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Edge AI-IoT Pivot Irrigation, Plant Diseases, and Pests Identification

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Abstract

Overcoming population growth dilemma with less resources of soil and water, the irrigated agriculture allows us to increase the yield and the production of several crops in order to meet the high requirements of demands of food and fibers. Efficiently, an irrigation system should correctly evaluate the amount of water and also the timing, when applying certain irrigation doses. Global warming of the planet, to which is added in some regions an irregular regime of precipitation and a scarcity of available water resources, requires precision irrigation systems. The rational use of water and inputs (mainly fertilizers and pesticides) is crucial in some areas of the planet suffering from a deficiency of water. Hence, in these regions where the environmental conditions are harsh to ensure an efficient crop growth. Moreover, plant diseases and pests impact the yields of crops. For these reasons is it why an early detection gives us the opportunity to treat the disease or pest as quickly and effectively as possible, in order, to reduce the impact of these latter. Nowadays, the identification of plant diseases and pest with Artificial Intelligence algorithms on video flow in real conditions with variable exposition are still being a very challenging problem. Researchers classically develop algorithms that are trained on calibrated exposition images, which does not perform well in real conditions. Furthermore, the processing of a video in real time needs specialized computing resources close to the pivot-center irrigation trained with AI algorithms on real images and then analyzes rapidly, detects problem, and then react accordingly. In this paper, we complete our previous proposed IoT system to optimize the water use and we displaced the computing of data at the edge level in order to be able to process videos locally, event the Internet connection is limited. This local computing power also allows us to manage the supply of fertilizers and the treatment of plant diseases, and pests.

Keywords: Center-pivot Irrigation; Connected Irrigation; Smart Irrigation; Water Requirement; Intelligent Irrigation

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1. Introduction

Soil and water availability have declined in parallel with population growth. In addition, climate change is responsible for a change in temperatures and the rainfall, which impact agriculture for the whole planet at different intensities. Humanity is facing an urgent need to increase agricultural production in order to face the demand of feeding the world population and adapt to the climatic condition that has impacted crop yields at different geographics locations worldwide. However, the pressure on the availability of sufficient quantities of water is only increasing in more regions of the world. It has become mandatory to optimize and rationalize its use to conserve or even increase the yields of agricultural production while saving it. Precision irrigation is one of the main ways to address this issue.

Irrigation is a process in which water is applying on the soil in order to improve the growth of crops or fruit trees, to revegetate degraded soil, or to maintain landscapes in areas where rains are insufficient or irregular [21]. Different techniques of irrigation allow us to substitute the lack of water by enhancing runoff surface or using an irrigation pivot or by a drip system. Only a part of water that is effectively absorbed, will be partially stocked in the soil and available for plants; the rest is mainly lost by runoff, percolation in the soil or evaporation during the routing of water to the irrigated areas. Water is a solvent of salts, sugar and other solute needs for the growth of plan. In addition, it also plays a crucial role in hydrolytic processes and acts as a reagent in photosynthesis.

This technique of water optimization must answer questions when how much and where to apply water to optimize the yield of crops affected by minimum water. To achieve this goal, many models have been developed to calculate the evapotranspiration of plants based on their phenotypic development, weather conditions, and the nature of the soil. Evapotranspiration can be defined as the amount of water transferred to the atmosphere, through ground-level evaporation from water tables, precipitation interception, and through plant transpiration. These models let us determine precisely the evapotranspiration (ET) of plant and compensate ET by irrigation. On the contrary, these models cannot evaluate the water effectively stored in the soil in case of this latter is heterogeneous. To address this dilemma, other models have been developed on the basis of networks of sensors that measure the environmental conditions and the soil humidity to estimate the irrigation doses to be applied and maintained according to a specific range of soil moisture. Nevertheless, they are not adaptable to any whereabout.

We propose a solution mixing targeted both approaches for center-pivot irrigation. We evaluate the potential evapotranspiration (ET_0) on basis of Penman–Monteith equation, recommended by FAO. Afterwards, this one is adapted in function of the development stage of the crop. A network of sensors placed in the soil to measure the moisture and to correct doses volume to compensate for obstruction and aging of the spray equipment, or the failed of a sprinkler.

In this paper, we complete our previous work [4] adding dynamic adaptation to environmental conditions and the detection of plant diseases and pests. The novelty of this paper is the combination of an Intelligent Variable Irrigation System, plant diseases, and pests' detection processed at the Edge of network on a micro heterogeneous cluster.

