Advances in Science and Technology
Research Journal

Advances in Science and Technology Research Journal, 18(7), 239–249
https://doi.org/10.12913/22998624/192595
ISSN 2299-8624, License CC-BY 4.0

Received: 2024.07.25
Accepted: 2024.09.18
Published: 2024.10.06

The Comparison of One-Variable and Two-Variable Polynomial Regression Models to Measure the Cellular Concrete Moisture Using the TDR Method

Magdalena Jastrzębska[1*], Anna Futa[1], Dominika Mikušová[2,3], Zbigniew Suchorab[3]

[1] Department of Applied Mathematics, Faculty of Mathematics and Information Technology, Lublin University of Technology, Nadbystrzycka 38, 20-618 Lublin, Poland

[2] Department of Physics, Faculty of Natural Sciences and Informatics, Constantine the Philosopher University in Nitra, Tr. A. Hlinku 1, 94901 Nitra, Slovakia

[3] Department of Water Supply and Wastewater Disposal, Faculty of Environmental Engineering, Lublin University of Technology, Nadbystrzycka 40B, 20-618 Lublin, Poland

* Corresponding author's e-mail: m.jastrzebska@pollub.pl

ABSTRACT

In the paper there are presented models for moisture assessment applying the two reflectometric sensors in the cellular concrete samples. The readouts express the dependence between the cellular concrete moisture, measured in gravimetric way and the apparent permittivity values achieved by the Time Domain Reflectometry method and two surface sensors. According to observed relationships, the two types of calibration models were derived – the first model is a traditional one-variable model covering only time of signal propagation and the second one two-variable model which together with signal propagation time takes into account signal attenuation. The aim of this paper is to verify the efficiency of multiple regression to improve the accuracy of moisture estimation using the TDR technique. The applied models that consider amplitude attenuation are used for this type of analysis for the first time. With the conducted research and analyses, it was shown that the measurement quality of the method could be improved by obtaining more favorable values of the determination coefficient, Residual Standard Error, Root Mean Squared Error. Also the correlation analysis shows a better fit of two-variable models than one-variable to the obtained data.

Keywords: analysis of regression, time domain reflectometry, building material moisture, multivariable regression model.

INTRODUCTION

The problem of moisture in building partitions is a real and immediate one related to the functioning of construction facilities and has a large impact on the indoor environment. For this reason, development of techniques for detecting moisture in partitions seems to play an important role, as also developing new methods and improvement and adaptation of existing ones [1]. It should be emphasized that the methods which allow for the most accurate determination of the water content in building partitions are the laboratory methods. These methods involve taking a sample from the partition, and then weighing and drying it, hence it is possible to direct and precise determination of the amount of water contained by weight in the partition. However, these techniques are in many cases useless due to the need to collect samples by drilling and long waiting times for the result. A good alternative are the indirect techniques that make quick measurements possible without disturbing the structure of the partition and maintaining high measurement precision. The most frequently applied indirect methods are the electric ones. Among them the electrical resistance method can be mentioned which relies on determination of the electrical resistance of the moist material.

Another approach to moisture evaluation utilizes the capacitance method. In this case, the measurement consists in measuring the capacitance of a capacitor filled with the tested material as a dielectric, which depends on the apparent permittivity of the medium between the capacitor plates. This parameter is also the basis for determining material moisture using the reflectometric method – TDR (time domain reflectometry). Another fairly commonly used indirect electrical method is the microwave method [2, 3]. The detailed description of indirect methods can be found in articles [4] and [5].

Among the indirect moisture detection techniques, the TDR plays an important role. It works on the principle reflectometric measurement of the dielectric parameters of the medium. In that case apparent permittivity is evaluated based on time of signal propagation along the sensors. In Figure 1 there are presented exemplary waveforms for three levels of moisture of porous material. Waveforms presented in Figure 1 show the influence of moisture on time of signal propagation. They are achieved by noninvasive sensor presented later in this article. In the diagram the time markers are presented by "A", "B", "C" and "D" letters. "A" letter represents the time marker for resistor being a part of the sensor construction and is generally independent on moisture, while "B", "D" and "C" letters represent time markers for sensor termination. It is visible that together with moisture increase position of the time marker is shifted to right. This phenomenon is essential for TDR method performance and the difference in time between the first "A" marker and termination markers is utilized to evaluate apparent permittivity. Additionally, it ought to be emphasized that together with propagation time increase signal amplitude decreases. This attenuation is caused by salt ions present in the moist porous material. In standard approach this phenomenon is not considered in TDR moisture evaluation, but it is typical and even more visible in old building barriers threatened by salinity, that's why it will be considered in moisture evaluation within this research. The TDR technique has been used in moisture measurements for many years. Recently, many successful initiatives have been undertaken to use its measurement potential to determine the moisture of materials and building envelopes. The most commonly used models for calibrating TDR sensors are empirical models created on the basis of laboratory measurements and based on correlating the results of moisture measurements using the gravimetric method with dielectric permittivity readouts. The most popular empirical model is the Topp model [6], which has the form of a third-degree polynomial:

$$\Theta = -0.053 + 0.0292\varepsilon - 0.00055\varepsilon^2 + 0.0000043\varepsilon^3 \quad (1)$$

where: Θ denotes the volumetric water content in the tested porous medium [cm^3/cm^3] and ε is the apparent permittivity of the medium measured using the TDR technique applying the traditional invasive probes.

