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A digital model application to optimize water consumption in agriculture

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Abstract

Agriculture is a key driver of global biodiversity and economy. In the recent years, the over-exploitation of water resources, climate change and pollution have led to a global water crisis, exposing the agricultural sector to significant risks in both the short and long term. For these reasons, the development, and the optimization of the technologies to efficiently manage the water consumption are the main weapons to reduce the impact on this valuable resource. The main aim of this study is to assess the application of a digital model (DM) to agricultural operations to ensure the correct supply of water and nutrients to crops, minimizing the consumption of resources and increasing the efficiency of the water management. The simulation model of an irrigation network has been developed on Flownex, a 1D, concentrated-parameter fluid dynamics simulation software dedicated to network simulations. To model the drip irrigation system a specific characterization was carried out through fluid-dynamic simulation (ANSYS Fluent). The developed tool has emerged as an evaluable solution to apply the benefits of DT to agricultural applications. Indeed, the DM can reliably predict the performance of the system in terms of water distribution considering different operating conditions.

Keywords: Water Management; Agriculture 4.0, Digital Twin, Flownex, ANSYS Fluent

1. Introduction

The main challenge for agriculture is to combine technology and digitalization with the tradition to achieve a balance between productivity, sustainability, and nutritional food availability (Abbasi et al., 2022). In the recent years, valuable resources such as water, soil and biodiversity have been overexploited and climate change and pollution have led to a global resource crisis. As a result, the agricultural sector is exposed to significant short and long-term risks (Okkan & Kirdemir, 2018). At the same time, the population growth is accelerating and according to FAO projections agricultural activities will need to produce almost 50% more food than in 2012 (Food and Agriculture Organization of the United Nations, 2023).

In this context, the adoption of smart agricultural practices can significantly increase food availability and security, reduce resource consumption and production costs (Javaid et al., 2022). Also, considering the effects of climate change, the development and optimization of technologies for the efficient management of water consumption are the main weapons to reduce the impact on this precious resource (Ingrao et al., 2023).

Starting from the review of the main technologies reported in the scientific literature, the low prevalence of digital twins (DT) for modeling agricultural water distribution and collection network was emerged (Purcell et al., 2023). The digital twin (DT) is an accurate digital representation of a real product, process, or a complex system (Cesco et al., 2023). Currently, DT is widely used in many disciplines such as manufacturing, automotive, aerospace, construction, smart cities, and energy sector (Zayed et al., 2023). According to (Purcell & Neubauer, 2023) there are three different data integration level between digital representation and real entity. The first level, called Digital Model (DM), is only a digital representation of the physical system, the Digital Shadow (DS) is the DM able to receive data from the real system autonomously and DT is the DS that can transfer information to the physical system.

The main aim of this study is to assess the application of DM to agricultural operations, in order to ensure the correct supply of water and nutrients to crops, minimizing the consumption of resources and increasing the efficiency and sustainability of water use. The developed digital model (DM) has been tested and validated in the living labs and the future development will allow to carry out the link between the simulation model and intelligent IoT systems in the field to implement the DT of the irrigation network.

In the next section, a state of the art is reported with the aim of analyzing the technologies for optimizing water management and DT application in the agricultural sector. Section 3 presents the description of the living lab, while section 4 highlights the details of the digital model developed and the results of the testing and validation of this model.

2. State of the art

A review of the scientific literature was carried out with the aim of performing an analysis of qualitative and quantitative methods for optimizing water use in agriculture. In (Benyezza et al., 2023), external conditions of the plant have been monitored to optimize the water management, such as the assessment of the soil and environmental conditions. Alternatively, the evaluation of the intrinsic plant parameters, such as the sap ion concentration, can be used to directly monitor the crop requirements (Vurro et al., 2019).

