Deployment of a smart irrigation control system with capacity-based moisture sensors on a production farm

Luis Orihuela[1], Erid Pacheco[2], Jorge Bareiro[3], Alejandro Tapia[4], and Jose M. Manzano[5]

[1]Research Fellow, Dept. Ingeniería Electrónica, Sistemas Informáticos y Automática, Universidad de Huelva, Avda. de las Fuerzas Armadas, s/n. 21007, Huelva, Spain. (corresponding author) E-mail: luis.orihuela@diesia.uhu.es

[2]Ph.D. Candidate, Dept. Ingeniería, Universidad Loyola Andalucía, Avda. de las Universidades, s/n. 41704, Dos Hermanas, Spain. E-mail: epacheco@uloyola.es

[3]Research Assistant, Fund. Alter Vida, Itapua 1372, Asunción, Paraguay. E-mail: jabsilvero.1997@gmail.com

[4]Assistant Professor, Dept. Ingeniería, Universidad Loyola Andalucía, Avda. de las Universidades, s/n. 41704, Dos Hermanas, Spain. E-mail: atapia@uloyola.es

[4]Research Fellow, Development Institute, Universidad Loyola Andalucía, Córdoba, Spain

[5]Assistant Professor, Dept. Ingeniería, Universidad Loyola Andalucía, Avda. de las Universidades, s/n. 41704, Dos Hermanas, Spain. E-mail: jmanzano@uloyola.es

ABSTRACT

This paper presents the demonstration of a smart irrigation system prototype, based on Internet-of-Things (IoT) devices and cloud computing, on a fully operating environment. The system architecture was carefully developed with a special focus on robustness against both environmental and human external factors. The platform, deployed in the cloud and connected to the edge-layer via a bidirectional LoRa wireless network, was based on data gathering from the field through a set of cost-effective capacity-based moisture sensors. An hysteresis-based control structure implemented in the cloud was in charge of sending the control commands. The demonstration was performed

in a strawberry production farm in Itaguá (Paraguay), during a two-month period. Details of the implementation are provided, as well as an assessment of the irrigation system performance. It was found that the automated irrigation systems consumes slightly less water than the farmer, but the efficiency of the automated system reached 91.4% compared to the 62.1% observed with the manual irrigation. Finally, a discussion on real-life issues encountered during the operation is included to illustrate the robustness of the prototype. In spite of these issues, the irrigation system was able to keep the moisture inside the prescribed band most of the time: around 71.1% of all the samples, reaching 87.9% under normal operation.

INTRODUCTION

Climate change, and its consequences, have been challenging the scientific community in recent years. In particular, and according to United Nations' Food and Agriculture Organization (FAO) and the World Health Organization in WHO (2021), climate change is worsening the water deficit. As reported in Vallino et al. (2020), agriculture constitutes one of the activities that suffers the most from this issue. According to FAO (2017), around 70% of worldwide fresh water consumption is employed in agriculture. In this context, the development of actions towards a more sustainable model for water management in agriculture is urgent.

In this sense, water monitoring provides a great framework to understand the potential strengths and weaknesses of irrigation systems, as detailed in Abioye et al. (2020). For example, Kamienski et al. (2019) built a water management platform, with application to large-scale crops. Apart from monitoring, automatic control may enable the application of optimal policies in the irrigation process, leading to a more efficient use of resources.

In the last years, this field has witnessed a current of researchers that contribute to this challenge and whose background is not pure agronomist, but electronics, automation or computer science. This fact, together with the rapid development of computing technologies, sensing devices, or microelectronics during the last years, has favored the appearance of new frameworks for the operation or management of irrigation systems. Terms such as IoT, cloud computing, wireless networks, or artificial intelligence are becoming commonplace in agricultural sciences. Two surveys of interest for the reader reader can be found in Abioye et al. (2020) and Obaideen et al. (2022). The first one covers an extensive search for advances in irrigation monitoring and advanced control systems published in the recent literature, with a special focus on monitoring and advance control. The latter presents a specific review of IoT applications in smart agriculture.

Some interesting platforms have been developed, including both the edge layer (the sensors and devices deployed in the field) and the cloud layer (the different services and applications, such as visualization, database, or alarm management). There can be found in the literature more applications of these kind of platforms in greenhouses. There are technical and economic reasons that might justify this. On the one hand, greenhouses demand stricter control requirements, and the deployment and maintenance of devices and equipment is easier. On the other hand, crops cultivated in greenhouses could generate bigger profits, allowing the farmer to invest more on technology. Some recent examples are presented by Méndez-Guzmán et al. (2022) for aeroponics greenhouses, or by Navarro-Hellín et al. (2015) that proposed similar architectures for monitoring and management of standard greenhouses. In what respect to farms, López et al. (2015) developed the GAIA2 platform for crop management, which was tested in two farms with organic broccoli and olive trees.

Advanced monitoring algorithms were explored and, experimentally validated, by Lozoya et al. (2021) and by Manzano et al. (2022a). The former presented a self-triggered mechanism that allowed to reduce battery consumption and was validated in an experimental farm of the university. The latter presented a deterministic inference algorithm to predict moisture and temperature in different spatial-temporal coordinates in a pepper farm.

Concerning irrigation control, many advanced algorithms have been developed, such as modifications of Model Predictive Control (MPC) in Abioye et al. (2021) and Cáceres et al. (2021, 2022), or receding horizon control in Park et al. (2009). However, the cited control methods were not validated in experiments, but only in simulations.

Even though closed-loop automatic control of irrigation theoretically implies savings, not only in terms of human resources, but also in water, energy, and supplies, farms in production do not completely trust this solution. Instead, they prefer to install and operate with open-loop controllers, this is, irrigation control systems that are activated according to some timetable, or that feed the farm with a prescribed volume of water. The reason is that the implementation of a closed-loop requires knowledge of some field variables, and the actual sensing technologies are either expensive or not reliable to achieve spatial-temporal representativeness.

Notwithstanding, several examples of feedback irrigation control systems with experimental validation can be found in the literature. Table 1 summarizes some important characteristics of these works (the last row is for the system proposed in this manuscript) that helps to understand the discussion in the following paragraphs.

First of all, it must be mentioned that the work Lozano et al. (2016) has been introduced in the table, in spite of the fact that it did not introduce a canonical closed-loop controller. The authors in that paper proposed to regulate the volume of water according to an evapotranspiration model, which was adjusted using data from the farm (lysimeters). This feedback data was collected manually and after some offline calculus, the volume was adjusted for a fixed time period. Other than that, this method was applied to a production farm with much bigger surface than the others, and it introduced a cross validation with four repetitions.

Please notice that most of the published control methods and designed platforms were tested in experimental fields, in which the boundary conditions were more easily controlled. Among them, only Sales et al. (2015) proposed a wireless network to connect the sensors. Wireless communication is a necessity in a production farm, as the wires generates many problems for the day-to-day tasks of the farmer. In fact, as far as the authors are aware, there is no example of a wired solution in a production farm.

Except from Krishnan et al. (2020), all the studies that introduced any advanced control law, other than ON-OFF, relied on TDR (time-domain reflectometry) or FDR (frequency-domain reflectometry) moisture sensors. Together with the neutron probes, that are used in Honari et al. (2017), TDR and FDR are the most reliable technologies, but the price is high compared to resistive or capacitive models. In particular, the works Lozoya et al. (2016) and Mohammed et al. (2021) were the only ones that tried a hysteresis control or MPC over a farm of relevant size. Those two, together with Angelopoulos et al. (2020) are, in the authors' opinion, the strongest papers in what respect to solutions closest to the market. The problem of MPC is the need for a model, which makes the approach heavily dependent for the particular farm, soil and crop.

