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Applying the Machine Learning Method to Improve Calibration Quality of Time Domain Reflectometry Measuring Technique

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ABSTRACT

The article presents the application of the time domain reflectometry (TDR) technique for measuring the moisture of porous building materials used in construction. The work is focused on using the potential of artificial intelligence to improve the quality of TDR measurements through a new approach to the interpretation of data obtained from the TDR readings. Machine learning is a data analysis technique, used nowadays in many scientific disciplines. The authors performed a measurement data analysis using the artificial intelligence algorithms to assess moisture of aerated concrete samples tested with a TDR multimeter using two non-invasive sensors which differ in thickness. Data analysis was carried out using supervised machine learning to analyse a series of reflectograms obtained during the measurement. For the data achieved by the classical and machine learning method interpretation, correlation analysis was conducted to confirm the potential of artificial intelligence to improve the quality of TDR measurement. The summary of the work discusses the obtained analytical results and highlights the effectiveness of moisture assessment using the Gaussian process regression method, which allowed achieving a level of 0.2–0.3% of the RMSE errors value, which is about 10 times lower than the traditional approach.

Keywords: time domain reflectometry, artificial intelligence, machine learning, moisture content, building materials.

INTRODUCTION

The high moisture content of porous construction materials is associated with many problems. These can be structural, hygienic or health problems of the residents of these buildings [1]. When solving these problems, it is therefore desirable to determine the moisture content of these buildings with high accuracy.

Time domain reflectometry (TDR) is an indirect measurement method for determining the moisture content of investigate media. The method allows samples to be tested outside the laboratory, while the testing takes a relatively short time and provides good accuracy. The mentioned properties are among the main advantages of the method. Disadvantages include the fact that the method can be affected by other factors, such as salinity [2]. In the past, this technique was used to determine the moisture content of mostly soil [3, 4], nowadays it is also widely employed in determining the moisture content of porous building materials [5–9]. In this method, the moisture of the material is determined using apparent permittivity as an indirect physical quantity. Porous building materials consist of three phases – solid, liquid, and gas. The solid phase, which forms the matrix, is characterised by a permittivity value of up to 15. The liquid phase, i.e. water, has a permittivity value of 80. The gas phase (air) has a permittivity value of 1. The great difference between the liquid phase and the solid phase is caused by the asymmetric distribution of the water charge. Due to this high difference in permittivity values the water content of the investigated material is possible to be determined [7].

The TDR device consists of a multimeter and set of probes. The multimeter generates the electromagnetic signal and in parallel analyses this signal [1]. The TDR probe is a pulse conductor that transmits signal along its elements. Several types of probes are used. Typically, the probe consists of two parallel conductive rods that are inserted into the medium under test. There are also surface sensors that do not require any material destruction. The measurement can be carried out on very hard materials, into which parallel conductive rods cannot be introduced [5–7]. The permittivity of the measured medium is determined using the propagation time of the electromagnetic signal along the conductors.

The relative permittivity of the environment ε is subsequently determined as:

$$\varepsilon = \left(\frac{c}{v}\right)^2 \quad (1)$$

where: c is the speed of light in vacuum and v is the propagation speed of the electromagnetic pulse along the measuring rods [$m \cdot s^{-1}$]. The equation expressed using the length of measuring rods L is also used:

$$\varepsilon = \left(\frac{ct_p}{2L}\right)^2 \quad (2)$$

where: t_p is the propagation time of the signal. The number two is in the denominator because the impulse propagates along the bars in both directions [7].