An alternative model that allowed for increased measurement accuracy was proposed in the work of Malicki et al. [7] which additionally considers material bulk density to improve the readouts. It needs emphasizing that both Topp and Malicki formulas are derived for invasive TDR probes unlike the sensors which were used in this research.

The analysis of regression may be used during the construction of empirical models for moisture assessment by applying the indirect detection

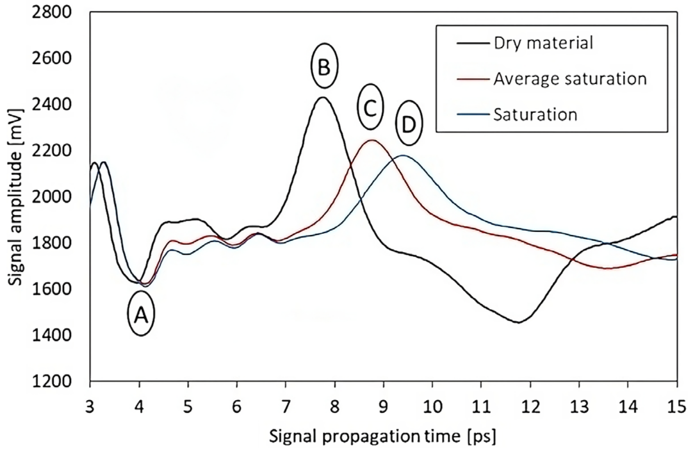


Figure 1. Exemplary waveforms achieved by TDR multimeter for dry, moist and saturated material (own research)

methods, as an alternative to the classic models. The regression model is one of the most popular methods of analyzing statistical data. The main idea of regression is prediction, forecasting data for a certain variable based on other variables. In other words, what value will a given variable take when the value of another variable is known. Namely, in order to be able to determine the value of one variable based on another variable, it is necessary to use the regression analysis to construct a regression model, i.e. the model that will predict the value or level of a given feature with an assumed statistical error, see [8]. The aim of the article is to compare two types of polynomial regression models as methods of calibrating non-invasive TDR sensors which allow to combine the apparent permittivity value read by the sensor and cellular concrete moisture. For this purpose, the analysis of regression methods will be used. The applying of the two-variable regression polynomial models focused on achieving better measurement characteristics than the one-variable regression models, which is detailed in the chapter titled as Results and discussion. The approach that utilizes two-variable regression models is not standard in applying the TDR method, where the essential estimated parameter is apparent permittivity depending on time of signal propagation. On the other hand, it must be emphasized that together with the time-shift, signal attenuation occurs which is a consequence of presence of the salt ions that are dissolved in water. This phenomenon is more influencing in the case of more moist materials but also with higher salinity levels. It should be explained that no additional data is required for signal analysis using two-parameter models, other than those received by the TDR meter from the sensors. They are contained in the return signal. The only difficulty here is to determine, in addition to the impulse propagation time, also the amplitude attenuation, and then build appropriate two-parameter models. And the solution to this problem is the novelty proposed in this article in the development of the TDR measurement technique.

MATERIALS AND METHODS

Measurement setup

Measurements were conducted by applying the following setup: VO-500 laboratory furnace (Memmert, Germany) for drying cellular concrete samples, WPT 6C/1 laboratory scale (Radwag, Poland), TDR setup involving a LOM laboratory multimeter (ETest, Lublin, Poland) and TDR surface sensor prototypes, i.e. narrow sensor and wide sensor (own manufacture) and a PC to control devices and collect data. The sensors have been detailed in [9, 10, 11]. Both sensors differ in thickness which may influence the readouts because it is well known phenomenon that depending on rods span the range of signal influence changes [12]. It is assumed that different span of the rods would influence the readouts and thus may impact the measurement errors. The research conducted by using two types of TDR sensors may reveal which solution provides better quality of the measurement.

The black polyoxymethylene, with an apparent permittivity value of 3.8 [10], was used to build both sensor prototypes. The narrow sensor is presented in Figure 2 (left). Its dimensions are as follows: 200 × 50 mm. The sensor consists of measuring rods, which were manufactured of brass flat bar with a cross-section of 20 mm^2. Distance between the measuring rods equals 30 mm. The wide sensor is presented in Figure 2 (right). Similarly, as in the case of narrow sensor, the used material was the same as also the construction of the sensor. The only difference was their dimensions, namely 200 × 100 mm and rods spacing equal 70 mm. The sensor waveguides were made of the same material and had the same cross-section dimensions as in the case of the narrow sensor. The total height of both sensors is similar and equals 85 mm.

Building materials tested using the TDR technique

For the purpose of the experiment cellular concrete samples were used as building material. We had assumed that cellular concrete would be a representative material for our tests because it is a porous medium with high absorptivity and would clearly reveal the differences of both methods of signal analyses. During the examination, samples of cellular concrete were applied. A set of the samples consisted of 5 specimens. The declared bulk density of the material was 500 kg·m^{-3}. The samples had the following dimensions: 250 × 120 × 65 mm. The dimensions of the samples were assumed knowing the length and width of both sensors and the range of signal influence of both prototypes. It was decided that

