Advances in Science and Technology Research Journal

Advances in Science and Technology Research Journal 2023, 17(5), 328–336
https://doi.org/10.12913/22998624/172010
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Received: 2023.07.18
Accepted: 2023.09.07
Published: 2023.10.20

Improving the Calibration of Surface TDR Sensors for Moisture Evaluation of Building Materials Using the ANCOVA Method

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ABSTRACT

The paper presents the models for moisture evaluation using a set of the reflectometric sensors in some types of building materials. The readouts reveal the relationship between the building material moisture, being assessed gravimetrically and the apparent permittivity values obtained by the TDR (Time Domain Reflectometry) method and surface sensors. Based on the readouts, equations describing this relationship were derived. These types of equations function as calibration equations and are used to calibrate the sensors. Most of the equations used to describe the examined relationships are linear regression. These equations very often refer to specific materials and cannot be applied to others that differ in density or chemical composition, which is the cause of many incorrect measurements. In this article, we propose the use of the analysis of covariance method (ANCOVA) for the analysis of reflectometric data. Using this method, it will be possible to determine the moisture content of materials, regardless of their type and construction of the sensor, which can significantly improve moisture measurements using the reflectometric method. For comparative aims data achieved in conducted research were analyzed using both traditional linear regression models and using the analysis of covariance method (ANCOVA). Both types of fitting models are discussed and their quality was compared in terms of accuracy expressed by the Residual Standard Error (RSE), the Root Mean Square Error (RMSE) and the determination coefficient (R^2) values. The paper showed that the use of the ANCOVA method allows for improvement the fit of the model in terms of the determination coefficient by 0.0174. Moreover, the average RSE and RMSE value in the ANCOVA models are smaller about 1.24 vol.% and 1.25 vol.% than the ones in the regression model, respectively, which means that the models obtained using ANCOVA more accurately describe the examined relationship.

Keywords: analysis of covariance, ANCOVA, Time Domain Reflectometry, dielectric permittivity, building material moisture.

INTRODUCTION

The moisture of the building materials is still a current problem. It is immediately connected with the existence of buildings. Moreover, it has a significant impact to the environment. These are the reasons, why elaboration of methods for detecting moisture in partitions, growth of new techniques, improvement and adaptation of the existing ones perform very significant role. The moisture measurement is carried out using many detection techniques starting from direct gravimetric methods described in the following article [1] through electric methods as resistance [2] or capacitance method described in [3] to microwave methods mentioned in following paper [4] where a very popular device by MOIST producer was presented. One of the most recognizable methods is reflectometric detection technique TDR (Time Domain Reflectometry). This is a indirect-type method. It means that the measured parameter is not moisture, but other factor related to it. Testing the moisture of various materials and building partitions is achievable using the TDR equipment consisting of multimeter, sensors, suitable software and calibration equations which is in detail described in articles by Soncela et al. and [5] Paśnikowska et al.[6]. The most popular devices applied in laboratory and in-situ research are produced by the following producers: Campbell Scientific [7], Tektronix [8], E-Test [9].

The TDR measurement method relies on setting the apparent permittivity ε [-] value of the medium using the measurement of the time of the electromagnetic pulse propagation along the elements of the measuring sensors. Apparent permittivity, denotes a measure of the behavior of matter particles if an external alternating electric field is used [10]. The dependence between the dielectric parameters which are displayed by wet porous media and the moisture of the medium is generally introduced by the physical and empirical models which were described by Černý [11] and He [12]. The more detailed information about the TDR technique is exhibited in papers [13] and [14] for soils and [15] for porous media. It ought to be emphasized here that the TDR method is relatively low sensitive on medium salinity which constitutes a significant problem in moisture behavior of porous materials [16]. Measurements that utilize this technique are invasive and require the installation of sensors into the tested material, which is difficult in the case of hard building materials and often requires boreholes what was presented in Barnat-Hunek et al. [17] and Freitas et al. [18]. The research results presented in the paper were obtained from surface sensors, in which the electromagnetic pulse propagates differently, which requires an individual method of its analysis and more advanced calibration methods that are described by coauthors of this article – for surface sensors [19] and for flat sensor of simplified construction [20]. The most common cited empirical model for TDR sensors calibration applied in the practical evaluation of medium moisture is the Topp model [10] of the following form:

$$\theta = -0.053 + 0.0292\varepsilon - 0.00055\varepsilon^2 + 0.0000043\varepsilon^3 \tag{1}$$

where: Θ – volumetric water content in the examined porous medium [cm³/cm³], ε – apparent permittivity of the medium measured using the TDR method [-].

This model is universal, but according to many authors, measurements using it are subject to large measurement errors [11]. In the paper [21] Schapp et al. showed that the range 0.05-0.15 cm^3/cm^3 describes the possible uncertainty of measurement. The reason of this fact can be the differences of solid phase structure of the analyzed building material. On the other hand, in the paper Černý obtained that 0.0468 cm^3/cm^3 is the standard uncertainty of moisture evaluation determined by the Topp's model. Therefore, models are often used that take into account other parameters, e.g. bulk density, which requires additional research (e.g. Malicki formula) [22]. Empirical models developed individually for each material or sensor have great application potential. They allow for high measurement accuracy, on the other hand, they require time-consuming calibration tests. Most often they take the form of linear [23] or polynomial equations as presented by Quinones et al. [24], Udawatta et al. [25], Ren et. al [26] and Ju et al. [27].

The aim of the article is to develop the possibility of a new method of calibrating non-invasive reflectometric sensors that will allow to combine the apparent permittivity value read by the TDR non-invasive sensor and building material moisture. For this purpose, the ANCOVA analysis method will be used, considered to be an extension of one of the most universal methods of mathematical description - the analysis of variance method (ANOVA). ANOVA was introduced by the English mathematician Ronald Fisher. This method makes it possible to compare more than two groups with each other and to investigate the influence of several factors on the examined feature. The purpose of analysis of variance is to test the significance of differences between means.

