Advanced Wireless Sensor Nodes and Networks for Agricultural Applications

Z. Stamenković, S. Randjić, I. Santamaria, U. Pešović, G. Panić, and S. Tanasković

Abstract — A review of advanced wireless sensor nodes, networks, and applications in precision agriculture has been presented. Features of several commercial and prototype sensor node platforms designed and implemented for agricultural applications have been described. Basics of sensor network protocols and topologies have been reviewed together with numerous applications. Advanced machine learning approaches in this field (especially, Kernel Methods, Gaussian Processes, and Deep Neural Networks) have also been discussed.

***Keywords* — Sensor network, agriculture, data processing**

I. Introduction

Due to the limited farming capacity, climate changes and various stress factors affecting agricultural production, increasing the quality and yield of feed and food will only be possible by using advanced agro-meteorological measures. In such a process, the real-time control and treatment of crops or terrestrial animals (so-called precision agriculture) is provided by an information technology based on smart sensor monitoring of parameters relevant for their development:

1. Meteorological parameters (temperature, humidity, carbon-dioxide and pollutant content, insolation, wind direction and speed, etc.) are the most crucial input in agriculture. Their monitoring on short-term basis or in real time is necessity.
2. Harmful organisms (or pests) like insects, plant pathogens, and weeds affect the plant and animal health causing numerous diseases. Pesticides are used to suppress (reduce or eliminate) the attack of different pests and diseases, and secure the quality and yield in plant production. At the same time, there are many concerns regarding their effects on the environment, animals, and human health.
3. Disorders in plants and animals substantially impact the agricultural productivity and public health (vector-borne diseases). Therefore, all components of management (data-monitoring, video-surveillance, epidemiology, diagnostics, prevention, and risk estimation) should be included.

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Taking into account numerous studies published in the last decade [1]-[25], wireless sensor networks (WSN) are the most promising information technology for agricultural applications.

This paper presents hardware and software tools, as well as network protocols and data processing techniques that can be applied in different fields of the precision agriculture: irrigation, nutrition and hydrozoning of plants, crops, food and feed inspection, and animal health monitoring.

Section II introduces sensor nodes as hardware platforms required for sensing and measurement of the monitored parameters, and preprocessing and wireless transmission of the prepared data. Section III describes network protocols, mainly, the data link layer and programmability features. Selected applications are presented in Section IV. Section V deals with data processing algorithms that identify the key dependences in observed sensor node data. Conclusions are drawn in Section VI.

II. Wireless Sensor Nodes

Sensors are compact, highly-accurate, power-efficient, and reliable electrical devices that have to be integrated with other electronic components in a sensor node (Figure 1). A wireless sensor node is equipped with a microcontroller, a radio device, and a number of dedicated sensors. The complete system is powered on with a rechargeable battery. Recharging is provided by some of the energy harvesting devices, usually, solar panels or wind mill generators.

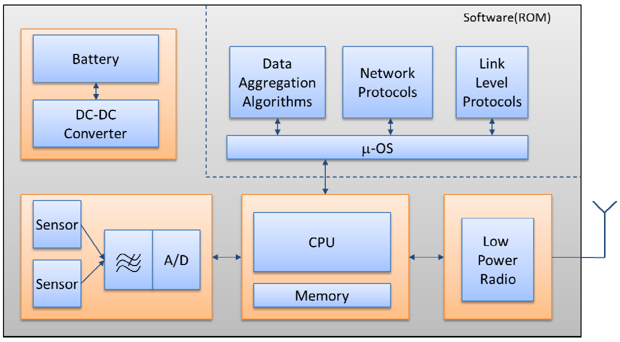

Figure 1: Architecture of a wireless sensor node

As sensor nodes in precision agriculture applications are deployed in thousands, their two most important features should be:

High readiness as a maturity for field deployment in terms of economic and engineering efficiency, and

High scalability to distributed agricultural monitoring tasks and, consequently, small size and low price to scale up to many distributed systems.

