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# *Soil moisture assessment with a waveguide spectrometer*

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**Abstract**— This paper describes a system for soil moisture measurement based on a waveguide spectrometer that acquires “gain” and “phase” spectra, with a frequency range of 1.5 – 2.7 GHz. The fundamental components of the system are a waveguide, containing TX and RX antennas, and an electronic circuit, generating the electromagnetic waves and elaborating data, driven by a microcontroller (MCU). This system was previously tested on samples created in laboratory, but a study of system behavior in environmental conditions was missing. Therefore, acquisition of measurements and samples were conducted on real soil, and these data were used to obtain a good calibration model between spectra and soil moisture values. Calibration coefficients were used to implement the moisture calculation directly in the MCU, obtaining a non-invasive and stand-alone system. The architecture shows promising results and prove the capability of electromagnetic waves to perform accurate and fast silty clay loam moisture assessments on a real environment.

**Keywords**— soil moisture, Partial Least Square Regression, waveguide spectroscopy, microwave

## I. INTRODUCTION

Nowadays, the most important and widespread techniques for indirect soil moisture assessment are Time Domain Reflectometry (TDR) and Frequency Domain Reflectometry (FDR). These are the primary alternative tools respect to the gold standard technique, the destructive and time-consuming thermogravimetric method [1-3]. Both TDR and FDR try to assess physical and chemical soil properties investigating soil dielectric properties [4]. These properties are related to the polarization of the molecules and described by a variable called apparent relative dielectric permittivity. This variable consists of a real component, that accounts for the energy stored in the system due to the alignment of dipoles, and an imaginary component that accounts for energy dissipation effects [5]. In particular, TDR and FDR are based on the fact that the apparent relative dielectric permittivity is much more affected by water ( $\epsilon'_{\text{water}} = 80$  at 20 °C) respect to air ( $\epsilon'_{\text{air}} = 1$ ) and solid particles ( $\epsilon'_{\text{soil}} = 3-7$ ) in the range of 100 MHz – 2 GHz.[6] This allows to correlate soil relative dielectric permittivity with the soil moisture through a calibration curve [1].

TDR principle is to use a probe to excite the soil with an electromagnetic impulse and measure their propagation time, directly related to the dielectric constant. These instruments need a specific calibration operation, related to the type of soil studied, which varies for textural properties, grain orientation and saline concentration [7, 9]. On the other side, FDR is based on the measurement of the charge time between plats of a capacitor probe, whose capacity is

influenced by the soil bulk electrical permittivity: the frequency of oscillation decreases with increasing moisture contents [10-12]. The latter, is the most widespread used technology, gaining more use, scientific attention and technical progress, being less time- and money-consuming, although it has worse performance in accuracy and precision. Moreover, in both techniques the probe must be in constant contact with the soil, making these approaches unstable during time [1]. This work focuses on a system that overcomes these issues, measuring the soil moisture starting from acquisition of “gain” and “phase” spectral data, through an open-ended waveguide.

In this manner the system is non-invasive and doesn't suffer from problems related to the probe insertion in the soil. The spectra are used as input for a multivariate statistical analysis called Partial Least Square Regression (PLSR), which permits to obtain a calibration model between spectra and soil moisture values. Calibration coefficients are used to implement the moisture calculation directly in the MCU of the system, allowing a fast and “stand-alone” measurement process.

## II. THE SYSTEM

The measurement system, shown in Fig.1, is composed of four principal parts: a waveguide, a gain-phase detector, a RF source and a data-control and elaboration system.



Fig. 1. System layout

The waveguide has a cut-off frequency of 1.56 GHz, thanks to its dimensions of 96 mm × 46 mm × 245 mm, and contains the TX and RX antennas. This waveguide acts as a high-pass filter with this cut-off frequency, so the frequency sweep goes from this value up to 2.7 GHz, provided with a 13 dBm power from the RF source, which becomes 5.4 dBm (at 1.5GHz) and 4.3 dBm (at 2.7GHz) after the splitting.

