# Low-Cost Wireless Monitoring and Decision Support for Water Saving in Agriculture

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***Abstract*— A decision support system based on the combination of the wireless sensor and actuation network technology and the fuzzy logic theory is proposed to support the irrigation management in agriculture. The farmers' experience and the irrigation best practices are modeled through fuzzy rule sets, and the outputs of numerical soil and crop models are used to provide a context-aware and optimized irrigation schedule. The suggested actions are devoted to reduce the waste of water and to maximize the crop yield according to the weather conditions and the real water needs. The proposed methodology is embedded in the network gateway making the system, a truly smart and autonomous wireless decision support system. The numerical validation and the experiments performed in a vineyard in the north of Italy point out a considerable water saving respect to other state-of-the-art methods based on parameters thresholding, and an improved exploitation of the irrigated water thanks to the reduction of the percolation phenomenon without affecting the quality of the crops.**

***Index Terms*— Wireless sensor network, smart actuation, fuzzy logic, decision support system.**

## I. INTRODUCTION

THE irrigated agriculture is one of the biggest consumer of fresh water with a share up to 80–90% in the developed countries. The increased demand for water and the arising climate changes are anticipating that the water resources for agriculture will be lower in the forthcoming decades. The efficient use of the water is becoming an increasingly important issue since the competition in terms of cost reduction and high crop quality is more and more tight [1]. The accurate scheduling of the irrigation will become a major challenge for irrigated agriculture since up to 50% of the water is wasted [2].

In the last years, the adoption of sensors for water management in agriculture has received an increasing attention with reference to the irrigation optimization and control. The most common sensors provide information about the soil status, such as the soil matrix potential, or the volumetric soil water content. Other sensors are devoted to measure the water quality and properties like the salinity. These sensors have been widely used in conjunction with wired instrumentation systems locally controlled by experts. More recently, with the development of the wireless sensor network (WSN) and of the wireless sensor and actuation network (WSAN) technologies the diffusion of embedded, low-cost, and autonomous sensing and actuation devices has considerably increased [3]–[5]. Different applications exploiting the distributed sensing features of WSNs arised, including environmental monitoring [6], emergency management [7], and more in general the smart cities and communities framework [8]–[11]. Thanks to the application-oriented properties of the WSN/WSAN, such technologies are suitable platforms to implement wireless systems for agricultural needs. The so-called *precision agriculture* has benefited from WSN/WSAN for the development of decision support systems (DSS) dedicated to improve the crop yield while preserving the environmental resources [12]. The role of the farmers is becoming more and more complex due to the stringent requirements and regulations, and DSS tools are becoming attractive to support the daily management of the agricultural processes.

The goal of this work is to develop a simple and low-cost WSAN-based DSS to support the farmers in the management of the irrigation, preliminary presented by Viani [13]. In particular, the DSS aims at (*i*) reducing the waste of irrigated water and (*ii*) improving the exploitation of the water resource by the cultivated crops. Toward this end, the proposed solution integrates in a WSAN architecture an innovative methodology based on the fuzzy logic (FL) to mimic the farmers' experience and best practices for crop irrigation. The sensing and actuation features of the WSAN represent the farmer's daily observation of the crop and the consequent activation of the irrigation system, while the FL strategy simulates the imprecise human reasoning based on the theoretical and practical knowledge of the agricultural processes. Although a fully automatic irrigation system has not yet been achieved nor accepted by most of the farmers' communities, the proposed DSS is a preliminary tentative to assist the decisions of the users toward a sustainable agriculture. The FL systems are unique in the ability to represent subjective knowledge in terms of mathematical models, as introduced by Zadeh in his pioneering work [14]. Therefore, they have been widely used in applications where the decision making involves all the intermediate possibilities between *yes* and *no*, such as in automatic controls. In order to fully exploit the FL properties as applied to the irrigation problem, a set of numerical models

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taken from the state of the art have been implemented and integrated in the DSS to learn the soil and the crop behaviour according to the sensor data measured by the wireless nodes. The objective of the FL-based methodology is to understand as accurate as possible the effects of the irrigation and of the weather on the soil and on the plants in order to suggest the actions that maximize the crop yield and the water saving, as well.

The proposed system has been numerically validated for a preliminary assessment and the developed prototype has been installed in an irrigated vineyard in the north of Italy for the experimental validation of the WSAN architecture and to assess the performance of the DSS methodology. A selected set of experiments and results are presented and discussed in order to point out the main limitations and advantages of the wireless DSS.

The rest of the paper is organized as follows. Section II reviews the main solutions for irrigation management based on WSN technologies. In Sect. III the key-components of the proposed WSAN-based DSS are presented and the FL strategy is formulated. A set of selected tests, calibrations, and irrigation experiments are presented and commented in Sect. IV. Finally, the conclusions are summarized in Sect. V.

## II. Related Work

The adoption of WSN systems in agriculture has been widely explored in the past decade [15], [16]. Many researchers have focused the attention on the study and design of the wireless platform itself in order to provide reliable data acquisition and transmission for monitoring and control. Kone *et al.* in [3] proposed the tuning of IEEE 802.15.4 MAC parameters to adapt the sampling frequency of sensor nodes according to the requirements of precision farming applications. Kaiwartya *et al.* [17], investigated the quality of sensor deployment patterns for precision agriculture, which is considered one of the promising use case of sensor deployment in regular terrain non-hostile environment [18]. Recently, heterogeneous and innovative sensors have been proposed to improve the environmental monitoring in agriculture and provide more and more advanced situational awareness of the crop status. Among the applications enabled by pervasive sensing in agriculture, the management of irrigation systems is one of the most investigated to achieve water saving [4], [5]. For example, Harris *et al.* [2] proposed in a low-cost chloride sensor suitable to be coupled with a WSN-based system to measure the quality and soil salinity of irrigation water. Jaguey *et al.* presented in [19] a smartphone-based sensor to capture and process digital images of the soil and estimate optically the water content. Heterogeneous sensing technologies have been integrated in WSN architectures in different combinations to simultaneously acquire multiple physical parameters and enable sensor fusion strategies [20]. As a matter of fact, most of the effort has been spent on the *sensing* capability of WSN systems, whereas the advanced processing of the near real-time data acquired by the networked sensors as well as the control of the agricultural processes and systems have been less investigated. One of the current challenges is to go beyond the raw sensor data measurement and to turn the sensors into truly *smart sensors* [21]. In this sense, the integration of decision support strategies in wireless sensor systems is attracting a lot of interest. The paradigm of *sensing as a service* has been recently proposed by Sheng *et al.* [22], pointing out the need to add value to the sensor data and enable advanced services. Dutta *et al.* [23], focused on the need to capture and integrate knowledge from the sensing sources through an ontology-based representation of information using linked data, unsupervised pattern recognition, and semantic ontology. This solution is devoted to address the ultimate challenge of DSSs to overcome uncertainty associated with the data quality. The integration of DSSs on top of WSN-based systems is still an open research issue. The demand for intelligent agricultural systems is becoming evident, and the timely analysis of vast amounts of sensor data is of paramount importance to increase the sustainability of agriculture [24]. As an example, a preliminary validation of a DSS based on fuzzy logic for the agrochemical dosage management and reduction has been presented in [12].

