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Angular distribution of scattered neutrons as a tool for soil moisture measurement: A feasibility study

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ABSTRACT

The conceptual design of a soil-moisture measurement instrument using a rectangular soil sample and an almost collimated ^{241}Am-^{9}Be source was proposed. Unlike previous studies and in a different simulation approach, the soil moisture was determined using the angular distribution of thermal neutrons using MCNPX2.6 Monte Carlo code, where a cylindrical BF_3 proportional counter located at different polar angles was responsible for thermal neutron detection. Both Monte Carlo library least-squares method (MCLLS) and artificial neural networks (ANN) were used to calculate the soil moisture based on BF_3 count rates with small relative error, about 2% and 10% maximum relative errors, respectively.

1. Introduction

Measurement of soil moisture is important in agriculture, civil engineering, meteorology, archeology, and airport construction, etc. Weighting is the most popular and accurate method for determining soil moisture (Hoogsteen et al., 2015). Other methods include time-domain electric charge reflectometry which is based on the variation of electrical permittivity of the soil (Srivastava et al., 2016), and neutron scattering. The latter technique is efficient, fast, reproducible, economical, non-destructive, reliable with a relatively high accuracy, and optimal for use in rocky soil (Su et al., 2014; Bogena et al., 2015).

Neutron scattering for moisture detection, since its introduction more than 50 years ago (Meigh and Skipp, 1960), found wide use in agriculture, forestry, and infrastructures such as road and dam constructions, coal and iron mines, etc. (Zhu et al., 2013).

Although, the use of neutrons in different soil moisture measurement techniques has a long history, these techniques are generally based on the effect of soil moisture on the neutron thermalization, and hence, more count rates in thermal neutron counters. In this paper, the determination of soil moisture content is based on the angular distribution of scattered neutrons, which has not been studied so far.

The objective of this paper is the introduction of a novel method for soil moisture measurement based on the detection of thermal neutrons surrounding a soil sample. This research aims to correlate the angular distribution of thermal neutrons to the soil moisture value through two different computational approaches, using MCLLS (Monte Carlo Library Least-Squares) and ANN (Artificial Neural Networks).

2. Materials and methods

The MCNPX Monte Carlo code (Hendricks et al., 2008) was used to model the soil moisture measurement system which included a rectangular soil sample (700 mm $\times$ 700 mm $\times$ 500 mm (depth), an LND20137 BF_3 counter (123.8 mm in length and 16 mm in diameter) (LND20137, LND inc.), a point ^{241}Am-^{9}Be neutron source, and a neutron collimator located at 25° with respect to horizontal (Fig. 1). Since the point source is placed well inside the collimator, it is anticipated that the results would not differ considerably from those of a small volumetric source (Balaghi et al., 2018). The soil sample was considered sufficiently large to represent an extended soil environment.

The composition of dry standard soil with density of 1.52 g/cm^3 (U.S. average Earth) used in the Monte Carlo calculation is shown in Table 1 (McConn et al., 2011). The neutron counter was an LND20137 cylindrical BF_3 whose gas pressure, gas density, and the ^{10}B enrichment were 400 torr, 2.99×10^{-3} g/cm^3 at 300 K, and 96%, respectively. BF_3 was selected over other detectors, such as those incorporating ^{3}He and ^{6}Li, because it is relatively inexpensive, easy-to-handle, and produces a higher number of electron-ion pairs per absorbed neutrons (Crawford,

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1993). The neutron source collimator was a cylinder made of heavy borated polyethylene measuring 60 mm in length with inner and outer radii of 10 mm and 32 mm, respectively. It was surrounded by a 2-mm layer of cadmium. The neutron source was modeled as a point-like source producing neutrons from 0.5 to 11.5 MeV (Vega-Carrillo and Martinez-Ovalle, 2016).

The MCNPX F4 tally, followed by the (n, α) reaction identifier (ID number 107 in tally multiplier FM4), was used to estimate the thermal neutron fluence around the soil sample, which is equivalent to BF_3 count rate in simulation. It should be noted that in order to avoid both shadowing and cross-talk effects, one has to simulate each detector location case separately. The number of histories was 5×10^8, which allowed the uncertainty less than 3%. Fig. 2 shows the mesh tally output of the MCNPX code.

