PANTHEON: SCADA for Precision Agriculture

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Abstract In this chapter, we introduce the vision of the H2020 project "Precision Farming of Hazelnut Orchards" (PANTHEON), which is to develop the agricultural equivalent of an industrial Supervisory Control And Data Acquisition (SCADA) system to be used for precision farming of orchards. PANTHEONs objective is to design an integrated system where a relatively limited number of heterogeneous unmanned robotic components (including terrestrial and aerial robots) move within the orchard to collect data and perform typical farming operations. In addition, an Internet-of-Things (IoT) agrometeorological solar-powered network is deployed to continuously monitor the environmental conditions of the orchard. The information so collected is then stored in a central operative unit that integrates the data to perform automatic feedback actions (e.g. to regulate the irrigation system) and to support the decisions of the agronomists and farmers in charge of the orchard. The proposed SCADA system will acquire information at the resolution of the individual plant, to drastically increase, compared to current best-practice, the detection of

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possible limiting factors at the level of the individual plant, and to react accordingly. Differently the current state-of-the-art in precision farming for large-scale orchards, the capability of monitoring the state and the evolution of each single tree will be the enabling-technology to allow more focused interventions. This will lead to a better average health of the orchard, and to an increased effectiveness of Integrated Pest Management (IPM) activities. In conclusion, the ongoing implemented architecture has the potential to increase production while, at the same time, being more cost-effective and environmentally-friendly. To summarize, we believe that the proposed SCADA paradigm for Precision Agriculture may represent an attractive opportunity for the design of a novel real-time software architecture. In other words, by allowing the processing of massive amounts of datasets derived from the SCADA architecture, it will be possible to step-up the current effectiveness of Precision Agriculture (PA) methodologies by providing real time answers to the questions posed by farm managers, when in need of timely decisions.

Contents

1 Precision Agriculture at Large

PA is a farming management concept based on observing, measuring and responding to inter and intra-field variability in crops [36]. Such variability may result from a number of factors. These include weather variables (temperature, precipitation, relative humidity, etc.), soil characteristics (texture, depth, nitrogen levels), cropping practices (till/no-till farming), weeds and diseases, among others. The goal of PA is to apply the right amount at the right time and in the right place, optimizing returns on inputs, while preserving resources and reducing production costs. In the broadest sense, PA is the application of management decisions in space and time, based on identifying, quantifying, and responding to variability. Even though farmers have always been aware of variability, the problem is that so far they lacked the tools to measure, map and manage it precisely.

The practice of PA has been enabled by technological developments: from gathering and analyzing data, to the subsequent decision-making process, including the application of different agricultural inputs in the field. The advent of GNSS has greatly contributed to the spread of PA. The farmer's and researcher's ability to locate their precise position in a field allows for the creation of maps of the spatial variability for as many variables as can be measured (e.g. crop yield, terrain feature, topography, soil characteristics, moisture levels, nutrients levels, and others) and computed or derived (e.g. chlorophyll index, Normalized Difference Vegetation Index (NDVI), water stress). Geolocating a field enables the farmer to overlay information gathered from different analyses and various sensors. Sensor arrays can be mounted on GPS-equipped vehicles, such as Unmanned Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs). The sensor arrays consist of instruments like laser scanners and different types of cameras, such as RGB, multispectal, hyperspectral and thermal cameras. These instruments measure several different variables, from which information such as 3D reconstruction of the field and trees, and vegetation indices (VIs) can be computed [51] [35] [45] [52]. Two of the earliest and most widely used VIs are the NIR/Red ratio [34] and the NDVI [47]. In general, datasets collected from sensors onboard UGVs and UAVs can be used in conjunction with information derived from airborne remote sensing and from Earth Observation (EO), with several satellites now providing imagery at centimetric resolution. Additionally, more variables can be measured with instruments such as field-based electronic sensors and spectroradiometers. Overall, it should be remarked that sensing techniques for biomass detection, weed detection, soil properties and nutrients are most advanced. On the other hand, sensing techniques for disease detection and water stress are more difficult to design and implement in the field.

Example of recent projects are here included to provide the reader with an idea of the most recent developments in the field of integrated systems for PA. Within the H2020 program, the most relevant projects in PA are SWEEPER, FLOURISH and APOLLO. The ambition of the SWEEPER project [15] was to bring the first-generation greenhouse harvesting robot onto the market. The idea was to apply the technology developed in CROPS [4] to introduce, test and validate a robotic harvesting solution for sweet peppers in real-world conditions. The idea of FLOURISH

[6] was to develop a setup composed of a small autonomous multi-copter UAV with a multi-purpose UGV to survey a field from the air, perform targeted interventions on the ground, and provide detailed information for decision support, all with minimal user intervention. This framework could potentially be adapted to a wide range of farm management activities and different crops, by choosing different sensors, status indicators, and ground treatment packages. The objective of APOLLO [2] was to develop and test affordable and user-friendly agricultural advisory services. This was achieved by making an extensive use of free and open EO data, such as those provided by the Sentinel satellites. These services monitor growth and health of crops, provide advice on when to irrigate and till the fields, and estimate yield. Other projects will be here briefly illustrated. The project FATIMA [5] aimed to create an effective and efficient monitoring and management system of agricultural resources to achieve optimal crop yield and quality, in a sustainable environment. Their comprehensive strategy covers five interconnected levels: a modular technology package (based on the integration of EO and wireless sensor networks into a WebGIS), a field work package (with exploring options of improving soil and input management), a toolset for multi-actor participatory processes, an integrated multi-scale economic analysis framework, and an umbrella policy analysis set based on indicators, accounting, and footprint approach. The TrimBot2020 [16] project has researched the underlying robotics and vision technologies to prototype the next generation of intelligent gardening consumer robots. The project focused on the development of intelligent outdoor hedge, rose and bush trimming capabilities, allowing the robot to navigate over varying garden terrain, approaching hedges to restore them to their ideal tidy state, and restore bushes to their ideal shape.

Several other projects were funded in the previous Framework Program (FP7). The objective of SAGA [12] was to demonstrate the applicability of swarm robotics principles to the agricultural domain. Specifically, SAGA targeted a decentralized monitoring/mapping scenario, and implemented a use case for the detection and mapping of weeds in a field with a group of small UAVs. In AGROSENSE [1] two different types of sensors were considered: i) static sensors distributed throughout the field in a form of wireless sensor network to monitor soil conditions, crop growth and other relevant bio-parameters and ii) remote sensing based on autonomous UAVs to provide valuable information, otherwise challenging to obtain from the ground. FUTUREFAM [7] aimed at the development of an integrated information system to advise managers of formal instructions, recommended guidelines, and implications resulting from different scenarios at the point of decision making during the crop cycle. RHEA [10] focused on the design, development, and testing of a new generation of automatic and robotic systems for both chemical and physical - mechanical and thermal - effective weed management, with application in both agriculture and forestry. It investigated a large variety of European products, including agriculture wide row crops (processing tomato, maize, strawberry, sunflower and cotton), close row crops (winter wheat and winter barley) and forestry wood perennials (walnut trees, almond trees, olive groves and multipurpose open woodland). The project CLAFIS [3] developed and demonstrated a pre-commercial intelligent solution prototype for communication between automation systems and IT systems in farms and forest related processes. It focused on the need for seamless data transfer between complex field devices/automation systems and IT systems for several stakeholders in the European agribusiness sector and in forestry production. Eventually, SODSAT [13] concentrated on increasing the competitiveness of turf grass producers by providing a remote-based intelligent turf management system based on Artificial Intelligence (AI) techniques and on satellite imagery. Its outcome was an expert system able to provide agronomical recommendations by relying on historic and current data, multispectral images, and on-site sensing.

Extending our analysis to outside Europe, several relevant initiatives have been carried out. The University of Minnesota developed algorithms that allow off-the-shelf robotics to work autonomously in complex environments, such as an apple orchard [14]. A project [11] led by the University of Pennsylvania uses human-operated drones to produce high-resolution, multi-dimensional maps to improve efficiency and yield. The MIT Media Lab Open Agriculture Initiative [9] builds open resources to enable the global community to accelerate digital agricultural innovation. Bringing together partners from industry, government, and academia in a research collective, they create collaborative tools, such as ”food computers” to explore future agricultural systems. In Australia, a project that received public funding [8] contributed to the development of multi-scale monitoring tools to manage Australian tree crops.