The conventional role of current WSN systems is often limited to the data acquisition and transmission, while the complex data analytics are carried out remotely. However, the increasing computational capabilities of wireless embedded technologies are creating the exciting opportunity to close the gap between sensing and processing, making WSNs themselves able to execute analytics and directly provide suggestions to the end-users rather than raw sensor readings.

## III. Wireless Decision Support System

The proposed system has been designed in order to support the end-user answering to the following main questions:

- *Does the crop need irrigation water?* The binary answer yes/no is inferred from the real-time monitoring of the crop status and is used to trigger the successive steps of the decision;
- *how much water is required?* The optimal volume of water is estimated according to the specific properties of the soil and to the crop typology;
- *how to irrigate the crop?* Besides the water quantity, the proper computation of the temporal and spatial distribution of the estimated water volume throughout the monitored field is fundamental to ensure the maximum absorption of the water and to reduce the percolation waste.

The answers to the above questions have been provided to the farmers through the innovative combination of the three main logical components described in the following sub-sections: (*i*) a low-cost wireless architecture for distributed sensing and actuation [Sect. III-A], (*ii*) an inference decision engine based on the fuzzy theory mimicking the farmers' experience and (*iii*) a set of numerical models of the soil and of the crop to estimate the status and the growth of the plants [Sect. III-B].

### A. Wireless Architecture for Sensing and Control

Let us consider a farming area $\Phi$, where a set of wireless sensing nodes are located in positions $\underline{r}^{(k)} \triangleq \left(x^{(k)}, y^{(k)}\right) \in \Phi$, $k = 1, \ldots, K$. The goal of each wireless node is to sample

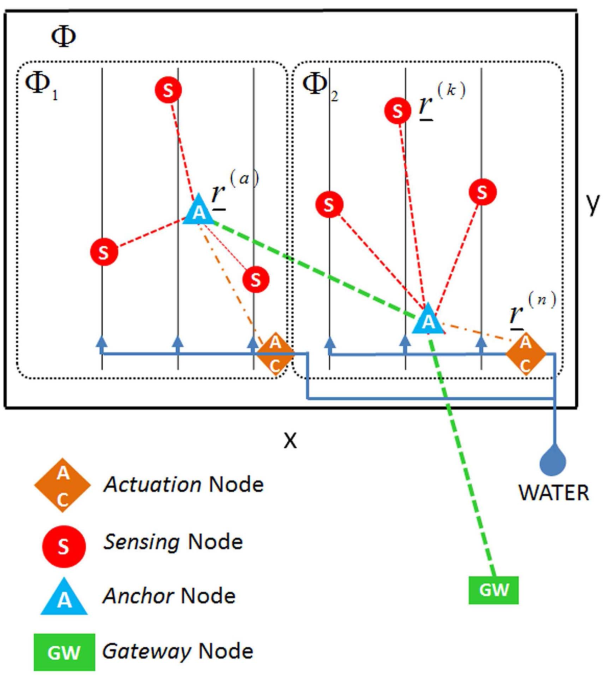


Fig. 1. WSAN architecture based on a hybrid star-mesh topology.

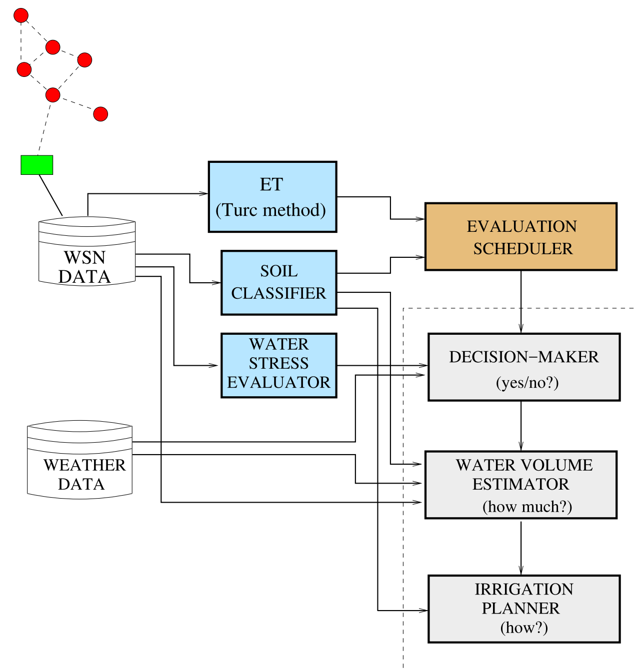


Fig. 2. Block-scheme of the proposed DSS.

the spatial distribution of heterogeneous environmental quantities, including air temperature $\tau_A\left(\underline{r},t\right)\big|_{\underline{r}=\underline{r}^{(k)}}$, air humidity $\mathcal{H}_A\left(\underline{r},t\right)\big|_{\underline{r}=\underline{r}^{(k)}}$, soil temperature $\tau_S\left(\underline{r},t\right)\big|_{\underline{r}=\underline{r}^{(k)}}$, and soil water potential $\mathcal{H}_S\left(\underline{r},t\right)\big|_{\underline{r}=\underline{r}^{(k)}}$, $k=1,\ldots,K$, where $t$ is the measurement time instant. A set of wireless actuation nodes are installed in positions $\underline{r}^{(n)}\in\Phi$, $n=1,\ldots,N$, close to the electric valves devoted to control the operation of the irrigation system. The $n$-th actuation node is designed to set the status $\eta^{(n)}\in\{0,1\}$ of the interconnected irrigation valve, where $\eta^{(n)}=0$ and $\eta^{(n)}=1$ are the *close* and the *open* valve status, respectively. In order to guarantee a robust wireless connectivity among the sensing nodes and the actuation nodes, an additional set of anchor nodes installed in positions $\underline{r}^{(a)}\in\Phi$, $a=1,\ldots,A$, is aimed at routing the sensing data and the actuation commands by means of a multihop strategy. The wireless network of $K+N+A$ nodes is managed by a dedicated gateway node, which integrates a rain gauge sensor for the measurement of the rain level $\mathcal{L}\left(\underline{r},t\right)\big|_{\underline{r}=\underline{r}_g}$ and hosts the decision support algorithm. The WSAN-based architecture based on the hybrid mesh-star topology is schematically shown in Fig. 1.

### *B. Decision Support Strategy*

The proposed decision support strategy is organized in multiple steps in order to estimate *when, if*, *how much*, and *how* irrigate the crop field according to the monitored data and the weather conditions. The block-scheme of the DSS is reported in Fig. 2 and the input-output of the main building blocks are described in the following sections.

*1) Evaluation Scheduler:* The first step of the approach is aimed at evaluating the proper timing for the computation of the DSS algorithm. More in detail, the goal of this step is to trigger the DSS evaluation when the water content of the soil $\delta(t)$ has reached a predefined intervention threshold $\delta^{th}$.