ANCOVA adjusts for the effect of a covariate to test whether there is a significant difference between the means of two or more groups. In other words, analysis of covariance is a statistical method of examining the responses of different groups to a dependent variable which adjusts for the influence of a variable that is not being tested but is nevertheless related to the dependent variable and therefore may influence the results of the scientific research. The appropriate techniques for determining variable importance using ANCOVA was presented in [28] Additionally, another examples of applying the analysis of covariance were showed in [29]. Analysis of covariance is considered to be a technique that somehow combines analysis of variance and analysis of regression, and from this point of view it can also be treated as one of the special cases of an even more general approach to modeling the interdependence of variables, which is the so-called general linear model. The best practices for applying covariance analysis methods was introduced in [30]. Moreover, the examples where using ANCOVA is inappropriate or doubtful were widely considered in [31]. The original achievement of the work is the application of the ANCOVA method, which has not been used in any work known to the authors, so its applying can be considered proprietary. The using of analysis of covariance allowed to obtain better measurement characteristics than the sensors used traditional calibration methods used by other authors, which is described in detail in the last paragraph of the chapter Results and discussion.

MATERIALS AND METHODS

Measuring setup

Measuring setup applied for testing consisted of the following elements:

- TDR multimeter (ETest, Lublin, Poland) and PC for device control and data acquisition (Figure 1);
- a set of TDR surface sensor prototypes (A,B,C,D) (own manufacture);
- electric oven VO-500 (Memmert, Germany);
- laboratory scales WPT 6C/1 (Radwag, Poland).

The surface TDR sensors were designed and manufactured in Lublin University of Technology. They are made of plastic called POM (polyoxymethylene) having the apparent permittivity value equal 3.8 [-], cf. [32]. Each sensor consist of the dielectric material (POM), measuring rods made of metal and a printed circuit to connect the measuring element with the TDR multimeter via a coaxial cable (Figure 2). The sensors differ from each other in such elements as width, shape of measuring element and thickness. The basic technical details of sensors used in research are summarized in Table 1.

Building materials tested using the TDR technique

The research concerns the following building materials: cellular concrete, clinker brick, ceramic brick, silicate brick and aerated lime silicate [33]. The samples of building materials were prepared in the form the tiles. The dimensions of the samples for sensors A and B were 220 × 120 × 10 mm. For the wider sensors of type C and D, the samples with dimensions of 230 × 130 × 10 mm were used. The specification of analyzed materials is presented in Table 2. All of tests were carried out at a constant temperature of 20 ± 1°C and a relative air humidity of 50 ±5%.

The samples were dried in an oven to constant weight. In order to provide sample homogeneity, the thin plates were combined into larger sets to achieve total thickness 50 mm. During measurement the surface TDR probe was placed on the sample (Figure 3) and a reading of the apparent permittivity was made with a TDR multimeter. In the next experiment steps, the samples were gradually saturated with a specific amount of distilled water using an atomizer, and at the end of the experiment, they were immersed in cuvettes until they were completely saturated. All measurements using TDR sensors were iterated 5 times for given material moisture level. With the described experiment the relationships between apparent permittivity and volumetric water content were determined,

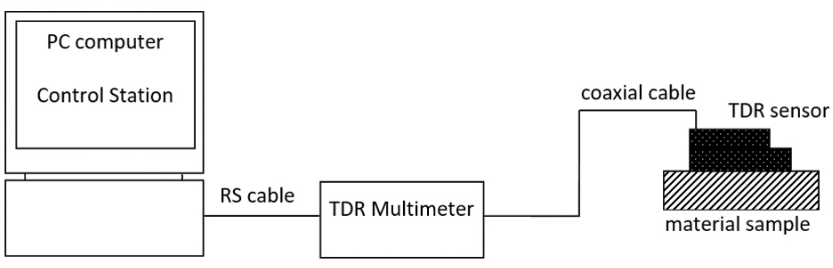

Fig. 1. Block diagram of the measurement setup

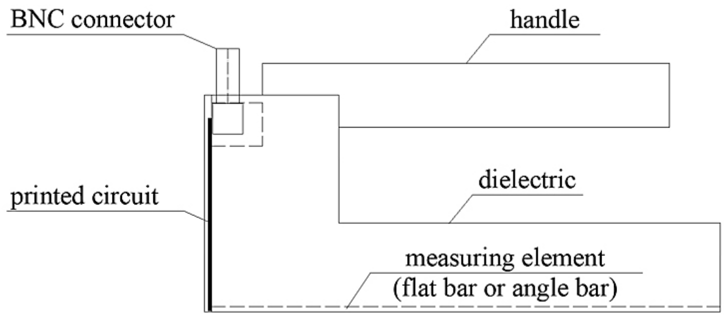

Fig. 2. Schematic view of a sensor

Table 1. Basic technical data of TDR sensors

Sensor symbol	A	B	C	D
Number of rods	2	2	2	3
Sensor length [mm]	200	200	200	200
Sensor width [mm]	50	50	100	100
Shape of measuring element	Angle bar (12×12 mm)	Flat bar (2×10 mm)	Flat bar (2×10 mm)	Flat bar (2×10 mm)

Table 2. The parameters of analyzed materials [34]

Material	Maximum absorptivity
Cellular concrete	0.42
Clinker brick	0.16
Ceramic brick	0.36
Silicate brick	0.27
Aerated lime silicate	0.92

which were later mathematically described using both standard linear regression models and mathematical models established by ANCOVA.