The next sections of the paper is articulated as follow: In section 2, we present a literature review organized in two parts. The first remind our background in term of Internet of Things, edge computing, and irrigation. The second part summaries related works with our research. In section 3, we describe our proposition using edge computing to optimize center-pivot irrigation, plant and pest detection at quasi real-time. In section 4, we describe our experimentation and discuss our findings. Finally, in section 5, we conclude in comparing our results with these findings in the literature and trace our future works.

2. Literature Review

This section is composed of two parts: Firstly, we give a brief overview about our background through previous works on edge AI and IoT, Internet of Things, and irrigation. Afterwards, we describe some major contributions in term of smart irrigation and approaches used to optimized amount of water distributed on the field.

2.1. Background

In our previous work, we suggested an automation system based on the Internet of Things (*IoT*), Geographic Information System (*GIS*) and quasi real-time in the cloud of water requirements to improve the efficiency of water use [4]. We also developed an AI-IoT architecture [12] tested on various use cases such as climatic enclosure

[11], smart poultry [9], and landslides monitoring [20]. Additionally, we developed a High Performance Computing (*HPC*) cloud architecture [18] and a Lambda cloud architecture developed on various use cases: landslides monitoring[25], bee health[19], irrigation [4], elderly and patient monitoring[13], AI-IoT[12], smart campus[3], smart home[7], smart city[8], smart building[16], cattle behavior[6][15][5][10], phenotyping[14][17], urban gardening[2], climatic enclosure[11], and smart bird[1].

2.2. Related Works

Jimenez et al. [23] proposed an inference system using a Raspberry Pi and a network of xbee devices acquiring soil moisture, soil and air temperatures, luminosity, and rain data. Their inference system determines the irrigation time on basis of membership functions and a Mamdani inference methodology. In addition, the luminosity and ambient temperature are used to determine periods with an important evapotranspiration, while soil moisture allows to determine the volume of water contained in the soil. A fuzzy logic mechanism effects the inference of the dose and timing in crop system [23].

Vilarrubia et al. [27] combined a multi-agent system using PANGEA, an open source platform to manage virtual organizations, which monitor and control irrigation system. In addition, a Wireless Sensors Network (WSN) that measures soil moisture, air temperature and humidity, conductivity, oxygen, water level, and pH. Agents interact autonomously and provide to the system a greater flexibility and intelligence [27].

Mendes et al. [24] have proposed a variable rate irrigation system (VRIS) that spatially vary the application of water on the field, especially, with different type of soils, and crops. It uses a fuzzy inference which create prescriptive map based on normalized differences vegetation index (*NDVI*), canopy temperature, and satellite images to adapt to pivot rotation speed [24].

González-Briones et al. [22] implemented a multi-agent system based on virtual organizations built with Java Agent Development Framework (*JADE*) over the cloud. These authors argue that the use of cloud allows an immediate access to evaluate the status of all sensors and devices. Furthermore, edge computing consumes less bandwidth, optimizes processes, and reduces latency [22].

3. Our proposition

Our proposition relies on our previously describe Edge AI-IoT architecture [12] based on Kubernetes and Docker which allows us to deploy easily Multi Agent Systems (*MAS*) and to adapt Artificial Intelligence (*AI*) algorithms on a heterogeneous cluster composed of Odroid N2 and Nvidia Jetson Nano. This Edge cluster helps us to process data close to the pivot center and gives a real-time analysis; and therefore, makes a quick decision. It can often use the cloud computing to train artificial intelligence algorithm or process data when capabilities of the edge cluster are temporary insufficient and that when a broadband connection is available.

As shown in Figure 1, a Wireless Sensors Network measures the soil moisture under each segment of center-pivot to control and adapt dynamically amount of water sprinkled on plant and soil. These sensor network support us to measures the soil temperature, and water content at 10cm and 30cm with SHT20 (Sensirion) sensors with a temperature accuracy of ±0.3°C and a moisture accuracy ±3%RH before and after irrigation and localization of the pivot extremity by GPS NEO-M9N (U-Blox). In the meanwhile, a weather station measures data needs to calculate potential evapotranspiration ET_O (see Fig. 3 with the Penman–Monteith equation.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma(900/T + 273)U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \tag{1}$$

