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Error Analysis in Soil Urea Prediction Based on RF Spectroscopy

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Abstract: **With the growing concern for environmental pollution and shrinking land resources available for agriculture, the need for sustainable agriculture is increasing. Soil sensing plays an important role in sustainable agriculture as it provides an insight into the various soil properties thus enabling the farmer to adjust the inputs accordingly. The aim of the study is to design a soil sensor and analyze the errors in the prediction of a soil nutrient. The manuscript describes a new method for soil nutrient sensing using RF spectroscopy. The technique can predict soil urea content and is based on multivariate analysis using the PLSR (Partial Least Square Regression) mathematical tool. Eight different combinations of five important soil nutrients (Urea, Potash, Phosphate, Salt, and Lime) at varying concentration were used to develop multivariate block. The Urea prediction algorithm takes into account the effect of various other soil nutrients present in the sample. The results obtained show that the percentage error in prediction of urea is within the tolerable limits of +/-5% of the actual value, when other soil nutrient concentrations are varied below and above their normal values. The method can be extended for sensing multiple nutrients simultaneously by modifying the algorithm.**

Keywords - RF spectroscopy, Multivariate, PLSR.

I. INTRODUCTION

Multiple issues like soil degradation, environment pollution, contamination of ground water resources etc., has made it necessary to switch from the use of traditional agricultural practices towards modern agricultural, which provide a means for practicing sustainable agriculture. The technique of management of agricultural resources at the micro level is called precision farming. Precision farming has gained wide popularity in the developed countries as it increases the crop productivity and also enables the use of resources in a sustainable manner [1]. Soil sensing is an important tool in precision farming, since it provides details about the various properties of soil. Conventional methods of soil testing done in laboratories provide results with high accuracy but, they are found to be time consuming, expensive and labor intensive. Precision farming requires soil sensing techniques that are fast, accurate and those, that take into account the variability exhibited by the soil at the farm level. Researchers are trying to develop various soil sensing techniques that can aid precision farming through the proper application of external inputs to the soil for a particular type of a crop. Most of the soil nutrient sensing techniques developed so far are based on two approaches which are as discussed below:

- Optical sensing – These methods are based on reflectance spectroscopy techniques where the interaction between the incident light and the soil properties is studied. Depending upon the amount of energy absorbed /reflected by the soil particles, the characteristics of the reflected light changes and a response spectrum is obtained.
- Electrochemical sensing – This technique makes use of ion selective electrodes wherein depending on the activity of selected ions a potential difference is developed between the ion selective electrode and the reference electrode which gives the measurement of selected ion concentration in the soil [2].

This paper describes a novel method based on RF spectroscopic technique for the sensing of soil nutrients. An RF signal is passed through the soil sample, and the corresponding attenuation at various frequencies for each soil nutrient is recorded. The characteristic spectra thus obtained for each soil nutrient are then fed to a multivariate system, which does the estimation of a particular soil nutrient.

II. EXPERIMENTAL SETUP

The experimental setup consists of a dielectric cell and a scalar network analyzer for obtaining the RF characteristics of various soil nutrients considered in the study. The dielectric cell works on the principle of radiation loss technique and is rectangular in shape with outer dimensions as 13cm x 2cm x 2.5cm. It is made up of acrylic sheets and the inside surface is lined with a gold foil. Gold plated SMA RF connectors are provided at each end of the dielectric cell and a gold wire runs through the centre of the cell between these two connectors. The RF signal is passed through this central wire into the soil sample placed inside the cell. The sensor is well shielded so as to neutralize the effect of external EMI interferences. The sample holding capacity of the cell is approximately 15ml. The scalar network analyzer consists of a Signal Hound tracking generator connected at the input end of the sensor and is used for generating RF signals in the range of 10MHz – 500MHz. The output end of the sensor is connected to a Signal Hound Spectrum Analyzer which produces the output response of the sample under test. The soil nutrients considered for the study are Urea, Potash, Phosphate, Salt and Lime. The samples are prepared by mixing specific amount of the soil nutrient in 15ml of distilled water. The quantity of soil nutrient required to prepare a sample was calculated from the data obtained from National Agricultural Institute. Thus 225mg of urea, 279.5mg of potash, 375mg of calcium carbonate, 219.75mg of sodium chloride and 3.78gm of phosphate in 15ml water constitute a normal concentration in fertile soil and are designated as "1" concentration. Other concentrations of the soil nutrients which are taken in the study are 0.5 for half the concentration of the normal, 1.5 for one and half times of the normal concentration and so on.