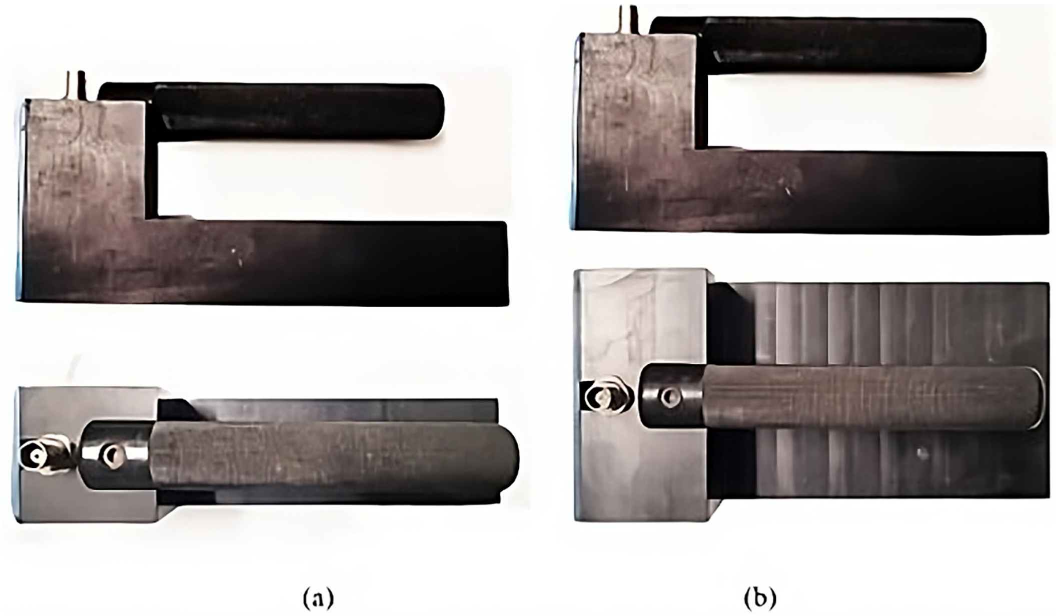


Figure 2. The construction of the TDR sensors, (a) – narrow sensor, (b) – wide sensor

the most efficient sample geometry would be adjusted to traditional bricks. Basic physical parameters of all used samples are presented in Table 1. All of samples were dried to the constant weight and progressively moistened using the pure water to achieve saturation status up to 0.32 cm^3/cm^3. Throughout the saturation process the moisture levels were obtained as follows: 0 cm^3/cm^3, 0.025 cm^3/cm^3, 0.05 cm^3/cm^3, 0.075 cm^3/cm^3, 0.1 cm^3/cm^3, 0.2 cm^3/cm^3, 0.3 cm^3/cm^3, and 0.32 cm^3/cm^3. Figure 3 presents the exemplary aerated concrete sample with the sensor during measurement procedure.

Subsequently, the samples were examined using a non-invasive narrow sensor and wide sensor to obtain reflectometric readouts. The research

Table 1. Basic physical parameters of the samples used in the experiment

Sample number	Mass in dry [g]	Bulk density	Mass of saturated sample [g]
1	987.8	506.56	1613.0
2	998.6	512.10	1618.1
3	986.2	505.74	1604.4
4	995.0	510.26	1620.4
5	998.6	512.10	1629.9

Figure 3. TDR narrow surface sensor on a cellular concrete sample

was based on the set of TDR waveforms at different moisture levels. All readouts were made on dry samples and next on the samples with moisture states mentioned before. The research was conducted under constant temperature (20 °C) and relative air humidity (50%) conditions.

Description of regression analysis method

Regression analysis is a statistical method used to study the relationship between one dependent variable and one or more independent variables. It relies on trying to fit a line (or curve) to the data to understand the nature of the relationship between variables. In linear regression, the relationship is modelled as linear, which means that the researcher tries to find the best fit of the line to the data [13]. The aim of regression analysis is to understand how a change in one independent variable affects the dependent variable. It can be used for forecasting, explaining cause-and-effect relationships and assessing the strength and direction of the relationship between variables [14]. A regression model is a mathematical equation which describes the relationship between dependent and independent variables. The simplest form of linear regression of one variable takes the form:

$$Y = a_0 + a_1 X + e \quad (2)$$

where: Y is the dependent (predicted) variable, X is the independent (observed) variable, a_0 is the intercept (Y-intercept), a_1 is the slope coefficient (shows how Y changes when X changes), e is the estimation error (the difference between the observed and predicted values Y).

The regression coefficients a_0 and a_1 determine what effect each independent variable has on the dependent variable. Positive coefficients indicate a positive impact, while negative coefficients suggest a negative impact. The higher the value of the coefficient, the stronger the influence of the independent variable on the dependent variable.

The most commonly used one-variable regression models are polynomial models, which can be written in the form:

$$Y = a_0 + a_1X + a_2X^2 + ... +a^nX^n + e \quad (3)$$

where: a_0, a_1,..., a_n are the structural parameters (coefficients) of the regression model and n is the degree of the polynomial.

Polynomial regression offers the possibility to model non-linear relationships between variables by adding polynomial terms to the regression equation. This is useful in cases where the relationship between variables is not simple and linear, but more complex.

An extension of one-variable regression is multiple regression, which allows to include at least two independent variables in the model. This allows for a more detailed analysis of the impact of multiple factors on the dependent variable, which is useful when many different variables may influence the outcome [15]. The basic multivariable linear regression model has the form:

$$Y = a_0 + a_1X_1 + a_2 X_2 + ... +a_n X_n + e \quad (4)$$

where: $X_1, X_2, \ldots, X_n$ are the independent variables included in the model.