The estimation of the soil water content is a complex task since the properties of the soil are highly variable in space and a large set of experiments are required to properly characterize the soil response to rain and/or irrigation. In this sense, a finite set of predefined soils already characterized in the state of the art [25] have been considered as a-priori information of a soil classifier $\Lambda$ based on the maximum likelihood estimation (MLE) technique:

$$C=\Lambda\left\{\nu\left[\overline{\mathcal{H}}_S(t),\,\mathcal{L}\left(\underline{r}_g,t\right)\right]\right\} \tag{1}$$

where $C\in[C_u;\,u=1,\ldots,U]$ is the soil label [the soil typologies given by the United States Department of Agriculture (USDA) [26] shown in Fig. 3 have been assumed], and $\nu[\cdot]$ is the diffusion rate of the water in the soil expressed as a function of the average soil water potential $\overline{\mathcal{H}}_S(t)=\frac{1}{K}\sum_{k=1}^{K}\mathcal{H}_S\left(\underline{r}^{(k)},t\right)$ and the rain level $\mathcal{L}\left(\underline{r}_g,t\right)$ [26]. Once the soil typology is classified by the MLE starting from the available measurement, the water content $\delta(t)$ is inferred applying the known response of the selected soil $C$ as follows:

$$\delta(t)=\beta\left(C,\overline{\mathcal{H}}_S(t)\right)\big|_{C=C_u} \tag{2}$$

$\beta(\cdot)$ being the empirical relation between the soil potential and the water content defined by the *Van Genuchten* model formulated in [25].

The time interval between two DSS executions is estimated as

$$\Delta t(t)=\frac{\left(\delta(t)^{max}-\delta^{th}\right)}{\varepsilon(t)} \tag{3}$$

where $\varepsilon(t)$ is the evapotranspiration (ET) computed using the widely adopted *Turc* method defined in [27], which estimates

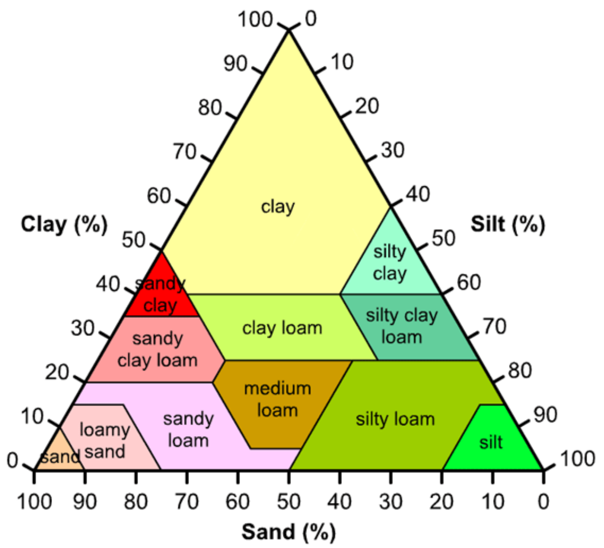


Fig. 3. USDA soil classification used to estimate the soil water quantity.

the soil water loss processing the air temperature $\tau_A\left(\underline{r}, t\right)$, the air humidity $\mathcal{H}_A\left(\underline{r}, t\right)$, and the solar radiation (the solar radiation is not measured by the proposed WSN-based system, but it is easily available from local weather services). Summarizing, $\Delta t\,(t)$ represents the time required by the soil water content to reach a predefined value $\delta^{th}$ starting from the maximum achievable content $\delta\,(t)^{max}$ because of the evapotranspiration phenomenon. This rough estimation of the soil and plant status based on the soil properties has been adopted as triggering solution because the estimated time $\Delta t\,(t)$ is not affected by the transient of the humidity caused by the last irrigation.

*2) Irrigation Decision-Maker:* The second step of the proposed strategy is executed when the time interval $\Delta t\,(t)$ computed at the time instant $t$ expires, and it is devoted to suggest the binary decision to irrigate or not to irrigate. Such a decision represents the core of the DSS, where the farmers' experience is fundamental to properly reproduce the best practices of the irrigation process. Toward this end, the ability of the FL to represent the human imprecise reasoning in problem solving has been exploited. A FL-based system is pictorially described through the block-scheme in Fig. 4($a$). The mapping of the input data to the desired output is performed in three main steps: the fuzzification, the fuzzy inference, and the defuzzification. The fuzzy rules database is the set of "*if-then*" statements, which contain the application-dependent and subjective knowledge of the farmers.

The inputs to the fuzzy engine are the soil potential $\mathcal{H}_S\left(\underline{r}, t\right)\big|_{\underline{r}=\underline{r}^{(k)}}$, $k = 1, \ldots, K$, the rain level $\mathcal{L}\left(\underline{r}, t\right)\big|_{\underline{r}=\underline{r}_g}$, and the root stock resistance $R$, which is a property of the cultivated plant and describes the robustness to the water scarcity [28]. The decision making phase is organized in two FL steps as shown in Fig. 4($b$). The first one implements a fuzzy estimator of the water stress level $W\left(\underline{r}, t\right)$ starting from the soil moisture and the root stock resistance (i.e., the block *water stress evaluator* in Fig. 2). It has to be noticed that the measurement of the water stress is a complex procedure

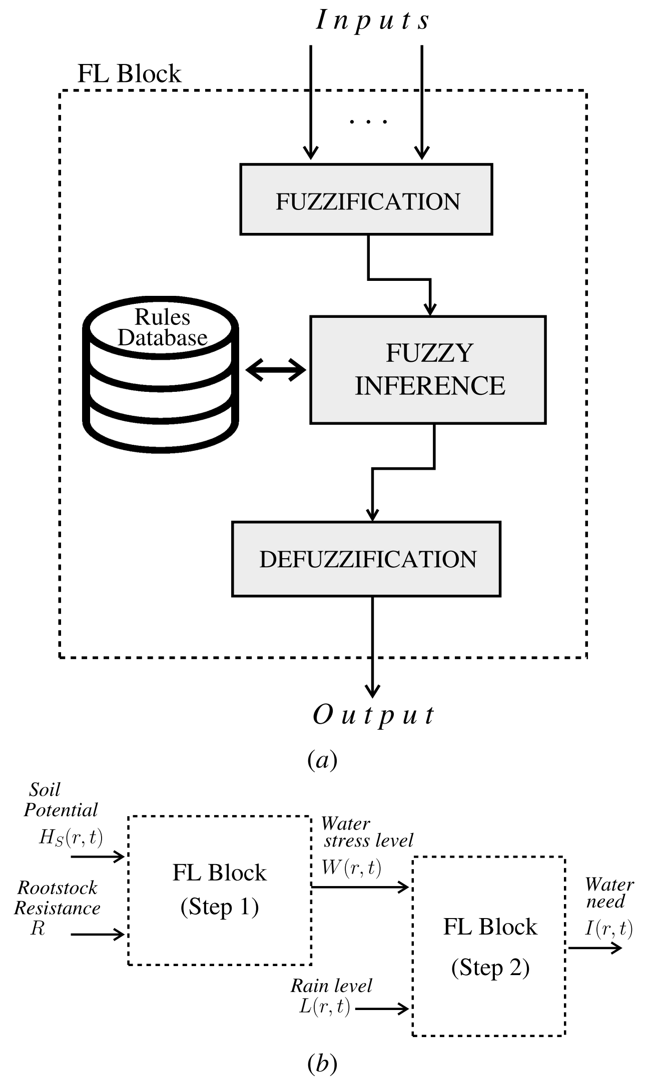


Fig. 4. Block-scheme of a FL system ($a$), and two-step FL approach for decision making ($b$).