Description of ANCOVA method

Analysis of covariance is a combination of analysis of variance and analysis of regression, it requires the following assumptions [35]

- linearity – there is a linear relationship between the independent variable and the dependent variable;
- homoscedasticity – the variance of the residuals is the same for all observations;
- the random component (residues) are uncorrelated and normally distributed;
- the number of cases is greater than or equal to the number of parameters derived from the regression analysis;
- the dependent variable should be measured on a quantitative scale;
- samples were taken randomly, independently for each of the analyzed groups.

In assumption ANCOVA method is used when the following conditions are satisfied: normal distribution of the studied dependent variables within the compared groups, equality of variances between the groups and assumptions regarding the random component of the linear model [36]. Because the analysis of covariance model has a regression component, the residuals in the model will take different values for measurements within each comparison group and between groups. The best test of the equality of variance assumption is to plot the residuals against adjusted group means. Simultaneously, due to the fact that the analysis of covariance model is a linear model and contains both qualitative and quantitative independent variables, there is an additional assumption that the regression coefficients within the compared groups are equal[37] .

Moreover, the two most important purposes for which ANCOVA is used are [36]:

- increasing the precision of comparisons between the studied groups by taking into account the variability that is caused by the accompanying variables;
- “adjustment” of comparisons between the study groups in the case that the average level of the covariate in the comparison groups also differs.

Currently, the analysis of covariance is a method commonly used in both experimental and observational studies, examples of such experiments can be found in [38].

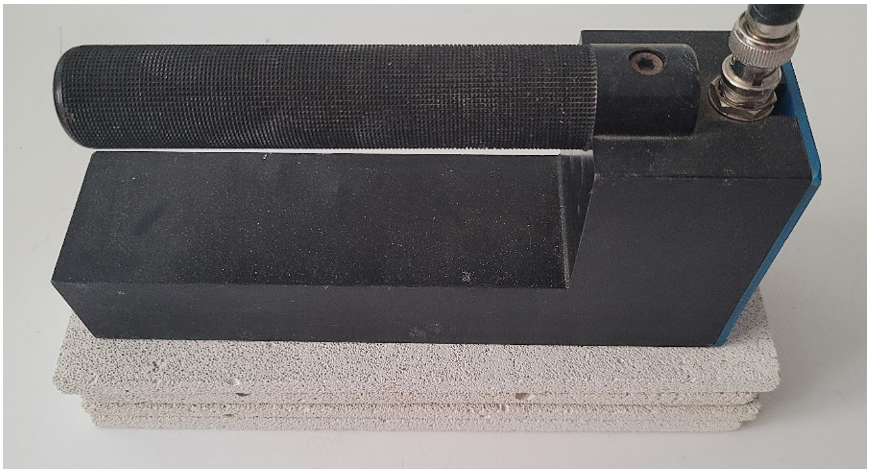

Fig. 3. Photograph of the sensor B and tested sample during measurement

RESULTS AND DISCUSSION

The result of the research is a set of data between material moisture evaluated gravimetrically and apparent permittivity read by the TDR equipment. All readouts are presented in Figure 4.

Most of the statistical analysis contained in this paper were carried out by using *RStudio* [39]. The research refers to the values of readouts of the relative permittivity by the TDR sensors of several types of the building materials. The first statistical method used to analyze the achieved data is linear regression analysis. It was applied to describe dependence between material moisture and apparent permittivity read by each TDR sensor. For this case four linear regression models describing the relationships between relative permittivity (ε) and moisture (θ) were obtained, presented in Table 3.

Table 4 contains the summary of characteristics for each model. The determination coefficients R^2 for all of the models vary from 0.9566 to 0.9811. The RSE value in the obtained models varies from 3.17 vol.% to 4.81 vol.% and RMSE