Similar to one-variable linear regression, the most commonly used multiple regression models are polynomial models [16].

During analyzing a multiple regression model, it is important to check its degree of fit to the data. The following measures of model fit are distinguished:

- determination coefficient R^2 – this coefficient shows what percentage of the variability of the dependent variable is explained by the independent variable; the R^2 value ranges from 0 to 1, values closer to 1 indicating a stronger relationship,
- adjusted determination coefficient R^2_{adj} – is a modification of the R^2 coefficient that takes into account the number of independent variables in the model and the sample size; this coefficient is used in multiple regression to determine the degree of intensity or effectiveness of the independent variables in explaining the dependent variable,
- residual standard error (RSE) – also called standard error of estimation; this coefficient is a measure of the degree of fit of the model to the data, which consists in estimating the average dispersion of residual values around the regression line,
- root mean squared error (RMSE) – the square root of the arithmetic mean of the squares of the differences between predicted and observed values; RMSE measures the average distance, expressed in original units, between the empirical values of the explained variable and the theoretical values based on the model.

More detailed information about multivariable regression analysis and fitting parameters can be found in [17] and [18].

RESULTS AND DISCUSSION

The result of the experiment is a set of data representing the relationship between moisture content of cellular concrete determined in gravimetric way and the apparent permittivity obtained by the TDR sensors. The similar analyses of the effect of moisture on other types of materials, namely: asphalt is presented in the paper by Wuttisombatjaroen et al. [19], expansive soil is analyzed by Al-Khazaleh et al. [20] and granular materials are considered by Tu et al. [21]. The utilized TDR equipment enabled to collect data which were characterized by two parameters: (1) apparent permittivity (ε) values depending on moisture, as a basic parameter measured using the TDR and (2) voltage (V) of the reflectometric signal's second peak that is also dependent on moisture and its value is attenuated together with moisture increase, which is shown in Figure 1 and marked with macros "B", "C" and "D". One-variable and two-variable polynomial regression calibration models were used to analyze the data, for the narrow and wide sensors, respectively. As a consequence, four regression models were determined. The first general one-variable model is of the following form:

$$\Theta(\varepsilon)=a_0 + a_1\varepsilon + a_2\varepsilon^2 + e \text{ [cm}^3\text{/cm}^3\text{]} \tag{5}$$

where: $\Theta(\varepsilon)$ denotes the volumetric water content of the cellular concrete determined by a polynomial regression model of one variable ε (apparent permittivity).

The dependencies between apparent permittivity and material moisture according to the formula (5) were presented in Figure 4.

The second general model of two variables has the form:

$$\Theta(\varepsilon, V) = a_0 + a_1\varepsilon + a_2\varepsilon^2 + a_3V + a_4V^2 + e \text{ [cm}^3\text{/cm}^3\text{]} \tag{6}$$

where: $\Theta(\varepsilon, V)$ is the estimated volumetric water content of the cellular concrete determined by a polynomial regression model of two variables ε (apparent permittivity) and V (voltage) of the second's peak on the waveform collected from the TDR multimeter.

The equations of polynomial regression models of one variable and two variables with determined values of the structural parameters of these models were presented in Table 2. Moreover, it is worth noting that in all regression models the significance levels of individual estimators (p-values) are from the interval [0, 0.001] denoted by (***), which means high level of statistical significance.

In order to compare the degree of fit of the obtained regression models, the following fit measures were calculated: R^2/R^2_{adj} (the coefficients of determination), RSE and RMSE. The values of these fitting parameters were presented in Table 3.

According to the results for the narrow sensor presented in Table 3, the determination coefficient for one-variable regression model is equal to 0.937 and for the two-variable model is equal to 0.957. This means that 94% and 96% variability of the dependent variable is explained by the independent variable(s), respectively. Therefore, the second model better fits the dataset than the first one. The RSE value in these regression models varies from 2.4 vol.% to 2.9 vol.% and RMSE varies from 2 vol.% to 3 vol.%. The smaller values of RSE and RMSE for two-variable model also confirm that multivariable model is a better fitted model.

Similarly, in the case of wide sensor the determination coefficient for one-variable regression

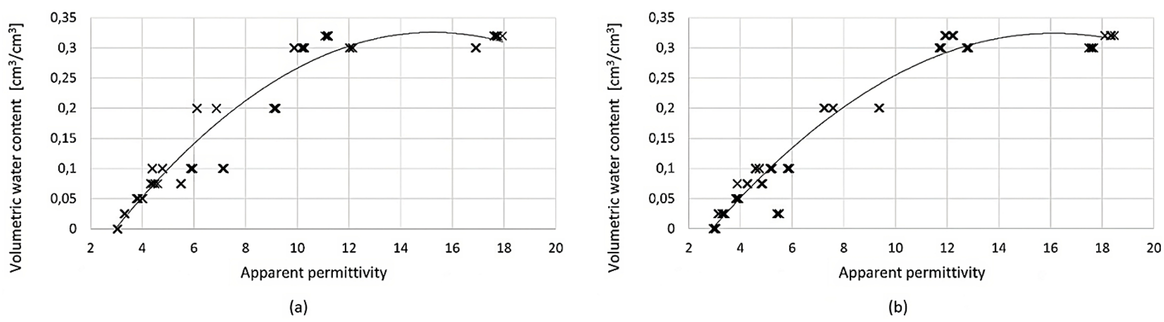


Figure 4. Dependences between apparent permittivity evaluated using the TDR method and material moisture for cellular concrete material measured by two types of sensors, (a) – narrow sensor, (b) – wide sensor