Using the calibration models, the apparent permittivity of the material is then converted to the water content in the material. Physical or empirical models are used. Physical models are not dependent on calibration measurements. However, the models often do not take into account the morphology and shape of the tested media, which affects their accuracy. Another disadvantage is the relatively complex mathematical formulations, which are difficult to apply in practice. Empirical models are therefore often used when carrying out measurements in practice. Empirical models are created by correlating with the gravimetric method. They can be universal or individual. The model proposed by Topp in 1980 is an often used universal empirical model [10]. This model uses only the measured permittivity to determine the moisture content of the material under investigation. In the case of universal models, inaccuracy is introduced into the determination of moisture content caused by their universality. Therefore, there was an effort to reduce the uncertainty of the measurement. Malicki et al. [11] proposed an empirical model, which includes the density of the investigated medium in its dry state. Individual models are designed specifically for the material under investigation and therefore often provide higher accuracy. There are many sources in the scientific literature that present empirical models. Since the TDR method was used in the past primarily to measure soil moisture. An example is the empirical models published by Ren et al. [12] or the models published by Mastrorill et al. [13]. In addition to these models, empirical individual models for determining the moisture content of porous building materials represent a significant contribution. An example is the work of the authors Sobczuk and Suchorab [8], which provides models for autoclaved aerated concrete with different densities ranging from 400 to 700 $kg \cdot m^{-3}$. Another example is a model designed individually for calcium silicate [14].

Artificial intelligence could be applied in the process of formulating the empirical models for evaluation of moisture using the indirect methods of detection as an alternative to the classical deterministic models. Artificial intelligence method is a method that is able to make decisions on its own based on input data. Machine learning represents a subdomain of artificial intelligence, where the user provides the data and the output or the desired results, and then machine learning generates a program or rules for the output attribute. Machine learning represents an automated process of traditional learning and increases the accuracy of analytical capability. The algorithms created in machine learning by processing training data create mathematical models on basis of which they subsequently predict situations [15].

Machine learning is a data analysis technique currently applied in many scientific disciplines. An example study by Shahi et al. [16] could be mentioned, where the authors comparatively studied the development of stock prices through deep learning. Another example is the contribution by Guefrechi et al. [17], where the authors proposed a classification model for detecting the COVID-19 viral disease, which achieved an accuracy of ~ 98%. Artificial intelligence was also used in the derivation of temperature-dependent material models for structural steel which was presented by Naser [18] or in the simulation of numerical data of water flow in pipes filled with copper porous medium [19].

In the available scientific literature, the artificial intelligence was also used for modelling of moisture properties of the soils. In the research described by Achieng [20], soil retention curves were determined. Soil moisture was measured using a TDR and the measured data was used to train and test artificial intelligence methods. The authors used the following methods to model the soil water retention curve: support vector regression models, single-layer artificial neural network and deep neural network. The results show that support vector regression Models achieved the best results among the tested techniques. The curve models obtained by artificial intelligence did not require knowledge of the physical parameters of the soil and provided reliable simulations of the soil water retention curve. In their work, Hong et al. [21] also presented the combination of TDR technique and deep neural network for determining electrical conductivity in saline medium with lead contaminated solution. With the use of artificial intelligence, the conversion relationship between the output value from the time domain reflectometry measurement and the volumetric electrical conductivity at different frequencies was developed.

Machine learning provides a simpler approach to problem solving, because it allows the user to train the system using examples of desired output-input behaviour instead of manually predicting the outputs of all possible inputs [15, 22]. Various algorithms have been developed for training. In supervised machine learning, these algorithms can be divided into two groups: classification and regression algorithms [23]. Well-known supervised machine learning algorithms are decision tree, support vector machine, linear regression and logistic regression.

Decision trees are very popular among classification algorithms. The algorithm uses a tree representation of options and maps the entire decision-making process. The input data is divided according to its most significant characters. The decision branches into tree structures until the algorithm reaches a prediction [23, 24]. Support vector machine can be used for both classification and regression. The algorithm creates hyperplanes and groups different classes. It is generally used for binary classification, but the algorithm can be extended to multiclass classification [24]. Simple support vector machine algorithms are used when solving linear regression or classification. Kernel support vector machines are used for non-linear data because they provide higher "elasticity" of distributions. Support vector machine algorithms can discover relatively complex connections between input and output information and can also work with relatively small amounts of data with relatively high accuracy [23]. Linear regression represents the simplest example of regression. The algorithm connects the scalar response with one (or more) inputs by linear dependence, which means that the response can be estimated using a linear combination of the input. Techniques such as simple linear regression, ordinary least squares, gradient descent, regularisation are used for model training [23, 25]. Another algorithm is logical regression, which is used in classification problems because its output is a discrete value. Despite its name, it is therefore a binary classification algorithm. This assumes that the variable under study can be classified into two different classes e.g. 0 or 1, true or false, etc. [24]. The algorithm is used when there is a need to predict the output as a dependent factor using an independent factor (input) [23].