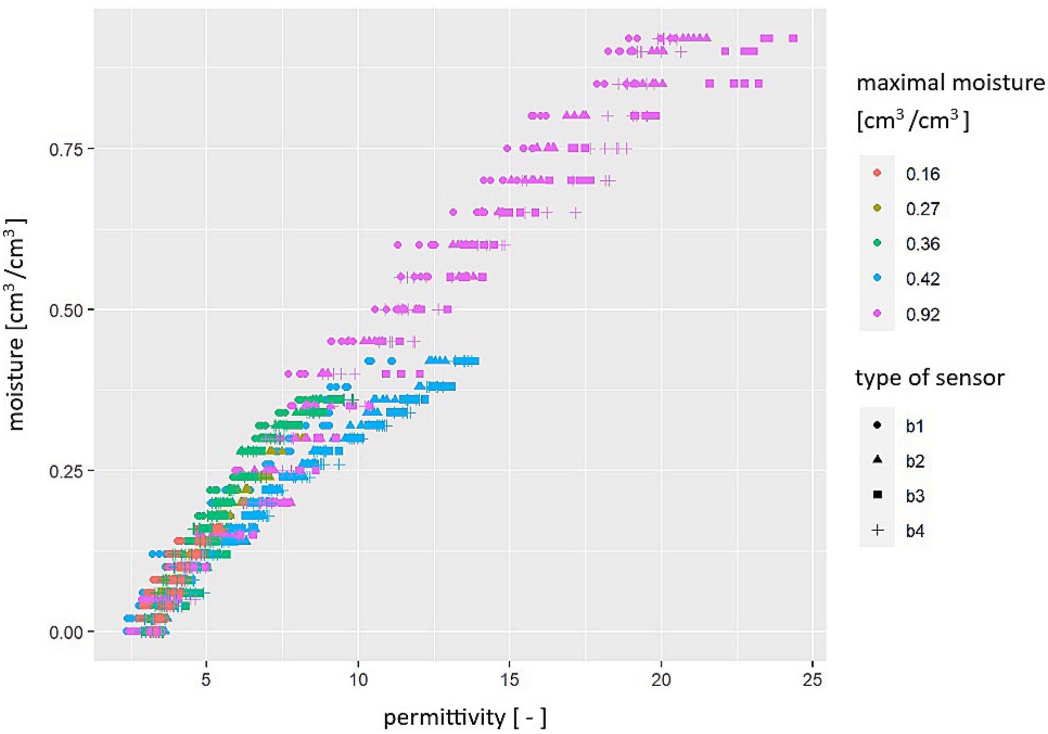

Fig. 4. All readouts achieved within the experiment

Table 3. The regression models for given data

Sensor	Regression model
A	θ = -0.11 + 0.055ε
B	θ = -0.133 + 0.052ε
C	θ = -0.106 + 0.045ε
D	θ = -0.121 + 0.049ε

of RSE and RMSE confirm that the models are well matched. Additionally, each model has all statistically significant coefficients, because in all cases p-value $< 2.2 \cdot 10^{-16}$.

The results of the correlation analysis are graphically presented in a so-called scatter plot, cf. Figure 7. The calculated correlation coefficient

Table 4. Characteristics of dependencies of moisture and relative permittivity by regression analysis

Sensor	R^2	F	RSE	RMSE
A	0.9811	17534	0.0317	0.03
B	0.9679	12468	0.0389	0.04
C	0.9649	9301	0.0432	0.04
D	0.9566	7444	0.0481	0.05

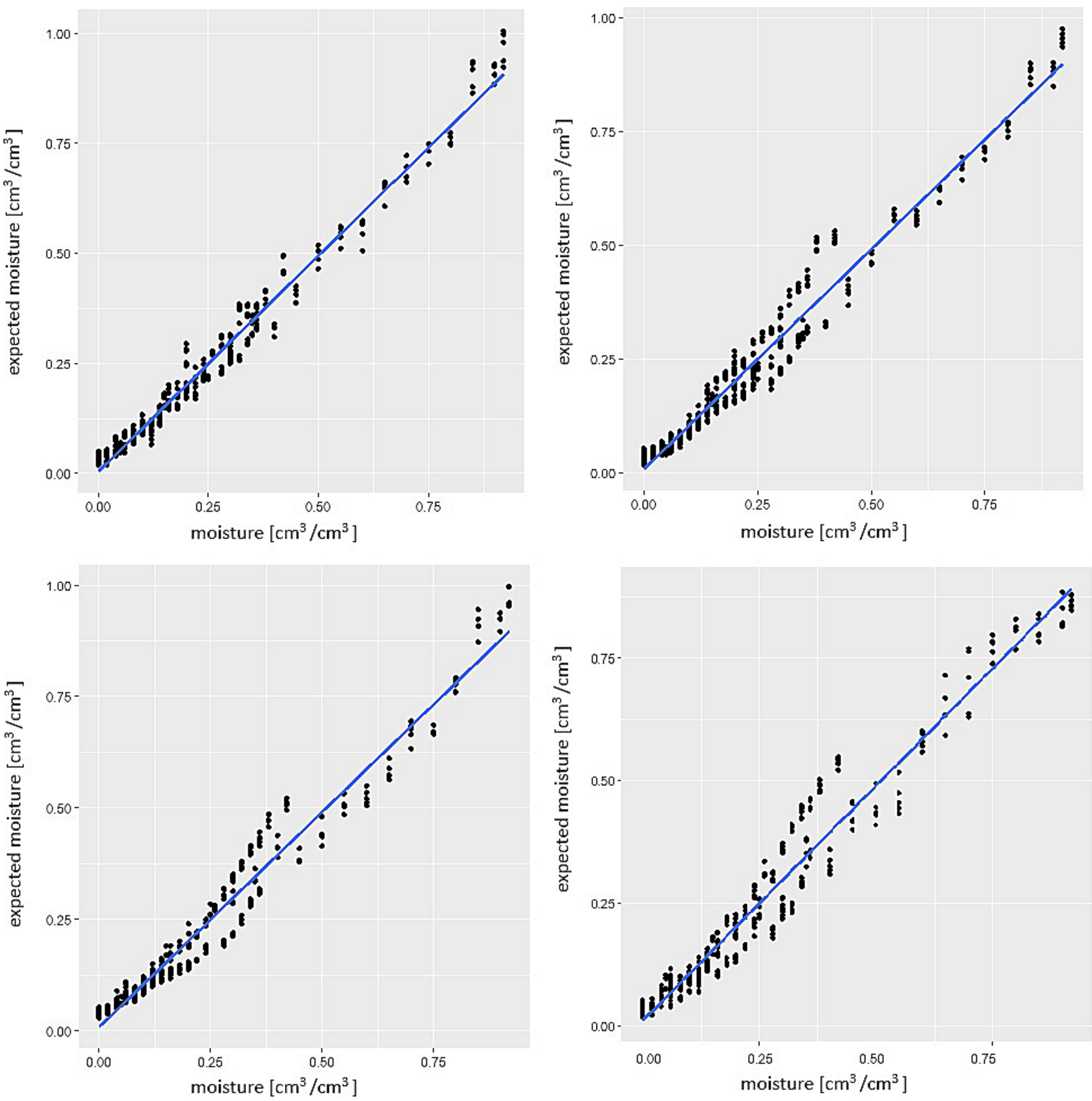

Fig. 5. The scatter plots describing correlations between expected moisture and moisture examined gravimetrically

varies from 3 vol.% to 5 vol.%. Moreover, each model has all statistically significant coefficients, because in all cases p-value $< 2.2 \cdot 10^{-16}$. The results of the correlation analysis are graphically presented in a so-called scatter plot, cf. Figure 5. The calculated correlation coefficients for sensors A-D vary from 0.97 to 0.99 and p-value $< 2.2 \cdot 10^{-16}$. Hence, in each case there is a statistically significant correlation between the expected moisture and the moisture of the examined material.