A common trait to the majority of these research papers and projects is the focus on annual crops, i.e. corn, strawberries, cotton, with only some of them having analyzed tree crops, such as almond trees. The reason behind this is the higher market values of annual cultivation, like corn, that represent a commodity in the stock exchange market. In the case of annual crops, PA has also been used for yield estimation of major crops, such as grain and cotton. However, only limited research has been conducted on yield estimation for specialty crops such as fruit trees [53]. Additionally, in the specific case of hazelnut farming, it represents a minor crop in the world scenario, which is not even part of the list of commodity products. As a consequence, in the past this has resulted in poor attractiveness for what concerns research projects and funds. Eventually, it should be remarked that real time computing has still to be properly integrated in PA. Indeed, some of the sensors, like weather stations, already provide near-real time data and also compute, in near-real time several derived variables from the measured ones. However, future challenges relate to the real time processing of the much larger volume of data collected by sensors onboard UGVs, UAVs, aircrafts and satellites.

2 Precision Agriculture for Hazelnut Orchards: A Case Study

PA in hazelnut farming is a relatively recent concept. As anticipated, this perennial crop, well adapted to temperate climatic conditions, has been considered until recently a minor crop. PA applications have been described in major perennial crops [56] such as as olive groves, vineyards, stones fruits orchards, to monitor and manage water balance through remote sensing [30] [17], to predict yield and for post-harvest monitoring and management [38] [55] [18] [44] [37] [54].

Lately, hazelnut cultivation is experiencing a renaissance period, due to several new and large orchards being planted both in traditional hazelnut countries, such as Italy, Spain and Oregon (USA), and also in new producer countries like Chile. This renewed interest for a nut crop, considered in the past highly suitable only for marginal areas, (i.e. slopes), has provided momentum for innovative farming approaches, leading to interesting first applications in the framework of PA.

The use of Differential Global Navigation Satellite System Real Time Kinematic (DGNSS-RTK) has been introduced to design the planting scheme and to mechanically plant single trunk trees in high density new orchards, that can then be managed with high levels of mechanization for what concerns, for example, pruning operations [24]. This new technology is mainly applied in large orchards. The design phase has been simplified, introducing surveying instruments that allow accuracy and precision in the phase of squaring the fields (Figure 1). The number of rows and plants can be automatically computed and the results displayed in a Geographic Information System (GIS) platform.

Fig. 1 Laser alignment system positioned in the field to allow accuracy and precision in squaring the field. The instrument is equipped of a software module that can show in real time plant positioning points.

In addition to the design phase, a transition from manual to mechanical planting has also taken place in the last years (Figure 2), as a consequence of technical and economic reasons, such as higher precision in planting operation and labor reduction.

Fig. 2 DGNSS-RTK mechanized transplanting operation in the field.

Mechanical transplanters are combined with laser alignment or control systems directly connected to a DGNSS positioning tool. Along the same line, more recently, an electro-hydraulic control system based on DGNSS-RTK technologies has been directly integrated into the machinery used for the transplanting phase. Analyses of the economic advantages of such technology have shown that for plantations larger than 30 hectares the proposed DGNSS-RTK control should be preferred to manual operations [24].

Fabi and Varvaro [25] described the first results of the application of Advanced Spectroscopic Imaging System (A.Sp.I.S.) to monitor the "Dieback of hazelnut", a bacterial disease caused by Pseudomonas syringae pv. coryli, that recently caused the loss of a large number of hectares in hazelnut orchards in the Viterbo province (Italy). The authors proved how A.Sp.I.S. can recognize the main part of a wilting or dead plant, allowing to set up a protocol of investigation, to both monitor and predict the spread of the disease in space and time with high accuracy. The derived prediction model mainly relied on temperature and rainfall for an accurate and rapid evaluation of the possible spread.

Suitability analyses, based on GIS, have been recently adopted to identify suitable areas to establish new plantations. To ensure the suitability of agricultural areas, several layers of GIS information are evaluated, such as slope, soil characteristics, weather characteristics, water presence, etc.

Applications of PA in hazelnut cultivation have also been attempted for irrigation management and efficiency. In this case, the main objective is to maximize the efficiency of water use, and to allow nutrients administration through fertigation, a technique still poorly applied in hazelnut orchards. Remote sensing for monitoring soil moisture and water status of the plant and IoT technologies are under investigation to provide higher efficiency in irrigation systems at a variable rate.

Mechanical pruning could also potentially be enhanced by PA. In particular, the pruning shape could be fit to each plant, depending on its current situation. At present, mechanical pruning, both in trials and in commercial orchards, is performed using a rotating blade bar carried by a tractor (Figure 3). The effectiveness of this operation, advisable for large orchards and in medium-high density plantations, is confirmed by a positive effects on production, obtainable in the medium-long term.

Fig. 3 Mechanical pruning of hazelnut trees: hedging cut of an adult and commercial orchard.

Mechanical pruning is performed with side cutting along the row (hedging) and also through cutting the top of the plants (topping). Hedging is executed when the branches of two contiguous rows overlap. To avoid a reduction in productivity, hedging is applied only to some of the plants of the orchard. Topping may be less frequent than hedging and is performed on the whole orchard every 5 to 8 years. Mechanical pruning has the aim of modifying the shape of the trees from bushes to hedges (Figure 4), so that the resulting orchard appears more similar to other industrial, high density fruit orchards, opening new opportunities for new PA applications.

It is worth mentioning that PA has also been recently introduced in other nut quality evaluation and in post-harvest management. This is generally performed using near infrared spectroscopy, to classify hazelnuts according to different standards.

Fig. 4 The “edge shape” of adult hazelnut orchard after mechanical pruning (Girona - Spain).

3 PANTHEON: A SCADA System for Agriculture

The vision of the H2020 project PANTHEON is to develop the agricultural equivalent of an industrial SCADA system to be used for the precision farming of orchards. By taking advantage of the technological advancements in the fields of control, robotics, remote sensing, and big-data management, the objective of the project is to design an integrated system where a relatively limited number of heterogeneous unmanned robotic components (including terrestrial and aerial robots) move within the orchard to collect data and perform typical farming operations. An IoT agrometeorological solar-powered network is deployed to continuously monitor the environmental conditions of the orchard. The information produced is collected and stored in a central operative unit that integrates the data coming from the different robotic vehicles to perform automatic feedback actions (e.g. to regulate the irrigation system) and to support the decisions of the agronomists and farmers in charge of the orchard. The proposed SCADA system is designed to acquire information at the resolution of the single plant. As a result, this allows to drastically increase the detection of possible limiting factors for each individual plant, such as lack of water or pests and diseases affecting the plant health, and to react accordingly. Compared to the current state of the art in precision farming, the PANTHEON SCADA infrastructure represents a relevant step ahead in the context of orchards management. In fact, the capability of monitoring the state and the evolution of each single tree represents an enabling-technology to allow more focused interventions. This results in a better average health of the orchard, and in an increased effectiveness of IPM activities. The proposed SCADA architecture has the potential to increase the production of the orchard while, at the same time, being more cost-effective and environmentally-friendly. For the experimental validation of the proposed PANTHEON SCADA system, a real-world (1:1 scale) orchard in the farm “Azienda Agricola Vignola” is considered.

3.1 A SCADA for Hazelnut Management

The objective of the project PANTHEON is to improve the current management of real-world hazelnut orchards. Briefly, the project focuses on the following aspects of orchard management:

- Estimation of the phytosanitary status of the orchard at the granularity level of the single plant;
- Automatic irrigation regulation;
- Automatic suckers treatment;
- Improvement of pruning practices;
- Automatic estimation of the production.

Extensive discussions were conducted with actors of the the agronomic community in order to list the most time consuming and labor-intense agronomic activities, and those that also involve attributing the status of few representative trees to the entire block. In the management of large orchards, several activities can potentially benefit from automation, however, according to the priorities of the interviewed agronomists and farm managers the previous 5 activities were identified as crucial. Focusing on these activities has been estimated as an achievable effort in the duration of the PANTHEON project.

To do so, PANTHEON is developing a system composed of an IoT-based agrometeorological monitoring network, which includes a weather station to collect meteorological data and several soil moisture probe nodes to record humidity and temperature of the soil, along with ground and aerial robots that navigate the orchard to collect several measurements using different sensors (including high-level imaging sensors such as LiDAR and multispectral cameras), achieving the resolution of the single tree. The information is collected by a central unit where the data is processed to extract synthetic indicators in order to describe for each tree:

- water stress;
- possible presence of pests and diseases;
- presence and size of suckers;
- geometry of the tree;
- estimated number of nuts on the tree.