requiring specific instruments and techniques [29], and the adoption of the fuzzy approach is aimed at managing this complexity through the rules database. The second FL step takes in input the estimated water stress level and the rain level in order to provide the water need indicator $I\left(\underline{r}, t\right) \in [0 \div 1]$. This output answers to the first main question *"does the crop need irrigation water?"* through the evaluation of the binary condition

$$I\left(\underline{r}, t\right) = \begin{cases} 1 \rightarrow (YES), & if\ \ I\left(\underline{r}, t\right) > I^{th} \\ 0 \rightarrow (NO), & otherwise \end{cases} \qquad (4)$$

where $I^{th}$ is a user-defined threshold to control the sensitivity of the decision making. More in detail, the FL method adopted in the two-step diagram reported in Fig. 4($b$) is formulated as follows:

- Fuzzification of inputs. A Gaussian membership function $g\,(\cdot)$ is applied to the input parameters by the fuzzifiers $\Omega_1\{\cdot\}$ and $\Omega_2\{\cdot\}$ to determine the membership levels of the inputs to the *antecedents* of the fuzzy rules sets $\Gamma_j^{(1)}$ and $\Gamma_j^{(2)}$, $j = 1, \ldots, J$.

- Activation of rules. After the fuzzification process, the rules are activated according to the degree of similarity between $g(\cdot)$ and the *antecedents* of $\Gamma_j^{(1)} \in \Gamma^{(1)}$ and $\Gamma_j^{(2)} \in \Gamma^{(2)}$. The activation is computed evaluating the intersections $g\left(\mathcal{H}_S\left(\underline{r}^{(k)}, t\right)\right) \cap \Gamma_j^{(1)}\left(\mathcal{H}_S\left(\underline{r}^{(k)}, t\right)\right)$, $g(R) \cap \Gamma_j^{(1)}(R)$, and $g\left(W\left(\underline{r}^{(k)}, t\right)\right) \cap \Gamma_j^{(2)}\left(W\left(\underline{r}^{(k)}, t\right)\right)$, $g\left(\mathcal{L}\left(\underline{r}_g, t\right)\right) \cap \Gamma_j^{(2)}\left(\mathcal{L}\left(\underline{r}_g, t\right)\right)$.
- Rules implication. The values of the activated rules determine the degree of truth of the *consequences* of $\Gamma_j^{(1)}$ and $\Gamma_j^{(2)}$, which are clipped off at the height of the corresponding *antecedents*.
- Output defuzzification. The defuzzifier converts the rules implication in a fuzzy output computed as the centroid of the area obtained by the super-position of the activated *consequences*.

The final output $I\left(\underline{r}, t\right)$ is a single-valued indicator taking into account all the uncertainties of the measured data and the farmers' knowledge expressed in terms of the linguistic variables (e.g., *low*, *medium*, *high*) of the fuzzy sets [31]–[33]. The FL-based modeling of the farmers' experience has been investigated by Viani *et al.* in [12] and Viani [13], but the two-step approach for the successive estimation of the water stress level and the water need indicator by means of two separate fuzzy rule sets has been never presented in the state of the art, from the best of the authors' knowledge.

*3) Water Volume Estimation:* Once the decision-maker has suggested to irrigate, this step is aimed at computing the water volume

$$V(t) = \frac{1}{K}\sum_{k=1}^{K} V\left(\underline{r}^{(k)}, t\right) = \frac{1}{K}\sum_{k=1}^{K}\left[\delta^{max}\left(\underline{r}^{(k)}, t\right) - \delta\left(\underline{r}^{(k)}, t\right)\right] - \mathcal{L}\left(\underline{r}_g, t\right) \quad (5)$$

required by the crop to reach the optimal water balance defined in [29]. Such a volume is obtained simply subtracting the expected rain quantity and the actual water content $\delta(t)$ to the desired soil water content at the field capacity $\delta(t)^{max}$. The water volume $V(t)\left[\frac{l}{m^3}\right]$ to be irrigated is expressed as the average value of the estimates computed in the sensing positions $\underline{r}^{(k)}$, $k = 1, \ldots, K$.

*4) Irrigation Planner:* The last step of the DSS strategy aims at estimating the best irrigation modality suggesting the spatial and the temporal distribution of the computed water quantity throughout the field. Toward this end, the information about the irrigation system are taken in consideration in order to properly control the status $\eta^{(n)} \in \{0, 1\}$, $n = 1, \ldots, N$, of the actuators. As an example, the characteristics of the irrigation sprinklers (e.g., number, position, and flow-rate) controlled by each actuator are used to estimate the on-off schedule of each valve. Let us define $\Phi_n \in \Phi$, $n = 1, \ldots, N$, the sub-domains of the farming area irrigated by the actuators located in $\underline{r}^{(n)} \in \Phi_n$, $n = 1, \ldots, N$ (as shown in Fig. 1 and Fig. 6). The sensing nodes are distributed in the sub-domains such that $K = \sum_{n=1}^{N} K_n$, where $K_n$, $n = 1, \ldots, N$, are the subset of nodes located in $\underline{r}^{(k)} \in \Phi_n$, $k = 1, \ldots, K$, $n = 1, \ldots, N$. The irrigation time computed for each actuator is

$$\pi^{(n)}(t) = \frac{1}{K_n}\sum_{k=1}^{K_n} \pi^{(k)}\left(\underline{r}^{(k)}, t\right)\Big|_{\underline{r}^{(k)} \in \Phi_n}, \quad n = 1, \ldots, N \quad (6)$$

where $\pi^{(k)}$ is the irrigation time computed in each sensing position according to the following rule:

$$\pi^{(k)}\left(\underline{r}^{(k)}, t\right) = \frac{V\left(\underline{r}^{(k)}, t\right)}{\phi^{(spr)}\left(\underline{r}^{(k)}\right)} = \frac{\pi^{(opt)}(t) \times \phi^{(opt)}\left(\underline{r}^{(k)}, t\right)}{\phi^{(spr)}\left(\underline{r}^{(k)}\right)} \quad (7)$$

$V\left(\underline{r}^{(k)}, t\right) = \pi^{(opt)}(t) \times \phi^{(opt)}\left(\underline{r}^{(k)}, t\right)$ being the water volume expressed in terms of the optimal irrigation time $\pi^{(opt)}$ setting the optimal water flow-rate[1] $\phi^{(opt)}$, and $\phi^{(spr)}\left(\underline{r}^{(k)}\right)$ the water flow of the adopted irrigation sprinklers.

Summarizing, the irrigation times $\pi^{(n)}(t)$, $n = 1, \ldots, N$, computed for all the actuators represent the optimal irrigation schedule computed every $\Delta t$ as defined in (3) and suggested to the farmers in order to irrigate the optimal water volume where required and taking in consideration the constraints given by the existing irrigation system.