The emitted and reflected waves are read and elaborated by the gain/phase detector (AD8302 by Analog Devices), that extract the gain (from -30 dB to 30 dB scaled to 30mV/dB) and the phase shift ( $0^\circ$  -  $180^\circ$  with 10mV/degree), which contain the moisture content information.

The RF source is made of two blocks in a chain: a Voltage Controlled Oscillator MiniCircuits ZX95-2700A and a Low Noise Amplifier (LNA) QORVO TQL9092. The first one takes the output voltage of the DAC as input and transforms it into an ideally sinusoidal wave.

Its most interesting features are the frequency of the wave, generated from 1.5 GHz to 2.7 GHz, the tuning voltage from 0.15 V to 25 V, the supply voltage of 5V, the low phase noise, and the typical output power of 3.3 dBm. However, this power is too low for the design specifications, so it is necessary to use the LNA amplifier, with an operating band from 0.6 to 4.2 GHz. Finally, the data control and elaboration system are composed of three modules: a microcontroller, a D/A converter, and a serial-USB converter. The microcontroller, a MICROCHIP PIC24FJ256GB606, manages the measurement process and the communication with the serial interface (UART/USB converter cable). It presents a SRAM data storage with a capacity of 32 Kbytes and 16-bit addresses: it is a very functional microcontroller for applications with significant amounts of data. The D/A converter connects the microchip with the VCO, converting the digital value provided by the microcontroller into an analog voltage. The data are sent by a USB cable to a PC (through MATLAB interface and GUI) or saved into a removable SD card. The whole schematic of the electronic circuit is shown in Fig. 2.

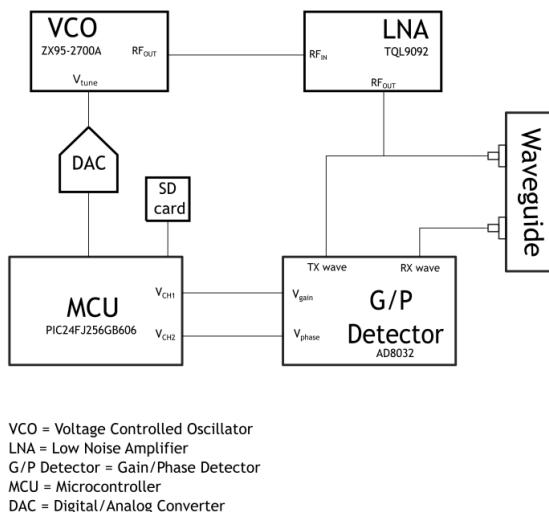


Fig. 2. Electronic system with an MCU architecture.

### III. METHOD

The first experimental phase consists in the acquisitions of measurements on a collection of samples of real soil. An analogous system was tested by Luciani et al. with good statistical results ( $R^2$  up to 0.909 in calibration), but only on samples created in the laboratory, without all the underground detritus and complications related to a real soil [8]. A total of 345 acquisitions were taken on a real soil in Romagna region (Italy), forming one of the two input dataset for statistical analysis. Acquisitions are done placing the waveguide on the soil, cleaned from superficial rocks and organic material. For each chosen location, three acquisitions were taken, rotating the system of about  $40^\circ$  between them. The measurement time for a single acquisition is about 45 s. For each of the three acquisitions a sample was taken with a coring technique, from which the soil moisture, within the first 10 cm of depth, was obtained by the gold-standard measurement, the thermogravimetric technique. A flowchart of the work is presented in Fig. 3, and images of system acquisition and samples extraction in Fig. 4.