These nodes can communicate with a gateway, which has the capability of communicating with other networks, such as a LAN, WLAN, WPAN, and cellular network. Wireless sensor nodes, available on the market, include temperature sensors, humidity sensors, barometric pressure sensors, soil moisture sensors, soil temperature sensors, wind speed sensors, rainfall meters, light sensors, and solar radiation sensors. They can use various wireless standards to communicate among themselves.

Wireless LAN (IEEE 802.11) is a flexible data communication protocol implemented to extend a wired local area network, such as the Ethernet. The bandwidth of 802.11b is 11 Mbits and it operates at 2.4 GHz frequency. Bluetooth (IEEE 802.15.1) is a wireless protocol that is used for short-range communication. It uses the 2.4 GHz radio band to communicate at 1 Mbit between up to eight devices. The Bluetooth is considered a cable replacement for mobile devices. It is mainly designed to maximize the ad hoc networking functionality. ZigBee (IEEE 802.15.4) is considered the most promising communication protocol for wireless sensor networks. It adds network, security, and application software to the IEEE 802.15.4 standard which is a physical radio specification (for 2.4 GHz, 915 MHz, and 868 MHz bands) providing for low data rate connectivity among relatively simple devices that consume little power and connect over short distances. It is ideal for sensing, monitoring, and control applications. Table 1 compares these three wireless standards that are most suitable for wireless sensor networks in agriculture.

Table 1: Comparison of WLAN, Bluetooth and ZigBee [1]

Feature	WLAN	Bluetooth	ZigBee
Radio	DSSS	FHSS	DSSS
Data rate	11 Mbps	1 Mbps	250 kbps
Nodes/master	32	7	64000
Latency	up to 3 s	up to 10 s	30 ms
Data type	Video, audio, graphics, pictures, files	Audio, graphics, pictures, files	Small data packets
Range	100 m	10 m	70 m
Extendibility	Roaming possible	No	Yes
Battery life	Hours	1 week	> 1 year
Cost	9 US$	6 US$	3 US$
Complexity	Complex	Very complex	Simple

There are various hardware platforms (sensor nodes) on the market that can be used for agricultural applications: MICAz™, TelosB™, IRIS™, Imote2™ (general-purpose), Waspmote™, eKo™ (customized), and others. These nodes include the embedded low-cost sensors and necessary electronics to connect with external instruments.

A sensor node based on the TNOde platform (quite similar to the Mica2 platform but with the Mica2Dot form factor) has been described in [2]. A TNOde together with a battery is packed into a waterproof PVC-based casing.

A hardware platform inspired by the original Berkeley mote, called Fleck, has been presented in [3]. This device incorporates numerous design features that make the platform ideal for long-term outdoor use: a Nordic radio with a range of 1 km that operates on the 433-MHz (Fleck-1 and Fleck-2) or 915-MHz (Fleck-3) band, an integral solar battery charging circuit, and many sensors and sensor interfaces.

MPWiNodeZ [6] is based on a wireless microcontroller JN5121 from Jennic (now part of NXP Semiconductors) that comprises an 802.15.4 RF transceiver and the ZigBee stack. By employing a scaled-down version of the IEEE 1451.1 object model for smart sensors, this device can convert raw data from low-cost analog sensors into meaningful information. Besides the microcontroller, it includes an external 12-bit A/D converter with eight single-ended analog inputs.

A wireless sensor node (GAIA Soil-Mote) with a SDI-12 interface and IP67 protection level has been described in [7]. The node allows for the installation of a large number of agricultural sensors in a crop, with wireless data transfer to a centrally-located base station. Wireless communication is achieved with a transceiver compliant to the IEEE 802.15.4 standard. The software implementation is based on TinyOS.