Based on these synthetic indicators, the system elaborates a synoptic report for the orchard manager. Such a report highlights possible situations that may deserve attention, provides suggestions of intervention and, if requested, offers a historical view of the status of the plant and of the treatments already performed. In addition, for some activities, algorithms to perform automatic decisions are considered. As a result, PANTHEON envisions a SCADA system capable of:

i) autonomously controlling the levels of irrigation,
ii) carrying out automatic suckers elimination.

The design of the SCADA architecture has been performed by keeping in mind:

i) the possibility to integrate, in the future, the automation of other operations (e.g. weed control),
ii) the possibility to extend its application to other fruit crops.

3.1.1 Hazelnut Remote Sensing

The reason behind the use of remote sensing in agriculture is the possibility of observing more than the human eye can and to detect changes, when possible, in the pre-symptomatic stage. Plant diseases and pest infestations affect plant physiology. This in turn can modify the colour of different parts of the plant, the canopy morphology, the plant density and the transpiration rate, and finally the interaction of solar and thermal radiation with the canopy [29] [28]. Thus, remote sensing technology is among the most advanced and effective methods for monitoring crop pests and diseases [40]. PANTHEON will utilize remote and proximity sensors to achieve the goals of pest and disease detection, water stress detection and fruit detection with spectral analysis.

3.1.1.1 Optical Sensing

Multispectral sensors measure the relevant features with well defined spectral bands. Typically the spectral characteristics of a band are achieved by spectral filters. Nearby narrow bands are capable of describing slight variations of the spectral features, but might be affected by a poor signal to noise ratio, as the energy received at the sensor depends on the bandwidth. Since high quality hyperspectral sensors are still rather expensive, multispectral cameras with bands customized for the specific application are generally used. In the last decades, various spectral indices have been developed to extract specific spectral features—e.g. associated with photosynthetic activity, plant health or water content—with a limited number of bands.

NDVI (see Equation 1) is a commonly used indicator for the presence of vegetation. It is based on the typical ratio of the high reflecting near infrared plateau—due to cell structure—and the low reflecting red region—due to absorption by pigments.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \tag{1}$$

The Photochemical Reflectance Index (PRI) is able to track diurnal changes in photosynthetic efficiency of plants [27]. This index is based on the reflectance at 531 nm R_{531} and a reference wavelength R_{REF}, typically 570 nm or 550 nm. Its sensitivity to short-term changes of photosynthesis and its stability against sun angle changes make it particularly useful to monitor plant activity. It can also be used to identify water stress [49]. With sufficient water supply, a reduced photosynthetic activity of hazelnut trees would indicate a health impairment.

$$PRI = \frac{(R_{REF} - R_{531})}{(R_{REF} + R_{531})} \tag{2}$$

3.1.1.2 Thermal Sensing

Thermal sensing at field scale has an enormous potential for the measure of the plant response to water deficit [32]. Canopy temperature is linearly related to the rate of water loss from the canopy, which is closely related to stomatal conductance [33]. Based on this observation, the Crop Water Stress Index (CWSI) [31], is considered an effective indicator for water stress. To derive CWSI for a given plant with temperature T_c, the index requires also the knowledge of the temperature of a plant with water deficit T_{dry} and the temperature of a well watered plant T_{wet} (see Equation 3). CWSI ranges from -1 to 1, with values close to 1 indicating no stress, while values ≤ 0 indicate extreme stress.

$$CWSI = \frac{(T_c - T_{dry})}{(T_{wet} - T_{dry})} \tag{3}$$

Since stomatal conductance responds rapidly to water deficit, CWSI is an early indicator for water stress. Thus, in PANTHEON it is planned to use CWSI to distinguish water stress from stress caused by pest and/or diseases. Given that CWSI does not provide information about the resilience of a plant against water stress, it is also scheduled to calibrate a resilience function for hazelnut trees, based on water stress experiments.

Since the difference between T_c and the air temperature T_a is linearly related to the Vapor Pressure Deficit (VPD), it is possible to define CWSI as in Equation 4 [19] [43]. The coefficients D_1 and D_2 are estimated from the linear regression of $T_c - T_a$ and VPD [43].

$$CWSI = \frac{((T_c - T_a) - D_2)}{(D_1 - D_2)} \tag{4}$$

3.1.1.3 Spectral Analysis

In PANTHEON, it is planned to use the spectral indices as indicators for drought stress, and for the detection of pests and diseases. Fruit detection can be addressed with direct and indirect techniques of image processing and 3D analyses [23] [48] [21].

4 Experimental Setup

For project PANTHEON, 3 fields were selected within the Azienda Agricola Vignola, a farm located in the municipality of Caprarola, in the province of Viterbo. They are displayed in Figure 5 and their characteristics are listed in Table 1.

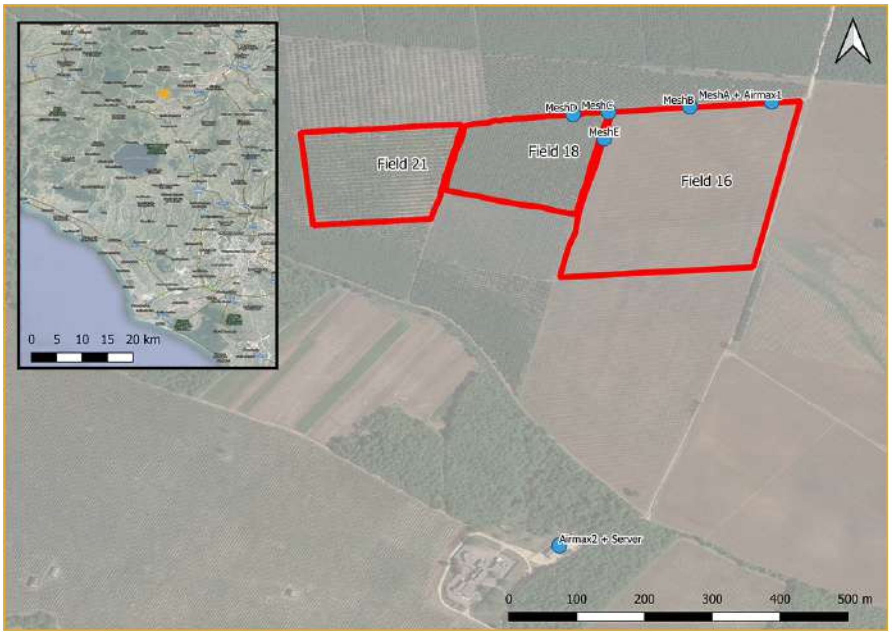

Fig. 5 Selected fields for the PANTHEON project.

Name Field	Area (ha)	Variety (-)	Density (m)	Age (year)	Irrigation (-)
16	9.1	Nocchione	4.5x3.0	Young: third leaf in the field	Underground drip irrigation: double line between the rows, 0.8m from the tree lines
18	3.1	Tonda Gentile Romana	5.0x5.0	Adult: 30	Underground drip irrigation: 1 line between the rows
21	3.8	Tonda Gentile Romana	8.0x4.0	Old: >40	Underground drip irrigation: 1 line between the rows

Table 1 Selected fields for the PANTHEON project and their characteristics.

Of the 3 fields that were offered to the consortium, only 2 contiguous ones were retained for the experimental setup. This precautionary redefinition of the fields derives from constraints due to the deployment of the communication network. Additionally, it should be noted that field 21 has rather similar characteristics to field 18, both in terms of variety, tree age and irrigation scheme. In conclusion, abandoning field 21 does not compromise the statistical significance of the experiments, also considering that the number of tree and their spatial distribution ensure a sound scientific experimentation.

A young orchard (field 16 - four years old at the beginning of vegetative season 2019) was selected to test and validate the automation of irrigation, suckers' detection and management, pruning policies, and production estimarion. The orchard design is 4.5 m x 3.0 m (Figure 6), with cultivar Nocchione. The trees are trained as multi stemmed bushes, selecting 3 to 4 main stems, and the field is irrigated with sub-irrigation system, namely underground drip irrigation with double line between the rows, at a distance of 0.8 m from each side of the tree lines.

Similarly, a mature orchard (field 18 - about thirty years old) has been chosen for the same trials as for field 16, with the addition of tests for major hazelnut pests and diseases. The orchard design is 5.0 m x 5.0 m (Figure 7), with cultivar Tonda Gentile Romana. The trees are trained as multi stemmed bushes and the field is irrigated with sub-irrigation system, in the specific case an underground drip irrigation systems, with one line between the rows.