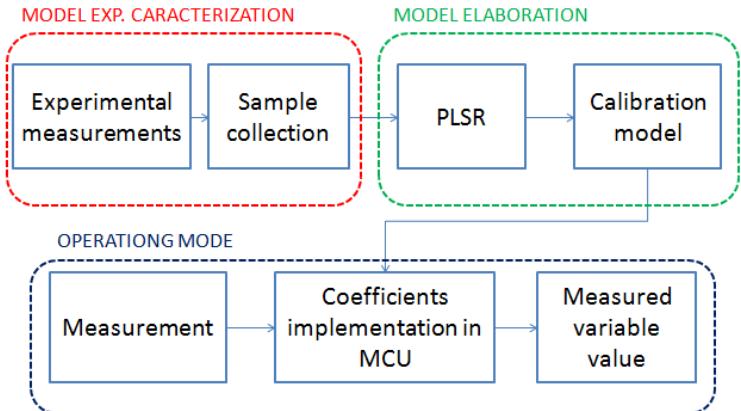


Fig. 3. Flowchart of the work on the non-invasive soil moisture sensor.



Fig. 4. System acquisition and soil samples coring on real soil.

At the end of this phase, a total of 115 samples and 345 acquisitions, each formed by 3700 values of “gain” and “phase”, were obtained, covering a moisture range from 9.3% to 31.7%. In Fig 5 the changes of mean soil moisture over the two months of measurements are reported, whereas Fig. 6 shown examples of gain and phase waveforms acquired at different soil moisture contents (%). The differences between the waveforms are caused by the influence in the spectra of the complex water-soil chemical-physical interactions. These experimental data were arranged in two different matrices in order to create the X (waveforms,  $3700 \times 345$ ) and Y (moisture values,  $345 \times 1$ ) input data sets for the statistical analysis, both subsequently divided into 2 different sub-dataset: one for calibration (80% of data) and one for validation (20% of data).

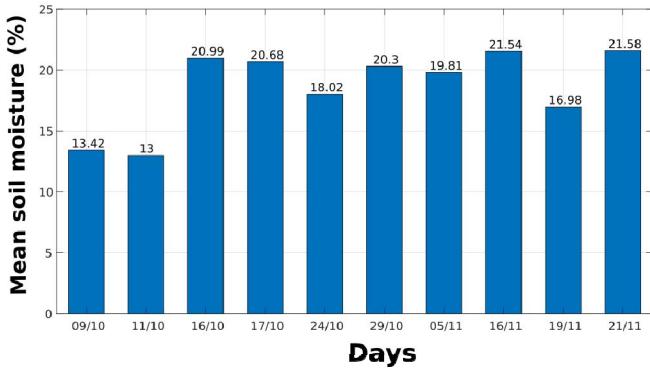


Fig. 5. Mean moisture changes over the two months

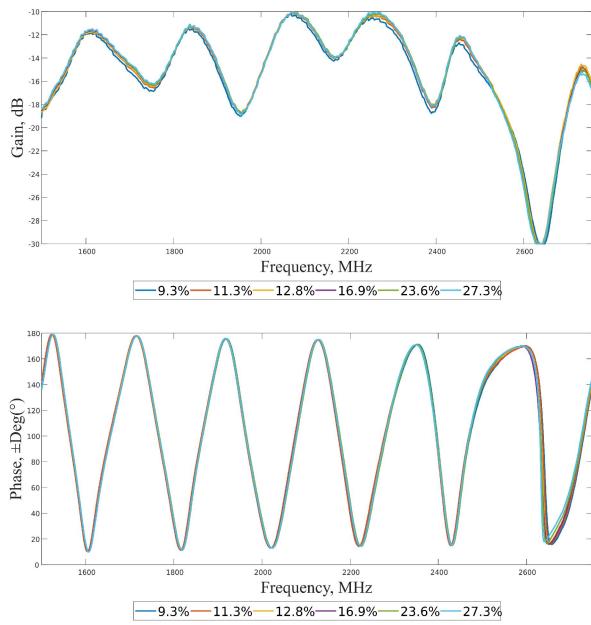


Fig. 6. “Gain” and “Phase” waveforms acquired at different soil moisture (%).

#### IV. ANALYSIS AND EXPERIMENTAL RESULTS

With X and Y calibration dataset as input, the Partial Least Square Regression was then executed, thanks to a software called Eigenvector [13]. This multivariate statistical analysis is based on the fact that X and Y datasets, despite being created with different measurements and data, come from the same system, and so are driven by the same underlying variables [14].