It is quite interesting to remark that both in Sales et al. (2015) and Krishnan et al. (2020) the authors introduced external climatic information in the decision mechanism. In particular, the probability of precipitation was used to modulate the activation of irrigation.

Attending to the previous discussion, the objectives of this manuscript are threefold: to design a fully-operative automatic irrigation system based on low-budget capacity-based sensors; to present its deployment in a strawberry farm; and to study its performance and robustness under real operating conditions. The technical novelty, compared with other works reported in Table 1, lies in the use of simple capacity-based sensors, and the way in which their not fully reliable information about the actual values of the moisture level can be used to deploy an automatic irrigation system in a production farm. The solution is based on a hysteresis control law that benefits from the accuracy of these sensors when capturing the trends of moisture, and also from an experimental tuning of the moisture thresholds based on the farmer and agronomists recommendations.

Finally, it is worth commenting on the regional interest of the site where the proposed automatic irrigation system is deployed. As reported in Gattini (2011), Paraguay is a country whose economy is strongly based on commodity-type agricultural production, representing 80% of the value of national exports. The agricultural sector in Paraguay faces important challenges, as those derived from extreme climatic phenomena. However, the introduction of innovative solutions in small-scale productions is scarce, this resulting in a notable loss of competitiveness. According to Rivas et al. (2012), the adoption of technologies that enable more precise irrigation could make a difference in productivity, and water and soil conservation in the region.

MATERIALS

For this experiment, a monitoring and control system was designed to automate the irrigation routines on a production farm. This section describes the designed platform and its implementation on a strawberry production farm in Paraguay.

System architecture

The system was organized using an architecture with two layers, edge and cloud (see Fig. 1). The first layer contained the monitoring and actuation devices, deployed in the field, and responsible for the crop monitoring and the irrigation node routines. The devices in this layer were connected to a gateway through a wireless wide area network using LoRa (LoRaWAN protocol), which provided long range field communications (up to 10 km) with a reduced consumption. On the other hand, the communication between this gateway and the cloud layer relied on a 3G network.

Two main edge devices were deployed in different parts of the farm: a moisture node and an irrigation node. Each of these consisted of a properly waterproofed unit equipped with a microcontroller and LoRa capabilities, to which sensors and/or actuators were wired. The main goals of these devices are described next:

- The moisture node collected, on a periodical basis, the data readings from a set of capacitive soil moisture sensors connected to a Lopy4 microcontroller, from Pycom. This microcontroller was responsible for processing and filtering the raw data from the different sensors into reliable moisture values, and its further transmission to the cloud via the gateway. These processing and filtering algorithms consisted of: 1) taking ten samples from each sensor, discarding outliers (out of range), and computing the median of the non-discarded samples to generate the actual moisture measurement; 2) a first-order moving average filter that considers the stored moisture level in the previous sampling time, and the actual moisture measurement.
- The irrigation node received the control instructions from the cloud and executed them by actuating on a centrifugal water pump, which was responsible for extracting water from a reservoir and injecting it into the irrigation pipe at the required pressure. To operate the pipes, an electrovalve was installed. To control such valve, an input/output module was employed. The End-Node LT-22222-L LoRa I/O Controller from Dragino was chosen for

this task. In addition, this node was in charge of monitoring the water flow fed to the field, whose information was periodically sent to the cloud.

In the cloud layer, the data was received in a The Things Stack server. The payloads received were processed and stored in a relational database built in Azure. This data was to be used as an input for the control law, executed on Amazon Web Services, and whose output instructions were sent back to the edge layer and processed by the irrigation node. Finally, an application programming interface or API was created to provide access to this database.

Field deployment

The experiment was performed in a strawberry production farm in Itauguá, in the Central Department of the Republic of Paraguay (about 30 km from the capital Asunción), at geographical coordinates W 57°22'04.9" and S 25°21'04.1". The region is characterized by a humid subtropical climate, with an estimated average annual temperature of 25°C, reaching maximum temperatures of 42°C in summer and minimum temperatures of 10°C. Based on the climatological yearbooks of the region, the average annual rainfall from 1991 to 2020 is 1302 mm, and the annual rainfall in 2022 was 1364 mm.

Concerning the farm, it had a sandy soil (86.63% sand, 11.2% silt and 2.17% clay), with a total size of 11.26×23 m. Preliminary agronomic works were done to prepare and level the soil. The crop was arranged in 7 planks, each of them containing 2 rows of 70 strawberry plants. An artificial small pond in the vicinity, fed by a natural water resource, was employed as water reservoir for the irrigation system. A photograph of this emplacement is shown in Fig. 2.

It is relevant to highlight that, because of the particular requirements of the production farm, such as the need of periodic fertigation routines by the farmer, the system was required to allow eventual manual operations. To do so, additional robustness features were required, as will be analyzed below.

The moisture node (see Fig. 3-a) was installed in the crop to collect moisture samples every 20 minutes. This sampling period was chosen to strike a balance between capturing system dynamics and battery life, allowing for battery replacement once a month. For the sake of reliability, a total of 6 moisture sensors were installed, distributed in two different depth levels, three of them at 10 cm and the rest at 20 cm, approximately. These depths were chosen after an analysis of the plant roots and wet bulb by an agronomist expert prior to the installation of the sensors.

The processing routine that was implemented in the node consisted in (i) averaging the measurements of the 6 sensors, obtained after the individual filtering described before, to get the final raw value for the moisture, and (ii) the transformation of the raw values into a quantitative measurement of the volumetric water content. It is relevant to note that the transformation from raw measurement to moisture values requires the determination of a mathematical correlation, generally defined as calibration function. In this case, and in a preliminary phase in the laboratory, the gravimetric method was employed. This method, that involves the extraction of field soil samples, is based on correlating the sensor readings with the actual moisture content of the samples, that is experimentally determined by comparing the weight of moist soil samples to their dry weight. For this work, a linear calibration function has been employed, whose adequacy had previously been assessed in Aranda et al. (2022).

It is relevant to note that, given the small volume of measurement of the used capacity-based sensors, their reliability is highly dependent not only on the calibration function but also on the type of terrain and the specific location, which constitutes a big challenge. This drawback, as will be discussed later, motivated the use of a method based on trend analysis, as an alternative to relying on the actual reading values.

The irrigation node (see Fig. 3-b) was installed next to the main irrigation pipe, wired to the corresponding servo-valve. To provide robustness in case of an eventual irrigation by the farmer, a flow-meter was installed downstream of the servo-valve to perform a measurement of the water flow rate every 5 min. This data, read by the previously described input/output module, permitted, on one hand, to monitor the manual irrigation periods performed and, on the other, to detect a possible water pump malfunctioning.

For manual operation, an additional electrical cabinet was installed next to the water pump (see

Fig. 4). This cabinet was equipped with a three-position selector switch to allow the farmer to switch to manual operating mode and to control the water pump. This cabinet was also responsible for accommodating the protection elements of the pump (thermal relays, magneto-thermal fuse and motor circuit breaker), including protection against pump activation under water unavailability, for which a water level buoy was installed in the reservoir.

Finally, in order to reduce the high pressures that were observed in the irrigation tapes, which would eventually cause the pump to overheat and the thermal protection to activate, a pipe diversion was installed at the pump outlet with the objective to act as a pressure relief by providing the impulsion with a partial flow recirculation. A manual ball valve was installed in the diversion to permit an adequate regulation. For the sight of a better understanding, a detailed scheme of the complete system deployed is shown in Fig. 5.