Having taken into account that the average maximum soil moisture content in different geographical regions is about 30% (Ratnayaka et al., 2009), the percentage of soil moisture was increased from 0% to 30% (with 2% steps) by adding water to the soil sample. The (n, α) reaction rates were calculated for 16 different moisture contents (*i.e.*, 15 water percentages and dry soil), within the active volume of the BF_3 counter. The simulation results for 26 different BF_3 locations (from 32.74° to 175.875°) and 16 different soil moisture contents are shown in Fig. 3.

The data of Fig. 3 can be presented in 16 columns (each corresponds to an individual moisture percentage) and 26 rows (each related to one counter location) to form a so-called response matrix, which will be further used in both MCLLS and ANN calculations.

2.1. MCLLS technique

In this technique, using Monte Carlo MCNPX code, a number of detector counts corresponding to different moistures and location angles were generated as the response matrix or the data library (Ghal-Eh et al., 2016). It was assumed that the BF_3 detector can be placed at 26 different angles to register the thermal neutrons when the soil sample with one of 16 different water contents was exposed to neutrons produced by a collimated ^{241}Am-^{9}Be neutron source. Therefore, the data library is a 26-row by 16-column response matrix. Whenever a soil sample of unknown moisture is given, using Eq. (1), the Y-values are calculated which are the squares taken on the subtraction values of $X_{mn}(i)$ and $X_{mn}(j)$, angle by angle, summed over 16 different moistures, as is shown in Eq. (1):

Table 1
Elemental concentration in standard soil (U.S. average Earth) (McConn et al., 2011).

Element	wt%
O	0.513713
Na	0.006140
Mg	0.001330
Al	0.068563
Si	0.271183
K	0.014327
Ca	0.051167
Ti	0.004605
Mn	0.000716
Fe	0.056283

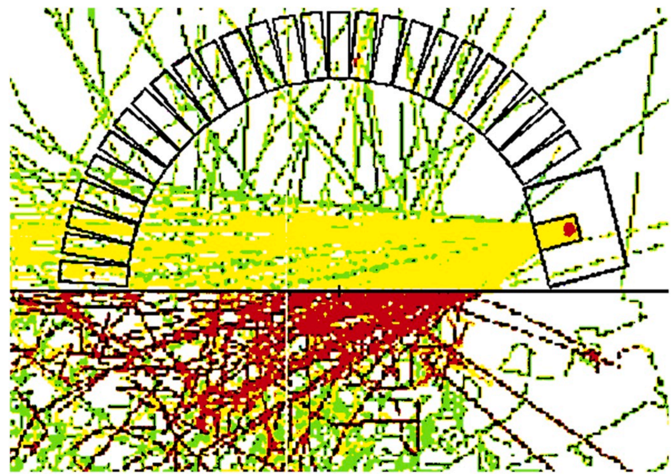

Fig. 2. The mesh tally output of the MCNPX code. Figure illustrates the neutron flux originating from ^{241}Am-^{9}Be source, scattering off the soil sample, and crossing 26 BF_3 locations.