The goal of PLSR is to change the data space of X and Y, searching for a set of variables, called Latent Variables (LV), that best explain X, Y and the covariance between these two [15]. In Eigenvector this is obtained thanks to an algorithm called SIMPLS, that allows faster computation and less memory requirements respect to the original one [16].

A scheme of the whole process is reported in Fig. 7. When the best calibration model is determined, X and Y prediction dataset are used to test the model prediction ability: moisture values are predicted from the X dataset with the new model, and compared to the real one, reported in the Y dataset. In this manner, Coefficient of determination ( $R^2$ ) and Root Mean Square Error (RMSE) values are obtained, allowing us to compare different models between them. The first one goes from 0 to 1, measuring how well observed outcomes are replicated by the model; the second one measures the differences between values predicted by the model and the values observed. The whole procedure was applied to two different models, one created with gain values and another with phase ones, in order to see which has more prediction ability.

The better one results to be the “gain” one, with 6 LVs, an  $R^2$  of 0.949 and an RMSE of 0.7 % in calibration, as shown in Fig. 8, respect to 5 LVs, an  $R^2$  of 0.741 and an RMSE of 1.9 % for the “phase” model.

Also the influence of soil temperature was studied: during the two months of acquisition (October – November season) temperature shifts from 17.5 °C to 8.1 °C. In Fig. 9 “gain” and “phase” waveforms at different temperatures are reported, showing that changes in temperature involve mostly shifts and offset variations in waveforms.

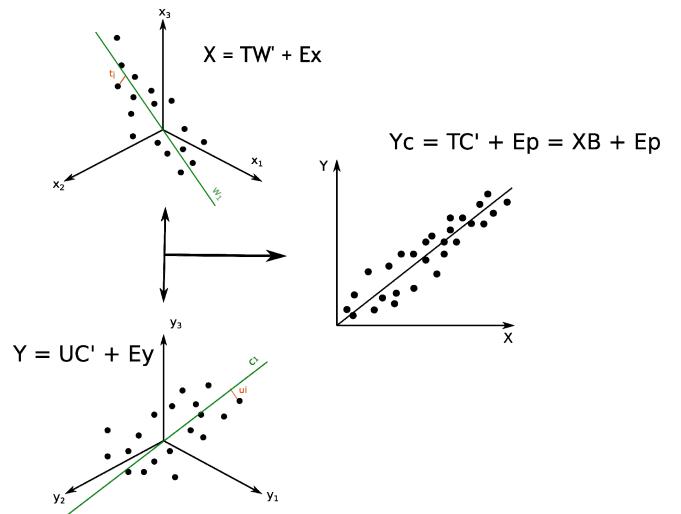


Fig. 7. Partial Least Square Regression.

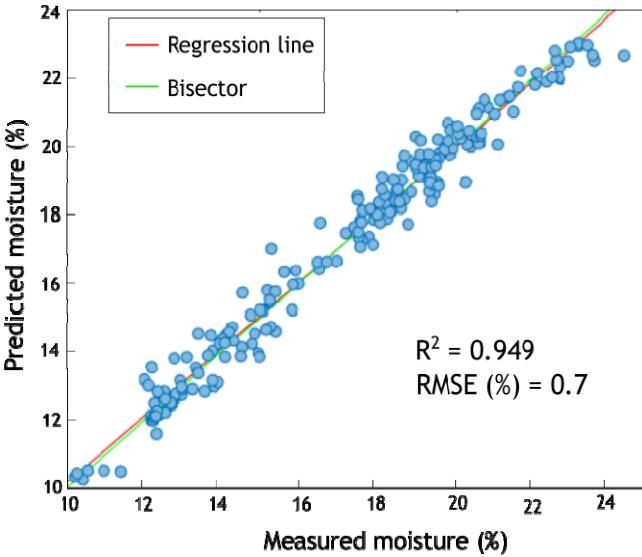


Fig. 8. Predicted versus observed values of the moisture content (%) for the gain model in calibration. The red line is the line regression for the test acquisitions, the green one is the bisector.