METHODS

The irrigation system implemented a hysteresis-based control law. This method, which relies on measurement trends and experimentally determined thresholds, was proposed to deal with the low reliability of the sensors. This lack of reliability arises as a consequence of their particularly small volume of influence, which translates into a low spatial representativeness.

In this section, the control law implemented is briefly introduced. Later, the approach used to deal with the lack of accuracy of the capacitive-based sensors is described in detail.

On-off hysteresis control law

The objective of the irrigation control system was to keep the soil moisture, $m(t)$, inside a band or, in other words, between a lower and an upper limit. Let us assume for the moment that these limits, m_{min} and m_{max}, were known.

Then, a possible solution was to implement a hysteresis control law. It is worth remarking that, by the very nature of the servo-valves, the control action could only take two possible values: opened or closed. Therefore, the solution implemented in the experimental validation was an on-off hysteresis control. In particular, the control action $u(t) \in \{\text{OPEN,CLOSE}\}$ to be applied to the servo-valve was:

$$u(t) = \begin{cases} \text{CLOSE}, & s(t) = 0 \\ \text{OPEN}, & s(t) = 1 \end{cases}, \tag{1}$$

where $s(t)$ was an internal state whose dynamic depended on both the actual value of the moisture and the lower and upper moisture thresholds. In particular, the state changed from 0 to 1 when the lower threshold was crossed, and from 1 to 0 when to upper threshold was crossed.

In an ideal operation framework, moisture rises with irrigation, and decreases without it due to evapotranspiration. In this sense, the control system intended to keep the moisture inside the band. However, this is not always possible. There are two main reasons:

- *External factors:* The moisture level does not respond as expected because some external factors are affecting to it, such as rains, manual irrigation, fertigation, or low pressure in the water pipes. The impact of these factors will be analyzed later in the Results section.
- *Internal factors:* Even in the absence of external factors, the moisture cannot be completely kept inside the band because the events that trigger a change in the state (moisture rising or decreasing) are not immediately detected. This is due to the fact that both the sensing and actuation devices are not continuously active, but operate according to periodic patterns described in the previous section. Enlarging the sampling and activation frequencies of sensors and actuators will mitigate this effect, at a cost of higher battery consumption. Moreover, and due to the absence of synchronization between the clocks of the devices in the edge layer and the cloud, there will always be a time lag between the detection of the event and the change of the state.

Experimental tuning of the moisture limits

To implement the control law described, it is mandatory, on one hand, to know the current soil moisture value, and on the other, to define the upper and lower band limits.

It is worth mentioning that reliable and expensive sensors (such as neutron probes, and FDR or TDR sensors) would noticeably simplify these tasks, since the information measured would be accurate after calibration, and thus the limits could be chosen based on agronomic motivations. Nevertheless, as previously argued, the solution proposed was based on capacity-based sensors, which drastically reduce the cost of the system at the expense of reliability limitations.

As a consequence, even with a proper calibration, the moisture measurements obtained are not expected to be reliable enough to be representative of the actual soil moisture. Nevertheless, if their installation is adequate, the sensor will efficiently capture the moisture trends, which are useful for the algorithm.

With this in mind, the experimental tuning shown in Fig. 6 was proposed for the tuning of the soil moisture thresholds. The method intended to initially learn from the behavior of the farmer, to later introduce further adaptations to adjust the limits after considering the measured data, and both the farmer and the agronomic expert's feedback.

The data collection phase took place from July 3rd until the end of July 10th. During those days, the farmer controlled the irrigation manually.

Then, by analysis of the histogram or the box plot (see Fig. 7) one could choose the initial values for the measured moisture limits. This means that, even if the measured moisture did not represent the actual moisture in the field, the irrigation control system could use a band which was initially obtained from the farmer irrigation policies, and later refined in the inspection phase.

RESULTS

This section summarizes the data and results obtained during the operation of the irrigation control policy described in the Methods section. The corresponding results are further analyzed in the Discussion section. The set of devices described in the Materials section were deployed by the end of June 2022, although the automatic control law was not implemented until July 12th, 2022.

The automatic operation remained active until the strawberries harvesting, which took place on September 17th 2022. That is to say, the irrigation control system was active for more than 2 months.

During such period, the system operation was affected by different factors that conditioned the normal functioning. For the sake of a deep analysis of the operating conditions, these have been categorized under the following groups: normal operation, manual irrigation or fertigation, rain, insufficient water pressure, and connectivity losses. Later, in the Discussion section, the different issues observed are discussed in detail. Over the 67 days that the experiment lasted, it was functioning under normal operation for 1185.2 hours (73.7% of the time). For a sum of 157.1 hours (9.8% of the time) it suffered from connectivity losses, and for 234.7 hours (14.6%) from insufficient pressure. Manual irrigation occupied a total of 23.8 hours (1.5%), and it rained for 7.1 hours (0.4%).

The figures in the results are all presented following the same structure, as shown in Fig. 8. The upper subplot represents the measured soil moisture of the node, against time, in UTC (Universal Time Coordinated). The moisture thresholds are represented in horizontal lines.

In the lower subplot, which matches in time with the upper one, two different signals are represented. The line that takes binary values, corresponding to the right vertical axis, indicates the relay state of the solenoid valve, that is, 1 if the relay aims to open the servo-valve, and 0 if it is closed. Note that even if the relay is set to 0, the farmer had the option to manually open the valve, for example to apply fertigation. The other line, whose scale is displayed in the left vertical axis, represents the cumulative sum of the water volume that have gone through the flow meter since July 12$^{\text{th}}$. Its absolute value is hence not that important, but rather the fact of whether the signal is increasing (water flowing) or not.

At this point, it is important to remark again that the capacity-based sensors are not completely reliable when measuring the actual values of the moisture (see previous section). Therefore, the values found in the vertical axis of the upper subplot could not have a correct agronomic meaning, in terms of the particular soil and crop characteristics, the saturation point or field capacity. However, and due to the tuning procedure described before, and depicted in Fig. 6, the irrigation control pursues to keep the moisture inside a band which is adequate for the farmer and the agronomic experts.

Normal operation

Normal operation encompasses the periods in which the rest of the aforementioned factors do not affect. During normal operation, the hysteresis control law was able to keep the moisture inside the band limits, except for the internal factors mentioned in the Methods section.

Two periods are shown to illustrate the normal operation. The first one (Fig. 8), ranging from August 13$^{\text{th}}$ to August 17$^{\text{th}}$, illustrates a steady normal operation, without any moisture band modifications.

The second period (Fig. 9), ranging from September 12$^{\text{th}}$ to September 17$^{\text{th}}$, illustrates an online modification of the moisture band without interruption of the normal operation. This was performed to reduce the soil moisture around mid-September, in accordance with the conversations maintained with both the farmer and the agronomists, together with a visual inspection of the data.

Manual irrigation - fertigation

As mentioned in the Materials section, the farmer was given the option to manually operate the servo-valve, either for an eventual manual irrigation or for the required applications of fertigation to the strawberries.

During the two-month period evaluated, the farmer applied fertigation 20 times, which implies 28.6% of the total irrigations made. An example can be seen in Fig. 10, where both water flow and soil moisture raises are observed without correlation with servo-valve openings.

Observing Fig. 10, it is interesting to note that the hysteresis law was active all the time. Notice that, as the soil moisture was kept over the lower limit the days after July 13$^{\text{th}}$, the internal state of the controller remained at $s(t) = 0$.