In the area covered by the IoT (see Figure 8), each selected tree has been attributed a specific ID, for both manual and automated monitoring, in order to have appropriate cal/val datasets. For a reasonable planning of orchard management activities, a certain pre-defined number of trees has been selected in each field, as reported in the following:

- Water stress: 20 trees selected in field 18 (adult orchard) and 20 trees selected in field 16 (young orchard), with each group divided in two sub-groups of 10 trees each (one sub-plot will be irrigated and one will be used as non-irrigated control).
- Suckers detection and control: 10 trees selected into the same row in field 18 and 10 trees selected into the same row in field 16.
- Tree geometry reconstruction: 15 trees were selected in field 16 and labeled as 3 different sub-groups of 5 trees each, with 3 different pruning protocols, one per sub-group (free multi-stemmed bush; regular multi-stemmed bush; single trunk system).
- Pests and diseases detection: 18 trees were selected in field 18, with 6 trees with pests and diseases infestation at a pre-defined time T1; 6 trees with pests and diseases infestation at a pre-defined time T2 and the remaining 6 trees to be protected against infestation.
- Fruit detection: 10 young trees selected in field 16 and 5 mature trees selected in field 18.

Fig. 6 Overview of field 16 (young hazelnut orchard) during the vegetative season (22 June 2018) and during winter rest (8 February 2019).

5 SCADA Hardware Components

The SCADA system designed within the PANTHEON project is composed of the following main components, which will be detailed in the following:

Fig. 7 Overview of field 18 (adult hazelnut orchard) during the vegetative season (22th June 2018) and during winter rest (8th February 2019).

1. Wireless Backbone Network
2. Unmanned Ground Robotic Platforms
3. Unmanned Aerial Robotic Platforms
4. IoT Agrometeorologic Monitoring Network

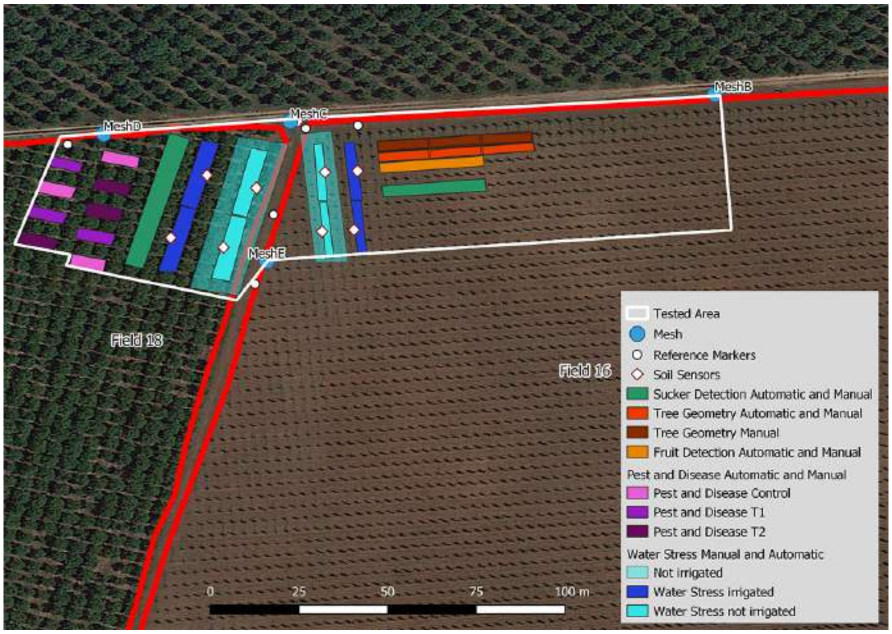

Fig. 8 Detailed view of the experimental setup of the PANTHEON project. One of the 9 LoRa nodes is located extremely close to MeshC. Reference markers indicate the position of ground control points to support drone imagery referencing. Fruit detection in Field 18 will be performed on every second tree, in the same row selected for "Sucker Detection Automated and Manual"

Notably, the interaction among the different components is ensured by (mostly) relying on the Robotic Operative System (ROS) [46]. Briefly, ROS provides a distributed modular solution for a seamless integration of all the hardware and software components, ranging from the drivers of the actuators to the interface with the data analytic engine. In this regard, as it will be detailed in the following, the Wireless Network Backbone serves as a medium for the the other components to interact over standard TCP/IP sockets for transporting message data.

5.1 Wireless Network Backbone

The Wireless Network Backbone (WNB) is the infrastructure required to keep all the ROS-based components of the SCADA system interconnected, from the central unit housing the farm-server with the farm-DataBase (DB) to the single robots moving in the field. The selected WNB architecture is based on a set of mesh antennas and two long-distance antennas. The former is required to create a mesh network on the field, so that UGVs and UAVs can operate in the field itself. The two long-distance

Fig. 9 Wireless Network Backbone.

antennas are required to connect the central unit, located in a remote warehouse, to the mesh network deployed in the field.

Figure 9 depicts the WNB developed within the PANTHEON experimental setup. In particular, the WNB consists of eight antennas and one router, specifically:

- 2 Airmax antennas (LiteBeam AC GEN2)
- 5 Unifi antennas (AC MESH PRO)
- 1 Router (IR615-S-EN000-WLAN)

Regarding the long-range Airmax antennas, as illustrated in Figure 10, one Airmax2 antenna, named Airmax2, is wired connected through an Ethernet cable to the central unit (located in a remote warehouse) and oriented toward the other antenna, named Airmax1, which is instead placed in the field and where the router is also present. This router, which has the sole functionality of managing the local network, has been placed into the field with the purpose of conceptually decoupling the two network segments, identified with the mesh network (in the field) and the central unit (in the warehouse). Indeed, this choice offers the advantage to avoid that a possible temporary failure of the point-to-point long-range connection between the central unit and the mesh network would prevent the usability of the unmanned vehicles on the field. Figure 9 depicts the two network segments and Figure 10 illustrates the point-to-point long-range connection.

Regarding the mesh network, as shown in Figure 11, the first Unifi antenna is wired connected to the antenna Airmax1 through an ethernet cable and to the router,

Fig. 10 Point-to-Point Airmax Antennas.

utilizing another ethernet cable. Any other Unifi antenna is wireless connected, i.e. through an uplink-downlink radio connection as specified by the Unifi protocol, in order to create a mesh network. In this way the signal is re-broadcasted through a desired network topology pre-configured from a software, i.e., Unifi Controller, permitting the connection between all devices in the field.

All the Unifi devices are conventional WiFi access point (with up to 183 m radius of area coverage with a maximum bandwitdh of 450Mbps). It is also possible to access them even with a mobile phone, which is useful for experiments and debugging purposes. The mesh established between Unifi antennas is necessary to cover all the area and is composed by a total of 5 devices for a field whose area is about 50 m x 200 m. In addition, as can be noticed in Figure 11, each Unifi device, which has a power consumption of 9 Watts, has been powered through a battery that can be autonomously charged by means of a solar panel to support a long operational time.

Fig. 11 Mesh Unifi Antennas.

5.2 *Ground Robotic Platforms*

Two ground vehicle prototypes, namely SHERPA HL robotic platform R-A and SHERPA HL robotic platform R-B, are required for the precision farming activities to be carried out within the PANTHEON project. Briefly, the two ground vehicle prototypes are based on the commercial SHERPA HL robotic platform, i.e., a general-purpose mobile platform originally designed to target logistics tasks, produced by the Robotnik Automation, S.L.L. The following agronomic activities have been identified for the ground robotic platforms:

- The main task of the SHERPA HL robotic platform R-A is to collect sensorial data for tree geometry reconstruction, for the assessment of the phytosanitary status of the plants and to mark branches for pruning.

- The main task of SHERPA HL robotic platform R-B is to apply chemicals on suckers with the scope to remove them and any related features.

The two SHERPA HL robotic platforms have been mechanically designed and customized to facilitate the execution of these specific precision farming activities. In particular two different kinematic models have been considered: i) the SHERPA HL robotic platform R-A is mechanically designed to operate according to the Omnidirectional kinematics, and ii) the SHERPA HL robotic platform R-B is mechanically designed to operate according to the Ackermann Steering kinematics. It should be noticed that, the SHERPA HL robotic platform R-A could also operate according to the Ackermann Steering kinematics by simply imposing that no steering is allowed for the rear tires. Indeed, this kinematic operation mode is made available by the core software library and it can be decided by the operator (or equivalently by the autonomous control law).