Table 2. Regression models for cellular concrete material and two types of sensors

Type of sensor	Regression model
Narrow	$\Theta(\varepsilon) = -0.1757408 + 0.0657846\cdot\varepsilon - 0.0021571\cdot\varepsilon^2$ (***) (***) (***)
	$\Theta(\varepsilon,V) = -4.513 + 0.07184\cdot\varepsilon - 0.00224\cdot\varepsilon^2 + 0.003671\cdot V - 0.000000779\cdot V^2$ (***) (***) (***) (***) (***)
Wide	$\Theta(\varepsilon) = -0.15813 + 0.059846\cdot\varepsilon - 0.001856\cdot\varepsilon^2$ (***) (***) (***)
	$\Theta(\varepsilon,V) = -6.984 + 0.0734\cdot\varepsilon - 0.002139\cdot\varepsilon^2 + 0.005955\cdot V - 0.000001306\cdot V^2$ (***) (***) (***) (***) (***)

Table 3. Fitting parameters of regression models for cellular concrete material and two types of sensors

Type of sensor	Number of variables	R^2/ R^2_{adj}	RSE [cm³/cm³]	RMSE [cm³/cm³]	F-statistic
Narrow	1	0.937	0.029	0.030	947.5
	2	0.957	0.024	0.020	716.8
Wide	1	0.957	0.024	0.020	1464.0
	2	0.974	0.019	0.020	1241.0

model is equal to 0.957 and for the two-variable model is equal to 0.974. This means that 96% and 98% variability of the dependent variable is explained by the independent variable(s), respectively. Therefore, the second model better fits the dataset than the first one. The RSE value in these regression models varies from 1.9 vol.% to 2.4 vol.% and RMSE values are the same and they are equal to 2 vol.%. The smaller value of RSE for two-variable model again confirm that multivariable model is better. The F-statistic values in all regression models also confirms that the statistical significance of these models.

Additionally, to examine the fit of both models, a correlation analysis was performed. Figure 5 and Figure 6 show the correlation lines expressing the dependence of volumetric water content measured by narrow and wide TDR sensors, respectively, and estimated volumetric water contents based on the derived regression models for cellular concrete samples.

Based on the relationships illustrated in Figures 5 and 6, the correlation equations were obtained and are presented in Table 4. Both for the narrow sensor and the wide sensor, the slopes of the correlation equations for the two-variable regression models are closer to 1 than in the one-variable regression models, moreover, the intercepts are closer to 0, which means that the two-variable regression models characterize the data better than the one-variable models. The main finding of the conducted research

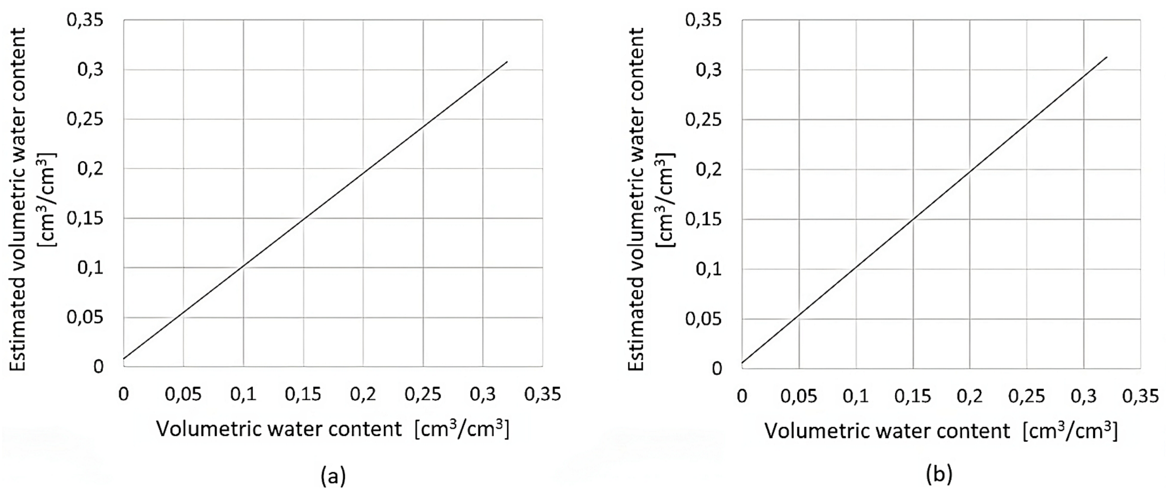


Figure 5. The correlation between measured volumetric water content and estimated volumetric water contents for cellular concrete samples using a narrow sensor: (a) θ and θ(ε), (b) θ and θ(ε,V)