In order to monitor agricultural operations, there are several challenges that need to be overcome, namely the huge amount of data (input and output) that needs to be collected, transferred, processed, and stored, the lack of power supply and a proper internet coverage network in the field (Codeluppi et al., 2020). In this regard, IoT technologies and a low-power wide-area network (LoRaWAN) can provide some advantages to this, as they are characterized by low power consumption (LPWAN), and they can provide long-range communication in the open field without Internet access (Peña Queralta et al., 2019). In (Angin et al., 2020), a smart agriculture framework using LoRaWAN for field devices and artificial intelligence for drone image processing has been implemented to prevent and detect plant diseases and drought stress. The proposed framework can help farmers to reduce resource consumption and production costs, improving crop yield and nutritional value of the crop.

The authors of (Preite et al., 2023) analyze the impact of the innovative strategies on reducing water consumption. They show that there are few studies that provide quantitative data to quantify the positive impact of the technologies used. In addition, the integration of different information sources, such as sensors, satellites, weather stations, etc., can be used to implement control systems and machine learning (ML) algorithms that manage the irrigation system based on the evaluation of different parameters. The integration of the control system with a machine learning algorithm led to the prediction of the drought situation considering different scenarios.

In (Pylianidis et al., 2021), a limited number of studies have been reported on the application of DT for water management optimization in the agricultural sector. Most of them, were developed from the FIWARE platform, an open-source technology for the implementing smart models in different disciplines.

This gap is an indication that the benefits of the digital twin, widely employed in other sectors, have not yet been applied in agriculture. Indeed, in agricultural sector there are several challenges that DT should overcome, such as limited investment made by the small holders and a deep interaction between non-living and living systems (Alves et al., 2023). However, DT can reduce operating costs, provide detailed information on various parameters, predict several operating conditions to implement a decision support system, perform predictive maintenance to develop an appropriate maintenance strategy, and make the system safer and more energy efficient, but often these have not yet been demonstrated in agriculture (Attaran & Celik, 2023).

As a result, considering the literature analysis, DT, the integration of different parameters, and machine learning algorithms may be the key to the development of autonomous robotic solutions that allow advanced mechanization and management of water resources based on the developed model.

3. Materials and methods

3.1. Living lab description

A living lab has been designed to develop and test the developed water management model in collaboration with *Azienda Agraria Sperimentale Stuard*, located in Parma (loc. San Pancrazio, Italy). The pilot case study focuses on a tomato crop. The tomatoes (Solanum lycopericum L. Cv. HEINZ 1301) were grown according to organic methods and were irrigated using a drip irrigation system with drippers every 30 centimeters. Organic fertilization was applied to each row of tomatoes with N, P, K; the fertilization plan was completed with the application of bio-stimulants.

The experimental tests were performed on three rows of tomatoes (referred to as experimental rows). As shown in Figure 1, for each experimental row, a different water management decision was assumed for each trial, namely the 100%, 60% and 30% of the conventional water requirement, respectively. This allows the water stress and the growing conditions of the crop to be assessed based on the water supply. For this reason, the three experimental rows were not adjacent to each other, but were separated by boundary rows to avoid any negative interaction between the different water management.

As can be seen in Figure 1, the distance between the each experimental and boundary row is 1.5 m and the length of each experimental row is 88 m. The irrigation network has been constructed using the following components:

- Pump
- Accumulator
- Pressure reducing valve
- Filters
- Flow meters
- Valves (ON/OFF)
- Soil Humidity sensors
- Pipes (1 inch diameter)
- Pipe junctions
- Pipe bends
- Drip irrigation system

Specifically, the drip irrigation system is characterized by a lightweight non-self-compensating dripline (1 inch diameter) with integrated flat drippers. The nominal flow rate of each one is 1 liter per hour.