However, the model prediction power does not seem affected by these variations, even without a dedicated preprocessing. It is possible to understand this behavior looking at the LVs calculated by PLSR. These variables are sorted in an ordered list: the first is the one that contains the higher % of system variance, the second one contains the higher % after the first, and so on. For this model, first LV explain 50.8 % of variance, the second one 38.6 %. Moreover, from data patterns in the score plot, it is possible to deduct that these variables are moisture and temperature, respectively. This means that the higher percentage of data variations is caused by moisture variations, and temperature influences the system to a lesser extent.

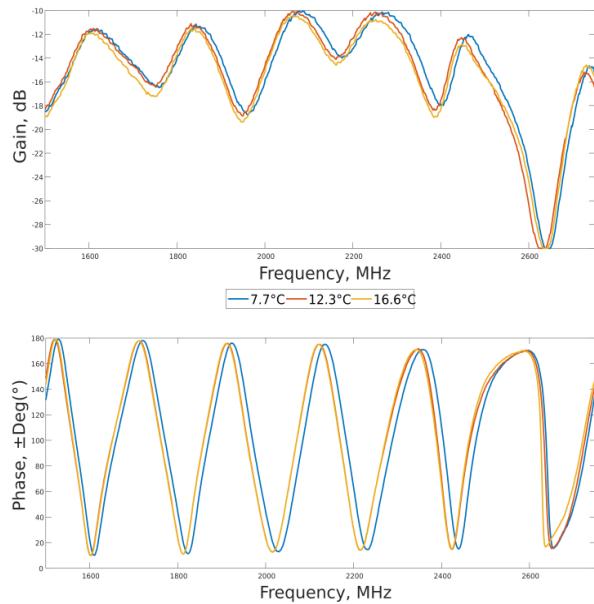


Fig. 9. "Gain" waveforms acquired at different soil temperatures ( $^{\circ}\text{C}$ ).

## V. MOISTURE CALCULATION IN MCU

Given its better statistical results, "gain" model was chosen for the implementation of soil moisture calculation in the system. Its calibration coefficients were extracted, in the form of an array A ( $3700 \times 1$ ) and a single value B.

Therefore, in operating mode, it is possible to find the moisture value  $\text{Y}_{\text{new}}$  directly from a new measure  $\text{X}_{\text{new}}$ , thanks to the linear formula of the characterized model:

$$\text{Y}_{\text{new}} = \text{AX}_{\text{new}} + \text{B} \quad (1)$$

This calculation was implemented directly in the MCU: after the acquisition for each frequency, the "gain" value, properly preprocessed, is multiplied by its corresponding coefficient in A, and all these values are summed with a for cycle. A and B were saved in the memory of the MCU, exploiting a feature of the chosen PIC called Program Space Visibility: it is possible to save constant values in the program memory, remapping part of it in the data memory, providing a quick access for reading and much more memory space. Finally, the moisture value is saved in the SD with gain and phase spectra, or send through serial to the PC, in order to be shown in the Matlab interface.

## VI. CONCLUSIONS

The potentiality of the proposed system, previously tested only in a laboratory environment, was assessed also on a real soil. Acquisition, done on a soil with moisture range from 9% to 32%, were used to create calibration models, thanks to a statistical analysis called Partial Least Square Regression: the best model results to be the one created with "gain" values ( $R^2$  of 0.949 and an RMSE of 0.7 %).

The influence of the soil temperature on the acquisition variance was studied, but LV analysis showed low dependence of the model with respect to the parameter. Calibration coefficients are extracted from the gain model, to implement moisture calculation in the MCU during the operating mode of the system.

The architecture was implemented in a small and stand-alone system, removing all the issues related to insufficient contact with soil or physical connection with other devices. Further studies are in progress, in order to assess the predictive power at higher depths, and the possibility to evaluate moisture at different soil levels. Another research could be conducted on the application of the system on different soils, with a collection of new acquisitions and samples.

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