The obtained regression models were improved by applying analysis of covariance (ANCOVA). The universal models obtained using the analysis of covariance method for each of four types of sensors were presented. In addition, it was verified that all assumptions of the analysis of covariance were satisfied. The relationships between relative permittivity (ε) and moisture (Θ) in considered models were presented in Figure 6. Each color of the regression line corresponds to a different level of the grouping factor, which is the maximal moisture content of the tested material. In the considered case, the qualitative variable (maximal moisture) assumes from four to five levels, depending on the tested building material, cf. Table 2. Then this variable is encoded as follows: one of these levels is specified as reference (in R, by default, this is the first level in alphabetical order), and for each remaining level a characteristic variable I is created, also called the null variable, and these variables are placed in the model. The indicator I, also called the characteristic function of a set, is a function that takes the value 1 on a fixed set and 0 outside of it. In analysis the dependent variable is the moisture of building material and the explanatory variable is the relative permittivity. The models obtained for data from measurements made by particular sensors were included in Table 5.

The summary of characteristics for each model was presented in Table 6. Namely, the determination coefficients R^2 for all of the models are similar and are greater than 0.98. It means that all these models fit the data very well, i.e. precisely describe the behavior of the examined dependent variable. The RSE value in the obtained models varies from 2.33 vol.% to 3.13 vol.% and RMSE varies from 2 vol.% to 3 vol.%. The small values

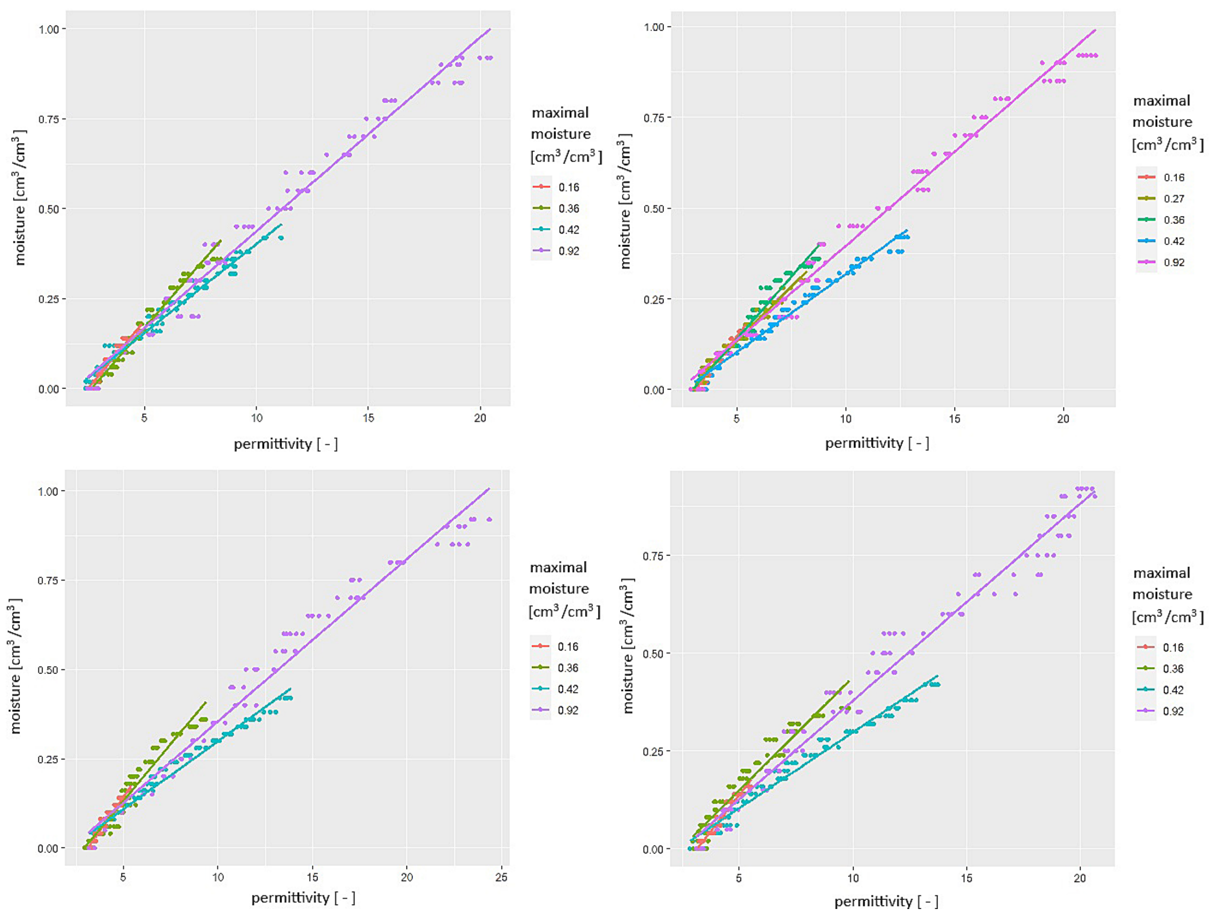

Fig. 6. The regression lines describing relationships between relative permittivity and moisture for given data