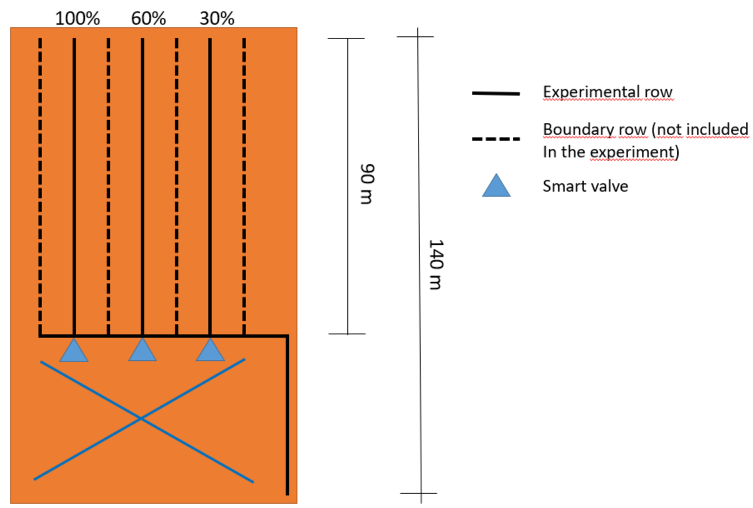

Figure 1. Layout of the designed living lab

3.2. Irrigation network modeling

As can be seen, the irrigation network has been designed using both standard components (i.e., pipes, bends, junctions) and unconventional devices (i.e., drippers of the drip irrigation system). To design the DM, all these components were digitally reproduced. For the former, the data were taken from software libraries and technical data sheets. For the latter, a specific characterization was carried out through fluid dynamic simulation.

The fluid dynamic properties of the pipes, bends, and junctions were set up using the Flownex® database. Specifically, a normal roughness for HDPE pipes (7 μm) was assumed for the pipes, while the normative ASME 16.9 was considered for the bends and junctions (ASME, 2023).

With the aim of modeling the drippers, ANSYS FLUENT was used to reproduce their characteristic curve, i.e., pressure drop vs. flow rate. As shown in Figure 2, a physical model of the drip irrigation system was designed, and the fluid dynamic simulation was performed by setting valuable boundary conditions on the physical model. Indeed, the characteristic curve has been evaluated by varying the inlet velocity of the water and fixing the atmospheric pressure at the outlet section of the dripper.

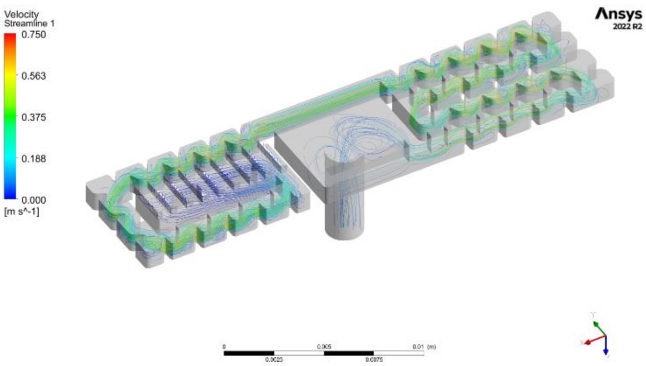

Figure 2. Fluid dynamic simulation performed in ANSYS FLUENT

As shown in Figure 3, the resulting characteristic curve was implemented into the Flownex® environment simulation to reproduce the behavior of the modeled component as a custom loss.

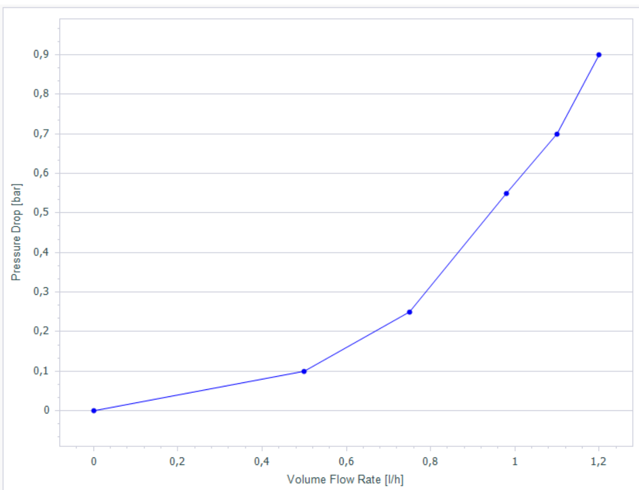

Figure 3. Evaluated dripper characteristic curve (i.e., pressure drop vs flow rate)

Finally, the boundary conditions of the model were set by evaluating the flow rate and pressure under different operating conditions. The flow rate and pressure data have been collected from the LoRaWAN meter and pressure gauge installed in the field, respectively.