A sensor node capable of microenvironment information acquisition, data preprocessing, and communication with a water potential sensing station, has been proposed in [11]. ATmega128 microcontroller has been selected because of ultra-low power consumption and wide work-temperature tolerance. The data can be acquired through eight SHT75 interfaces, eight analogue voltage inputs, a serial interface to canopy temperature sensor, and a pulse signal interface to wind speed sensor.

WSN802G node [12] is connected to the various sensors with analogue outputs via a multiplexer used for signal gating. A General Purpose Input/Output (GPIO) of the node selects two particular signals to be sent to ADC. The measured and converted signal values are then transferred to a selected server connected to same network via a standard wireless router.

A customized sensor node composed of the ARM Cortex M1 processor with memory, A/D converter with multiplexer, and I/O interface for integrating digital peripherals like USB, UART, SPI, and I^2C has been presented in [17].

A sensor node based on GSM technology has been proposed in [19]. The two sensors (LM35 and SY-HS-230) are connected to MCP3208 analog-to-digital converter and AT89S52 microcontroller. The microcontroller compares the received values from ADC with the pre-loaded values of temperature and humidity and sends the indication signal.

XBee wireless sensor node and network technology [21] has been introduced by XBee alliance (Philips, Motorola, Honeywell, Invensys, and Mitsubishi Electric) under IEEE 802.15.4 standard. It operates in the 2.4 GHz band with a data transfer rate of 250 kbps and it supports peer to peer, point to point and point to multipoint networking methods. The node comprises a moisture sensor, microcontroller (PIC 16F876A), and XBee communication module. This node sends data to the hub that is connected to the PC in order to deposit data into a database.

IHPNode has been developed as a flexible and modular hardware platform for WSN and Internet of Things [26]. It is based on the MSP430F5438A microcontroller and three RF transceivers, one working in the 868 MHz and two working in the 2.4 GHz frequency band. The two of these (CC1101 and CC2500) are supporting flexible proprietary networking protocols, while the third (CC2520) provides a network coprocessor for ZigBee protocol integration.

An embedded sensor node microcontroller (TNODE) designed to support wireless sensor network applications with high security demands has been described in [27]. This ASIC chip features a low-power 16-bit IPMS430 processor, DSSS baseband, advanced crypto accelerators, embedded flash and data RAM, and 8-channel 12-bit analog-to-digital converter, as well as the advanced low power techniques like clock-gating, power-gating, and frequency-scaling [28].

Waspmote™ [29] allows monitoring multiple physical parameters involving a wide range of applications. It has been provided with sensors for air and soil temperature and humidity, luminosity, solar visible radiation, wind speed and direction, rainfall, atmospheric pressure, leaf wetness, and fruit diameter. Up to 15 sensors can be connected at the same time. The Waspmote agriculture board 2.0 is shown in Figure 2.

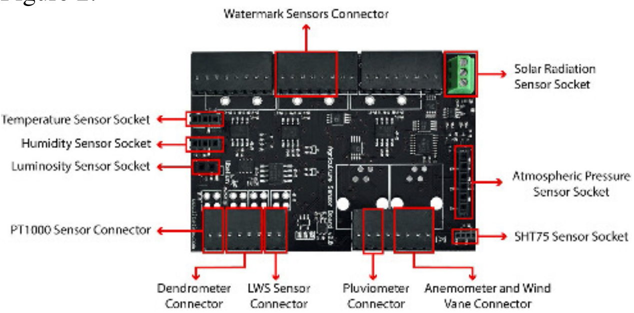

Figure 2: Upper side of Waspmote agriculture board

eKo™ node [30] comprises two types of nodes and can be used to monitor ambient temperature, relative humidity, radiation and barometric pressure. Moreover, thanks to their protective casing, these nodes can be used for both open-air and greenhouse crops. It incorporates a small solar panel and can be linked to up to four sensors.