Where ET_0 is the potential evapotranspiration [$mm.day^{-1}$], Rn is the net radiation at the crop surface [$MJ.m^2.day^{-1}$], G is the soil heat flux density [$MJ.m^{-2}.day^{-1}$], T is the mean daily air temperature at 2m height of soil [$°C$], U_2 is the wind speed at 2m height of soil [$m.s^{-1}$], $e_s - e_a$ is the saturation vapor pressure [kPa], Δ
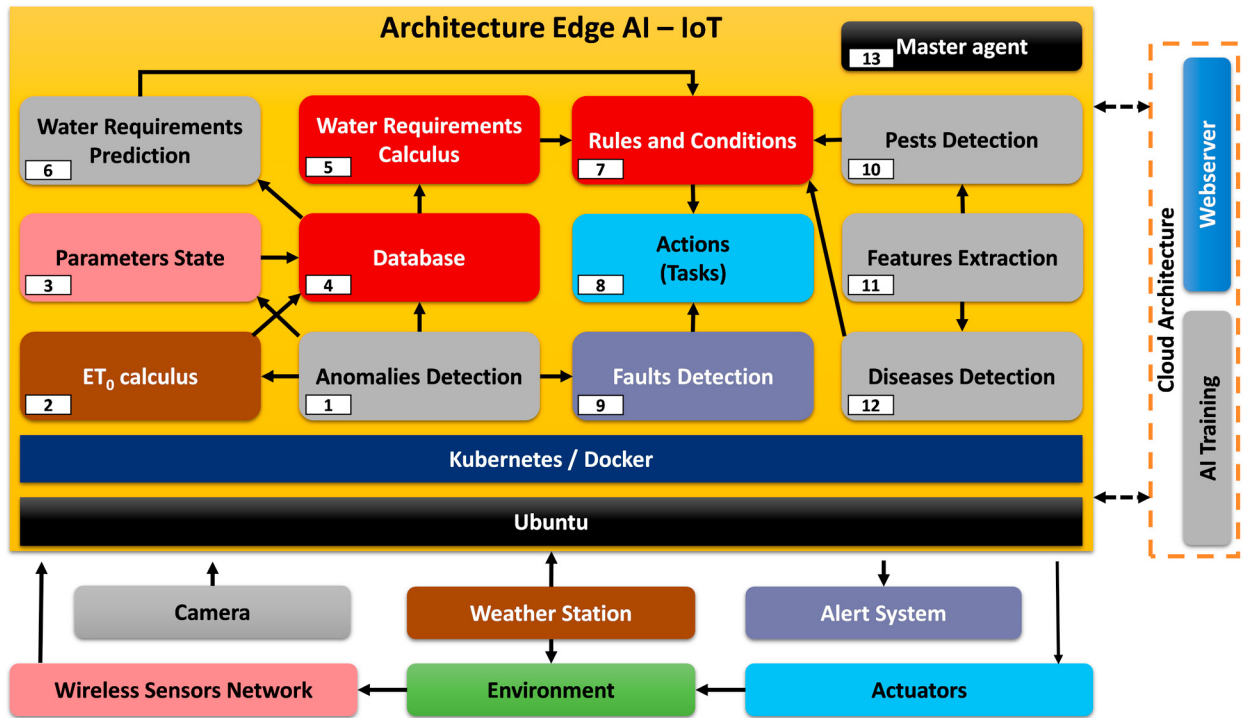
Fig. 1. Architecture Scheme

is the slope of the vapor pressure curve [$kPa.°C^{-1}$], γ is the psychrometric constant [$kPa.°C^{-1}$].

This latter is built around an ESP32 LoRA v2 and equipped with a win vane and anemometer Davis, a hygrometer, thermometer and barometer BME280 (Bosch Sensortec), a rain gauge RG-15 (Hygreon), a net radiometer SN-500 (Apogee Instruments), which measures respectively the wind direction [°], the wind speed [m/s], air humidity [%], air temperature [°C], air pressure, rainfall [mm], net radiation [$W.m^{-2}$] for pivot irrigation in the vicinity. Actuators are also built around an ESP32 LoRa V2 equipped of solenoid valve and flow sensors, which gives us the opportunity to manage the flow and control applied one at sprinklers level. The data is transmitted with LoRa to a gateway that route data them up to the edge cluster using TCP/IP.

Table 1. Power consumption according to manufacturer's data and interface of connection.