3.3. Flownex simulation environment

The irrigation network model has been developed on Flownex®, a 1-D concentrated parameter fluid dynamics simulation software dedicated to thermal-fluid network simulations. Flownex® is developed within an ISO 9001 and ASME NQA1 accredited quality system and it is also an extensively Validated and Verified (V&V) simulation software (Flownex, 2023).

Thermal-fluid network analysis is based on the numerical solution of the governing equations of fluid dynamics and heat transfer. The software can solve the differential equations for mass (1), momentum (2), and energy conservation (3) to calculate the mass flow, pressure, and temperature distributions along a modeled network. For this purpose, it is essential to specify appropriate and realistic boundary and initial conditions for the modeled network (Sena & Hassan, 2023).

According to the Eulerian framework, the governing equations are:

$$\frac{Dm}{Dt} = \oint_{CS} \left(\rho \vec{V} \cdot d\vec{A} \right) + \frac{\partial}{\partial t} \int_{CV} \rho dv = 0 \tag{1}$$

$$\frac{D(m\vec{V})}{Dt} = \oint_{CS} \vec{V} \left(\rho \vec{V} \cdot d\vec{A} \right) + \frac{\partial}{\partial t} \int_{CV} \rho \vec{V} dv = \Sigma \vec{F} \tag{2}$$

$$\frac{D(me)}{Dt} = \oint_{CS} e \left(\rho \vec{V} \cdot d\vec{A} \right) + \frac{\partial}{\partial t} \int_{CV} \rho e dv = \dot{Q}_H - \dot{W} \tag{3}$$

Since in a mathematically complete system of equations the number of the equations must be equal to the number of the unknown variables, additional equations can be introduced. The unknown variables in most thermal fluid networks are flow velocity, pressure, and temperature. By solving the mathematical system for both steady-state and transient conditions, the software displays the distribution of these variables in various valuable formats. In addition, other processes, such as heat exchange or controller operation can be performed using a single environmental simulation.

In particular, the differential governing equations and the additional closure equations were solved sequentially by Flownex® using a state-of-the-art implicit pressure correction solution method (IPCM) (Vikram et al., 2023). The flowchart describing the steps of this method is shown below in Figure 4. In this way, various parameters of the process can be evaluated and adjusted by acting on the number of iterations and on the convergence criteria for the solution.

In the Flownex® environment simulation, elements, nodes, and boundary conditions can be used to create the basic building blocks to model a specific network. An element can be used to simulate a pressure drop or pressure rise component, such as a pipe or a duct and its length, an orifice, a fan, a pump, a valve, or other components. The characterization of a specific device can be combined with a secondary information, such as for example secondary pressure loss components (Zubair et al., 2021).

To define the boundary conditions of a network, a boundary condition component associated with a node can be used. For the latter, the inputs can be the pressure, temperature, quality, enthalpy, mass source and volume flow. Since the software is based on solving the equations of conservation of mass, energy, and momentum, the inputs can only be in appropriate combinations (Flownex, 2023).