III. METHODOLOGY

In order to study the effect of various soil nutrients on the prediction of urea, samples are prepared by mixing various concentrations of the soil nutrients mentioned earlier and the spectra for each of these combinations is recorded. The spectra obtained are then used as an input to Partial Least Square Regression (PLSR) based on multivariate analysis for the prediction of unknown urea concentration. PLSR technique is useful in cases where there are large number of independent variables (i.e. predictors) and from these predictors, a set of dependent variables are predicted [3]. The PLSR technique works by extracting a small number of orthogonal factors which are mutually independent linear combinations of original responses and uses these factors for least square regression instead of the original data. PLSR emphasizes on the development of predictive models and not on the understanding of the underlying relationship between the variables [4]. The PLSR tool used in this study is ParLe's software developed by R. A. Viscarra Rossel [5]. The calibration file consists of 8 samples with concentration of each component varying in the range of 0.5 to 1.5 times the normal as given in Table 1.

Table 1: Samples taken in the calibration set.

Sample No.	Urea	Salt	Potash	Lime	Phosphate
1.	0.5	0.5	0.5	0.5	0.5
2.	0.75	0.75	0.75	0.75	0.75
3	1	0.75	0.75	0.75	0.75
4.	1.5	1.5	1.5	1.5	1.5
5.	1.25	1.25	1.25	1.25	1
6.	1.5	1.25	1.5	1.25	1.25
7.	0.75	1.25	1.25	0.75	1.5
8.	0.75	1.25	1	1.25	1.25

The spectra obtained for a typical combination of the samples prepared as per Table 1 are as shown in fig. 1.

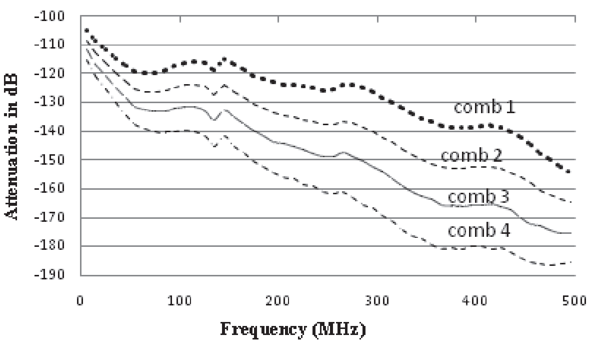

Fig. 1: Combination spectra in the frequency range of 10MHz-500MHz

IV. RESULTS AND DISCUSSIONS

It is found that the variation in the phosphate content has a large effect on prediction of urea concentration. This paper discusses the errors in prediction of soil urea when phosphate concentration is varied from below normal to above normal values.

A sample spectrum for prediction is fed to the system by keeping the concentration of urea and the other components in the sample at their normal concentration value, while the concentration of phosphate is varied from 0.5 to 2 times the normal. Table 2 shows the percentage error in prediction of urea when the concentrations of phosphate are changed, with other components in the sample kept at their normal values.

Table 2: Effect of changing concentrations of Phosphate on Urea Prediction

Urea_ conc.	Phosphate	Salt	Potash	Lime	Urea_ Actual	Urea_ Pred.	%Error
1	0.5	1	1	1	225	225.73	0.32
1	0.75	1	1	1	225	224.85	0.06
1	1	1	1	1	225	225.04	0.017
1	1.25	1	1	1	225	223.64	0.604
1	1.5	1	1	1	225	223.37	0.724
1	2	1	1	1	225	222.16	1.26

The bars chart in fig.2, shows the error percentage when the concentration of phosphate is changed as per Table 2.

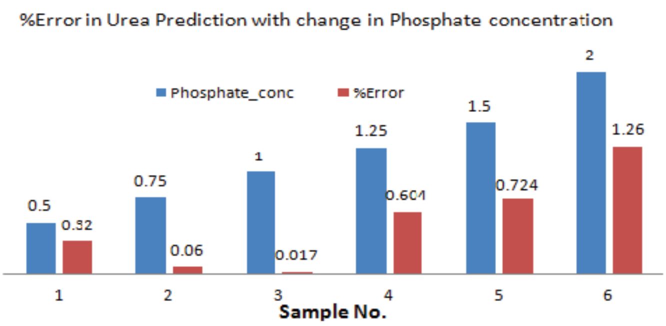

Fig. 2: Chart showing the effect of phosphate on urea prediction

It can be seen that the effect of changing the concentration of phosphate on prediction of urea value is minimum when all the other components in the sample are at their normal value, but as the concentration of phosphate is changed below and above the normal value, the error in the prediction of urea concentration in the sample is found to be increasing. This is due to the fact that the calibration set, as given in Table 1 for phosphate used in the multivariate block does not have values below 0.5 and above 1.5 concentrations.

V. CONCLUSION

The study was done to find out the errors in the prediction of urea when the concentration of phosphate in the soil was varied from below normal to above normal. The prediction accuracy is within 1 percent when phosphate concentration is within the range of 0.5 to 1.5(i.e. 1.89 gm/15ml to

5.67gm/15ml). The error reaches 1.26 percent when phosphate concentration doubles in the samples. It is also possible to use similar analysis for other components used in the study. Thus, a practical system can be developed for urea prediction using FPGA. The PLSR algorithm can be embedded into the FPGA and other features that make the system user friendly can also be added, such as providing information about the fertilizer requirement for a particular crop.

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