to Table 2, it is possible to understand that GradientBR model exhibits the best performance for the "SoilMoisture(t + 1)" parameters, with the lowest RMSE of 9.67 and the highest R^2 of 0.91. ExtraTR model outperforms others in the "SoilMoisture(t + 6)" and "SoilMoisture(t + 12)", with the lowest RMSE of 18.16 and 19.53, and the highest R^2 of 0.68 and 0.57, respectively. In the long-term prediction for "SoilMoisture(t + 24)", AdaBoost model performs the best with an RMSE of 20.66 and a R^2 of 0.48.

Figures 24, 25, 26, and 27 present a comparative analysis of the best predictive models for the parameters "SoilMoisture (t + 1)", "SoilMoisture(t + 6)", "SoilMoisture(t + 12)", and "SoilMoisture(t + 24)" for the ID3SAS system, respectively.

Overall, the *Artificial Intelligence* component of the ID3SAS methodology is important for improving the system's capabilities through advanced predictive modelling. By taking advantage of ML algorithms to predict soil moisture levels ("SoilMoisture(t + n)"), this component generates accurate forecasts and actionable insights, which are essential for a more efficient, sustainable, and proactive management of agricultural activities.

G. DECISION SUPPORT COMPONENT

The *Decision Support* component of ID3SAS is classified as a hybrid DSS [14], [15], [79], integrating elements from data-driven, model-driven, and knowledge-driven DSS types to optimise agricultural decision-making. It retrieves real-time data from various sensors such as air temperature, humidity, soil moisture, and UV, providing valuable insights for monitoring. It also leverages predictive ML models to forecast soil moisture levels and determine optimal irrigation times, incorporating expert knowledge and rules for improved decision-making. Additionally, it uses AI-based techniques like Fuzzy Logic to recommend optimal irrigation periods based on specific rules and parameters.

The primary function of the *Decision Support* component is to decide whether irrigation is necessary and, if so, how much water is required. This decision-making process can be broken down into three possible cases: no irrigation, rain forecast feature, and the FLS. In the first case, if soil moisture is above a predefined threshold, no immediate action is needed, preventing unnecessary irrigation. In the second case, if soil moisture is below the threshold, the system analyses weather forecast data to determine if rain is expected within the next 12 hours, potentially suspending irrigation to optimise water usage by relying on natural rainfall. In the third case, if soil moisture is below the threshold and no rain is forecasted, the *Decision Support* component employs a FLS to calculate the precise irrigation time needed based on sensor data.

In the present case study, the *Decision Support* component utilised the rain forecast feature frequently due to the unusual weather conditions in Torres Vedras (Portugal) during June 2024. Over the 20-day experiment (from June 13th to

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

	SoilMoisture(t+n)							
	t+1		t+6		t+12		t+24	
Model	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
RF	10.30	0.90	18.82	0.66	21.39	0.46	21.11	0.46
ExtraTR	10.01	0.91	18.16	0.68	19.53	0.57	21.02	0.46
GradientBR	9.67	0.91	19.26	0.65	22.33	0.49	20.83	0.47
AdaBoost	11.36	0.89	20.18	0.61	20.22	0.54	20.66	0.48