Table 5. The models for given data obtained by ANCOVA

Sensor	Model
A	$\hat{\theta} = -0.181 - 0.004I_{[\theta=0.36]} + 0.091I_{[\theta=0.42]} + 0.082I_{[\theta=0.92]} + \varepsilon\left(0.074 - 0.003I_{[\theta=0.36]} - 0.025I_{[\theta=0.42]} - 0.02I_{[\theta=0.92]}\right)$
B	$\hat{\theta} = -0.238 + 0.071I_{[\theta=0.27]} + 0.035I_{[\theta=0.36]} + 0.126I_{[\theta=0.42]} + 0.115I_{[\theta=0.92]} + \varepsilon\left(0.077 - 0.017I_{[\theta=0.27]} - 0.008I_{[\theta=0.36]} - 0.034I_{[\theta=0.42]} - 0.025I_{[\theta=0.92]}\right)$
C	$\hat{\theta} = -0.237 + 0.052I_{[\theta=0.36]} + 0.155I_{[\theta=0.42]} + 0.138I_{[\theta=0.92]} + \varepsilon\left(0.076 - 0.013I_{[\theta=0.36]} - 0.038I_{[\theta=0.42]} - 0.031I_{[\theta=0.92]}\right)$
D	$\hat{\theta} = -0.232 + 0.094I_{[\theta=0.36]} + 0.143I_{[\theta=0.42]} + 0.108I_{[\theta=0.92]} + \varepsilon\left(0.074 - 0.016I_{[\theta=0.36]} - 0.035I_{[\theta=0.42]} - 0.024I_{[\theta=0.92]}\right)$

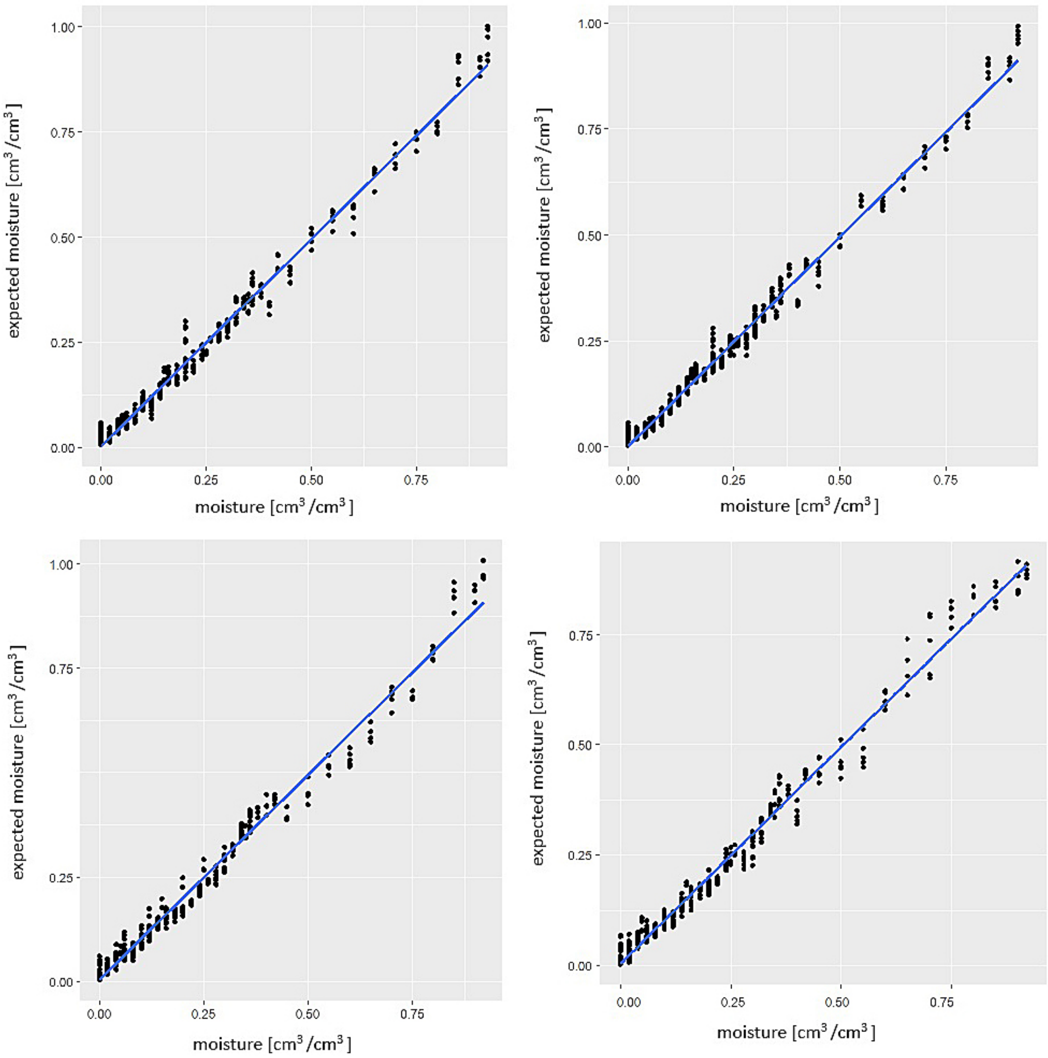

Fig. 7. The scatter plots describing correlations between expected moisture by ANCOVA and moisture examined gravimetrically

for all sensors is greater than 0.99, where p-value $< 2.2 \cdot 10^{-16}$. This means that in each case there is a statistically significant correlation between the expected moisture content and the moisture content of the tested material. This is a very strong relationship (because it is close to 1) and the correlation is positive. In each case the slope of the line is approximately equal to 45 degrees and the line starts in the origin. All of this confirms that the models describe well the relationship between permeability and moisture content of building materials. Based on the characteristics

Table 6. Characteristics of dependencies of moisture and relative permittivity by ANCOVA

Sensor	R^2	F	RSE	RMSE
A	0.9870	3602	0.0266	0.03
B	0.9887	3927	0.0233	0.02
C	0.9820	2582	0.0313	0.03
D	0.9821	2597	0.0312	0.03

contained in Table 4 and Table 6, the determination coefficients R^2 for all of the models obtained by ANCOVA method are greater than for linear regression models. It means that all models achieved by ANCOVA fit the data better than regression models, i.e. more precisely describe the behavior of the examined dependent variable. Moreover, the smaller values of RSE and RMSE for ANCOVA compared to the ones in regression method also confirm that the all models determined by analysis of covariance method are better. Finally, it can be concluded that the models obtained using the analysis of covariance better describe the relationship between moisture and relative permittivity than linear regression models. Using ANCOVA, the quality of measurements can be improved.