The aim of this study is to check if artificial intelligence can be utilised as a method to assess the moisture of porous materials using raw time domain reflectometry signal and verify if it is possible to achieve smaller measurement errors than when using the traditional processing method.

MATERIALS AND METHODS

Materials

Equipment consisted of the following devices: VO-500 laboratory furnace (Memmert, Germany) for drying aerated concrete samples to a dry form, WPT 6C/1 laboratory scale (Radwag, Poland), TDR equipment including a LOM laboratory multimeter (ETest, Lublin, Poland) and TDR surface sensors, i.e. sensor A and sensor B (own design and manufactured at the Lublin University of Technology) previously presented in the following articles [9, 26] and a personal computer supporting the TDR multimeter control and data management. The non-invasive sensor A (Figure 1a) is made of black polyoxymethylene, characterised by an apparent permittivity value of 3.8 [-] [26]. The length of the measuring element A is 200 mm and its width is 50 mm. Measuring rods are made from brass flat bar with a cross-section of 2 × 10 mm^2. Sensor A communicated with the TDR meter via an angled BNC connector. The connector was soldered to the circuit board connecting the measuring rods to the connector. A flat bar is placed in the dielectric of sensor A. The sensor B is shown in Figure 1b. It is similar in construction and made from the same material as the sensor A. Its length is 200 mm, and its width is 100 mm. As in the case of the sensor A, the waveguides of the probes were made from a brass flat bar with a cross section of 2 × 10 mm^2.

Methods

Aerated concrete was used for the tests as the building material. In the presented research, samples of 450 $kg·m^{-3}$ of aerated concrete were used. Five samples were prepared for non-invasive measurements. The dimensions of the samples used for non-invasive tests were 220×120×40 mm. In Table 1, there are presented data of all dried samples used in the experiment.

The samples were dried to the constant weight and gradually moistened with pure water to obtain saturation status up to 64%. During saturation process the following moisture states were achieved: 5%, 10%, 15%, 20%, 40%, 50%, 60%, and 64%. The samples were then tested with a non-invasive sensor A and then with sensor B to obtain reflectometric readouts.

The tests involved the collection of TDR waveforms at various moisture values. Measurements were made on dry samples and then on the samples with moisture levels mentioned before. The tests were carried out under constant temperature (20 °C) and relative air humidity (50%) conditions.

Data processing methods

Classical TDR evaluation method

Data analysis using the standard approach relied on estimation of apparent permittivity (ε) value utilising the formula [2], where t_p is a time of signal propagation [ps] between two-time markers (negative on resistor soldered to a printed circuit of a sensor, and positive on sensor termination) minus the sensor dead time associated with the passage between the resistor and the beginning of the measuring element. Graphical presentation of the TDR signals are presented in the "Results" section. L is the measuring element length, which in case of the applied sensor was always equal 20 cm. With apparent permittivity values established for both sensors and material moistures calibration formulas were developed which were, according to the previous research, second grade polynomial functions presented in table 1. To evaluate the quality of the applied models

Table 1. Basic physical data of aerated concrete samples used in the experiment

Sample	Mass [g]	Apparent density [$kg·m^{-3}$]
1	865.1	444
2	877.1	450
3	878.9	451
4	866.2	444
5	872.4	447
Average	871.9	447

a) b)