## IV. Numerical and Experimental Validation

The effectiveness and the potentialities of the proposed system have been numerically verified as well as experimentally assessed in a real vineyard located in Trentino, in the north of Italy.

Concerning the numerical validation, the analytical model of the soil formulated in [30] has been implemented in order to model the soil water content balance and simulate the reaction of the soil to the proposed irrigation schemes. The main physical phenomena of water precipitation, infiltration, evapotranspiration, and percolation have been considered. The inputs of the soil simulator are the temperature $\tau_A\left(\underline{r}, t\right)$ and the rain level $\mathcal{L}\left(\underline{r}, t\right)$, whereas the main output is the soil potential $\mathcal{H}_S\left(\underline{r}, t\right)$. Such a simulator has been adopted to preliminary compare the performance of the proposed FL-based solution with two state of the art methods, namely the *threshold-based* (T-based) approach proposed in [1], and the *multi-threshold-based* (MT-based) method presented in [5]. The T-based irrigation strategy is based on the continuous monitoring of the soil water potential during the irrigation in order to control the actuation according to the simple following rule

$$\eta^{(n)} = \begin{cases} 1 & if\ \overline{\mathcal{H}}_S^{(n)}(t) < \mathcal{H}_S^{th} \\ 0 & otherwise \end{cases}; \quad n = 1, \ldots, N \quad (8)$$

where $\mathcal{H}_S^{th}$ is the soil potential threshold defined by the user as a target value, and $\overline{\mathcal{H}}_S^{(n)}(t) = \frac{1}{K}\sum_{k=1}^{K} \mathcal{H}_S^{(n)}\left(\underline{r}^{(k)}, t\right)\Big|_{\underline{r}^{(k)} \in \Phi_n}$ is the average soil water potential measured by the nodes located in $\underline{r}^{(k)} \in \Phi_n$, $k = 1, \ldots, K$, $n = 1, \ldots, N$. As a matter of fact, this kind of strategy is widely used because of its low complexity, but any a-priori consideration about the water need or the soil properties are considered in the actuation.

[1]The optimal water flow-rate $\phi^{(opt)}$ is calculated as a function of the soil diffusion rate $\nu[\cdot]$.

The MT-based approach selected for the sake of comparison is based on the thresholding of two parameters, the soil temperature $\tau_S^{(n)}(t)$ and the soil potential $\overline{\mathcal{H}}_S^{(n)}(t)$. The goal of the strategy is to determine the proper time instant to activate the irrigation system, while the duration of the irrigation is successively regulated according to the indications of the farmers on the water volume. Accordingly, the actuation starts when $\overline{\mathcal{H}}_S^{(n)}(t) < \mathcal{H}_S^{th}$ and $\tau_S^{(n)}(t) > \tau_S^{th}$.

Two indicators have been defined to quantify the performance of the methods from both the quantitative and the qualitative viewpoint. The quantitative performance indicator is

$$\omega(t) = 100 \times \frac{\widetilde{V}(t) - V(t)}{\widetilde{V}(t)} \tag{9}$$

where $\widetilde{V}(t)$ is the reference water volume used to compute the percentage of the quantitative improvement in terms of water saving when the volume $V(t)$ is evaluated by the considered strategy.

The second indicator $\zeta(t)$ used to analyze the qualitative improvement has been defined as follows:

$$\zeta(t) = \begin{cases} low & if\ W(\underline{r}, t) < 30\% \\ medium & if\ 30\% \leq W(\underline{r}, t) \leq 70\% \\ high & if\ W(\underline{r}, t) > 70\% \end{cases} \tag{10}$$

taking in consideration the guidelines on the water stress level given in [29] and from the visual inspection of the plants performed periodically by the expert farmers, who evaluate the stress of the plants looking at the leaf volume and color, and the status of the branches.

The numerical validation has been performed simulating one irrigation event applying the FL-based, T-based, and MT-based methods. The threshold of the T-based method has been set to $\mathcal{H}_S^{th} = -40$ $[cbar]$, while the thresholds of the MT-based approach to $\mathcal{H}_S^{th} = -85$ $[cbar]$ and $\tau_S^{th} = 15$ $[°C]$. The proposed FL-based method has been configured to obtain the desired water potential $\mathcal{H}_S(\underline{r}, t) = -15$ $[cbar]$, which is slightly lower than the field capacity and represents a good condition in terms of soil moisture. The obtained results are reported in Fig. 5 to compare the computed irrigation schedules and the arising soil potentials. The irrigation schedules started at $t = 1:50$ PM and different durations have been computed according to the methods' key principles. As it can be noticed, the transitions of the soil water potentials point out that the desired potential has been correctly reached by the FL-based strategy after $\pi = 2.3$ $[h]$ of irrigation and a total water volume $V(t) = 3.03$ $[l]$ (with a flow rate $\phi^{(opt)} = 1.32$ $[l/h]$). An irrigation time $\pi = 2.7$ $[h]$ (water volume $V(t) = 5.4$ $[l]$ and flow rate $\phi^{(opt)} = 2.0$ $[l/h]$) has been computed by the T-based method, whereas the MT-based solution an higher value $\pi = 3.75$ $[h]$ (water volume $V(t) = 7.5$ $[l]$ and flow rate $\phi^{(opt)} = 2.0$ $[l/h]$). Accordingly, assuming the water volume computed by the MT-based method as the worst reference $\widetilde{V}(t)$, the quantitative indicator points out a water saving of $\omega^{MT-T}(t) = 28$ $[\%]$ and $\omega^{MT-FL}(t) = 59.6$ $[\%]$ obtained by the T-based and FL-based methods, respectively. The T-based and MT-based method exceeded the field capacity ($\mathcal{H}_S(\underline{r}, t) > -10$ $[cbar]$) leading to waste of water for percolation. Moreover, assuming the T-based method as the reference for the comparison, the FL-based solution has reached a water saving $\omega^{T-FL}(t) = 43.8$ $[\%]$.

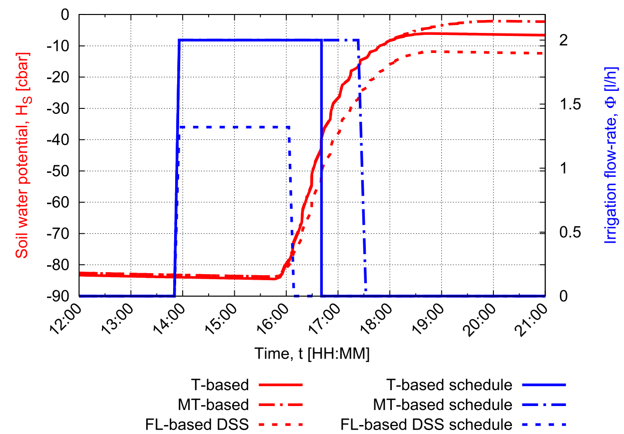


Fig. 5. Comparison of the simulated soil response in presence of different irrigation strategies computed by the proposed FL-based, and the state of the art T-based and MT-based methods.