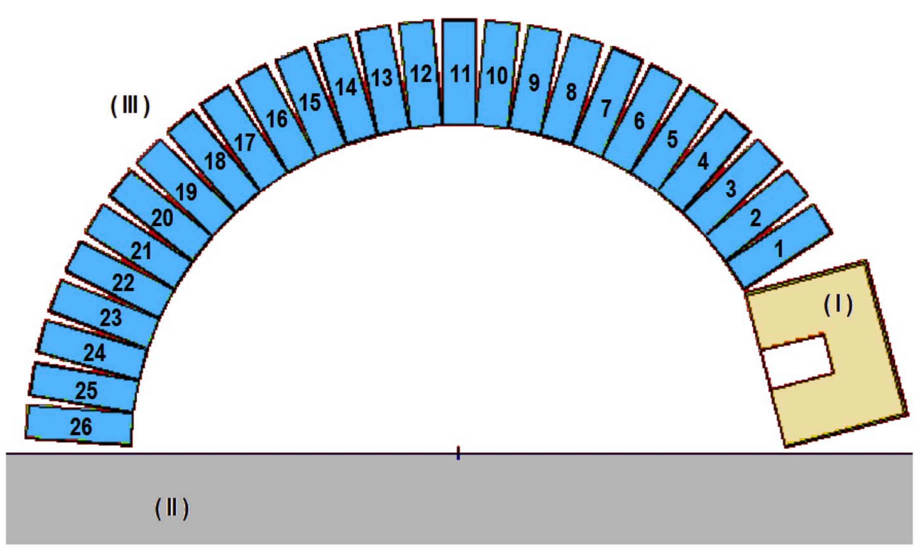

Fig. 1. Proposed soil moisture measurement system: (I) ^{241}Am-^{9}Be neutron source and collimator, (II) Rectangular soil sample, and (III) Cylindrical BF_3 counter located at different angles.

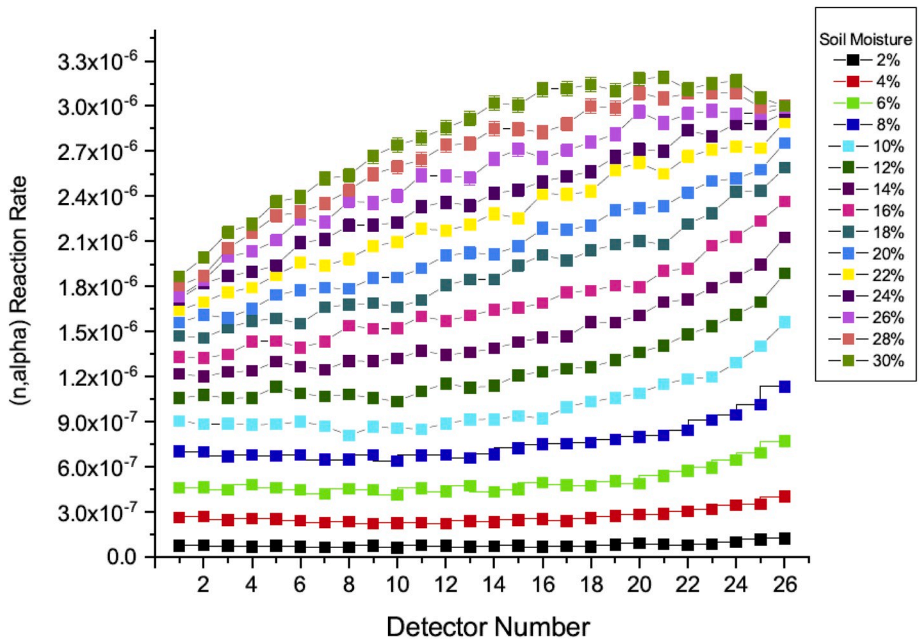

Fig. 3. (n, α) reaction rates for 26 different BF_3 locations and 16 soil moisture contents. The horizontal axis values correspond to BF_3 location number as shown in Fig. 1.

$$Y_m = \sum_{n=1}^{16} (X_{mn}(i) - X_{mn}(j))^2, \ m = 1 \ to \ 26 \tag{1}$$

where, $X_{mn}(i)$ and $X_{mn}(j)$ stand for the detector count rates assigned to the samples of unknown and known moistures denoted by n at the location denoted by m, respectively. The above equation was used to calculate 26 different Y values. The two smallest values are selected and they are assigned as Y(α) and Y(β) which correspond to the samples of α and β moisture contents, respectively. The corresponding data (*i.e.*, detector count rates) for α and β samples are X(α) and X(β). The following equation can be written in terms of two known X(α) and X(β) moistures and the unknown moisture, X, in a linear combination form like Eq. (2):

$$X = P.X(\alpha) + Q.X(\beta) \tag{2}$$

where P and Q are the probabilities for finding moistures α and β in the unknown sample, respectively. For example, P = 1 and Q = 0 correspond to a sample of moisture α only, and P = Q = 0.5 corresponds to the moisture (α + β)/2. Both P and Q, representing the specific moisture percentage, vary between 0 and 1 such that whose summation equals unity. Having determined P and Q by varying their values between 0 and 1, the unknown moisture content can be calculated. The difference between the calculated moisture content, X, and the actual moisture content of the unknown sample is the error of the MCLLS technique (See Fig. 4).