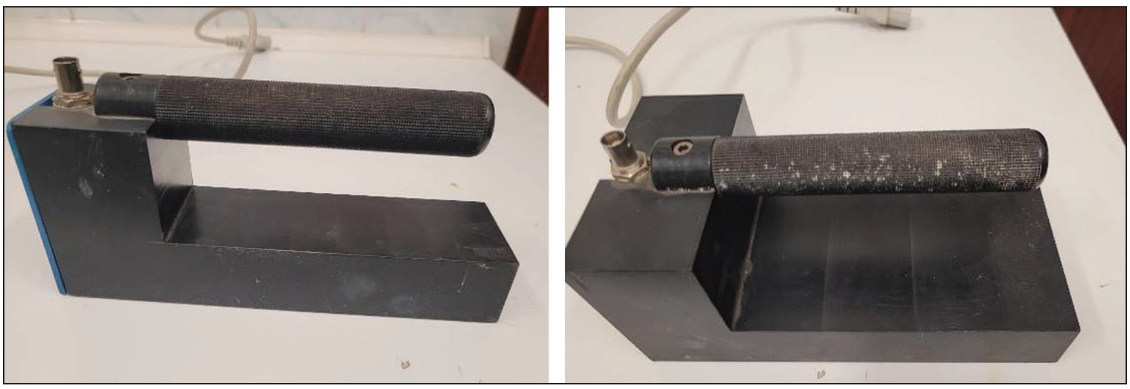

Figure 1. TDR sensors used in experiment (a) Sensor A, (b) Sensor B

coefficients of determination (R^2) and root mean squared error (RMSE) values were calculated.

Data analysis using the supervised machine learning

Artificial intelligence method was applied as an alternative for TDR data analysis. Machine learning regression models were used to obtain the expected relationships. The used models have the potential to allow moisture estimation based on raw data measured using the TDR technique. For this purpose, the supervised learning method was used, and the analyses were carried out in the Matlab software using the Regression Learner App tool [27]. This tool offers several regression models in different categories, such as linear regression model, regression trees, support vector machine, efficiently trained linear regression or Gaussian process regression. Three machine learning methods were selected that provided a fairly wide range of expected results:

- support vector machine – coarse gaussian,
- linear support vector machine,
- gaussian process regression.

Support vector machine – Coarse Gaussian technique is a non-linear supervised machine learning algorithm. The technique can be used equally in regression and classification analyses. The calculations work with a training dataset that contains predictor variables (x) and response variables (y). During the training of the model, this dataset is uploaded, which is subsequently cross validated [28, 29]. Mathematically, Coarse Gaussian kernel algorithm can be expressed by the following formula [28]:

$$K(x, x_i) = e^{-y|x-x_i|^2} \tag{3}$$

where: Kernel scale set = P·4, where P is the number of predictors.

The linear support vector machine algorithm uses a linear model to divide domains. Similar to the previous model, the data contain predictor variables (x) and response variables (y). The linear support vector machine is mathematically expressed as [30]:

$$y = wx^T + \gamma \tag{4}$$

where: $\gamma \sim N(0,\sigma^2)$.

Symbol σ^2 represents the error variance and together with the coefficient w they are estimated from the input data [31]. The input data is first linked with a set of answers and then the data domain is linearly divided into classes.

Gaussian Process Regression are nonparametric probabilistic models, which are used for interpolation between points in the input space, usually high-dimensional [31, 32]. The training data set represents the set $\{(x_i, y_i); i = 1, 2,..., n\}$, where $x_i \in R^d$ is the predictive value and $y_i \in R$ is the response and n is number of observation. This model is based on a linear regression model, formula (4). Gaussian process regression model clarifies latent variable from Gaussian process $f(x_i)$, $i = 1, 2, ..., n$ and basic function h. Gaussian process represent a set of variables and any finite number from this set have a joint Gaussian distribution. When is n observation ($x_1, x_2, ..., x_n$) and $\{f(x), x \in R^d\}$ is a Gaussian Process, then joint distribution of the random variables $f(x_1), f(x_2), \ldots, f(x_n)$ is Gaussian. Gaussian process is defined by covariance function $f(x, x')$ and by its mean function $m(x)$, then $E(f(x)) = m(x)$ and $cov[f(x), f(x')] = E[\{f(x) - m(x)\}\{f(x') - m(x')\}] = k(x, x')$ [27].