Moreover, the use of the ANCOVA method allowed to obtain better measurement characteristics than the sensors used by other authors using traditional calibration methods [12]. In 1990 in the paper [40] Roth et al. proposed the model which RMSE varies from 0.8 vol.% to 3.7 vol.% depending on the type of examined material. On the other hand, the model given by Malicki in [22] was characterized by the RMSE equals 3 vol.%. The values of the RMSE obtained in this paper varies from 2 vol.% to 3 vol.% and are slightly smaller than presented in the cited literature. However, it should be noted that obtained formulas are universal and this is the reason of a little bit smaller quality of data fitting. Suchorab et al. in the work [20] obtained the RSE values between 2.9 vol.% and 3.8 vol.%. In this paper the RSE values varies from 2.33 vol.% to 3.13 vol.%. Smaller RSE values mean that the model obtained using the ANCOVA method is better. The obtained values of the determination coefficient are slightly smaller than 0.988-0.993 which are the values obtained in the paper [20]. Such a small difference does not affect the quality of the model. The similar comparison of the effectiveness of two another methods, i.e. the K-means method and the genetic algorithm (GA), was presented in [41].

CONCLUSIONS

The article emphasizes the advantages of application of the ANCOVA method over the linear regression techniques to estimate material moisture using the TDR method. With analyzing the data achieved with the described experiment the following conclusions can be noted. The average value of the coefficient of determination for models obtained using the ANCOVA method is 0.9850 and for linear regression models it is 0.9676, which means that the ANCOVA model better describes the phenomenon than the regression model. The average RSE value in the ANCOVA models is smaller about 1.24 vol.% than the average RSE value in the regression model, which means that the models obtained using ANCOVA more accurately describe the examined relationship. The average RMSE value in models determined by the ANCOVA method is smaller about 1.25 vol.% than the average RSE value in the regression model, which also confirms the better fit of the ANCOVA-model;

All presented models can be used as calibration equations for measuring the moisture of porous media using the reflectometric method, but the use of the ANCOVA method allows for better results. Both RMSE and RSE values for the calibration formulas obtained using ANCOVA method are smaller than presented in the literature for the standard invasive-type sensors using the classical empirical calibration formulas.

REFERENCES

1. Hoła J., Matkowski Z., Schabowicz K., Sikora J., Nita K., Wójtowicz S. Identification of moisture content in brick walls by means of impedance tomography. COMPEL - Int J Comput Math Electr Electron Eng. 2012; 31(6): 1774–92.
2. Rajak A.R.A. Emerging Technological Methods for Effective Farming by Cloud Computing and IoT. Emerg Sci J. 2022; 6(5): 1017–31.