Fig. 12 Common Sensorial Equipement of SHERPA HL robotic platforms.

5.2.1 Common Sensorial Equipment for localization, safety and navigation system

The two SHERPA HL robotic platforms R-A and R-B share the same sensorial equipment for the localization, safety and navigation system. This choice has been made to simplify the development of control, localization and navigation algorithms. In particular, as depicted in Figure 12, the following sensorial equipment has been considered: i) a Trimble MB-Two GNSS Receiver with GPS-RTK capabilities; ii) an SBG Ellipse2-E IMU with an integrated compass; iii) two Sick S300 Safety Laser Scanner, and iv) a velodyine VLP-16 Puck LITE 3D LIDAR.

5.2.2 Ground Robot R-A Farming Sensorial Equipment

The main features of SHERPA HL robotic platform R-A are illustrated in Figure 13. In particular, the telescopic arm, composed of an elevator and a rotational bar, can be noticed. The sensorial equipment for the remote sensing activates is also highlighted. Briefly, this is composed of a FARO Laser Scanner Focus S70 LiDAR, a

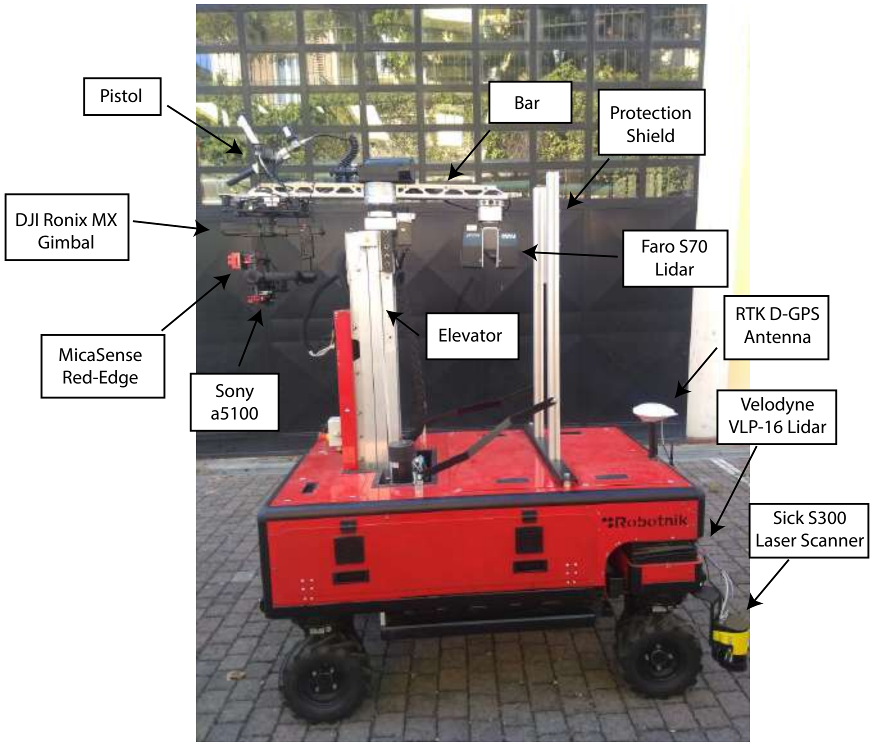

Fig. 13 SHERPA HL robotic platform R-A.

MicaSense RedEdge-M and a Sony Alpha α5100 mounted on a gimbal DJI Ronin MX, and a Velodyne VLP-16 Puck LITE LiDAR. In addition, a Sick S300 Safety Laser Scanner (another one is placed on the opposite corner on the rear of the robotic platform), and an Antenna for the RTK D-GPS system are included in the system.

In PANTHEON it is planned to measure each tree with the robotic platform R-A from four positions to gain an all around view. As illustrated in Figure 14, at each position the tree is scanned twice, once with the laser scanner and once with the cameras, after rotating the robots rotational bar by 180°. This procedure allows for a later spectral enrichment of the laser scans, due to the similar viewing perspectives. Thus, a spectral analysis of the point clouds can be achieved for an improved detection of relevant features, like sucker's branches or fruits.

To measure the relevant spectral information with the UGVs, a MicaSense RedEdge-M multispectral camera is used. Its five discrete spectral bands with an image resolution of 960x1280 pixels and a radiometric resolution of 12 bit are optimized for agricultural applications. Table 2 summarizes the spectral characteristics of the camera. Although within the orchard the incidence of light might be poor, this camera provides images of a sufficient signal to noise ratio.

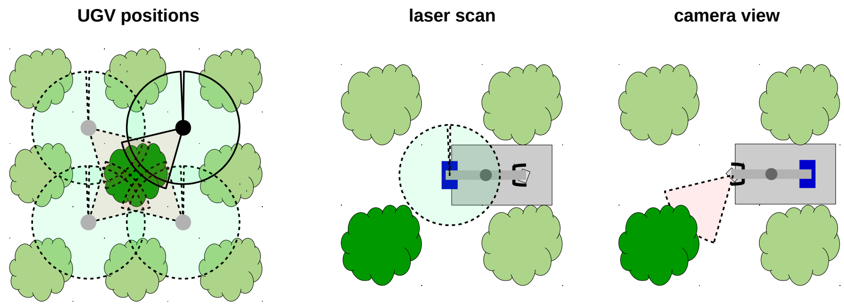

Fig. 14 Data acquisition concept for the robotic platform R-A.

Band	Center Wavelength (nm)	Bandwidth FWHM (nm)
Blue	475	20
Green	560	20
Red	668	10
Near IR	840	40
Red Edge	717	10

Table 2 Spectral characteristics of the MicaSense RedEdge-M.

As a counterpart to the professional multispectral camera, a custom Sony α5100 RGB camera is used, because of its high geometrical resolution and its robust design. To achieve high quality close range images with a large field of view, the camera has been equipped with an optical lens (Sony SEL-28F20) with 28 mm focal length and F2.0 light intensity. The spectral characteristics, with only visible and broad diversified bands, are not suitable for a meaningful spectral analysis. However, the high geometrical resolution is particularly suitable to apply object recognition techniques, e.g. for fruit detection.

To record high density 3D point clouds of the trees, a Faro Focus S70 laser scanner is used. It allows for all around scans with a vertical field of view of 300°. It measures at a wavelength of 1550 nm, with a minimum step width of 0.009° [26]. With these resolution capabilities, detailed structures, like suckers or fruit clusters, can be recorded by the scanner. With a point precision of about 2 mm at a distance of 10 m, the laser scanner provides point clouds of a sufficient quality to reconstruct the geometry of hazelnut trees.

Figure 15 illustrates a young tree captured with the RGB and multispectral camera from the same position. Taller trees require multiple photo shots from the same position, to capture the canopy completely.

Fig. 15 Images of RGB and multispectral camera taken form the same position (RGB, blue, green, red, red-edge, NIR).

5.2.3 Ground Robot R-B Farming Sensorial Equipment

The main features of SHERPA HL robotic platform R-B are summarized in Figure 16. In particular, it can be noticed that the atomizer is composed of a sprayer along with an electrical driven pump and a tank for treating suckers. In addition, two Sick S300 Safety Laser Scanners, a Velodyne VLP-16 Puck LITE LiDAR and an Antenna for the RTK D-GPS system are visible.

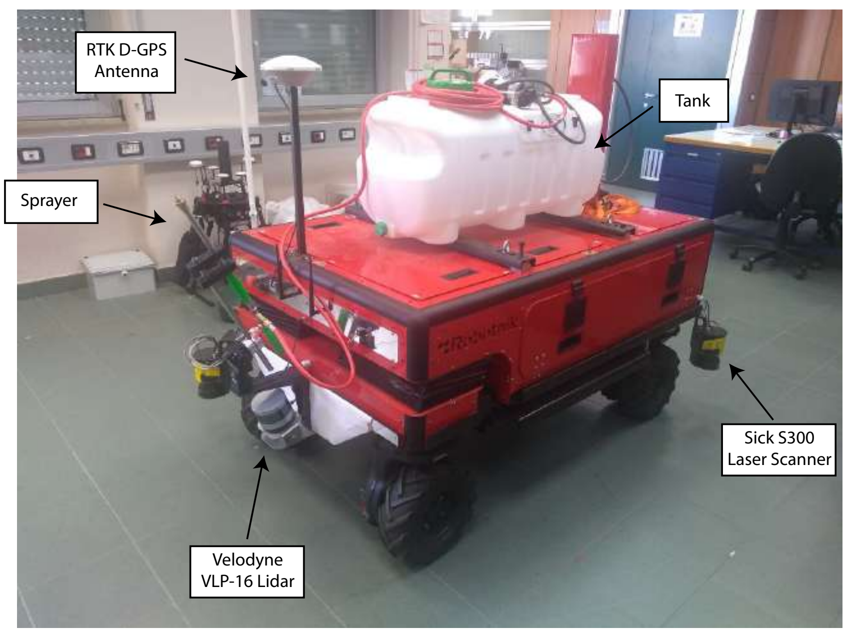

Fig. 16 SHERPA HL robotic platform R-B.