III. Wireless Sensor Networks

Wireless Sensor Network (WSN) is a type of wireless network consisting of a number of sensor nodes which are distributed on a geographical area in order to gather environmental parameters and send collected data through the network to a central node for data fusion and further distribution. Wireless sensor networks use wireless communication, so each sensor node, besides sensing functionality, has communication functionality implemented in form of a network protocol. Network protocols are designed as a layered structure, called protocol stack, in which each layer has the specific functionality. Layered structure of network protocols enables that same upper layer services can be provided no matter of functionality of lower layers. Main design goal for network protocols for WSN is to increase node's energy efficiency in order to prolong the node's lifetime. Besides use of energy efficient hardware, the energy savings can be achieved through various network protocol layers.

Physical layer in WSN protocol stack specifies set of requirements and functionalities for WSN transceiver. Wireless transceivers most commonly use radio waves for communication, but light or sound waves can be used instead in some specific applications. For example, light and radio waves poorly propagate in underwater and underground environment which requires use of ultrasound based communication. WSN radio transceivers are monolithically highly integrated components which include transmiter and receiver on same silicon chip, which share common antenna. Radio receivers for WSN networks are designed for low power, low data rate radio transmission and use advanced digital modulation and coding techniques. Most WSN radio transceivers operate in license free radio band using signal-spreading techniques such as DSSS (Direct-Sequence Spread Spectrum) of FHSS (Frequency Hopping Spread Spectrum) in order to enable coexistence with other types of radio devices which also operate in these bands. More advanced radio transceivers use the pulse position modulation in wide frequency bands known as UWB (Ultra Wide Band). Also, the advanced transceivers can use multiple antennas for realization of MIMO (Multiple Input Multiple Output) communication or guide radio signal propagation in a certain direction using beamforming techniques.

Main goal for MAC (Medium Access Control) protocols is to provide efficient access to the shared medium by avoiding collisions between nodes. MAC protocols for WSN use long periods of inactivity to fully exploit low power modes of the node's hardware components in order to maximally extend battery life. These modes increase the energy efficiency but create problems in the exchange of information between nodes. Depending on organization of the medium access, the two types of MAC protocols can be defined: time-scheduled and event-driven protocols [31], [32], [33]. Time-scheduled protocols use a time schedule for channel access defined by the central network node, which is followed by all other nodes in the network. Communication in the active period is divided into time slots. These time slots are reserved either for the specific device or for nodes content in order to gain access to the time slot. During the inactive period, all nodes in the network are inactive. Time-scheduled MAC protocols increase energy efficiency because they eliminate the effects such as packet collision, packet overhearing, idle listening, and over-emitting which cause serious energy loss. On the other hand, this type of centralized protocols increases latency and is poorly adaptable to changes of the network topology. Event-driven protocols enable data transmission at any time, so this type of MAC protocols offers low latency. Since there is no predetermined time schedule, these protocols are also highly adaptable and scalable to network topology changes. They are not energy efficient so as time-scheduled protocols due to idle listening, packet collision, and packet overhearing.

A network layer in communication protocol is necessary if the network coverage area is larger than the radio range of a single coordinator node. Since in such a type of network, a node cannot communicate to all other nodes, it needs to use other nodes as relays to deliver the message to the destination node. Network topology defines the type of routing protocols to be used. The cluster tree topology represents a centralized, well-planned topology, where each node can communicate only with its parent or child node. Cluster tree networks use a simple address allocation routing protocol [34] in which a node can easily determine where the packet should be transferred, to its parent node or one of the child nodes, as shown on Figure 3. Such routing protocols are simple end energy efficient but they are not reliable and adaptable to network topology changes, since these changes would require reforming of the entire cluster tree. On the other hand, mesh networks are much more reliable and adaptable since they allow for communication with almost any node in its radio range, which creates a number of redundant paths. Networks with a mesh topology usually require implementation of complex routing protocols in order to achieve high energy-efficiency [35]. If a node on active path becomes inaccessible, the routing protocol simply finds an alternate route without affecting operation on entire network, as shown in Figure 4.