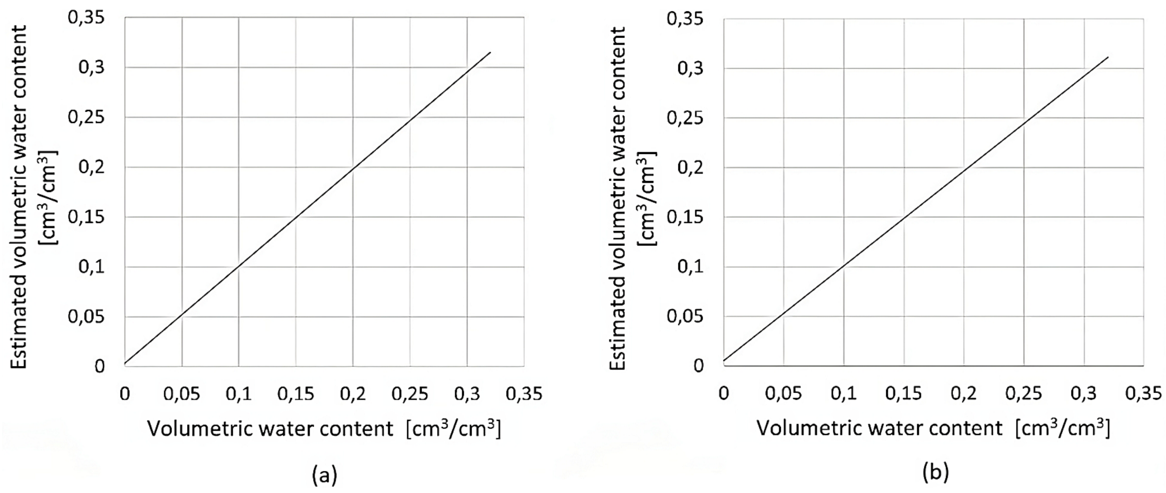


Figure 6. The correlation between measured volumetric water content and estimated volumetric water contents for cellular concrete samples using a wide sensor: (a) θ and $\theta(\varepsilon)$, (b) θ and $\theta(\varepsilon,V)$

Table 4. The correlation equations for cellular concrete material and two types of sensors

Type of sensor	Number of variables	The correlation equations
Narrow	1	$\Theta(\varepsilon) = 0.0079 + 0.937\cdot\Theta$
	2	$\Theta(\varepsilon,V) = 0.0059 + 0.9582\cdot\Theta$
Wide	1	$\Theta(\varepsilon) = 0.0053 + 0.957\cdot\Theta$
	2	$\Theta(\varepsilon,V) = 0.0032 + 0.9741\cdot\Theta$

is the determination of the influence of multiple regression on the improvement of the measurement quality of the tested sensors. Measurement errors were determined using the RSE and RMSE parameters and it was found that taking into account the signal amplitude attenuation allows for a reduction of these values and a simultaneous improvement of the measurement quality. At the same time, it was found that the RSE and RMSE values obtained for the wide sensor are more favourable compared to the narrow sensor.

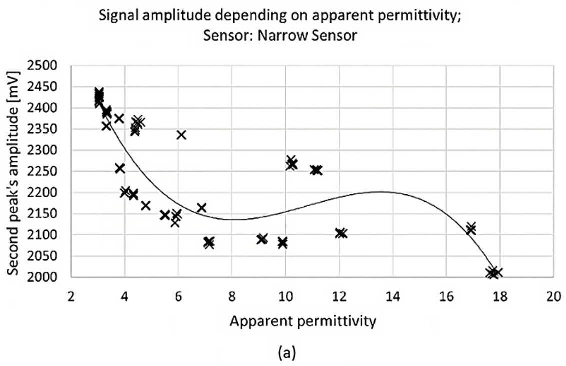
Comparing the achieved results to other research the most convenient is to use RMSE as a comparing parameter, which is often used in the literature to determine the quality of the adopted calibration formulas for moisture measurements using traditional, invasive TDR probes. The RMSE values obtained by both sensors, regardless of the calibration method used, are in the range of 0.02–0.03 cm^3/cm^3. Comparing these values to those obtained using the Topp model [6] and [22] determined by [23] for soil media and invasive probes, which are 0.01–0.066 cm^3/cm^3, it should be stated that they are comparable and, in many cases, even more advantageous. A similar situation concerns the RMSE values obtained for the popular calibration formula proposed by Malicki et al. [7], set at 0.03 cm^3/cm^3. It should be noted that the Malicki formula is also a two-parameter model, in which, in addition to the apparent permittivity, the bulk density of the material is considered. In the case of the model proposed by Roth et al. [24], the RMSE assumed values of 0.008–0.037 cm^3/cm^3. It should be noted that in most literature sources the proposed models were of a universal nature. For this reason, the quality of fit to the measurement data could be lower. The models presented in this study are individual, hence they better represent the dependencies $\theta(\varepsilon)$ or $\theta(\varepsilon,V)$ for a given sensor and material. The RMSE values are also comparable to the values determined by Udawatta et al. [25] for regression models developed individually for each of the materials (0.008–0.034 cm^3/cm^3) and invasive probes. Many of these models are also two-parameter models, which in this case take into account the temperature of the tested medium.

The results obtained in the conducted studies using less accurate surface sensors are characterized by RMSE values comparable to, and often better than, those reported in the literature. It should be noted that in most of the mentioned above literature sources the proposed models were of a universal nature. For this reason, the quality of fit to the measurement data could be lower. The models presented in this study are individual, hence they better represent the dependencies θ(ε) or θ(ε,V) for a given sensor and material. The use of multiple regression allows to improve these favourable parameters to a certain extent by about 0.005 cm^3/cm^3 for both type of sensors. The reason for this is the fact that the attenuation of the electromagnetic pulse amplitude is taken into account, which is caused by the presence of salt ions in the water contained in the material. It should be noted that salt ions are always present in building materials and soils; taking this phenomenon into account in calibration models allows for reducing measurement errors of this method. Summarizing, the two-variable polynomial regression models are better models for both types of sensors. Therefore, they were used to estimate material moisture using apparent permittivity and voltage. To avoid impossible situations of combinations of permittivity and voltage amplitudes, ranges of possible values that they take have been determined. Based on experimental studies, the range from 2.9 to 18.3 was assumed for the apparent permittivity. To determine the voltage ranges, the property shown in Figure 7 was used, which shows the relationship between the apparent permittivity and the amplitude of the second peak. The voltage ranges are from 1965.85 to 2414.18 and were determined based on the formulas in Table 5. These formulas result directly from Figure 7.