Rain

Weather is probably the most evident external condition that affect the normal operation, and unfortunately can lead to very different consequences. On one hand, low and moderate rain naturally increases soil moisture, thus minimizing the system activations. An example can be seen in Fig. 11, where the increase on soil moisture around August 6$^{\text{th}}$ is not caused by manual or automatic irrigation (the flow meter reported a steady value). On the other hand, heavy rain and storms can harm the devices and/or temporarily affect the connectivity, as described later.

Insufficient pressure

The performance of the irrigation pipe network is strongly conditioned by an adequate pressure level at the input. An insufficient pressure level can reduce or even impede proper flow through the drippers, with independence from the servo-valve position.

In the field implementation, an insufficient low pressure value could arise as a consequence of two possible causes: (i) the reservoir fill level was too low, so that the pump was not capable of introducing pressure in the main pipe, and (ii) an incorrect position of the pressure-relief valve (see Fig. 5), causing an excessive fraction of water recirculation that plummets the outlet pressure. Although only the first was entirely caused by external factors, the latter was likely to happen because of the frequent manual operations, who might leave the valve partially opened if the farmer was not cautious.

Both cases translated in a lack of water that can be identified through monitoring, as can be clearly seen in Fig. 12. During different periods of time, the soil moisture dropped below the lower limit. According to the hysteresis control law, the state changed to $s(t) = 1$ and an OPEN command was sent to the servo-valve (note the orange line in the lower subplot of Fig. 12). However, as water did not flow through the drippers, the flow meter signal did not increase, and neither did the soil moisture.

When the pressure was recovered, water flowed again to the crop (see the effect on August 27$^{\text{th}}$, or September 7$^{\text{th}}$) and, once the moisture surpassed the upper limit, the state changed to $s(t) = 0$ and the valve was automatically closed.

Another interesting situation happened on September 2$^{\text{nd}}$, in which the moisture was still below the limit but could not rise because of the low pressure. Then, it suddenly rained, rising the moisture level (this was not manual or automated irrigation, because the flow meter showed no increment). Since moisture went again over the upper limit, the servo-valve was commanded to close. Some hours later, the level dropped down the lower limit and the servo-valve was opened again. However, the pressure problem still persisted until near September 8th.

This clearly shows that the irrigation control was active all the time, monitoring the evolution of the moisture in spite of water availability. During the experiment, 50 automatic commands were sent from the cloud to begin irrigation, 41 of which (82%) were carried out successfully. The remaining 9 (18%) suffered from insufficient pressure, and they were not completed until the pressure was restored.

Connectivity losses

Connectivity losses refer to a situation in which the data is either not received from the field or not transmitted at all. The reasons behind these losses are heterogeneous: nodes running out of batteries means no moisture data is received in the cloud; cuts in the power supply affect both the gateway and the control devices; interruptions of the telephone network might isolate the gateway from the Internet; or loss of LoRa connection might interrupt uplink and downlink transmissions, among many others.

They are, unfortunately, quite frequent, as power outages occur regularly in this region of Paraguay. The loss of connection between gateway and the Internet often happens as well, because the coverage is lost intermittently in the farm. An analysis of the frequency of the connectivity losses is presented in Table 2. They represent approximately 10% of the time, over the more than two months of the experimental validation.

The consequences have been observed before, in Fig. 12, from September 5th to 8th. A better example is shown in Fig. 13, in which several connectivity losses occurred after a huge storm hit the region. It is relevant to note the short connectivity losses on July 28th and 29th, and the long blackout on July 31st. During these periods, neither the moisture measurements or the flow meter signal were received. Nevertheless, the devices deployed were active, the algorithm kept running in the cloud, and the operation automatically came back to normal functioning when the connection was restored, which illustrates the robustness of the strategy adopted.

DISCUSSION

The discussion of the results is organized in four parts: main results and findings; comparison with other solutions; strengths and limitations; and future works.

Main results and findings

The proposed smart irrigation control system proved itself robust and reliable during a two-month continuous operation in a strawberry full-scale production farm. Those two features, robustness and reliability, are, probably, two of the most important features to boost the technology acceptance. We can establish that the system has reached a Technology Readiness Level or TRL 7 (prototype demonstration in operational environment).

The moisture level in the field was kept inside the band most of the time: 3053 samples out of 4293, which implies an approximate 71.1% of the total samples. The exceptions were due to the set of problems described in the Results section, which implied 547 samples above the band and 693 below it. In particular, considering only the periods of normal operation, the percentage of samples inside the band rose up to 87.9%. Please notice that, by the very nature of the hysteresis algorithm, at least two samples outside the band are required for each irrigation period. By considering so, the maximum percentage is 97.4%.

With respect to the comparison against the manual irrigation carried out by the farmer, it was found out that the automated irrigation system watered approximately the same number of liters in average per irrigation pulse than the farmer (1252 L, compared to 1290 L of the farmer). One might think that the automatic irrigation system should pursue a reduction in the water consumption compared to the farmed. But in the authors' opinion, it is the efficiency of the irrigation what matters. And this was found to be very different between the two irrigation methods. The efficiency of the irrigation pulses can be defined as the ratio of the useful to the total volume irrigated in the pulse. The useful water is the difference between the total volume and the excess water, this is, the volume of water that has been irrigated with moisture values over the higher limit. Assuming that the band is adequately adjusted according to the farmer recommendations, this excess water is not needed and is likely to be lost by evaporation or gravity through the soil. The efficiency for the manual irrigation was found to be 62.1%, whereas for the automated irrigation was 91.4%.

Remark. A more accurate and useful measure for the efficiency would be related to the yield and the water consumption, measured in kg/L. Unfortunately, the total yield of the two plots was unknown, so this value could not be computed. Furthermore, in order to provide this value with statistical robustness, several repetitions of the experiment would be required, which were not possible since the farmer changed the crop after the harvest. However, as the efficiency is computed here for each irrigation pulse, and there are many irrigation pulses in the two months, the metric proposed here as efficiency is more statistically robust, although it only measures how the irrigation sticks to the limits that are considered adequate by the farmer.

Comparison with other solutions

The proposed irrigation control system has reached a technology readiness level comparable with the works by Lozoya et al. (2016), Angelopoulos et al. (2020) and Mohammed et al. (2021) and, possibly have gone beyond them in several aspects. It is still far from the level attained in the monitorization platform of López et al. (2015), or the evapotranspiration-based control setup described by Lozano et al. (2016). In particular, it lacks from the standard cross-validation analysis, linked with productivity, possibly required by any end-user.

The reduction in water consumption per irrigation with respect to the farmer attained in this experiment (3%) is smaller than that reported by Lozoya et al. (2016) (39%), and by Mohammed et al. (2021) (64%). However, this metric is not conclusive, since it might be biased by many factors, such as the farmer behavior, the particular crop or soil. For example, as readers of Lozoya et al. (2016) or Mohammed et al. (2021), we are not sure about the way the farmer irrigates. Even more so when in Mohammed et al. (2021) the experiment took place in a farm in the university, where one could not expect a really experienced farmer. In the case reported in this manuscript, the experiment took place in a production farm. The farmer who irrigated the manual plot comes from a farming family and, in addition to having more than 40 years of experience in manual irrigation, is a farmer who has received continuous training and advice on agro-ecological production and efficient irrigation. Then, if the automated irrigation pours approximately the same amount of water than the farmer is reassuring for both the designers and farmer. The efficiency of the irrigation pulses, which was shown to be higher with the automated irrigation system, was not measured in those works.