The experimental validation has been performed in a farming area $\Phi$ of size $5 \times 10^2$ $[m^2]$, where $K = 6$ sensing nodes, $N = 2$ actuators, and $A = 2$ anchors have been deployed in known and fixed positions. The sensing nodes have been distributed in the field close to the plants, while the actuators have been installed in proximity of the existing electric valves of the irrigation system to control their status. The farming area $\Phi$ has been partitioned in $N = 2$ sub-domains $\Phi_n$, $n = 1, \ldots, N$, each one controlled by a wireless actuator as shown in Fig. 6. The two sub-domains have been irrigated in different ways for comparison purposes. The first one ($\Phi_1$) following the suggestions of the proposed FL-based DSS, while $\Phi_2$ applying the T-based strategy, which provided a higher water saving than the MT-based one.

The wireless devices have been developed using low-cost off-the-shelf components in order to reduce as much as possible the hardware complexity. The working frequency of the adopted wireless transceivers compliant to the IEEE 802.15.4 standard has been set to $f = 2.4$ $[GHz]$. The maximum transmitting power has been limited to $P_{TX} = 0$ $[dBm]$ in order to control the power consumption. The power unit of the sensing and actuation nodes has been designed in order to guarantee a system lifetime of at least 1 year. Concerning the anchor nodes, a solar panel has been integrated [Fig. 7(b)] to manage the higher power consumption due to the frequent transmissions of the multi-hop communications. The sensing nodes integrate the *Sensirion SHT11* sensor for the measurement of the air temperature and humidity, the *DS18B20* probe for the soil temperature acquisition, and the *Watermark 200SS* probe[2] to measure the soil moisture [34]. The soil temperature and the soil moisture have been measured at a fixed depth comparable to the maximum depth of the grapevine roots. The developed prototypes of the sensing, actuator, and anchor nodes installed in the test site are shown in Fig. 7.

[2]The Watermark is a solid-state electrical resistance sensing device measuring the soil water tension.

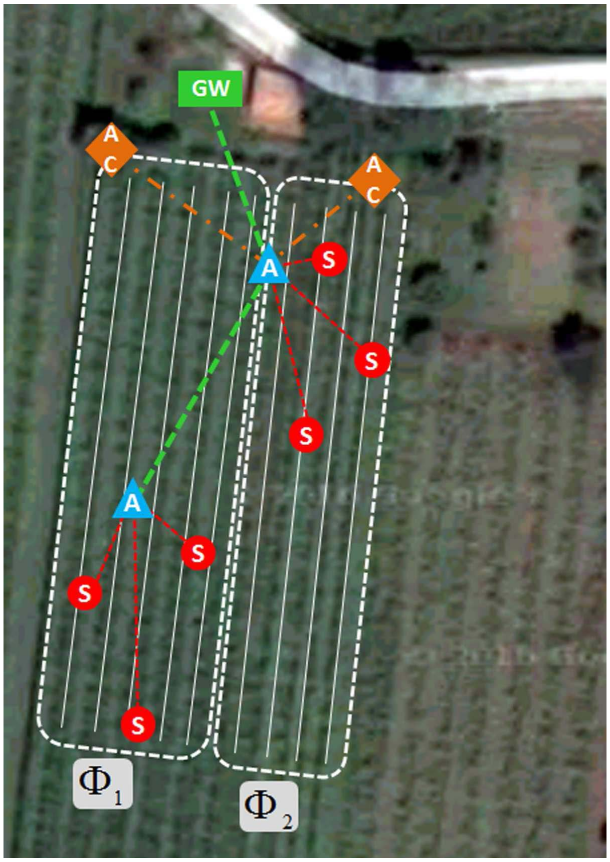


Fig. 6. Wireless architecture deployed in the test-field for experimental validation.

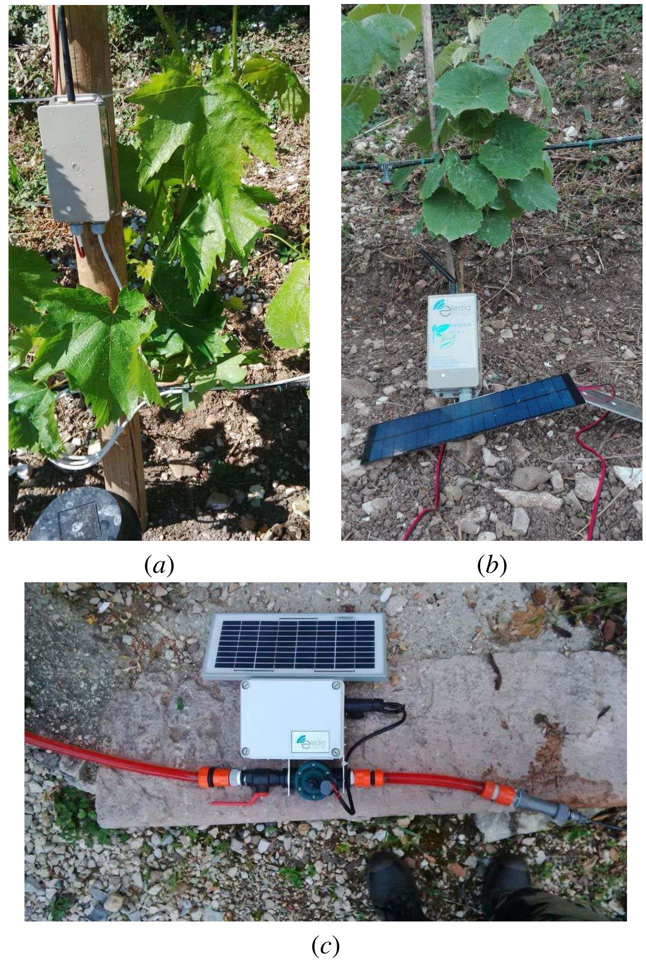


Fig. 7. Prototypes of the wireless *sensing* node (*a*), the wireless *anchor* node (*b*), and the wireless *actuation* node (*c*) installed in the vineyard.

The experiments described in Sect. IV-A are devoted to calibrate the FL-based DSS strategy, while in Sect. IV-B the evaluation scheduler as well as the soil classifier have been validated. The results of an actuation example are presented in Sect. IV-C to point out the advantages of the proposed system in terms of water saving (quantitative improvement) and water stress (qualitative improvement) compared to the T-based technique.

### A. Fuzzy Logic Calibration

The calibration of the FL system schematically represented in Fig. 4(*b*) involves several choices. As a matter of fact, the two FL steps require the configuration of the fuzzification typology (e.g., singletone or non-singletone), of the membership functions, of the rules activation and implication phases (e.g., minimum inference, or product inference), and of the defuzzifier (e.g., centroid, maximum value, mean-of-maxima, etc.). The proposed solution has been calibrated following the criterion of the *computational simplicity* in order to focus the attention on the engineering application of the FL rather than on the FL itself. Therefore, simple triangular and trapezoidal membership functions have been selected to represent the linguistic variables (such as *low*, *medium*, *high*) in terms of fuzzy sets. A simple minimum inference has been adopted in the implication phase, and the centroid computation has been used as defuzzification method.