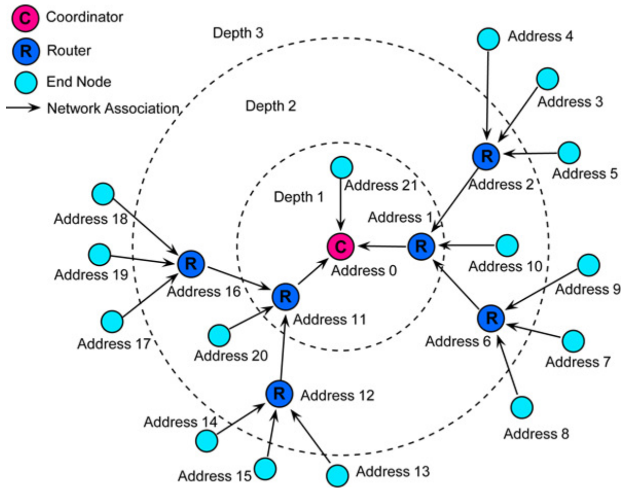

Figure 3: Cluster tree topology

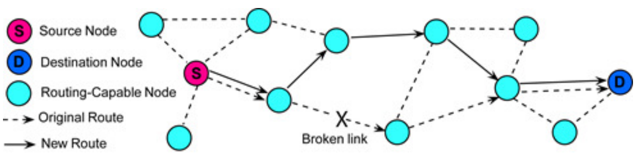

Figure 4: Mesh topology

An energy-efficient network layer routing protocol for agricultural applications has been recently proposed in [36]. This threshold-sensitive region-based hybrid routing protocol uses a regional static clustering approach to provide efficient coverage of the agricultural area. The fuzzy-based hybrid routing approach is used for transmitting the sensed data to a base station that minimizes the energy consumption of nodes.

Role of application layer is to provide an interface between user applications and protocol stack. It may also provide partitioning of user data onto packets and use of compression techniques in order to reduce amount of data that needs to be sent through WSN.

WSN node includes numerous hardware resources which are usually allocated in an orderly and controlled manner by the node's operating system (OS) [37]. OS enables easier development of target applications, since the application programmer can invoke already implemented OS services through system calls.

IV. Applications

Wireless sensor networks have been extensively applied in agriculture. Thanks to the deployment of sensor nodes on a large area, farmers can receive comprehensive information on the condition of environment and crops. Due to the low energy consumption, small dimensions and simple communication protocols, intelligent sensor nodes can be distributed with a high density. This makes possible to measure accurately climate and plant parameters in the area that is being monitored. At the same time, the data is obtained in real time and the decisions are made on the basis of real field data, not statistical values.

By measuring the critical parameters like temperature, humidity, insolation, moisture, carbon-dioxide and nitrogen concentration, or detecting the economically important pests, the farmer is able to react promptly and treat crops and animals accordingly. Gathered data of deployed WSN is transmitted by a WSN gateway to a central computer which can store, analyze, and, if necessary, process it. By linking the central computer to the Internet (by a Web server or cloud system), the processed data is accepted and distributed to all concerned parties (farmers, technicians, specialists, manufacturers, and retailers). This data is used to increase the yield and quality of feed and food. Structure of an agro-meteorological sensor network based on a ZigBee sensor node and a ZigBee network gateway to the Internet is presented in Figure 5. On the basis of the information contained within this system, it is possible to develop a decision support system which can affect the course of agricultural production and help to protect healthy and treat diseased plants and crops, in particular, taking into account the temporal and spatial variability of environmental parameters.