The use of low-cost capacitive moisture sensors, shown in this manuscript for the first time on a real production farm, is quite interesting. Not only large farms with added-value crops, but also small-size farms, as the familiar case described in this work, might be willing to try this closed-loop control method.

Strengths and limitations

The main strengths of the deployed irrigation control system were:

- Reliability and robustness against external factors, such as rains, storms or connectivity losses, that occur in a real operation.
- The design allowed for a completely manual operation. This was not only necessary for fertigation, but also increased the confidence of the farmer, as the control of the irrigation can be regained at any moment.
- The deployed infrastructure could be used to implement more complex control laws. The hysteresis control law could be substituted by any other algorithm in the cloud that generates ON/OFF commands.
- Measuring soil moisture and using it as feedback allowed for a control of the water applied, in line with the amount the plant needed, and it was robust against rainfall, in contrast to open-loop controllers programmed with timers, which must be manually switched off if it rains.

During these two months, several limitations were highlighted, either from the farmer or the agricultural engineers that collaborate with the authors. The most relevant were:

- It was not possible to set a maximum amount of volume of water per day, or forbidden slots of time for irrigation.
- If the connectivity was lost right when the servo-valve is open, there was no way for the system to stop the water flow, since it had to wait for the command from the cloud.

- The moisture level was oversampled when the variable was decreasing, and undersampled when it was rising, due to the periodicity of the monitoring devices. This produced undesired peaks when the moisture was rising.
- The adaptation of the moisture limits was quite a manual operation that needs to be improved.
- The climate predictions were not exploited by the platform.

Future works

There are many open lines of research, some of them pointed out by the limitations. In particular, one of the most relevant might consist in the application of model-predictive control, as done by Cáceres et al. (2021), to consider not only the moisture limits, but also future climate predictions and operational constraints.

Another interesting step will be the isolation of the edge layer from the cloud layer, so that the edge layer can be capable of operating the irrigation control autonomously during an eventual period of time in which the unavoidable connectivity problems arise.

Finally, the introduction of additional servo-valves and nodes will be considered a relevant step to be performed in other experiments, so that the irrigation considers the possible spatial variability in the farm. In this case, it will be required to trade-off the costs of the new devices against the agricultural benefits for the farmer.

CONCLUSIONS

This manuscript has presented a platform that allows for the automated control of the irrigation. The platform included both the edge layer, this is, the devices deployed in the farm, and the cloud layer, in which the control algorithm was executed. The manuscript reports a two-month operation in a production farm. During this two months, several events occurred that have tested the behavior of the algorithm and platform. Namely, rains, manual fertigation, connectivity losses, or low pressure in the water pipes. The results are encouraging both in robustness, water usage, and in irrigation efficiency. Although more experiments needs to be done, they invite to explore more complex control laws in the future.

Furthermore, the impact in the production, the soil, the water usage, and other agronomic variables needs to be studied in depth by performing more experimental validation. Repetitions of the same experiment are also needed to provide statistical robustness to the conclusions drawn.

APPENDIX I. DATA AVAILABILITY STATEMENT

All data used during the study are available online, in accordance with funder data retention policies, in Manzano et al. (2022b).

APPENDIX II. ACKNOWLEDGMENTS

The authors would like to thank the Agencia Española de Cooperación Internacional al Desarrollo (Grants 2020/ACDE/000192 and 2022/ACDE/000116) and the Junta de Andalucía (Grants PY20-RE-017-LOYOLA and 0INN005/2021) for partially fund this work.

The authors would like to thank José Manuel García Campos and Adrián Rocha, from Fundación Ayesa, for their work involved in the development of the platform in the cloud. Finally, the authors gratefully thank the agricultural engineers Miguel Ángel Ken Morilla and Hernán Hortellado for their valuable agronomic inputs.

REFERENCES

Abioye, E. A., Abidin, M. S. Z., Aman, M. N., Mahmud, M. S. A., and Buyamin, S. (2021). "A model predictive controller for precision irrigation using discrete lagurre networks." *Computers and Electronics in Agriculture*, 181, 105953.

Abioye, E. A., Abidin, M. S. Z., Mahmud, M. S. A., Buyamin, S., Ishak, M. H. I., Abd Rahman, M. K. I., Otuoze, A. O., Onotu, P., and Ramli, M. S. A. (2020). "A review on monitoring and advanced control strategies for precision irrigation." *Computers and Electronics in Agriculture*, 173, 105441.

Abraham, N., Hema, P., Saritha, E., and Subramannian, S. (2000). "Irrigation automation based on soil electrical conductivity and leaf temperature." *Agricultural Water Management*, 45(2), 145–157.

Angelopoulos, C. M., Filios, G., Nikoletseas, S., and Raptis, T. P. (2020). "Keeping data at the edge of smart irrigation networks: A case study in strawberry greenhouses." *Computer Networks*, 167, 107039.

Aranda, D., Tapia Córdoba, A., and Millan Gata, P. (2022). "Calibración y caracterización de sensores capacitivos de bajo coste para la monitorización de humedad de suelo." *XLIII Jornadas de Automática*, Universidade da Coruña. Servizo de Publicacións, 479–485.

Cáceres, G., Millán, P., Pereira, M., and Lozano, D. (2021). "Smart farm irrigation: Model predictive control for economic optimal irrigation in agriculture." *Agronomy*, 11(9), 1810.

Cáceres, G., Pereira, M., Millán, P., and Lozano, D. (2022). "Pulse-based, periodic MPC for irrigation in smart and sustainable agriculture." *2022 American Control Conference (ACC)*, IEEE, 2045–2050.

FAO (2017). "Water for sustainable food and agriculture. a report produced for the G20 presidency of Germany." *Report No. 1*, Food and Agriculture Organization of the United Nations, Rome.

Gattini, J. (2011). “Competitividad de la agricultura familiar en Paraguay.” *Nuevos aportes para las políticas públicas en Paraguay*, 5, 1–29.

Honari, M., Ashrafzadeh, A., Khaledian, M., Vazifedoust, M., and Mailhol, J. (2017). “Comparison of HYDRUS-3D soil moisture simulations of subsurface drip irrigation with experimental observations in the south of France.” *Journal of Irrigation and Drainage Engineering*, 143(7), 8–p.

Kamienski, C., Soininen, J.-P., Taumberger, M., Dantas, R., Toscano, A., Salmon Cinotti, T., Filev Maia, R., and Torre Neto, A. (2019). “Smart water management platform: IoT-based precision irrigation for agriculture.” *Sensors*, 19(2), 276.

Krishnan, R. S., Julie, E. G., Robinson, Y. H., Raja, S., Kumar, R., Thong, P. H., et al. (2020). “Fuzzy logic based smart irrigation system using internet of things.” *Journal of Cleaner Production*, 252, 119902.

López, J. A., Navarro, H., Soto, F., Pavón, N., Suardíaz, J., and Torres, R. (2015). “Gaia2: A multifunctional wireless device for enhancing crop management.” *Agricultural Water Management*, 151, 75–86.

Lozano, D., Ruiz, N., and Gavilán, P. (2016). “Consumptive water use and irrigation performance of strawberries.” *Agricultural Water Management*, 169, 44–51.

Lozoya, C., Favela-Contreras, A., Aguilar-Gonzalez, A., Félix-Herrán, L. C., and Orona, L. (2021). “Energy-efficient wireless communication strategy for precision agriculture irrigation control.” *Sensors*, 21(16), 5541.