Component	Model	Interface	Accuracy	Operation mode	Supply Current (Max)	Voltage
Microcontroller	ESP32 Lora V2	Multiple	N/A	power / output	135mA / 500mA	2.7-6VDC
Sol moisture	SHT20	I^2C	±3%	sleep mode / measuring	0.4μA / 330μA	2.1-3.6VDC
Sol temperature	SHT20	I^2C	±3°	sleep mode / measuring	0.4μA / 330μA	2.1-3.6VDC
Air temperature	DS18B20	1-Wire	±5%	Standby / Active	1μA / 1.5 m	3.3-5.5VDC
Air temperature	BME280	I^2C	±1°	sleep mode / normal	0.1μA / 1 μA	1.7-3.6VDC
Hygrometer	BME280	I^2C	±3%	sleep mode / normal	0.1μA / 0.8 μA	1.7-3.6VDC
Barometer	BME280	I^2C	1hPa	sleep mode / normal	0.1μA / 1.8 μA	1.7-3.6VDC
Anemometer	Davis anemometer	Digital	1m/s	N/A	N/A	5VDC
Win vane	Davis anemometer	N/A	3°	N/A	N/A	5VDC
Rain gauge	RG-15	Serial	0.02mm	nominal / raining	110μA / 2-4mA	3.3VDC
Net Radiometer	SN-500	Analogic	5%	power	740mA @ 12VDC	5.5-16VDC
GPS	NEO-M9N	Serial	*2mhorizontal*	acquisition / tracking	100mA / 36mA	2.7-3.6VDC

The Edge cluster hosts virtual organizations that may be deployed preferably on Odroid N2 and artificial intelligence algorithms choose to run on Nvidia Jetson Nano. All the hosted virtual organizations and agents are detailed as follow (See Fig. 1 and Fig. 2):

(1) The **Anomalies Detection** virtual organization contain an agent that transform data and three agents that use Kalman Filter to detect respectively anomalies on values measured by the weather station and used for the ET_0 calculus, values of soil moisture, and flows measured on the center-pivot. These parameters are acquired by the Wireless Sensors Network (WSN). The verified data are then sent to Database agent (**4**).

(2) The ET_0 **calculus** agent determines the values of the potential evapotranspiration with Penman-Montheith equation from data provided by the weather station and validated by (**1**). The calculus result is then store in database by (4).

(3) The **Parameters state** virtual organization content four agents. The first analyzes the state of soil from values acquires by soil moisture sensors. The second verify via the flow measurement associated with each solenoid valve that the water dose is correctly applied by each sprinkler. The third agent evaluates the water pH. While the fourth agent controls the water conductivity that controls the input concentration. States of all parameters monitored by agents of the organization are sent to database agent (4) in order to be stored.

(4) The **Database** agent store raw data received from the virtual organization "Anomalies Detection", calculated value from the agent "ET_0 Calculus", and states of soil and flows evaluated by the virtual organization "Soil and Flow State".

(5) A **Water Requirements Calculus (WRC)** agent evaluates water requirements on basis of values of soil moisture sensors, precipitation, irrigation supply, potential evapotranspiration calculated by (2), and plant state of development.

(6) A **Water Requirements Prediction (WRP)** agent estimates the future needs of plant for the next rotation of the pivot in order to plan the volumes of water necessary for irrigation. The prediction of these volumes of water and irrigation flows are also important when treatments must be applied to the irrigated perimeter.

(7) The **Rules and Conditions** virtual organization contain three agents. The first make decisions on amount of water to apply on each segment of the pivot on basis of soil state, precipitation, previous irrigation, crop evapotranspiration, and water requirements calculated and predicated. The second make decisions when pest is detected by several "pest detection" agents (10). However, the third agent make decisions when several disease detection agents detect the same anomaly (12).

(8) The **Actions** virtual organization allow to control actuators such as valve solenoid, pesticides, fungicides, and fertilizers addition pump in the irrigation circuit, and so on.

(9) The **Faults detection** virtual organization aim to detect anomalies in the operation of the pivot. It controls by means of sensors placed in critical points of the pivot: flows, pivot speed, pressure in the main pipeline. When a fault is detected, depending on its severity, a warning is added to the logs. In addition, in case of a major fault, a message is sent to the manager by means of the Alert System.

(10) The **Pest Detection** agent recognizes the different stages of development of the pests of the crop in place. The early identification allows to quickly cure the crop and limit the impact on the harvest. The Pest detection is a specific artificial algorithm trained on the cloud, compressed in TFLite and deployed on Jetson Nano nodes to detect the presence of crop pest.

(11) The **Features extraction** virtual organization analyze images acquired from camera place on the pivot, preprocess them, and detect zone of interest, which are sent to pest detection (10) and disease detection (12) agents to predict the presence or any threat absence.