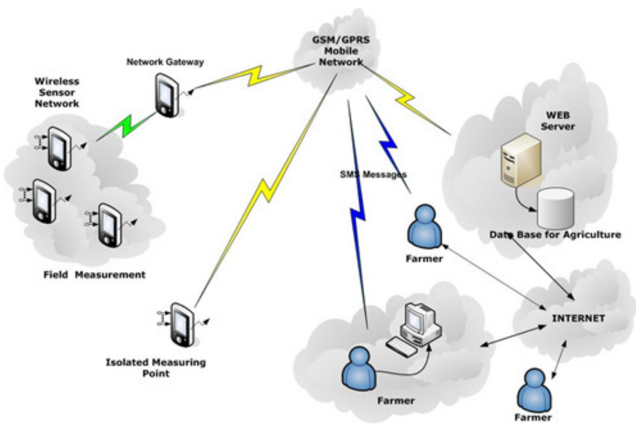

Figure 5: Structure of a decision support information system

The crop quality and quantity is drastically reduced by lack of irrigated water. On the other hand, overbalance of water will destitute soil from nutrients and provoke different microbial infections. Measuring the soil moisture, accurate water needs in the crops and fields can be determined. Soil moisture deepens on many factors such as soil type, air temperature, evaporation, etc. Therefore, a precise soil and air moisture control using WSN can drastically improve the production. An example of using WSN and mobile phones in agricultural crop monitoring has been presented in [38]. This is done by intimating the farmers using mobile phones to monitor soil moisture, temperature, pH level, and weather condition. If the air temperature goes beyond 45 °C, it sends an alert message to the farmers and automatically turns on a pumping motor which pours water in the field. A shunt motor will be turned on if the level of water in the field goes above the threshold value. The pH value limit is 7: if the pH value goes above or below 7, a sprinkling motor will be turned on.

Moreover, the greenhouse production requires control of air temperature and relative humidity, which is achieved with combination of heating, ventilation, and mist spraying. Assurance of optimal climate conditions has a direct influence on crop growth performance, but it usually increases the required equipment cost. In order to reduce this problem, an event-based system in combination with wireless sensor networks has been proposed for greenhouse climate control [39]. Low-frequency dynamics variables are controlled and corrective actions are carried out against events caused by external disturbances. Using WSN, an online microclimate monitoring and control system for greenhouses has recently been developed [40]. The system is field-tested in a greenhouse in Punjab (India), evaluating its measurement capabilities and network performance in real time.

Insects can be detected by using the *species specific* pheromone traps which attract the males of different species. Senor node with a camera can picture and count the caught specimens in order to detect their presence in the agricultural field and define an economic threshold [41]. In this way, the right time for chemical treatment (for example, the use of pesticides) can be determined. Practically, this technic enables reducing the amount of applied pesticides that leads to a decreased level of residues in fruits and edible plant parts. Also, side effects to beneficial organisms and pollinators, especially bees, become insignificant. Sensor nodes with cameras can be also used to visually monitor plant habitus and register symptoms of presence of different harmful organisms.

An important aspect of WSN application in agriculture is to provide quality living conditions for honey bees during the growing season. Intelligent sensors and their network can be used for monitoring bee colonies and their behavior [42], [43]. A broad range of sensors can be deployed for monitoring conditions within a beehive including oxygen, carbon dioxide, pollutant levels, temperature, and humidity. Meteorological and environmental conditions outside the hive can be also monitored. This is particularly important in terms of the safe application of pesticides in the areas populated by honey bee colonies.

Fruit orchards are highly susceptible on frost during the blossoming. WSN can be used to detect frosts (which could damage the fruit embryo) and initiate defensive measures, such as generation of smoke or spraying mist with special protective agent [44].

Integrating WSN technology with latest developments of Internet technology (Internet of Things), a system for identification of rodents and activation of repellent in grain stores has been designed [45].

V. Data Processing and Knowledge Extraction

This section is a brief survey of the state-of-the-art data processing and machine learning techniques [46] that can be used to acquire knowledge in agro-meteorological wireless sensor networks. In a WSN, each sensor node is capable of only a limited amount of processing, being typically restricted to signal conditioning, filtering, and simple distributed averaging or detection. Then, these filtered or averaged measurements are wirelessly transmitted to a central entity where more sophisticated machine learning techniques can be applied to infer relevant agro-meteorological parameters and their relationships. Many of these techniques can also be applied in a distributed fashion, which is a requirement to reduce the energy consumption and extend the network lifetime.