Lozoya, C., Mendoza, C., Aguilar, A., Román, A., and Castelló, R. (2016). “Sensor-based model driven control strategy for precision irrigation.” *Journal of Sensors*, 2016.

Luthra, S., Kaledonkar, M., Singh, O., and Tyagi, N. (1997). “Design and development of an auto irrigation system.” *Agricultural Water Management*, 33(2-3), 169–181.

Manzano, J., Orihuela, L., Pacheco, E., and Pereira, M. (2022a). "Results on spatio-temporal estimation of temperature and soil moisture in la colmena (paraguay)." *IFAC-PapersOnLine*, 55(32), 265–270.

Manzano, J., Orihuela, L., Tapia, A., Pacheco, E., and Bareiro, J. (2022b). "Smart irrigation control system data with soil moisture, flow meter and electrovalve relay, V3." *Mendeley Data* https://data.mendeley.com/datasets/cjb4vy4mzj. Accessed January 20, 2023.

Méndez-Guzmán, H. A., Padilla-Medina, J. A., Martínez-Nolasco, C., Martinez-Nolasco, J. J., Barranco-Gutiérrez, A. I., Contreras-Medina, L. M., and Leon-Rodriguez, M. (2022). "IoT-based monitoring system applied to aeroponics greenhouse." *Sensors*, 22(15), 5646.

Mohammed, M., Riad, K., and Alqahtani, N. (2021). "Efficient iot-based control for a smart subsurface irrigation system to enhance irrigation management of date palm." *Sensors*, 21(12), 3942.

Navarro-Hellín, H., Torres-Sánchez, R., Soto-Valles, F., Albaladejo-Pérez, C., López-Riquelme, J. A., and Domingo-Miguel, R. (2015). "A wireless sensors architecture for efficient irrigation water management." *Agricultural Water Management*, 151, 64–74.

Obaideen, K., Yousef, B. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., and Ramadan, M. (2022). "An overview of smart irrigation systems using IoT." *Energy Nexus*, 100124.

Park, Y., Shamma, J. S., and Harmon, T. C. (2009). "A receding horizon control algorithm for adaptive management of soil moisture and chemical levels during irrigation." *Environmental Modelling & Software*, 24(9), 1112–1121.

Rivas, G. G., Gutiérrez, I. A., Ramírez, F., Padilla, D., Suchini, J. G., Hernández, L., Rodríguez, L., and Juárez, M. (2012). "Hacia el fortalecimiento de una agricultura familiar: pilar de los territorios rurales." *Síntesis para decisores. Policy Brief*.

Rivas-Sánchez, Y. A., Moreno-Pérez, M. F., and Roldán-Cañas, J. (2019). "Environment control with low-cost microcontrollers and microprocessors: Application for green walls." *Sustainability*, 11(3), 782.

Roy, S. K., Misra, S., Raghuwanshi, N. S., and Das, S. K. (2020). "AgriSens: IoT-based dynamic irrigation scheduling system for water management of irrigated crops." *IEEE Internet of Things Journal*, 8(6), 5023–5030.

Sales, N., Remédios, O., and Arsenio, A. (2015). "Wireless sensor and actuator system for smart irrigation on the cloud." *2015 IEEE 2nd World Forum on internet of things*, IEEE, 693–698.

Vallino, E., Ridolfi, L., and Laio, F. (2020). "Measuring economic water scarcity in agriculture: A cross-country empirical investigation." *Environmental Science & Policy*, 114, 73–85.

WHO (2021). *The State of Food Security and Nutrition in the World 2021: Transforming food systems for food security, improved nutrition and affordable healthy diets for all*, Vol. 2021. Food & Agriculture Org.

List of Tables

TABLE 1. Table of characteristics for reviewed irrigation control systems with experiments. A hyphen symbol (-) is introduced when the corresponding information is missing from the reference

Reference	Farm/crop[a] (ha)	Duration	Validation[b]	Control[c]	Feedback (technology[d])	Network[e]
Luthra et al. (1997)	Exp./- (0.250)	12 days	None	ON-OFF	Moisture (Tensiometer)	Wired
Abraham et al. (2000)	Exp./Okra (<0.001)	3 months	None	ON-OFF	Moisture (Resistive) Leaf Temp. (Thermistor)	Wired
Sales et al. (2015)	Exp./Peach (<0.001)	3 days	Manual	Hysteresis	Moisture (FDR)	ZigBee
Lozano et al. (2016)	Prod./Strawberry (~1)	9 months	Cross	Open-loop	Evapotransp. (Lysimeter)	None
Lozoya et al. (2016)	Prod./Pepper (0.060)	2 months	Manual	MPC Hysteresis Open-loop	Moisture (FDR)	ZigBee
Rivas-Sánchez et al. (2019)	Exp./Green wall (<0.001)	45 days	None	ON-OFF	Moisture (Resistive) Rain (Resistive)	Wired
Angelopoulos et al. (2020)	Prod./Strawberry (0.040)	3 months	Manual	ON-OFF	Moisture (FDR)	ZigBee
Krishnan et al. (2020)	Exp./- (-)	15 days	Manual	Fuzzy	Moisture (Resistive) Temperature (Thermistor) Humidity (Capacitive)	Wired
Mohammed et al. (2021)	Exp./Date (0.135)	1 year	Cross	Hysteresis Open-loop	Moisture (TDR)	Wired
Roy et al. (2020)	Exp./Rice (<0.001)	4 months	Manual	ON-OFF Hysteresis	Moisture (TDR)	Wired
This work	Prod./Strawberry (0.026)	2 months	Manual	Hysteresis	Moisture (Capacitive)	LoRa

[a] "Prod." for full production farms; "Exp." for experimental farms (small plots or experimental fields in the universities or research centers).
[b] "Cross", when several repetitions of the same experiment are made; "Manual", when the results are compared with the traditional irrigation of the farmer; "None", when no validation is explicitly done.
[c] "ON-OFF" laws activate the irrigation according to a given threshold in the feedback variable; "Hysteresis" control intends to keep the variable inside a band; "MPC" or "Fuzzy" stands for Model-Predictive or Fuzzy Control.
[d] "FDR" and "TDR" stands for Frequency and Time Domain Reflectometry, respectively.
[e] Network defines the way in which the sensors and actuators devices are connected

TABLE 2. Statistics of the connectivity losses of each device, over the two-month experiment

Device	Correct transmissions	Failed transmissions
Electrovalve	18572 (91%)	1875 (9%)
Flow meter	18555 (91%)	1892 (9%)
Moisture node	4569 (89%)	542 (11%)

List of Figures

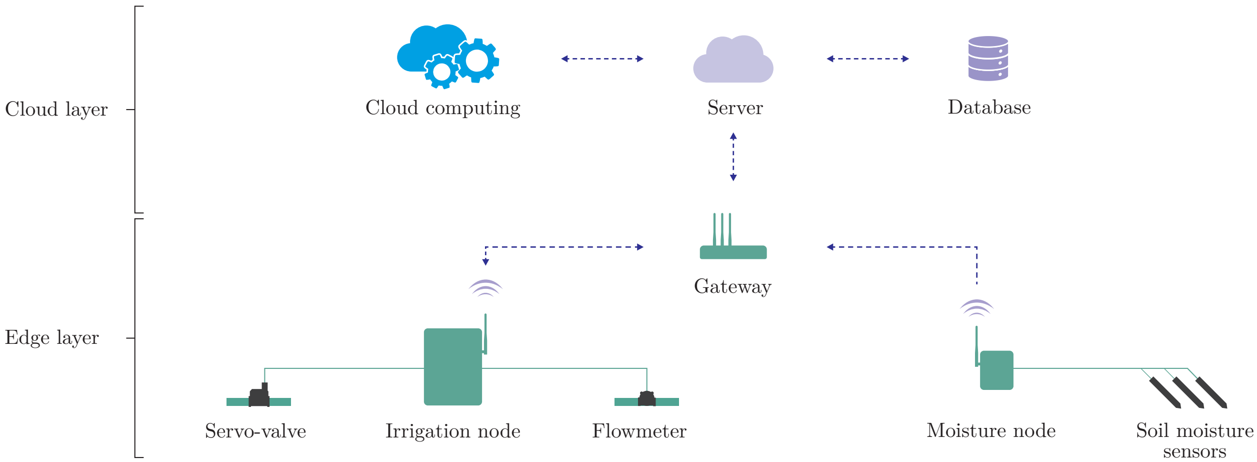

Fig. 1. Two-layers system architecture implemented.