(12) The **Disease Detection** agent identifies disease of the in-place crop. The early identification of diseases allows us to cure quickly, limit the extension of the disease, and preserve yield of the crop. This agent is an artificial algorithm specifically trained on the cloud, compressed in TFLite, and deployed on Jetson Nano nodes to detect the presence of any disease that may harms the crop.

(13) The **Master** agent plays a crucial role of coordination between all other agents and virtual organizations.

The Figure 2 shows a more detailed views of agents and the agents contained in Virtual Organizations (*VO*).
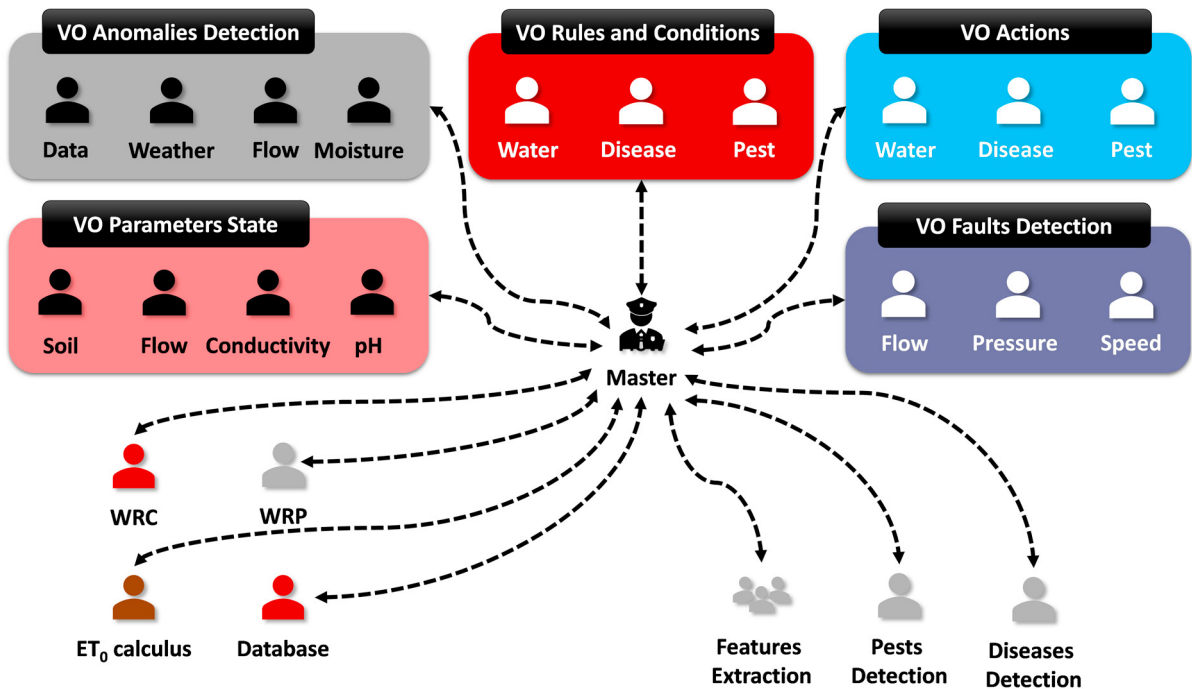

Fig. 2. Detailed View on Agents and Virtual Organizations

The cloud architecture hosts two mains components namely an Apache web server with Mapserver [26] an open source platform used to publish online interactive maps and GIS data of all pivot data. The second is the training environment of disease and pest detection.

The use of a Multi Agent System (*MAS*) coupled with docker containerization and Kubernetes orchestration allow to manage dynamically the virtual organization size. Moreover, MAS offers a great reactivity, which provides the system to adapt dynamically to deal with events such as for example to compensate dynamically a fail sprinkler or the decreasing of the effectiveness of sprinklers due to their aging.

4. Experimentation and discussion

We have experimented our architecture on a pivot installed at In Salah, Algeria with a wheat crop planted on November 25, 2019. The water requirements have been calculated with CropWat 8.0[1] which uses Penman-Monteith equation to estimate water requirements theoretically on basis of weather data. The daily estimation of water requirements has been achieved on basis of Climwat database[2]. It contains needed to calculate the potential evapotranspi-

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[1] http://www.fao.org/land-water/databases-and-software/cropwat/en/
[2] http://www.fao.org/land-water/databases-and-software/climwat-for-cropwat/en/

ration: mean daily maximum temperature [$^{\circ}C$], mean daily minimum temperature[$^{\circ}C$], mean relative humidity [%], mean wind speed. [$km.day^{-1}$], and mean solar radiation [$MJ.m^{-2}.day^{-1}$].