The use of machine learning techniques in this field dates back to the nineties, where some basic classification tools were applied to identify rules for the diagnosis of soybean diseases. In this early application, the similarity-based learning program AQ11 was used to analyze data from over 600 questionnaires describing diseased plants [47]. Each plant was assigned to one of 17 disease categories by an expert collaborator, who used a variety of measurements describing the condition of the plant. Figure 6 shows a sample record with values of some of the attributes given in italics.

Environmental descriptors	Condition of leaves
time of occurrence *July*	leaf spots
precipitation *above normal*	leaf spot color
temperature *normal*	color of spot on other side
cropping history *4 years*	yellow leaf spot halos
damaged area *whole fields*	leaf spot margins
severity *mild*	raised leaf spots
plant height *normal*	leaf spot growth
Condition of seed *normal*	leaf spot size
mold growth *absent*	shot-holing
discoloration *absent*	shredding
discoloration color *absent*	leaf malformation
size *normal*	premature defoliation
shriveling *absent*	leaf mildew growth
	leaf discoloration
Condition of fruit pods *normal*	position of affected leaves
fruit pods *normal*	condition of lower leaves
fruit spots *absent*	leaf withering and wilting

Figure 6: Example of the soybean disease classification

The diagnostic rule for the *Rhizoctonia root rot* had been generated by AQ11, along with a rule for every other disease category, from a set of training instances which were carefully selected from the corpus of cases as being quite different from each other.

In the recent years, however, we have witnessed an explosion of sophisticated machine learning techniques such as Kernel Methods [48], Gaussian Processes [49] or Deep Neural Networks [50] which are showing impressive results in many applications such as speech or image recognition (to mention just two representative examples).

In the field of precision agriculture there is also a need to develop and incorporate novel knowledge extraction algorithms and predictive analysis mechanisms over huge volumes of data collected by WSNs to enhance decision-making processes. Therefore, these data-driven machine learning techniques and, in particular Gaussian Processes (GPs), might as well be ready for widespread application in the field of precision agriculture.

In particular, rainfall patterns, water supply or the fertilizer usage patterns can be viewed and analyzed as time series that convey useful information to improve the yield and quality of crops. Most of these problems can be cast as regression or classification problems that can be efficiently solved within the GPs framework [51]. Gaussian Processes are the Bayesian state-of-the-art tools for discriminative machine learning (for example, regression, classification, and dimensionality reduction) first proposed by O'Hagan and Kingman [52].

GPs can be interpreted as a family of kernel methods with the additional advantage of providing a full conditional statistical description for the predicted variable (e.g. soil moisture or nitrogen concentration), which can be primarily used to establish the confidence intervals and set the hyper -parameters. In short, GPs assume that a GP prior governs the set of possible latent functions (which are unobserved) and the likelihood (of the latent function) and observations shape this prior to produce the posterior probabilistic estimates. Consequently, the joint distribution of training and test data is a multidimensional Gaussian and the predicted distribution is estimated by conditioning on the training data. Figure 7 shows an example of the probabilistic estimates provided by GP regression: inferred latent function, representing any agro-meteorological time series, is shown as a blue curve, noisy measurements taken by WSN are represented by red crosses, and data 95%-confidence interval directly provided by the GP regression is grey colored.

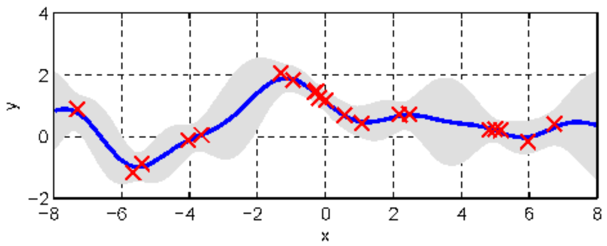

Figure 7: GP regression over the noisy data

As a couple of representative examples, GPs have been applied for creating detailed soil maps with predictive properties [53], which is an expensive and time-consuming task. More recently, Holman et al. [54] conducted a study using GPs to estimate reference evapotranspiration, which refers to the combination evaporation from the soil surface and transpiration from the crop, for irrigation management.