Fig. 2. Artificial pond used as water reservoir for the experiment in the strawberry farm.

(a) Moisture node. Note the wires corresponding to the soil moisture sensors, that were installed under the ground surface, and the LoRa antenna

(b) Irrigation node, with two input/output modules employed to control the water pump and to read the flow-meter

Fig. 3. Photographs of the two nodes deployed for the experiment

Fig. 4. Photographs of the centrifugal water pump (left) and the electrical cabinet deployed for the experiment

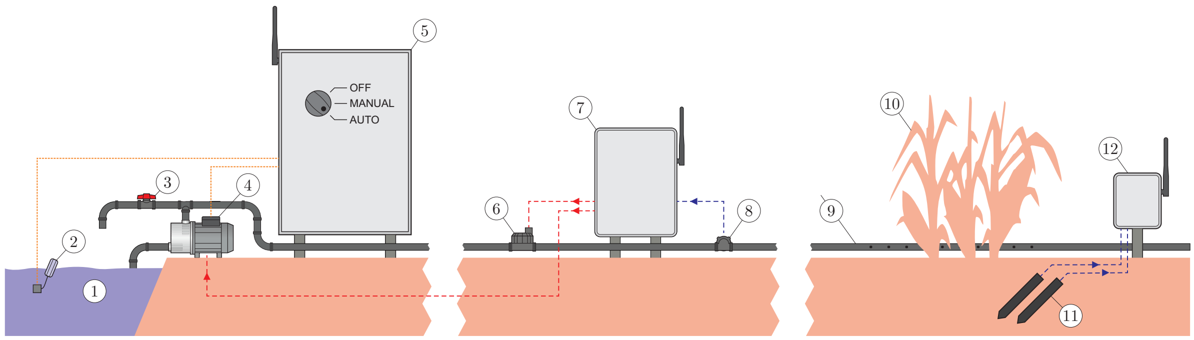

Fig. 5. Scheme of the system components and connectivity: (1) water reservoir, (2) water level buoy, (3) pressure relieve valve, (4) water pump, (5) electrical cabinet with control panel, (6) servo-valve, (7) irrigation node, (8) flow-meter, (9) irrigation pipe, (10) crop, (11) soil moisture sensors, (12) moisture node. Dashed lines represent wired connections for sensoring (blue), actuating (red) and protection (orange)