These values have been used as baseline to compare on one hand, with evapotranspiration of the crop based on measurement of our weather station to demonstrate; on the other hand, the performance of our position, and shows water saving obtained. More details have been given in our previous paper on the evapotranspiration calculation [4].

Table 2. Water requirements.

Month	Decade	Stage	Kc Coefficient	Theoretical ETc $mm.day^{-1}$	Real ETc $mm.day^{-1}$	Practical Etc $mm.day^{-1}$
November	1	Initial	0.30	1.04	1.02	0.88
December	2	Initial	0.30	0.90	0.90	0.75
December	3	Initial	0.30	0.77	0.87	0.74
December	4	Initial	0.30	0.78	0.82	0.71
January	5	Development	0.35	0.95	0.93	0.81
January	6	Development	0.54	1.46	1.48	1.35
January	7	Development	0.74	2.19	2.25	1.98
February	8	Mid-season	0.94	3.01	2.95	2.74
February	9	Mid-season	1.12	3.86	3.82	3.66
February	10	Mid-season	1.16	4.42	4.42	4.22
March	11	Mid-season	1.16	4.85	4.89	4.59
March	12	Mid-season	1.16	5.28	5.36	4.95
March	13	Mid-season	1.16	5.89	6.03	5,65
April	14	Mid-season	1.16	6.51	6.65	6,34
April	15	Late season	1.10	6.76	6.83	6.49
April	16	Late season	0.89	5.71	5.73	5.58
May	17	Late season	0.68	4.52	4.60	4.28
May	18	Late season	0.46	3.20	3.20	2.98
			Total:	621.0 mm	627.5mm	587.0mm

Table 4 shows water requirements obtained based on statistical data from Climwat database provided by Food and Agriculture Organization (*FAO*)[3]. The theoretical calculus gives water requirements for our wheat crop of 621.0 mm. However, the amount of water calculated with the same equation (Penman-Monteith) with data from our weather station give a real evapotranspiration of the crop evaluated to 627.5 mm. This value is similar to the theoretical evaluation which allows us to ensure that the values provided by our weather station are sufficiently accurate to be able to obtain a sufficiently precise evapotranspiration calculation. The practical evapotranspiration used for the irrigation; this one is corrected with soil moisture measurement achieved by the wireless sensors network. Our systems allow a reductions of irrigation water amount of 5% compared to the theoretical calculation based on meteorological statistics and 6% compared to the calculation on the actual meteorological data.

The performance of the plant diseases recognition have archived in our previous paper describing the Edge AI-IoT architecture with which several AI algorithms are tested on plant village database, a database of several species taken in real conditions [4] [12] and was used to validate the operation of our architecture before testing it in real conditions.

5. Conclusion and perspective

In this paper, we propose Multi Agent System (*MAS*) deployed with docker containerization and orchestrated by Kubernetes on an Edge AI-IoT architecture place in the vicinity of a set of pivots. A Wireless Sensor acquires environmental data for each pivot allowing the evaluation and the actualization of water requirements each 5 minutes. A common weather map ensures the measurements of parameters needed to calculate precisely the potential evapotranspiration which is multiplied with a pondering coefficient (*Kc*) to calculate the water requirements for the crop.

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[3] http://fao.org
[4] https://data.mendeley.com/datasets/tywbtsjrjv/1

Our proposition based on a multi agent system to better address water requirements and compensate in particular for the loss of performance of the sprinklers or the defectiveness of one of them. In addition, our system integrates plant disease and pest recognition and provides the crop to be treated using the irrigation pivot.

The proposed solution can be adapted to drip irrigation where camera images must be replaced by regular drone flies and photos captured by farmers. In our future works, we would like to evaluate our architecture on drip irrigation. Indeed, the plant disease and pest identification must be improved adding preprocessing to normalize image before the prediction to reduce the impact of photo exposure (variable light intensity in outdoor conditions). Water saving can be improved by limiting the amount of water supplied by irrigation to 70% of the field capacity, i.e. the maximum amount of water that a soil can retain under drainage normal conditions.

In our future works we plan to test the scalability of our approach on several pivot-center irrigation to demonstrate definitively the feasibility of our proposition with industrial partners.

Acknowledgments

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