The graph in Figure 8 shows the relationships between volumetric water content, apparent permittivity and second peak's voltage values for cellular concrete using two types of TDR sensors.

More specifically, the graph in Figure 8 describes the relationship of apparent permittivity and volumetric water content in ε-Θ plane, voltage and volumetric water content in V-Θ plane and the relationship between apparent permittivity and voltage in ε-V plane. The graph shows that as the material moisture increases, the apparent permittivity increases, while the second peak voltage values decrease.

The advantage of the method of building calibration models that take into account signal attenuation proposed in the article is a more detailed analysis of the TDR signal, which in turn reduces measurement errors of this method. Algorithms of this type are not commonly used, despite the fact that they do not require additional tests, because the information contained in the same waveform, on the basis of which the pulse travel time is determined, which is used to build the models. Therefore, the aim of this article is to recommend that this quantity be taken into account when deriving the calibration formulas. However, it should be borne in mind that there is a certain limitation of this method in practical applications. Namely, it is difficult to predict in real conditions, and often in laboratory conditions, the behaviour of salts present in porous materials, which may undergo crystallization or hydration processes under specific



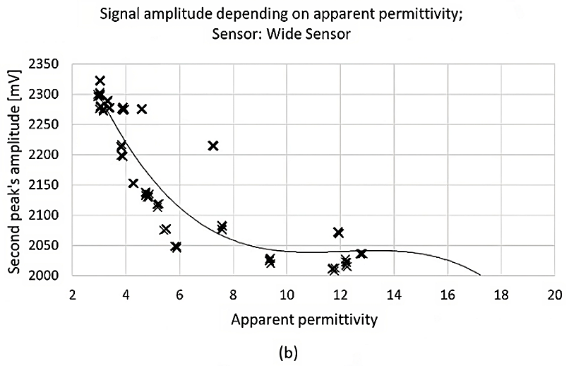


Figure 7. Dependences between signal voltage read on sensor termination measured by TDR and material moisture for cellular concrete material measured by two types of sensors, (a) – narrow sensor, (b) – wide sensor

Table 5. Equations estimating second peak's voltage levels

Type of sensor	Regression model	R^2
Narrow	$V(\varepsilon) = 3005.9 - 268.54 \cdot \varepsilon + 26.509 \cdot \varepsilon^2 - 0.8171 \cdot \varepsilon^3$	0.733
Wide	$V(\varepsilon) = 2661.4 - 156.93 \cdot \varepsilon + 13.07 \cdot \varepsilon^2 - 0.3591 \cdot \varepsilon^3$	0.845

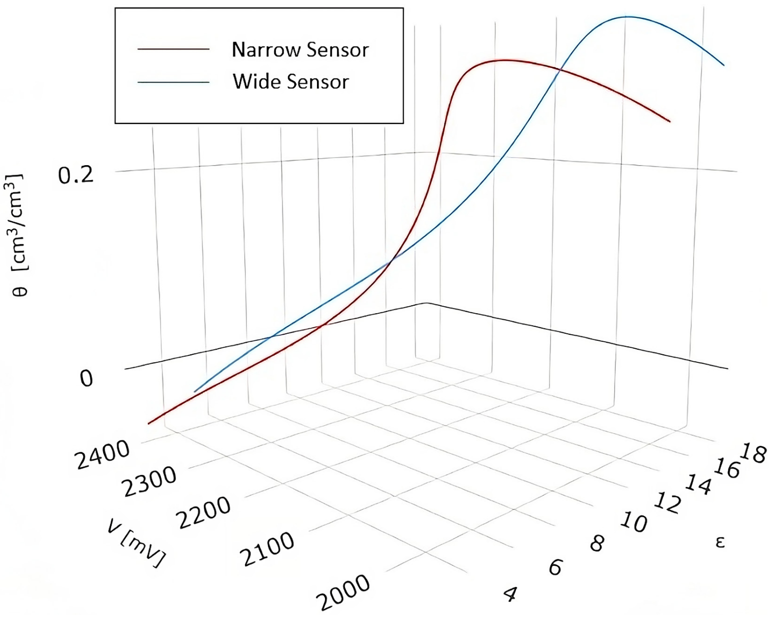


Figure 8. Graphs presenting the dependence of moisture (Θ) on permittivity (ε) and voltage (V) for cellular concrete samples for two types of sensors

humidity and temperature conditions, thus in a way that is difficult to predict on pulse attenuation. In order to eliminate this factor or reduce its impact on the results, a series of tests of this type should be carried out on samples not only saturated with water but also with salt solutions.