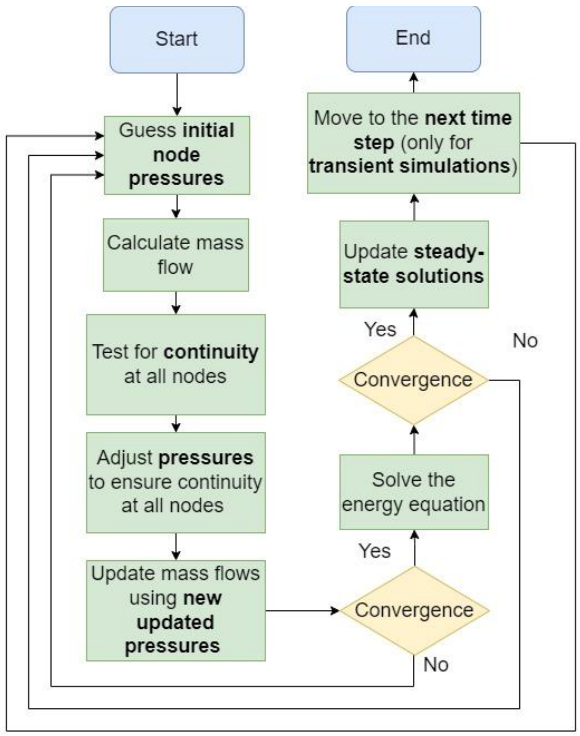

Figure 4. Implicit pressure correction solution method (IPCM) flowchart

3.4. LoRaWAN network

A LoRaWAN network has been implemented to monitor and control the irrigation system.

The network consists of the following components:

- Flowmeters to measure water flow periodically (every 10 minutes) for each experimental row.
- Soil moisture sensors capable of assessing the relative humidity, temperature, and soil conductivity (Milesight EM500-SMTC, 2023). They transmitted data every 10 minutes.
- Environmental sensor to monitor some environmental parameters, such as temperature, pressure, and Co2 concentration (Milesight EM500-CO2, 2023). At the same, the data is collected every 10 minutes.
- On/Off hydraulic valves installed in each experimental row to control the water supply (MClimate T-Valve, 2023).
- Gateway provides the connection between the above component and a cloud where the data is collected and processed (Gateway LoRaWAN Milesight UG67, 2023).
- Network Server (NS).

Specifically, the flowmeters, sensors and valve communicate with the gateway via LoRa. The gateway transmits the data to the NS over an IP-based network. At this level, the collected data is processed to test and validate the DM. In addition, future development will allow the connection between the NS and the DM to take a leap to develop a DT of the irrigation system.

4. Results and Discussion

4.1. Digital Model development

As can be seen in Figure 5, the digital reproduction of the irrigation network has been performed using the Flownex® component, the Flownex® database, the evaluated characteristic curve of the drippers, and the collected data.

The DM provides the distribution of the water along the network by setting the following boundary conditions:

- Flow rate of the header pipe
- Atmospheric pressure at the dripper outlet

4.2. Data Acquisition

The LoRaWAN devices installed in the field were used to monitor and collect the data on valuable parameters. Specifically, the flowmeters transmitted the cumulative value of the water supply every 10 minutes for each experimental row. This means that the flow rates have been calculated by dividing the transmitted values by the water supply period.

In this way, the evaluated flow rate of the header pipe was used as a boundary condition to set up the digital model. In order to carry out the research activities, each experimental row is characterized by a different water supply, reflecting the assumed water management decision.

4.3. Testing and validating of the digital model

The developed DM was tested and validated considering different operating conditions. Specifically, four field tests were carried out during the 2023 crop season. With the aim of preliminary evaluating different operating conditions, the water distribution along the network was monitored by varying the flow rate in the header pipe.

In this step, the value of the header pipe pressure, and the flow rates for each experimental row were collected and the error between the simulation estimate and the measured parameters was calculated using the following equation (4):

$$error = |1 - (Simulated\ Value)/(Collected\ Value)| \quad (4)$$

As a result, the distribution of the evaluated errors is displayed in Figure 6.