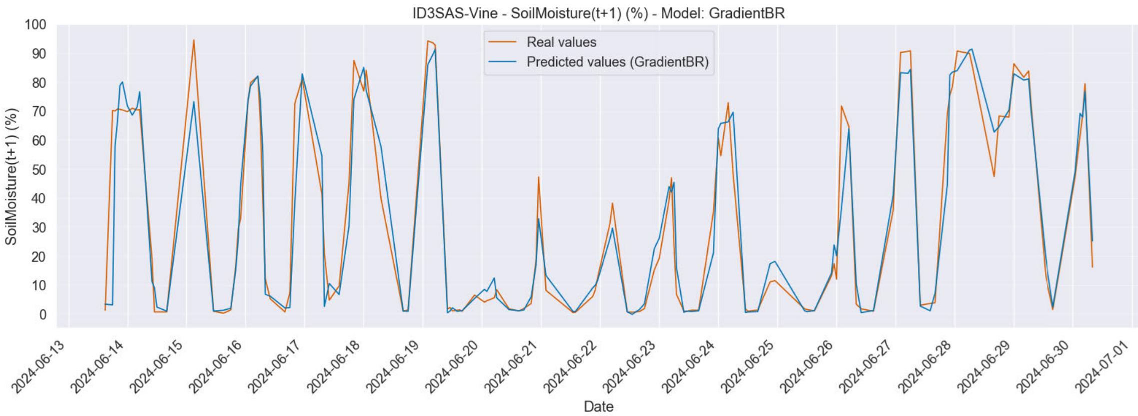


FIGURE 24. Comparison of real values and predicted values (GradientBR model) for "SoilMoisture(t + 1)" parameter.

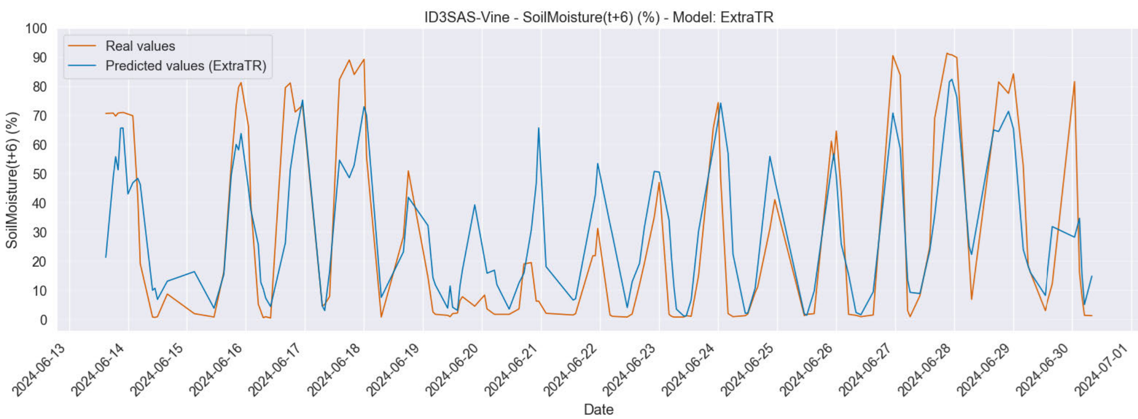


FIGURE 25. Comparison of real values and predicted values (GradientBR model) for "SoilMoisture(t + 6)" parameter.

July 2nd), rain or showers occurred on 11 days, creating a dynamic environment for testing the system's ability to make informed irrigation recommendations based on real-time and forecasted weather data. This frequent and unpredictable rainfall presented a robust scenario to evaluate the system's responsiveness to changing weather conditions.

The ID3SAS system, lacked actuators for autonomous irrigation and thus functioned primarily as a monitoring tool. It provided essential monitoring, alerts, and recommendations without directly controlling irrigation systems. Despite this limitation, the ID3SAS system proved valuable by predicting weather patterns and soil moisture levels, ensuring that irrigation recommendations were made only when necessary. This demonstrated the system's effectiveness in managing irrigation based on real-time and forecasted conditions.

H. HUMAN-MACHINE INTERFACE COMPONENT

The *Human-Machine Interface* component of the ID3SAS system includes two key modules that simplify user interaction and decision-making in agriculture. These modules are designed to be user-friendly, allowing farmers to engage with the system effectively with minimal training. The Dashboard (sub-subsection III-H1) is a user-friendly interface with seven distinct tabs. The Alert system (sub-subsection III-H2) sends email notifications when soil moisture levels fall below a predefined threshold, including irrigation recommendations to prompt timely actions. This ensures users are alerted to critical conditions promptly, enhancing system robustness and enabling effective management to prevent potential losses. Together, these components integrate data visualisation, alerting, and decision support, providing a complete tool for modern agriculture. Future enhancements, such as battery