3. Oates M.J., Ramadan K., Molina-Martínez J.M., Ruiz-Canales A. Automatic fault detection in a low cost frequency domain (capacitance based) soil moisture sensor. Agric Water Manag. 2017; 183: 41–8.
4. Orr S.A., Young M., Stelfox D., Leslie A., Curran J., Viles H. An 'isolated diffusion' gravimetric calibration procedure for radar and microwave moisture measurement in porous building stone. J Appl Geophys. 2019; 163: 1–12.
5. Soncela R., Sampaio S.C., Boas M.A.V., Tavares M.H.F., Smanhotto A. Construction and calibration of tdr probes for volumetric water content estimation in a distroferric red latosol. Eng Agric. 2013; 33(5): 919–28.
6. Paśnikowska-Łukaszuk M., Wlazło-Ćwiklińska M., Zubrzycki J., Suchorab Z. Comparison of Measurement Possibilities by Non-Invasive Reflectometric Sensors and Invasive Probes. Appl Sci. 2023; 13(1).
7. Instruction Manual-TDR200 (Revision 4/17). (accessed on 26 August 2023). [Internet]. Available from: https://s.campbellsci.com/documents/ca/manuals/tdr200_man.pdf
8. Application Note (TDR Impedance Measurements: A Foundation for Signal Integrity), Tektronix, (accessed on 26 August 2023) [Internet]. Available from: https://download.tek.com/document/55W_14601_2.pdf
9. Instruction Manual FOM2/mts, E-Test. Available [Internet]. Available from: https://www.e-test.eu/uploads/5/4/4/3/54435037/fom2mpts-v1.2.pdf
10. Topp G.C., Ferre T. Time-domain reflectometry. In: Encyclopedia of Soils in the Environment [Internet]. Elsevier; 2023. p. 436–43. Available from: https://linkinghub.elsevier.com/retrieve/pii/B9780128229743002846
11. Černý R. Time-domain reflectometry method and its application for measuring moisture content in porous materials: A review. Meas J Int Meas Confed. 2009; 42(3): 329–36.
12. He H., Turner N.C., Aogu K., Dyck M., Feng H., Si B., et al. Time and frequency domain reflectometry for the measurement of tree stem water content: A review, evaluation, and future perspectives. Agric For Meteorol. 2021; 306.
13. Kirkham M.B. Chapter 8 - Time Domain Reflectometry. Princ Soil Plant Water Relations. 2005.
14. Majcher J., Kafarski M., Wilczek A., Szypłowska A., Lewandowski A., Woszczyk A., et al. Application of a dagger probe for soil dielectric permittivity measurement by TDR. Meas J Int Meas Confed. 2021; 178.
15. He H., Aogu K., Li M., Xu J., Sheng W., Jones S.B., et al. A review of time domain reflectometry (TDR) applications in porous media. Adv Agron. 2021; 168: 83–155.
16. Basack S., Goswami G., Khabbaz H., Karakouzian M. Flow Characteristics through Granular Soil Influenced by Saline Water Intrusion: A Laboratory Investigation. Civ Eng J. 2022; 8(5): 863–78.
17. Barnat-Hunek D., Smarzewski P., Suchorab Z. Effect of hydrophobisation on durability related properties of ceramic brick. Constr Build Mater. 2016; 111: 275–85.
18. Freitas T.S., Guimarães A.S., Roels S., de Freitas V.P., Cataldo A. Is the time-domain reflectometry (TDR) technique suitable for moisture content measurement in low-porosity building materials? Sustain. 2020; 12(19).
19. Suchorab Z., Widomski M.K., Łagód G., Barnat-Hunek D., Majerek D. A noninvasive TDR sensor to measure the moisture content of rigid porous materials. Sensors (Switzerland). 2018; 18(11).
20. Suchorab Z., Majerek D., Kočí V., Černý R. Time Domain Reflectometry flat sensor for non-invasive monitoring of moisture changes in building materials. Meas J Int Meas Confed. 2020; 165.
21. Schaap M.G., De Lange L., Heimovaara T.J. TDR calibration of organic forest floor media. Soil Technol. 1997; 11(2): 205–17.
22. Malicki M.A., Plagge R., Roth C.H. Improving the calibration of dielectric TDR soil moisture determination taking into account the solid soil. Eur J Soil Sci. 1996; 47(3): 357–66.
23. Anokye-Bempah L., Phetpan K., Slaughter D., Donis-González I.R. Design, calibration, and validation of an inline green coffee moisture estimation system using time-domain reflectometry. J Food Eng. 2023; 341.
24. Quinones H., Ruelle P. Operative Calibration Methodology of a TDR Sensor for Soil Moisture Monitoring under Irrigated Crops. Subsurf Sens Technol Appl. 2001; 2(1): 31–45.
25. Udawatta R.P., Anderson S.H., Motavalli P.P., Garrett H.E. Calibration of a water content reflectometer and soil water dynamics for an agroforestry practice. Agrofor Syst. 2011; 82(1): 61–75.
26. Ren T., Noborio K., Horton R. Measuring Soil Water Content, Electrical Conductivity, and Thermal Properties with a Thermo-Time Domain Reflectometry Probe. Soil Sci Soc Am J. 1999; 63(3): 450–7.
27. Ju Z., Liu X., Ren T., Hu C. Measuring soil water content with time domain reflectometry: An improved calibration considering soil bulk density. Soil Sci. 2010; 175(10): 469–73.
28. Karpen S.C. Misuses of regression and ANCOVA in educational research. Am J Pharm Educ. 2017; 81(8): 84–5.
29. Riggs M.R., Haroldson K.J., Hanson M.A. Analysis of Covariance Models for Data From Observational Field Studies. J Wildl Manage. 2008; 72(1): 34–43.
30. Huitema B.E. The Analysis of Covariance and

Alternatives: Statistical Methods for Experiments, Quasi-Experiments, and Single-Case Studies: Second Edition. Anal Covariance Altern Stat Methods Exp Quasi-Experiments, Single-Case Stud Second Ed. 2011; 1–672.

31. Miller G.M., Chapman J.P. Misunderstanding analysis of covariance. J Abnorm Psychol. 2001; 110(1): 40–8.
32. Skierucha W, Wilczek A, Alokhina O. Calibration of a TDR probe for low soil water content measurements. Sensors Actuators, A Phys. 2008; 147(2): 544–52.
33. Suchorab Z., Malec A., Sobczuk H., Łagód G., Gorgol I., Łazuka E., et al. Determination of Time Domain Reflectometry Surface Sensors Sensitivity Depending on Geometry and Material Moisture. Sensors. 2022; 22(3).
34. Suchorab Z. Zastosowanie techniki reflektometrii w domenie czasu do oceny stanu zawilgocenia przegród budowlanych. 2016.
35. Rutherford A. ANOVA and ANCOVA: A GLM Approach. Sage. 2001; 1–344.
36. Jamieson J. Analysis of covariance (ANCOVA) with difference scores. Int J Psychophysiol. 2004; 52(3): 277–83.
37. Jennings M.A., Cribbie R.A. Comparing Pre-Post Change Across Groups: Guidelines for Choosing between Difference Scores, ANCOVA, and Residual Change Scores. J Data Sci. 2021; 14(2): 205–30.
38. Lai K., Kelley K. Accuracy in parameter estimation for ANCOVA and ANOVA contrasts: Sample size planning via narrow confidence intervals. Br J Math Stat Psychol. 2012; 65(2): 350–70.
39. The R Project for Statistical Computing [Internet]. 2016. Available from: www.r-project.org
40. Roth K., Schulin R., Flühler H., Attinger W. Calibration of time domain reflectometry for water content measurement using a composite dielectric approach. Water Resour Res. 1990; 26(10): 2267–73.
41. Hung S.L., Kao C.Y., Huang J.W. Constrained K-means and Genetic Algorithm-based Approaches for Optimal Placement of Wireless Structural Health Monitoring Sensors. Civ Eng J. 2022; 8(12): 2675–92.