2.2. *Artificial neural networks technique*

Artificial neural networks (ANN) or connectionist systems are computing systems that are inspired by, but not necessarily identical to, the biological neural networks that constitute animal brains (Mainkar, 2018). Such systems learn to perform tasks by considering examples, generally without being programmed with any task-specific rules. The brain, as a parallel-structure data processing unit, consists of numerous connecting neurons. A neural network is a group of neurons that are responsible for transferring information and messages from one point to another point of the body. All neurons have identical functions; however, their sizes and shapes may vary depending on their positions in the neural system.

In the present study, the MCNPX-simulated library data were fed into an ANN, within the framework of MATLAB ANN toolbox (Mathworks Inc., 2019), to evaluate the moisture content of an unknown sample. In order to train the network and to achieve a reasonably small relative error, a large data library is normally required. Here, to train the network and to control the ANN response, 16 different moisture

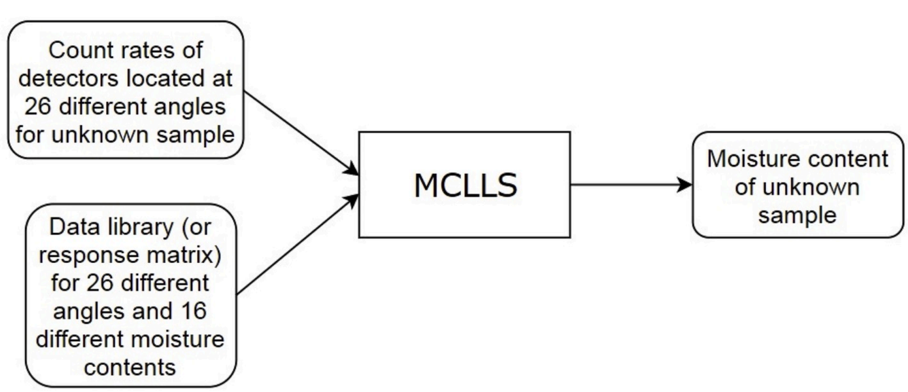

Fig. 4. Block diagram for unknown moisture calculation based on MCLLS method.

contents, from 0% (*i.e.*, the dry sample) to 30% with 2% steps, were simulated and the corresponding detector counts were calculated with the MCNPX code to form a 16 × 26 response matrix. The 11 × 26 and 5 × 26 sub-matrices were considered for the network training and network response control, respectively.

The function of the ANN can be monitored by comparing the ANN response and the expected values from control data which were randomly chosen. In the ANN toolbox of MATLAB, a multi-layer network consisting of an input layer, a hidden layer, and an output layer is utilized. The training function *traingdx*, transfer function *tansig*, and linear transfer function *purelin* were used in input, hidden, and output layers, respectively. The input data consist of 26 neurons, each corresponding to a detector count, whilst the hidden and output layers consist of 15 and 1 neurons, respectively. The input, hidden, and output layers are shown in Fig. 5, and the network is trained using the back-propagation algorithm.

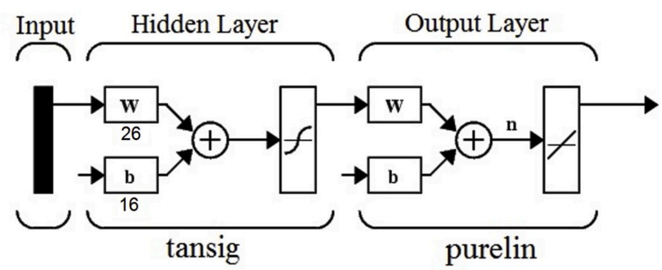

Fig. 5. A neural network design for estimating unknown moisture content in a soil sample.