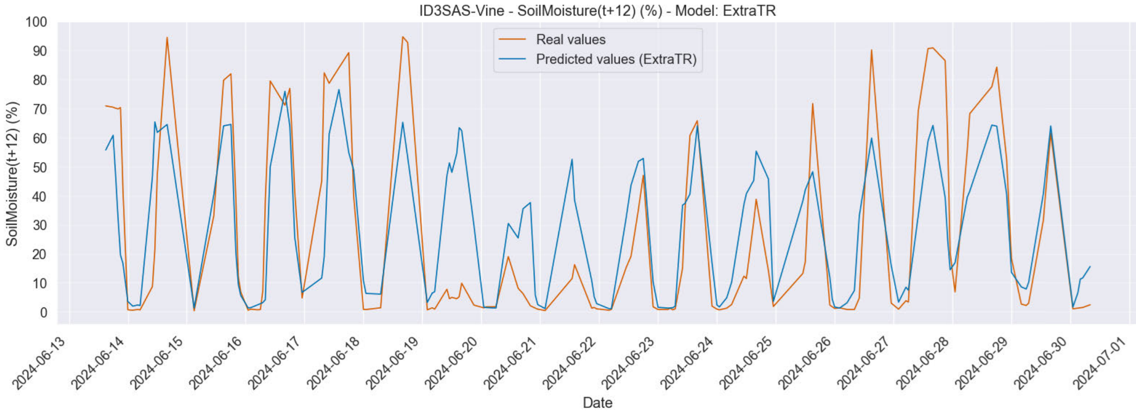


FIGURE 26. Comparison of real values and predicted values (ExtraTR model) for "SoilMoisture(t + 12)" parameter.

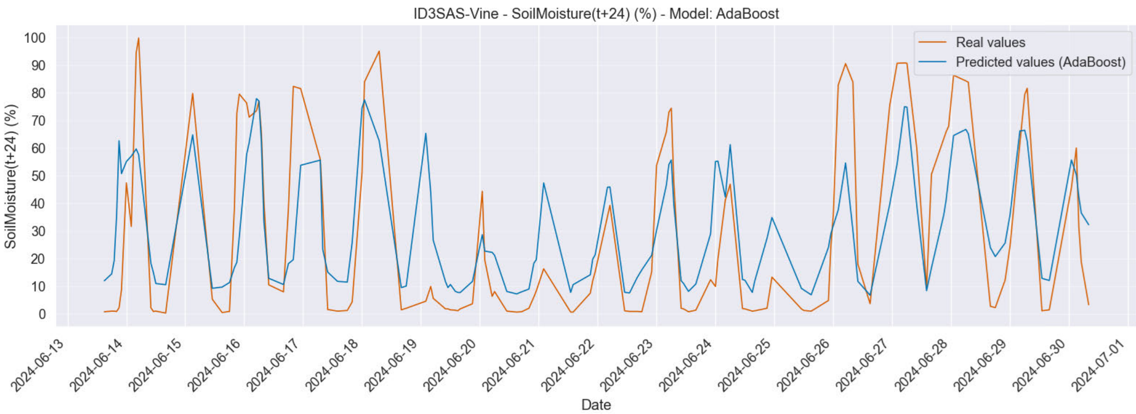


FIGURE 27. Comparison of real values and predicted values (AdaBoost model) for "SoilMoisture(t + 24)" parameter.

monitoring, will further improve the system's functionality and reliability.

V. CONCLUSION, LIMITATIONS, AND FUTURE WORK

A. CONCLUSION

The research presented in this paper demonstrates the potential of integrating proximal sensing, AI, LoRa technology and sustainable power solutions in modern viticulture. A proximal sensing node installed on-premise collected data over a 20-day period, providing valuable insights through ML-based predictive modeling. The use of LoRa technology facilitated long-range and low-power communication, crucial for real-time data transmission in areas lacking Wi-Fi coverage, which is the case of the vineyards. The enclosure of the ID3SAS system proved to be robust, maintaining consistent performance despite challenges such as variable weather and potential interference from small animals (mainly insects). The inclusion of a solar-powered power module further highlighted the system's sustainability, ensuring continuous operation without the need for external power sources. Additionally, the custom-designed PCB enhanced the system's reliability and ease of deployment, enabling a more streamlined assembly process and facilitating the transition from prototype to a practical, field-ready solution. While this case study did not leverage the FLS of the *Decision Support* component, due to the vineyard's reliance on natural irrigation, the potential of this feature to optimise irrigation in other agricultural contexts was explored and detailed.