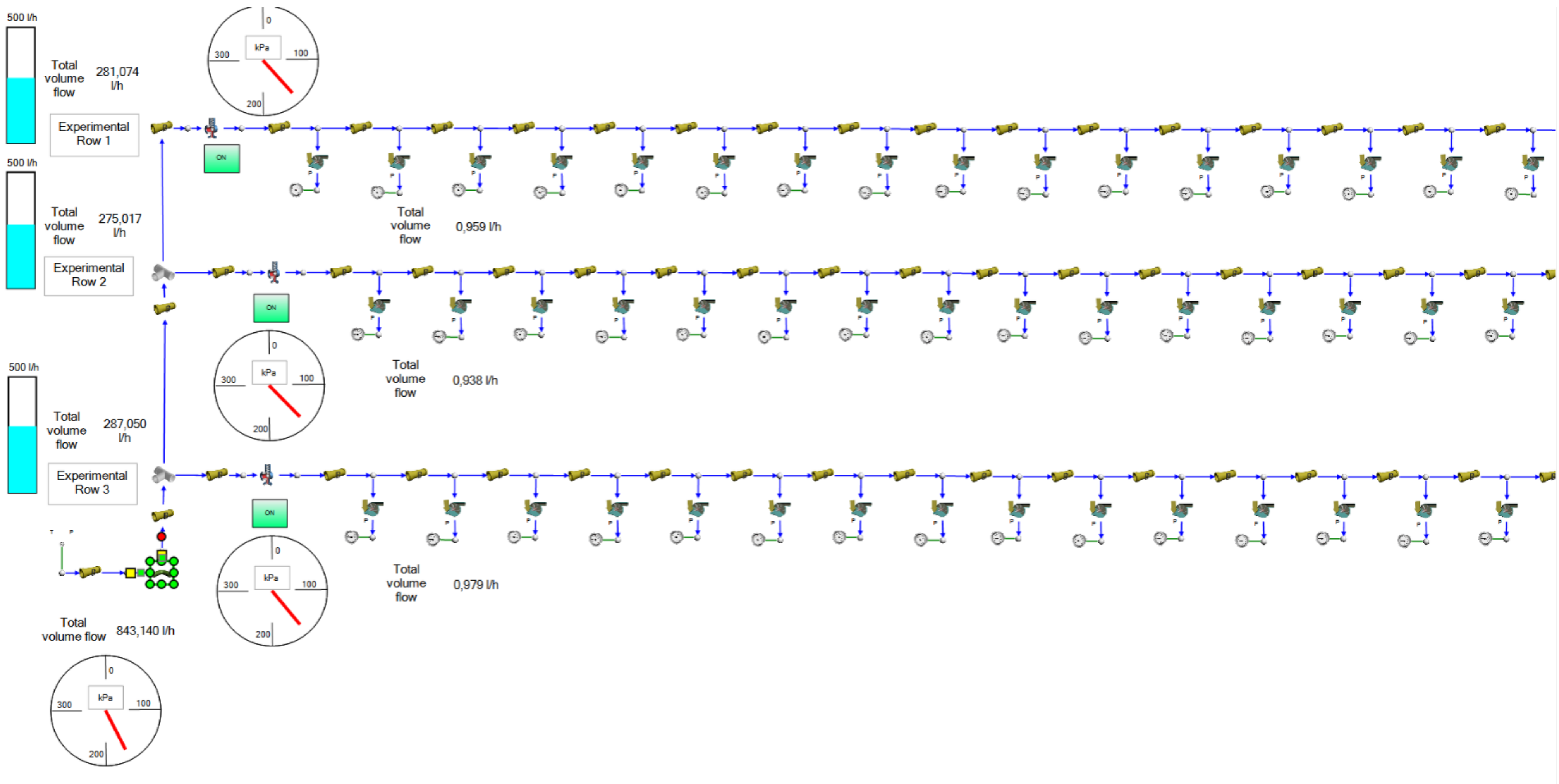

Figure 5. DM of the irrigation network

Specifically, the x-axis shows the range of the errors considered, while the y-axis reports the number of defect occurrences for each indicated range. As can be seen, most of the error percentages are between 0% and 4%. Approximately, more than 80% of the samples are characterized by an error within this range. This result indicates that the DM perform with a high degree of accuracy for the tests performed.

Once the DT is developed, the DM will have to be tested and validated in order to evaluate and compare the accuracy with which it performs.