Nevertheless, besides the aforementioned simplifications, a careful tuning of the fuzzy rules has been performed with an empirical comparison between the estimated FL outputs (i.e., the water stress level $W\left(\underline{r}, t\right)$ and the water need indicator $I\left(\underline{r}, t\right)$) and the opinions of the farmers involved in the experiments. Starting from such a measure of effectiveness and from the known reference configurations of rule sets reported in the literature [35], the calibrated FL antecedents and consequences pictorially represented in Fig. 8 have been deduced.

### B. Validation of the Evaluation Scheduler

The first step of the proposed DSS has been validated processing a one-year period of the measurement campaign. The goal of this experiment is to verify the proper computation of the time interval $\Delta t\,(t)$ between two consecutive evaluations of the DSS. Figure 9 shows the scheduling of the DSS computations during the whole considered period. As it can be noticed, a strict relation with the evapotranspiration $\varepsilon$ computed by the *Turc* method exists, pointing out a decrease of $\Delta t\,(t)$ when $\varepsilon\,(t)$ increases, as expected. A number of 71 executions of the DSS has been totalized during the one-year period, and 87 [%] of such executions effectively

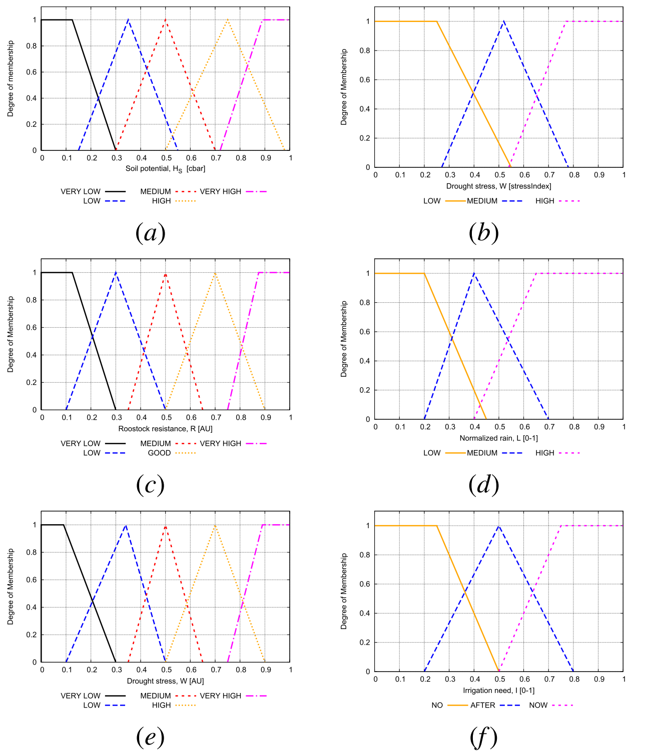


Fig. 8. Rules set of the first (left) and second (right) FL steps. Antecedents of the first inputs $(a)(b)$, of the second input $(c)(d)$, and consequences $(e)(f)$.

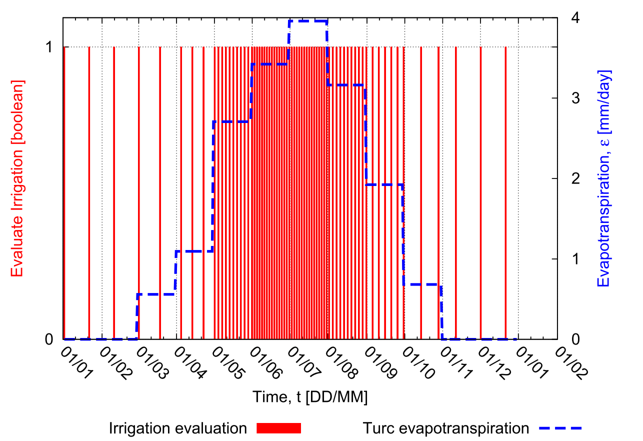


Fig. 9. Scheduling of the DSS during one-year period compared to the computed evapotranspiration.

triggered an irrigation (the remaining 13 [%] of the DSS executions returned *"do not irrigate"* due to unexpected rainfalls).

The results provided by the scheduler have been obtained assuming the soil classified as "sandy loam". The soil typology has been estimated by the MLE classifier $\Lambda$ taking in input the water diffusion rate $\nu = 70.6$ $[mm/h]$ (computed from the data measured during the selected one-year period), and starting from a set of $C_u$, $u = 1, \ldots, U$, $U = 4$ known soils (i.e., clay, clay loam, silty loam, loamy sand) taken from the USDA classification shown in Fig. 3. The result of the classification has been empirically verified by the farmers, who confirmed that "sandy loam" is representative of the actual field soil, rich in pebbles and sand and with few organic material.

### *C. Actuation Example - FL vs Standard Threshold*

The decision-making phase, the water volume estimation, and the irrigation planning have been validated in the experimental test field by applying the irrigation actions suggested by the proposed DSS. Two independent irrigations have been triggered in $\Phi_1$ and in $\Phi_2$ (setting $\eta^{(1)}$ and $\eta^{(2)}$ with the FL-based and the T-based strategies, respectively) starting in the same time instant and with the same initial conditions of soil water content. Figure 10 shows the temporal variation of the water potential $\mathcal{H}_S^{(1)}\left(\underline{r}^{(1)}, t\right)$ ($\underline{r}^{(1)} \in \Phi_1$) and $\mathcal{H}_S^{(2)}\left(\underline{r}^{(4)}, t\right)$ ($\underline{r}^{(4)} \in \Phi_2$), caused by the two irrigation schedules started at $t = 10:00$ AM. The effects of the irrigation have been evaluated and compared in the two reference measurement points $\underline{r}^{(1)}$ and $\underline{r}^{(4)}$ since the two corresponding sensing nodes have been installed in proximity of the roots' grapevine. In this sense, the results represent the effects on a single grapevine assuming a root depth $h_R = 0.25$ $[m]$ and a horizontal surface $s_R = 0.25$ $\left[m^2\right]$, according to the suggestion of the farmers. The total irrigated water can be easily computed by multiplying the estimated irrigated water by the number of cultivated grapevines.

The irrigation time intervals $\pi^{(n)}(t)$, $n = 1, \ldots, N$, $N = 2$ have been also reported in Fig. 10 in order to point out the main differences between the two computations. More in detail, the irrigation time provided by the proposed DSS has been estimated starting from the execution of the two-step FL decision-making, which computed a water stress level $W\left(\underline{r}^{(k)}, t\right)\Big|_{\underline{r}^{(k)} \in \Phi_1} = 83$ $[\%]$ at the first FL step, and a water need indicator $I\left(\underline{r}^{(k)}, t\right)\Big|_{\underline{r}^{(k)} \in \Phi_1} = 0.73$ at the second step of the strategy. The obtained value of the water need indicator corresponds to the linguistic rule "*irrigate now*", and consequently the volume estimation and the irrigation planning have been executed. The actual water content $\delta(t)|_{t=10:00AM} = 264.8$ $\left[\frac{l}{m^3}\right]$ has been inferred through the *Van Genuchten* model, and the target value has been set to $\delta^{max} = 392.1$ $\left[\frac{l}{m^3}\right]$, which corresponds to a soil water potential $\mathcal{H}_S^{(1)}\left(\underline{r}^{(1)}, t\right) = -15$ $[cbar]$ (the field capacity is commonly set to $\mathcal{H}_S^{max} = -10$ $[cbar]$ [1]). The arising estimation of the required water volume turns out $V(t)|_{t=10:00AM} = 127.3$ $\left[\frac{l}{m^3}\right]$, which leads to the water quantity $\widehat{V}(t) = V(t) \times h_R \times s_R = 7.9$ $[l]$ irrigated in position $\underline{r}^{(1)}$. Finally, the irrigation time $\pi^{(1)}(t)\big|_{t=10:00AM} = 3.9$ $[h]$ has been estimated assuming the sprinkler flow rate $\phi^{(spr)}\left(\underline{r}^{(1)}\right) = 2.0$ $\left[\frac{l}{h}\right]$.