CONCLUSIONS

The main conclusion related to the carried-out research is that the proposed two-variable calibration models are better to estimate the cellular concrete moisture applying the TDR setup than the one-variable models. During the data analysis obtained in conducted research the following conclusions can be observed:

- In the case of both sensors, the coefficient of determination in multivariable models is greater than the determinant coefficient in one-variable models, which means that the first ones better describe the data than the second ones;
- The RSE values in both multivariable regression models are less than the RSE values in the one-variable models. Moreover, the RMSE values of two-variable models are less or equal to the RMSE in the one-variable models. Therefore, the smaller values of RSE and RMSE for two-variable models also confirm a better fit of these models for both types of TDR sensors;
- Both RSE and RMSE values achieved by one-variable and multivariable models are better for the wide construction sensor, which indicates that this sensor solution provides better quality of readouts than the narrow one;
- The slopes of the correlation equations for the multivariable regression models are closer to 1 than in the one-variable model and the intercepts are closer to 0 in multivariable case, which means that the two-variable regression models better describe the phenomenon than the one-variable models,
- Despite treating the TDR method as a time dependent method, it ought to be remembered that water present in building materials consists of some salt ions that affect signal attenuation, considering its influence together with the apparent permittivity determination makes is possible to improve the measurement quality of the method.

REFERENCES

1. He H, Aogu K, Li M, Xu J, Sheng W, Jones SB, González-Teruel JD, Robinson DA, Horton R, Bristow K, Dyck M, Filipović V, Noborio K, Wu Q, Jin H, Feng H, Si B, Lv J. A review of time domain reflectometry (TDR) applications in porous media. Adv Agron. 2021; 168: 83–155.
2. Majcher J, Kafarski M, Szypłowska A, Wilczek A, Lewandowski A, Skierucha W, Staszek K. Prototype

of a sensor for measuring moisture of a single rapeseed (*Brassica napus* L.) using microwave reflectometry. Meas. 2023; 214: 1–9.

3. Suchorab Z, Tabiś K, Brzyski P, Szczepaniak Z, Rogala T, Susek W, Łagód G. Comparison of the moist material relative permittivity readouts using the non-invasive reflectometric sensors and microwave antenna. Sensors. 2022; 22(10): 3622–3638.
4. 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.
5. 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.
6. Topp GC, Ferre T. Time-domain reflectometry. In: Encyclopedia of Soils in the Environment [Internet]. Elsevier; 2023; 436–43. Available from: https://linkinghub.elsevier.com/retrieve/pii/B9780128229743002846
7. Malicki MA, Plagge R, Roth CH. Improving the calibration of dielectric TDR soil moisture determination taking into account the solid soil. Eur J Soil Sci. 1996; 47(3): 357–66.
8. Arkes J. Regression Analysis: A Practical Introduction. Br Libr Cat. 2019.
9. Suchorab Z, Widomski MK, 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).
10. 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).
11. Futa A, Jastrzębska M, Paśnikowska-Łukaszuk M, Wośko E, Suchorab Z. Improving the calibration of surface time domain reflectometry sensors for moisture evaluation of building materials using the analysis of covariance method. ASTRJ. 2023; 17(5): 326–336.
12. Suchorab Z, Malec A, Sobczuk H, Łagód G, Gorgol I, Łazuka E, Brzyski P, Trník A. Determination of Time Domain Reflectometry Surface Sensors Sensitivity Depending on Geometry and Material Moisture. Sensors. 2022; 22(3): 735.
13. Verzani J. Linear regression. Munro's Stat. Methods Heal Care Res. Sixth Ed. 2011: 339–370.
14. Izenman AJ. Modern Multivariate Statistical Techniques. Artif Neural Networks. 2008: 101–118.
15. Aki R, Roberts JM. Multiple Regression: A Practical Introduction. United States SAGE Publ. 2020;
16. Royston P, Sauerbrei W. Multivariable Model - Building: A Pragmatic Approach to Regression Anaylsis based on Fractional Polynomials for Modelling Continuous Variables. Wiley Series in Probability and Statistics. 2008; 322.
17. Keith TZ, Multiple regression and beyond: An introduction to multiple regression and structural equation modeling. Routledge. 2019: 1–639.
18. Dhakal CP. Interpreting the Basic Outputs (SPSS) of Multiple Linear Regression. Int. J Sci Res. 2018; 8: 1448–1452.
19. Wuttisombatjaroen J, Hemnithi N, Chaturabong P. Investigating the influence of rigden void of fillers on the moisture damage of asphalt mixtures. Civ Eng J. 2023; 9(12): 3161–3173.
20. Al-Khazaleh M, Al-Masri DO, Al-Khodari MHS, Hamdan DAY, Hamdan AAY, Bani Atta MNM. Utilization potential of glass fiber and crumbled rubber as subgrade reinforcement for expansive soil. J Hum Earth Future. 2023; 4(3): 332–344.
21. Tu P, Vimonsatit S, Hansapinyo C. The Influence of Moisture on the Frequency Spectrum of Time Varying Mass Engineering Structure. Civ Eng J. 2023; 9(1): 17–28.
22. Majcher J, Kafarski M, Wilczek A, Szypłowska A, Lewandowski A, Woszczyk A, Skierucha W. Application of a dagger probe for soil dielectric permittivity measurement by TDR. Meas J Int Meas Confed. 2021; 178.
23. Ju Z, Liu X, Ren T, Hu C. Measuring soil water content with time domain reflectometry: An improved calibration considering soil bulk density. Soil Science. 2010; 175(10): 469–473.
24. 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: 2267–2273.
25. Udawatta RP, Anderson SH, Motavalli PP, Garrett HE. Calibration of a water content reflectometer and soil water dynamics for an agroforestry practice. Agrofor. Syst. 2011; 82(1): 61–75.