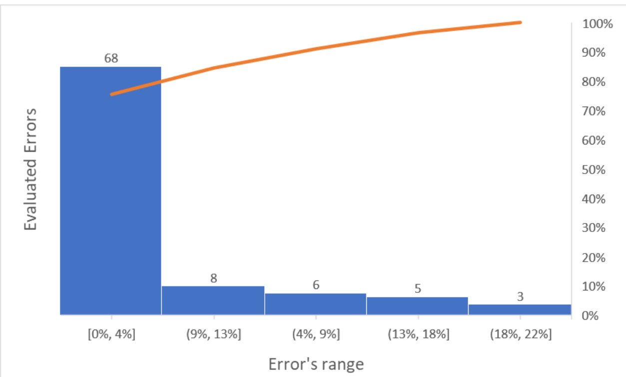

Figure 6. DM error distribution

4.4. Proposed framework for digital twin

The proposed framework provides a solution for monitoring and controlling the water supply to the crop. As shown in Figure 7, the water supply adjustments will be performed by collecting the soil relative humidity (%RH) data to meet the applied water management decision for each experimental row. Specifically, the LoRaWAN valves will be activated/deactivated by comparing the acquired soil relative humidity value with the maximum and minimum control values set by the user. The latter parameters reflect the different water management decision and are set by evaluating the texture and the water capacity of the soil.

In addition, the developed DM will be able to detect anomalous operating conditions by analyzing the fluid dynamic parameters. In this case an alarm message will be sent to the user to check and restore the performance of the network.

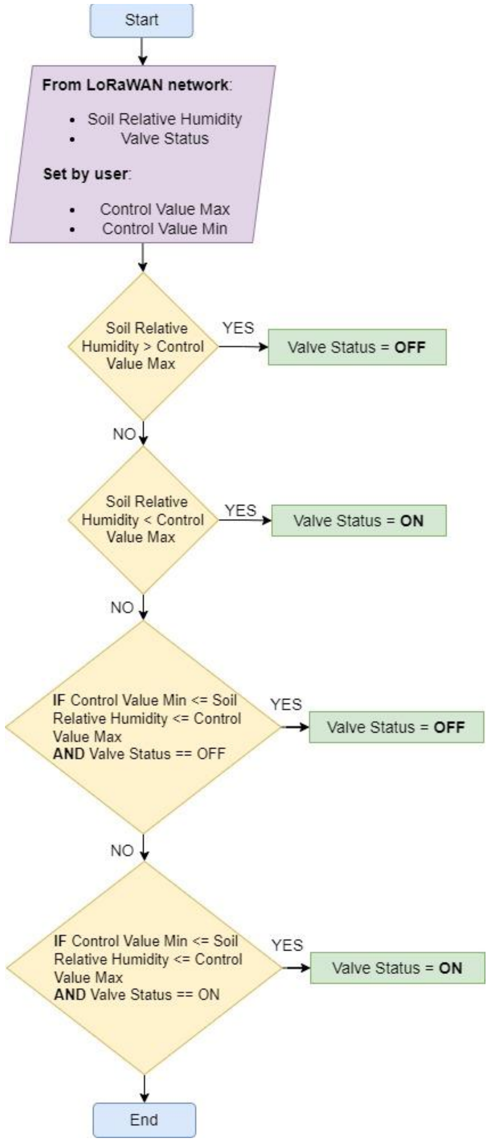

Figure 7. Framework to control water supply for each experimental row

5. Conclusions

Agricultural operations are facing with several challenges in recent years. The application of agriculture 4.0 with the interaction between IoT technologies and smart model can help the farmers to manage water efficiently. The developed DM has emerged as an evaluable solution to apply the benefits of DT to agricultural applications. Indeed, the developed DM can reliably predict the behavior of the system in terms of water consumption under different operating conditions.

Future development will allow to set up the DT by connecting the DM to the implemented LoRaWAN network. This means that the DT will be a control tool able to interface with IoT instruments in the field both in input (data acquisition from sensors) and in output (valve control).

In addition, once the DT is tested and validated, ML algorithms can be implemented to improve the performance of the system.

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