5.3 Aerial Robotic Platforms

One aerial vehicle prototype is required for the precision farming activities to be carried out within the PANTHEON project. This vehicle is based on the commercial UAV DJI Matrice 600 Pro, produced by DJI. The model chosen is a six-rotor flying platform designed for professional aerial photography and industrial applications. The main task of this robotic platform is to collect sensorial data to estimate the phytosanitary status of the plants.

The model has been customized to execute the sensing activities required in precision farming. The UAV is equipped with a DJI A3 Pro triple-modular redundancy system and advanced intelligent flight functions, a DJI D-RTK system which allows high accurate positioning and a gimbal DJI Ronin MX where 3 sensors are installed. All this can be controlled with a ruggedized on-board computer DJI Manifold added on the top of the aircraft.

The A3 Pro flight controller provides three GPS modules and IMUs which add triple modular redundancy to reduce the risk of system failure. This system is complemented with an RTK module which, using a ground station, provides corrected GPS signals to improve its accuracy. These elements can be seen in Figure 17.

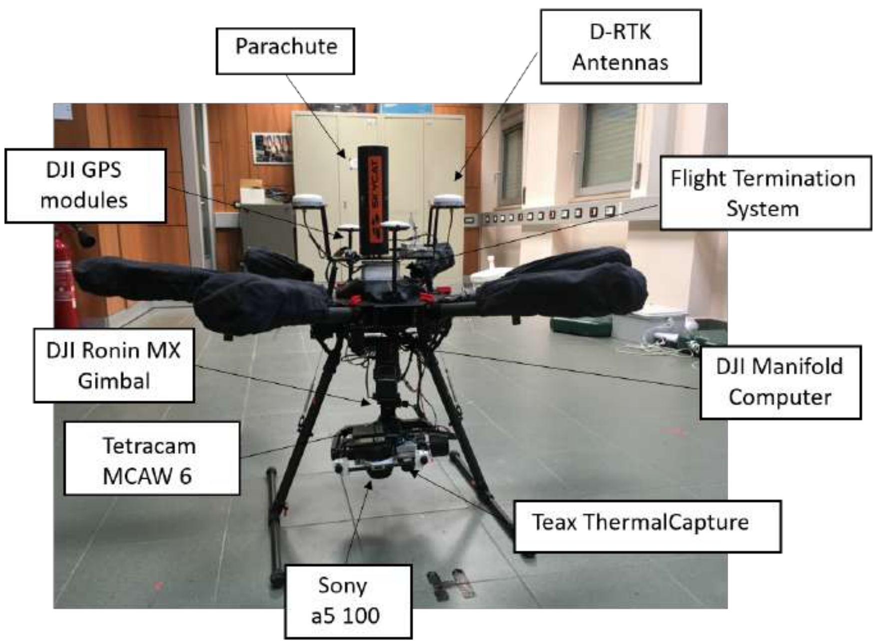

Fig. 17 Aerial robotic platform.

Additionally, a flight termination system and a security parachute are mounted on the top of the aircraft. Both security systems are optional, depending on the risk of the mission, and can be activated or deactivated previously to the flight.

5.3.1 Sensorial Equipment

The UAV has been equipped with the multispectral camera array Tetracam MCAW. It is a composition of six individual cameras with a focal length of 9.6 mm and a snapshot shutter. Its CMOS sensors with a size of 1280x1024 pixels and a radiometric sensitivity of 10bit have been equipped with customized spectral filters according to Table 3. These narrow filters were selected to be able to derive the relevant spectral indices, like NDVI and PRI.

Band	Center Wavelength (nm)	Bandwidth FWHM (nm)
Green	530.7	3
Green-Yellow	550.0	10
Yellow-Green	570.0	10
Red	680.0	10
Red-Edge	720.0	10
Near Infrared	900.0	10

Table 3 Spectral characteristics of the Tetracam MCAW.

Similarly to the UGV, a custom Sony α5100 RGB is used as a counterpart to the multispectral camera, because of its high geometrical resolution and its robust design. To achieve high quality close range images with a large field of view, the camera has been equipped with an optical lens (Sony SEL-35F18) having 35 mm focal length and F2.0 light intensity.

The ThermalCapture 2.0 thermal camera contains a FLIR Tau2 model equipped with a 19 mm lens and a thermal sensor of 640x512 pixels with a radiometric industrial grade sensitivity of 0.03K and a frame capture rate of 30 Hz. The device records fully radiometric information per pixel [50]. The inherent thermal camera sensor is one of the most widely used camera type for UAV applications.

5.4 IoT Agrometeorologic Monitoring Network

An IoT agrometeorological monitoring network has been developed within the PANTHEON project and deployed in the experimental field to continuously monitor the environmental conditions of the orchard. This IoT network, which relies on LoRa (Long Range), i.e., a communication technology for long-range transmissions (more than 10 km in rural areas) with low power consumption, consists of the following modules:

- 1 weather station to collect meteorological data;
- 9 LoRa nodes to record humidity and temperature data of the soil;
- 1 LoRA/RoS Gateway of the network.

Fig. 18 Weather Station.

The modules of the network collect data from the sensors at a desired rate and send them to the Gateway, which is responsible for converting data into the ROS standard for storage in the primary DB server. The gateway interfaces the LoRa network with the WNB, creating a convenient decoupling between the IoT network and the ROS network infrastructure. Notably, this decoupling is motivated by the fact that while the IoT network must continuously collect data over time, the ROS-based network, which is exploited for instance by the ground robots, must operate intermittently.

Figure 18 shows the weather station which is responsible for monitoring the weather conditions, such as air humidity, air temperature, air pressure and rainfall. The station is powered by a 12 V - 7.2 A battery and a 10 W solar panel to ensure continuous operation over time. Table 4 indicates the weather station sensors along with their accuracy/resolution. The weather station is installed because of two reasons. First, it is required to calculate the VPD in the field for the derivation of CWSI. Second, information on precipitation, air humidity, temperature and solar radiation are valuable accompanying data to distinguish whether the observed stress derives from lack of irrigation or from the presence of pests and diseases. The collected data is transmitted by the station to the Gateway by exploiting a LoRa communication module.

Weather Station Data	Accuracy/Resolution
Rainfall (Davis DW-6463M)	resolution 0.2mm
Air Temperature (Sensirion SHT75)	minimum 0.04, typical 0.01, maximun 0.01 °C
Air Humidity (Sensirion SHT75)	minimum 0.4, typical 0.05, maximun 0.05 %RH
Wind speed/direction (Davis DW-6410M)	3 - 322 kph, sampling all the pulse in a 60s window time / 1 degree
Solar radiation (Davis DW-6450)	5% of full scale, full scale 1800 W/m2, resolution 1W/m2
Air pressure (First Sensor 144s)	70 mbar to 10 bar, 1 to 150 psi

Table 4 Weather Station.

Figure 19 depicts the LoRa nodes, which are scattered in the field and inserted in the soil at two different depths of 15cm and 40cm, respectively. These nodes are responsible for the monitoring of soil properties (such as soil moisture and soil temperature). They are powered by a 7.2V lithium battery at 6800 mA and a 5 W solar panel to enable continuous operation over time. Table 5 indicates the LoRa nodes sensors along with their accuracy/resolution. Soil moisture and soil temperature values measured by the LoRa nodes provide valuable reference data to monitor the water stress experiments. As per the weather station, the collected data is transmitted by each node to the Gateway by exploiting a LoRa communication module.