A received-signal-strength-indication based distributed Bayesian localization algorithm for solving the approximate inference problem has been presented in [55]. The algorithm is designed for precision agriculture applications, such as pest management and pH sensing in large farms, where greater power efficiency is needed but location accuracy is less demanding.

A related set of machine learning tools of interest for agricultural WSNs is provided by Kernel Methods, which are powerful nonlinear techniques built on the framework of reproducing kernel Hilbert spaces (RKHS). They are based on a nonlinear transformation of the data from the input space to a high-dimensional feature space, where it is more likely that the problem can be solved in a linear manner. Probably, the most well-known kernel methods are the so-called Support Vector Machines (SVM), which are powerful non-linear classifiers, typically used in the agricultural field for classifying crops and plants from remote sensing measurements [56]. Kernel Methods also provide powerful tools to estimate non-linear correlation between variables that might help to build accurate models for future precision agriculture applications. Using these tools, it is possible to estimate whether crop increase or decrease is associated with a specific pattern in the fertilizer use; or to understand the relationships between the soil characteristics and the nutrient status [57].

A novel method based on an Extreme Learning Machine (ELM) algorithm and KELM (Kernel based ELM) has been proposed in [58] to predict the microclimate in a practical greenhouse environment at a very short training time of 0.0222 s. Indoor temperature and humidity are measured as data samples via WSN nodes.

A major recent breakthrough in artificial intelligence has been the concept of deep learning and, especially, Deep Neural Networks (DNNs) [59], which have achieved impressive success in solving important challenges in many fields including speech recognition, natural language processing, computer vision and image processing. Since images are a key component of our envisioned WSN, DNNs will be an important component of our decision support system. DNNs use a cascade of multiple layers of simple nonlinear processing units (or linear convolutions) for feature extraction and transformation, where each layer uses the output from the previous layer as input. Figure 8 shows an example of a DNN. Although the fundamental principles behind DNNs are still under discussion, there is consensus that DNNs essentially establish a hierarchical and distributed representation of data, by means of which hidden data invariances are revealed [60]. Another important ingredient for the successful application of DNNs is the availability of large amounts of unlabeled data, which allows the unsupervised learning of the multiple representations of data in hidden layers. Although the application of DNNs in precision agriculture is still largely unexplored, some recent work [61] has also shown significant improvement in the classification of plant diseases from the images of plant leaves.

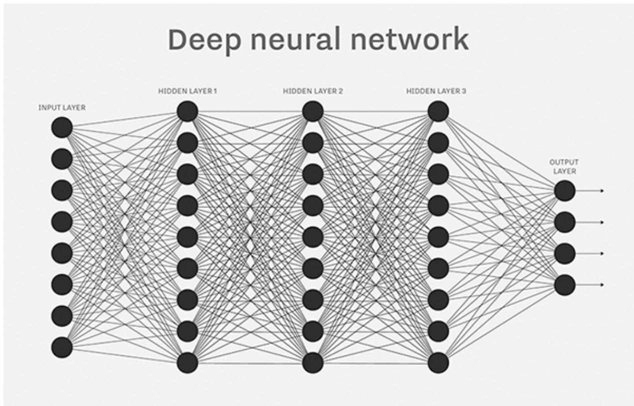

Figure 8: Architecture of a deep neural network

VI. Conclusion

Wireless sensors and their networks can be effectively employed in the agricultural sector. They help to gather and cross-correlate critical data to make meaningful and timely operating decisions that enhance the production yield and profitability.

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