The implementation of the ID3SAS system significantly enhanced the monitoring capabilities of the vineyards. While INIAV and SFCOLAB had an existing decision support module based on current monitoring [77], it lacked the ability to predict future soil moisture degradation and reliance on rule-based reasoning. ID3SAS complemented this with advanced predictive functionalities, allowing farmers to plan their irrigation practices more effectively based on accurate forecasts. This integration provided substantial added value by enabling proactive management and optimising resource usage, ultimately leading to better crop health and improved yield quality.

The ID3SAS system also significantly enhances the agricultural decision support process by leveraging real-time data from proximal sensors (*Sensing* component), external data sources such as weather forecasts (*External Source* component), and AI-driven predictive modeling (*Artificial Intelligence* component). Central to this process is the *Decision Support* component, which integrates and analyses the data from these sources to provide real-time recommendations and actionable insights. This enables more accurate and timely decision-making, as well as facilitates medium-term planning, empowering farmers to make informed decisions about resource allocation. Regarding its applicability, ID3SAS is designed to be versatile across various agricultural settings, as detailed in [27], goal 6 - *Achieve general applicability to different scenarios*. This can include outdoor fields (*e.g.*, vineyards, orchards, or row crop farms) and controlled environments (*e.g.*, greenhouses, growth plant chambers, vertical farms). ID3SAS achieves this versatility through its "Plant's Info" feature (Figure 21), which provides detailed data on different crops, such as optimal temperature, humidity, and light requirements. This feature allows the system to automatically adjust to meet the specific needs of selected plants, enabling tailored and adaptive strategies for diverse agricultural scenarios. Additionally, the system's robust physical design ensures it can withstand outdoor conditions, making it suitable for diverse agricultural scenarios.

B. LIMITATIONS

While the ID3SAS system has shown promising results, there are a few limitations to consider for future research and development. One key limitation is the partial calibration of the capacitive soil moisture sensor, which was done using linear interpolation. This method may lead to inaccuracies in real-world applications, and improved calibration techniques, such as multiple points calibration and regular re-calibration, are recommended for greater accuracy. Another limitation is the sensor placement. Optimal positioning, both in depth and spatial distribution, is crucial for accurate and representative soil moisture data. In this study, the sensor was placed at a depth of approximately 15 cm, targeting root zones, but a more strategic placement across the field could enhance the reliability and relevance of the data collected. Additionally, installing additional sensor nodes spread throughout the field could also contribute to improve the representativeness of the data. Furthermore, the data collection period for this study was limited to 20 days, which represents a relatively short timeframe for assessing the performance of the ID3SAS in terms of seasonal variability. Factors such as air temperature, humidity, and soil moisture fluctuate throughout the growing season. Without taking these long-term variations into account, the system's predictions for irrigation and resource management may not be fully generalizable to an entire growing season. Finally, the absence of control elements, such as automated actuators for irrigation or fertilisation, limits the system's ability to fully implement the decisions generated by the *Decision Support* component.

C. FUTURE WORK

Future research should focus on integrating control systems, such as actuators for irrigation and fertilisation, to enable the ID3SAS system to autonomously execute the decisions made by its *Decision Support* component. This would create a fully automated system, reducing the need for manual intervention and improving the efficiency of resource management. Another key area for development is scaling the system to different agricultural contexts, from small farms to large-scale industrial operations. Integrating other IoT devices, such as drones and automated machinery, would enhance the system's adaptability to diverse crops, climates, and farming practices. Advancing the ML models used in the system is also essential. Incorporating deep learning algorithms would improve the accuracy of predictions by capturing complex relationships in the data. Expanding these models to predict additional agricultural parameters would make the system more versatile and applicable to a wider range of agricultural scenarios. Improving the human-machine interface and usability of the ID3SAS system will also be important. Adding features like battery monitoring for field sensors and multilingual support would enhance the system's reliability and accessibility for a broader user base. Finally, conducting life cycle assessments would help evaluate the sustainability impact of the system. By optimising resource use, the ID3SAS could significantly reduce the environmental footprint of agriculture, promoting sustainable practices and minimising the carbon footprint of farming operations.

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