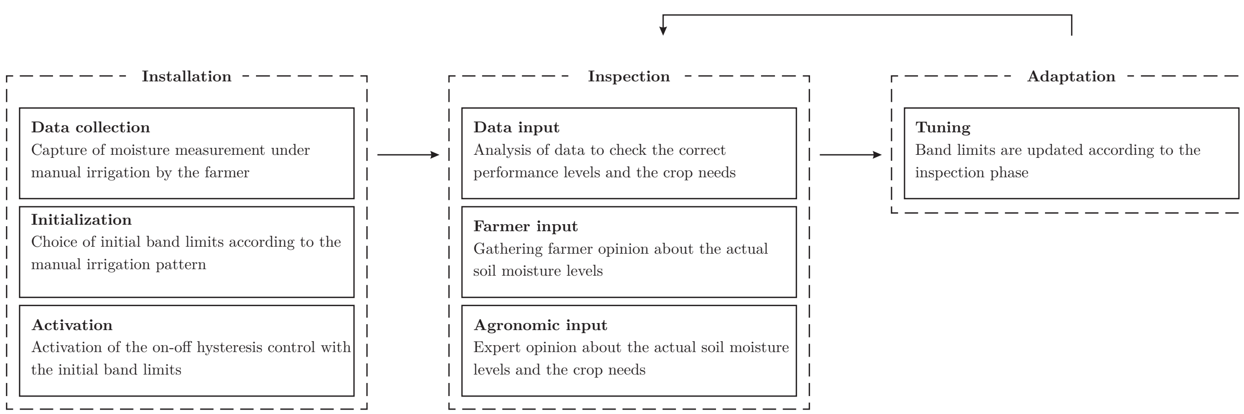

Fig. 6. Experimental moisture limits tuning procedure

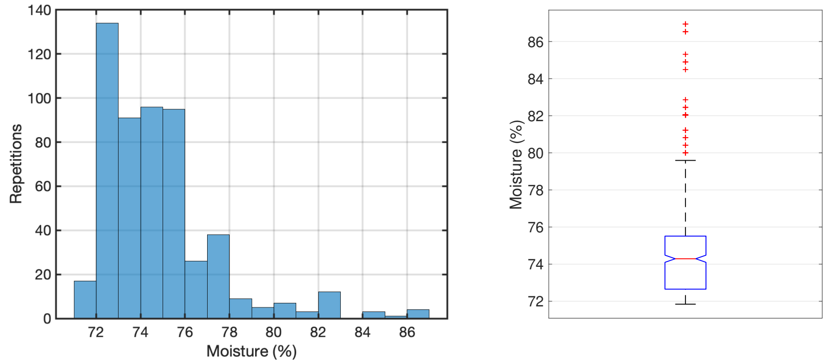

Fig. 7. Analysis of the data collected for the choice of the initial limits

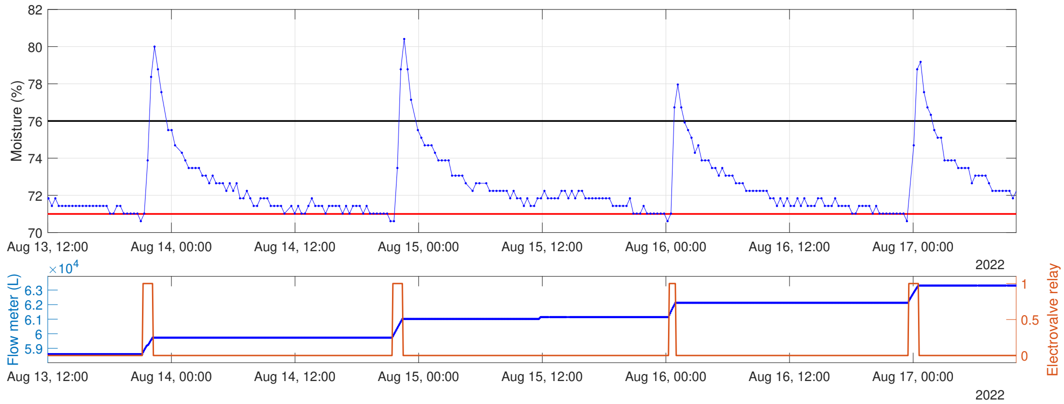

Fig. 8. Normal operation of the irrigation control

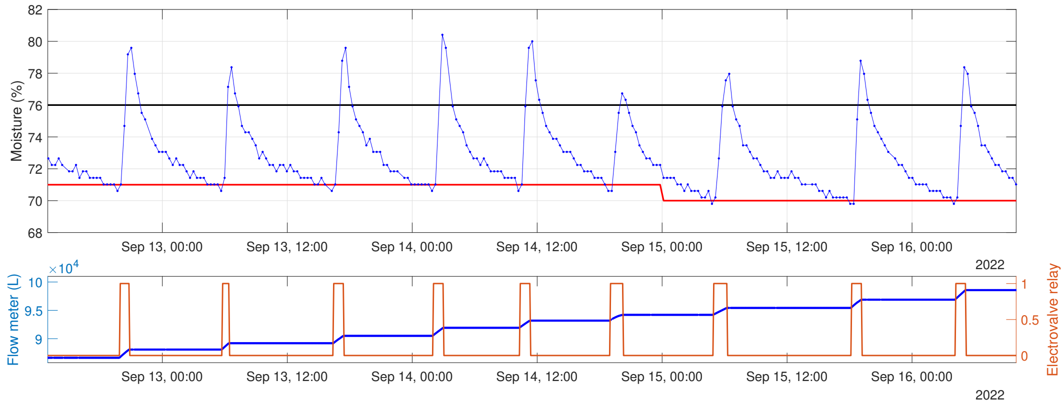

Fig. 9. Online change of the moisture band during normal operation

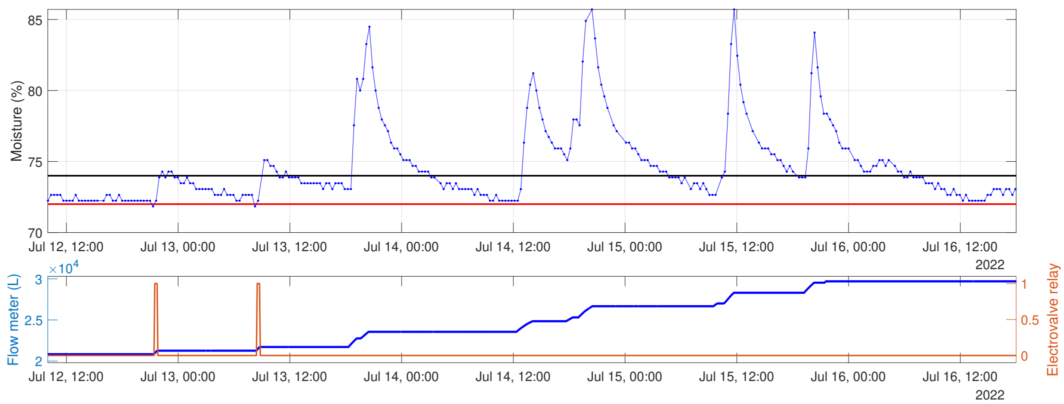

Fig. 10. Manual operation for fertigation

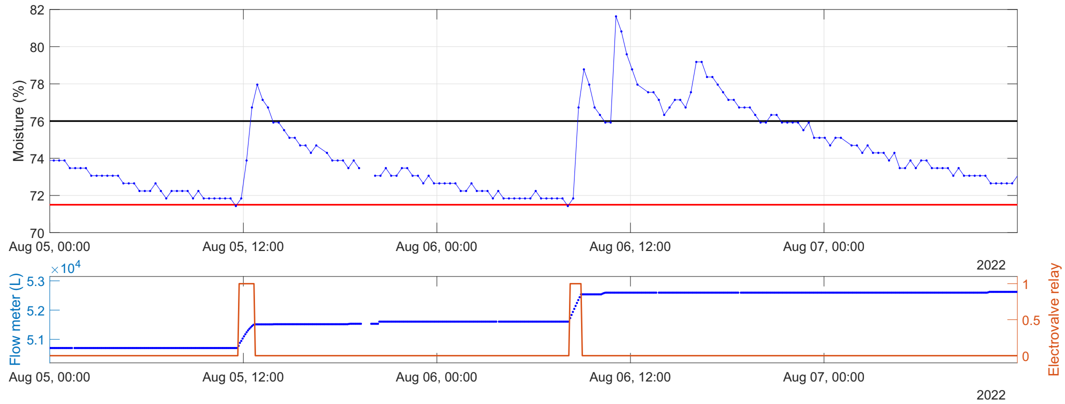

Fig. 11. Effect of rainfall

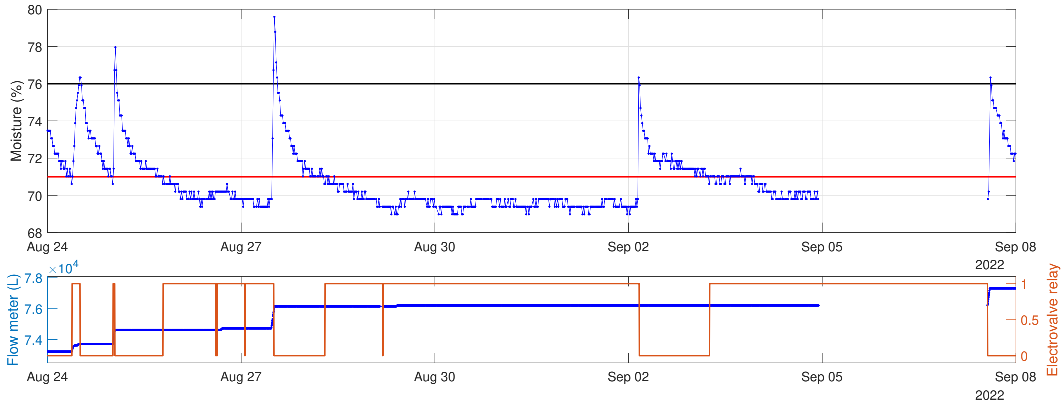

Fig. 12. Operation under low pressure in the water pipes

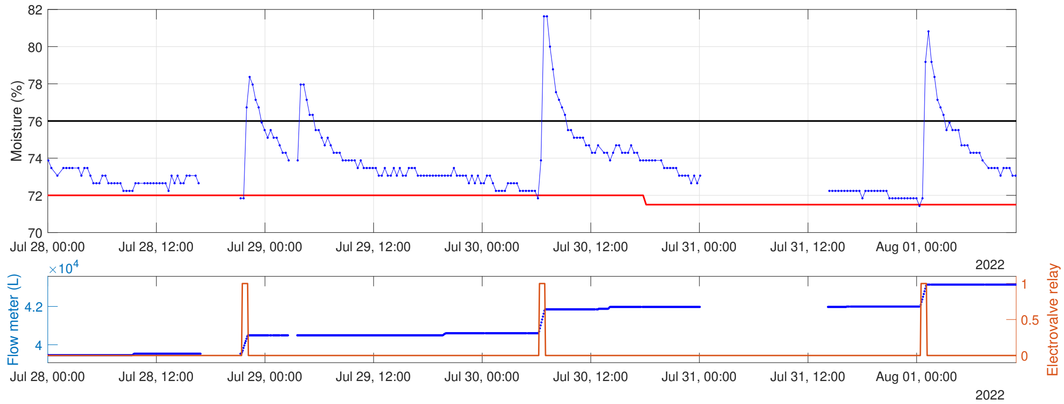

Fig. 13. Operation subject to connectivity losses due to the storm