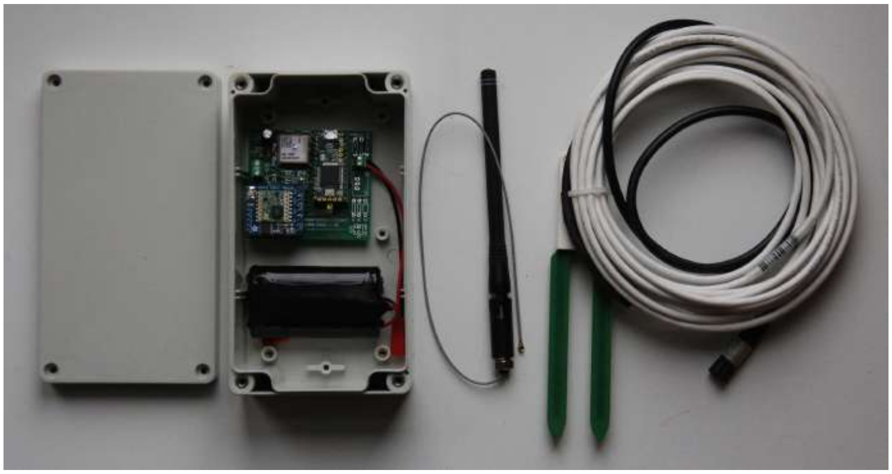

Fig. 19 Soil Monitoring Node.

Nodes Data	Accuracy/Resolution
Soil volumetric water content measurement (Deltaohom)	measuring principle Capacitive; measuring range 0-60% VWC; resolution 0.1% - accuracy (@23 °C) +/- 3 % between 0 and 50% VWC (standard mineral soil, EC $<$ 5 mS/cm)
Soil temperature (Deltaohom)	resolution 0,1 °C - accuracy +/- 0,5 °C

Table 5 LoRa node.

Figure 20 depicts the Gateway, which is based on a Raspberry 3B+ and is responsible for bridging the IoT agrometeorological monitoring network, for which communication is based on the LoRa technology, with the ROS network, for which the communication is instead based on standard TCP/IP over the WNB.

6 SCADA Software Architecture

Regarding data collection and analysis, the architecture of the software system has been defined with the aim of managing a high volume of data that are heterogeneous by nature, arrive at high speed, and come from various hazelnut fields. In addition, the system must be able to operate both in real-time, for the monitoring of plantations, and in batch mode, for the processing of large collections of historical data oriented to predictive analysis and support of strategic decisions. Another criterion of choice is the preference for open-source libraries and tools.

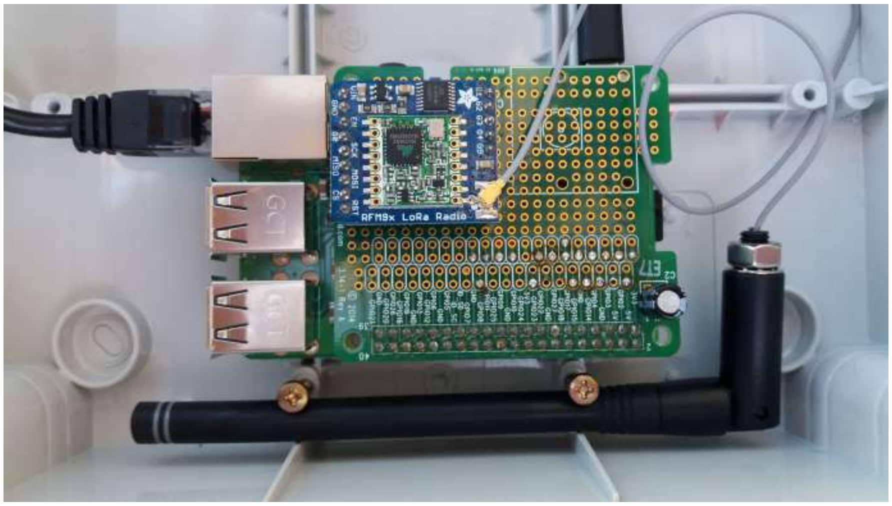

Fig. 20 IoT Agrometeorological Network Gateway.

This is a typical scenario of big data analysis [41] and for this reason we have chosen modern technologies based on the Hadoop ecosystem and NoSQL technologies [20, 22] able to support efficiently this kind of data processing.

6.1 Software Architecture

The architecture of the data collection and processing system capable of meeting the above requirements is shown in a schematic form in Figure 21 and is composed of three main components, which implement three operational levels:

- The “Data Collection and Pre-processing” layer (DCP layer in the following): this component is replicated for each hazelnut field and is dedicated to the collection of data from the various sources located in the field: sensors, weather stations, ground robots (UGV) and drones (UAV).
- The “Data Transfer” layer (DT layer in the following): this is a middleware that deals with the transfer of data between the other two levels, in both directions, and between the overall system and the final users of the software;
- The “Data Storage and Processing” layer (DSP layer or center in the following): it consists of a centralized unit in which all the data coming from the various DCP components are stored and on which massive analyses are carried out, mainly for knowledge extraction and decision support.

In the following, these three components will be described in more detail.

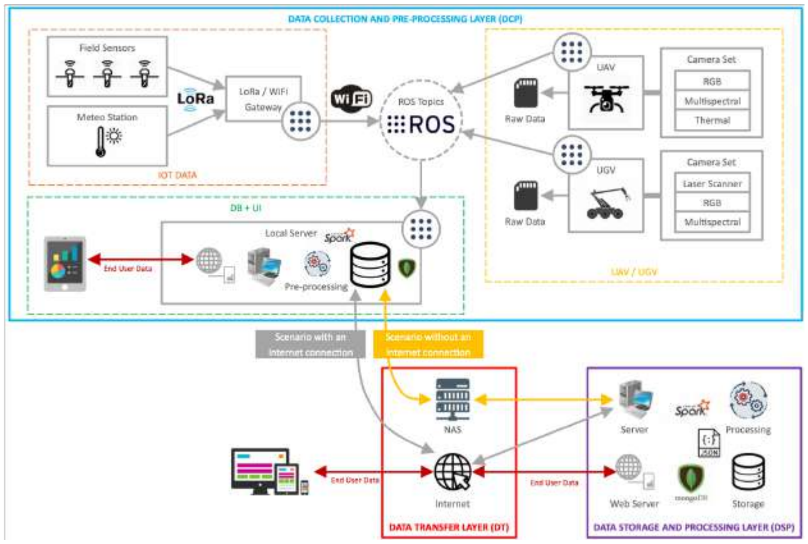

Fig. 21 The global architecture of the software system.

6.1.1 Data collection and Pre-processing Layer

Through a local communication network, the data coming from the *collection nodes* (sensors, weather stations, UGV and UAV) will be conveyed to the local server positioned in the warehouse near the hazelnut fields. The ROS protocol is used for data communication, as it is able to manage data transfers with all the collection nodes mentioned above (including the IoT nodes via a gateway with the LoRa network) and is based on the publish/subscribe mechanism, which allows the decoupling between data collection and data processing. However, data can also be stored on the internal mass storage of the various devices and then transferred manually to the local server. This guarantees, on the one hand, the possibility of not losing acquired data even in the event of a malfunction of the communication network and, on the other hand, of not occupying excessively the communication band, for example in the case of acquisitions of large spectral images by the UGVs.

The local server acts as a first point of collection and management of all the data coming from one hazelnut field. It is configured as a ROS node to communicate with the various collection nodes and will store data using MongoDB, a NoSQL database system. This choice was dictated by the amount of data to be managed, by their heterogeneity, and by the need to scale nicely as data volumes increase. In particular, MongoDB lends itself very well to IoT applications, especially those framed in the smart-farming area [42]. All raw data acquired from the field will be stored on the database together with the result of data processing carried out locally or in the data storage level, as described below.

More specifically, some pre-processing activities will be performed on the system with the aim of:

- carrying out operations of data cleaning and transformation, oriented for example to eliminate grossly incorrect data and to standardize formats;
- executing pre-aggregations to reduce the amount of data to be transmitted to the DSP layer and to make them more suitable for the subsequent analyses to be executed;
- performing, through a local software application, activity monitoring on the collected data and provide information to the farmers on the status of the field in real-time.

The local application will be Web-based, in order to be accessible using various types of devices, and will be developed using big data technologies, such as Spark, for processing large quantities of data at high speed. This application can be accessed directly by the operators in the field using the local server or through mobile devices, such as tablets and smartphones. An Internet connection is not required to access the application since it operates on the local database and so the network available in the field can be used for this purpose.