The T-based technique has been configured setting $\mathcal{H}_S^{th} = -40$ $[cbar]$. As shown in Fig. 10, the irrigation has been stopped at $t = 3:35$ PM when the measured soil potential satisfied the condition $\mathcal{H}_S^{(2)}\left(\underline{r}^{(4)}, t\right) \geq \mathcal{H}_S^{th}$. An irrigation time $\pi^{(2)}(t)\big|_{t=3:35PM} = 5.6$ $[h]$ and an irrigated water volume $\widehat{V}(t) = 11.2$ $[l]$ have been obtained with the same sprinkler flow rate $\phi^{(spr)}\left(\underline{r}^{(4)}\right) = 2.0$ $\left[\frac{l}{h}\right]$.

As it can be observed, even if the threshold $\mathcal{H}_S^{th} = -40$ $[cbar]$ has been set much lower than the target value

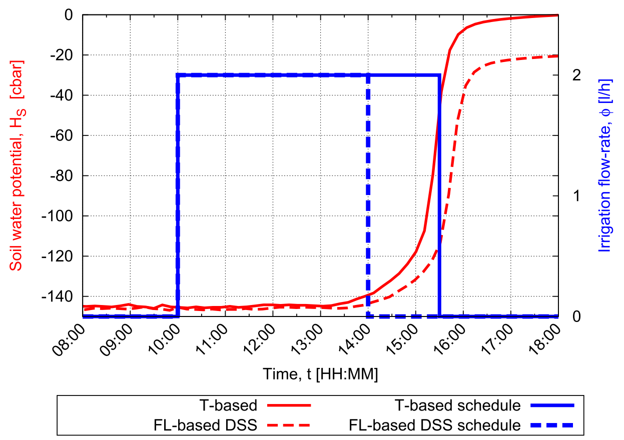


Fig. 10. Effect of a FL-based irrigation on the soil status compared to the T-based irrigation.

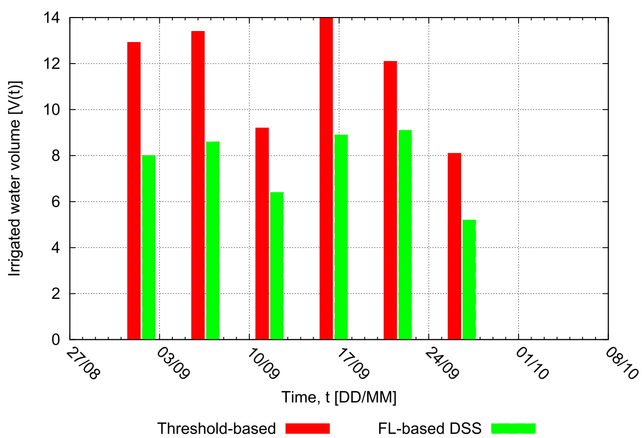


Fig. 11. Water saving comparison between the FL-based DSS and the T-based technique - Irrigated water level during a period of one month.

given to the FL-based DSS ($\mathcal{H}_S^{(1)}\left(\underline{r}^{(1)}, t\right) = -15$ [$cbar$]), the threshold-based strategy has led to worst performance in terms of water saving since the water potential has exceeded the field capacity, generating waste of water due to percolation. This is mainly caused by the fact that the time delay of the soil transient is not considered by this simple strategy. On the contrary, the soil potential obtained using the proposed DSS reached a suitable maximum value $\mathcal{H}_S^{(1)}\left(\underline{r}^{(1)}, t\right) = -20$ [$cbar$], which is slightly lower than the desired target and represents a good soil condition in terms of both water availability for the grapevine and of the reduction of water waste for percolation.

The comparison between the two techniques has pointed out an average water saving of $\omega^{T-FL}(t) = 29.5$ [%] using the proposed FL-based DSS (i.e., an irrigated water volume $V(t) = 7.9$ [$l$] instead of $V(t) = 11.2$ [$l$]) and an improved exploitation of the water resource since the percolation phenomenon has been avoided. Moreover, the qualitative indicator has been estimated by the expert farmers to analyze the water stress level of the plants in $\Phi_1$ and $\Phi_2$. The outcome of the visual inspection has been summarized in the indicators $\zeta^T(t) = low$ and $\zeta^{FL}(t) = low$, pointing out that a water stress level $W\left(\underline{r}, t\right) < 30\%$ has been caused by both the T-based and FL-based irrigation methods.

The actuation has been performed for a time period of one month in order to further compare the water saving performance of the proposed method with the T-based one. The obtained water volume $V(t)$ has been reported in Fig. 11. The six actuations triggered by the evaluation scheduler have pointed out an average water saving $\omega^{T-FL}(t) = 34$ [%] provided by the FL-based DSS, confirming the results of the comparison shown in Fig. 10.

## V. Conclusion

In this paper, a wireless decision support system for the optimized management of the irrigation in agriculture has been presented. The properties of the WSAN technology have been exploited to acquire heterogeneous environmental parameters and to control the functioning of the irrigation system. The FL-based methodology has been designed and calibrated according to the indications of the farmers in order to mimic the human experience and to properly understand the status of the crop. The innovative integration of the low-cost WSAN architecture and the FL-based DSS has led to the following advantages of the proposed smart irrigation technique:

- An improved water saving compared to a single threshold T-based and a multi-threshold MT-based technique proposed in the state of the art ($\omega^{MT-T}(t) = 28$ [%], $\omega^{MT-FL}(t) = 59.6$ [%], $\omega^{T-FL}(t) = 43.8$ [%] simulated, and $\omega^{T-FL}(t) = 29.5$ [%] experimentally measured);
- a low water stress level ($\zeta^{FL}(t) = low$) even if a lower water volume has been irrigated, since only the percolation phenomenon has been limited without negative effects on the crops;
- a high practical value of the suggestions given to the farmers, which are directly supported in the daily irrigation schedule without any specific input or calibration required by the proposed methodology;
- a completely autonomous wireless system, thanks to the sensor lifetime higher than 1 year and the integration of the control algorithm directly in the gateway unit.

Current research activities are focused on the integration of additional sensors for the measurement of physical quantities required to support the farmers also on the agrochemical application, and on the customization of the FL-based strategy in order to support multiple decision support functionalities.

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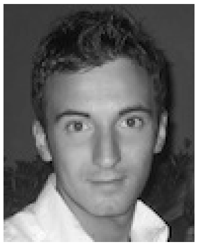

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