3. Results and discussion

The results of MCNPX calculations of (n, α) reaction rates inside the active volume of the BF_3 counter can be used in two different analysis techniques for moisture determination of a soil sample with unknown moisture content: (1) MCLLS and (2) ANN. In the following, the incorporation of these techniques into the count rates registered by a thermal neutron detector to obtain the soil moisture percentage is discussed.

It was decided to consider a test case for the simulation studies, where the unknown sample consisted of 15.75 wt%. The moisture content of the unknown sample is far from both minimum (*i.e.*, 2%) and maximum (*i.e.*, 30%) available moisture contents as shown in Fig. 3.

The simulated detector counts, when exposed to incident thermal neutrons from unknown soil sample for 26 different detector locations, are considered as input data to the MCLLS program as shown in Fig. 4. The soil moisture calculated with MCLLS was 15.72 which represented 0.19% relative error.

Fig. 6 exhibits the average values obtained from ANN versus the appropriate expected values. As can be seen, there is a linear correlation between these two groups of data. The fitting line slope is about 0.9 which is not very far from the ideal value of 1.0.

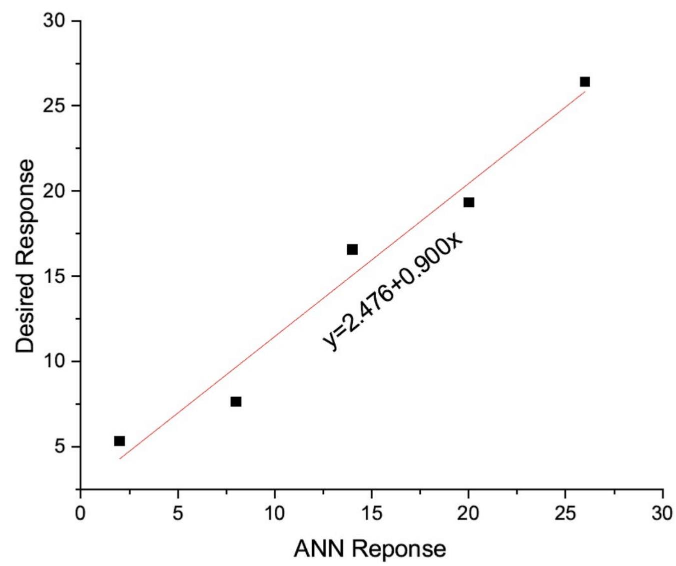

Fig. 6. The correlation between the average values obtained from 5 different simulations and the neural network optimal values.

4. Conclusions

A soil moisture measurement system based on the detection of thermal neutrons at 26 different angles around a soil sample has been presented. The input data library for both Monte Carlo library least-squares (MCLLS) and artificial neural networks (ANNs) programs, generated by the MCNPX, consists of 26 detector locations at different polar angles and 16 moisture contents.

The MCLLS results confirm that the information on the angular distribution of thermal neutrons simulated with the MCNPX code can be used as an appropriate tool in soil moisture determination.

Moreover, in a different approach, the ANNs have been incorporated, in which 16 different detector counts corresponding to 16 different location angles have been simulated with the MCNPX code; 11 for training and 5 for network response control. The ANNs results represent a linear correlation between the network and the desired responses with about 10% error, which can be reduced by increasing the number of training responses.

The number of primary neutrons (*i.e.*, histories) used in the MCNPX simulations was 5×10^8 to allow the calculated moisture uncertainty less than 3%. Therefore, since each millicurie of an ^{241}Am-^{9}Be neutron source approximately provides 2200 neutrons per second (Knoll, 2010), if one would like to measure the soil moisture, for example, within 3 min of acquisition live time, it is necessary to use an ^{241}Am-^{9}Be neutron source of at least 1.3 Ci activity.

The comparison between MCLLS and ANN methods shows that the MCLLS results in more precise moisture data. However, it requires more initial detector counts than the ANNs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Masoud Ghaemifard: Data curation, Software. **Nima Ghal-Eh:** Writing - original draft, Supervision, Methodology, Conceptualization. **Reza Izadi Najafabadi:** Supervision, Methodology. **Hector R. Vega-Carrillo:** Writing - original draft, Methodology, Writing - review & editing.

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