6.1.2 Data Transfer Layer

Data exchange between the database, stored in the local server, and the central database, located in the DSP layer, will occur using an Internet connection when available. If the area is not covered by an Internet connection, a portable device equipped with a large mass storage device, called NAS (Network-attached storage), will be used for data transfer. In this case, the NAS device will be physically transported from the hazelnut field to the central database. Figure 22 shows the two communication scenarios: with and without the presence of an Internet connection.

In both cases, only the data collected from the last data transfer (usually called Δ-*data*) is actually copied. In the first scenario, Δ-data is directly transferred from the local to the central database and added to the "Global Collected Data" (1). The results of data analysis carried out in the DSP center are stored in a special archive called "Global Processed Data" (2). The results obtained from Δ-data (called "New Processed Data" in Figure 22) are transferred back to the local server (3) so that they can be exploited by users operating on the field even when the DSP center is not directly accessible or the communication is low. In the second scenario, data transfer needs an intermediate step involving the storage and the transport of Δ-data in NAS devices.

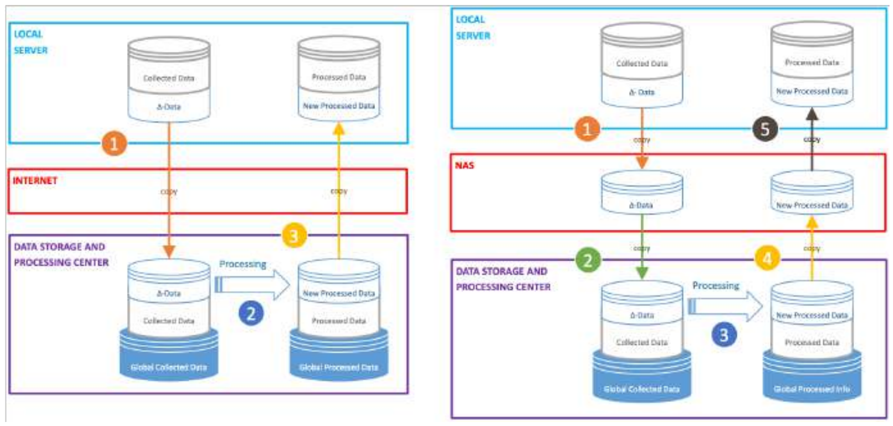

Fig. 22 Data exchange between the DCP and the DSP components.

6.1.3 Data storage and processing layer

The DSP center is equipped with a computer infrastructure that is based on a cluster of computers whose nodes can be dynamically increased according to the requirements of storage and processing of the overall application. These requirements are driven by: the volume of data to be stored, the data replication policies, the physical distance between the DSP center and the hazelnut fields (e.g., located in different countries) that can be relieved by geographical clustering, and the need to support high workloads of data processing.

The computing nodes of the cluster will be equipped with CPUs supporting parallel computation and with a RAM and a mass storage of a size suitable for the overall needs of data storage and processing. All the collected data will be also stored in a MongoDB database, in order to be easily exchanged with the databases saved in local servers of the DCP layer. Data processing and analysis is activated at the DSP center when new raw data arrives from the DCP layer. The results of data processing are stored in the database itself.

All of these choices follow the so called “data lake” approach, in which a large repository is used for storing any kind of data, coming from different sources and possibly heterogeneous, for later use, aimed usually at knowledge extraction [39].

6.2 Features of the Software Application

Figure 23 shows a sketch of the entire software application from the user point of view. The application is Web-based and provides to the users two main features,

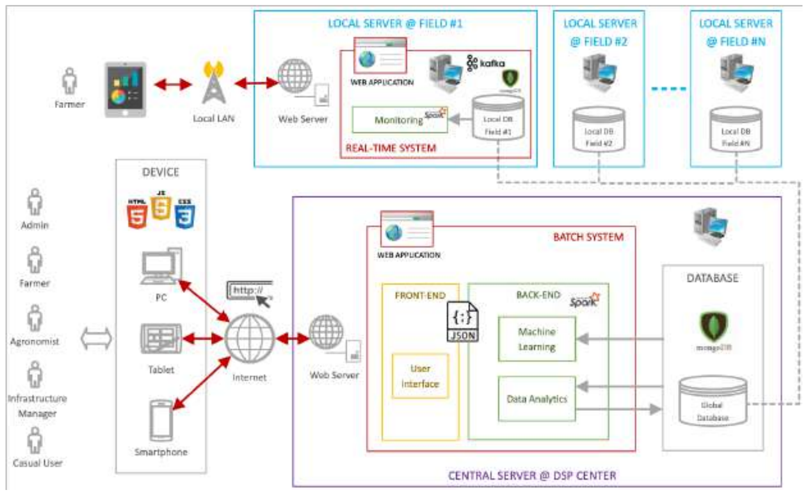

Fig. 23 The overall application from the user point of view.

which are supported by two sub-components of the software system:

- the real-time monitoring system, which operates in each hazelnut field on the data collected locally, combined appropriately with the results of large-scale analyses carried out in the central system. This component is in charge of producing the indicators mentioned in previous sections able to describe the current status of the field, such as the water stress of trees and the presence of pests or diseases; this system will also monitor the weather conditions and their impact on the health of the plantation;
- the batch processing system, which supports decision making and predictive analysis by operating in the DSP center on all the available data that has been collected in various hazelnut fields and stored in the central server. This component is in charge of applying analytics and machine learning techniques for knowledge discovery over agricultural data such as time-series analysis, data clustering, automatic classification, and outliers detection, with the already mentioned goals of product estimation and automated prediction, among others.

A data anomaly detection algorithm will also be developed on the batch processing system to detect malfunctions of the SCADA infrastructure. It will include data driven and model-based approaches to validate the gathered measurements. This validation will exploit the correlation between the measurements provided by the ground and aerial robots, as well as statistical change detection/isolation algorithms to perform the early detection of malfunctions. This will allow maintenance operations before a fault has a significant effect on the system.

Many users have different roles in accessing system features via a Web browser and through different devices. The application is equipped with a front-end, which presents the result of data analyses to the user, and a back-end, which accesses the database (local or central) and manipulates the data stored in it. The front-end will be designed with the goal of producing modern, easy-to-use and standard-based user interfaces.

Finally, driven by the software and hardware requirements, the following choices have been made for data organization and for the software solutions used for the development and usage of the application:

- All data will be represented in JSON, an open-standard file format that can be used for describing both structured and unstructured information;
- The batch will be implemented using Spark, an open-source distributed and general-purpose framework for data analytics over big data that supports machine learning;
- To implement the real-time system, we will use Kafka, an open-source stream-processing platform to handle efficiently real-time data feeds, and Spark Streaming, a component of Spark supporting real-time analysis over stream;
- As we have already mentioned, both the local and the global database will be implemented using MongoDB, an open-source, NoSQL database management system that stores and manipulates data in JSON format;
- Linux will be used as the operating system of all the computers, C++ will be used for the automation of robots, and Python will be used as the host language for data processing;
- HTML, CSS and JavaScript will be used for the implementation of the client component of the application.

7 Conclusions

In this chapter, we described the vision of the H2020 project PANTHEON, which focuses on the development of the agricultural equivalent of an industrial SCADA system to be used for the precision farming of orchards. In this regard, we first presented the current state-of-the-art in the context of precision farming at large, as well as in the context of large-scale (hazelnut) orchards in order to highlight major limitations of current best-practice. Indeed, this motivated the objective of the PANTHEON project, that is to propose an integrated system composed of heterogeneous robotic components along with an IoT agrometeorological network and a central computing unit to acquire information at the resolution of the individual plant. We explained how this architecture, by reaching the resolution of the single tree, compared to the current state-of-the-art in precision farming for large-scale orchards, allows to drastically increase the detection of possible limiting factors of each plant individually, and react accordingly. We also described how this new paradigm to precision farming may lead to a better average health of the orchard, and to an increased effectiveness of IPM activities. Thus, leading to an increase of the orchard production while, at the same time, being more cost-effective and environmentally-friendly. We also described the experimental setup that has been built within the PANTHEON project to validate the effectiveness of the proposed SCADA system in a real-world (1:1 scale) hazelnut orchard. To conclude, we believe that the proposed SCADA paradigm for Precision Agriculture may represent an attractive opportunity for the design of a novel real-time software architecture. In other words, by allowing the processing of massive amounts of datasets derived from the SCADA architecture, it will be possible to step-up the current effectiveness of PA methodologies by providing real time answers to the questions posed by farm managers, when in need of timely decisions.

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