RESULTS

The results of the experiments are series of reflectograms acquired during measurements. The reflectograms are the curves showing the electromagnetic pulse propagation along the sensors. In abscissa, there is presented time of signal propagation in nanoseconds, and in ordinate, signal voltage is presented. In Figure 2, four exemplary waveforms used in further calculations are presented. Within the experiment two sets of waveforms were acquired for two types of sensors. Each set of data consisted of moisture values (between 0% and 64%) that were evaluated in laboratory measurement using gravimetric method and waveforms.

DISCUSSION

Classical TDR approach

In the first step, apparent permittivity values were calculated based on the waveforms, and then they were used to formulate the calibration models representing the dependence between apparent permittivity and moisture. Figure 3 shows the dependence for sensor A, and Figure 4 for the sensor B. Table 2 presents the developed

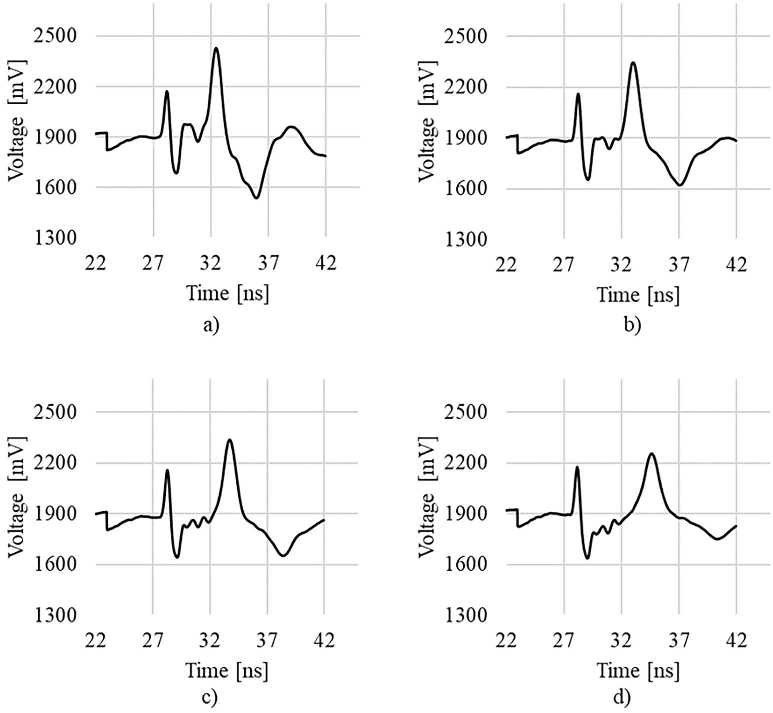

Figure 2. TDR signal. Exemplary diagrams showing the waveforms for dry (a), wet – 20% (b), wet – 40% (c) and saturated – 64% (d) materials (sensor A)

regression formulas based on the measurement data.Figures 3, 4 and Table 2 clearly show that models fit the measured parameters well. The resulting model in both case is described by polynomial function, which is typical for this type of sensors and was frequently applied by many scientists [7, 10–13]. The coefficient of determination is close to value 1, which indicates a good accuracy of the models.

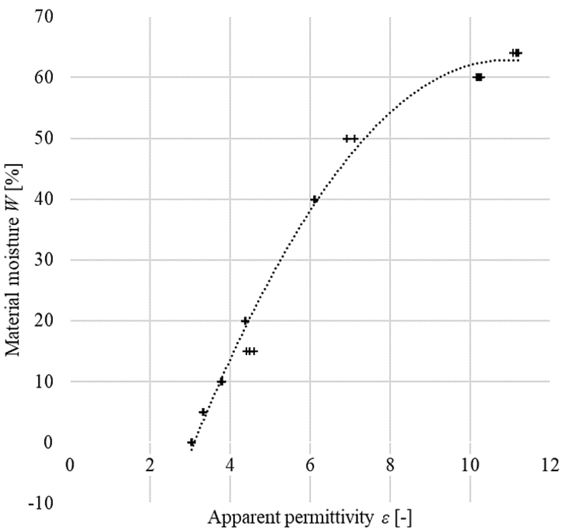

Figure 3. Calibration model developed for sensor A and examined aerated concrete

Machine learning method

To compare the potential to evaluate moisture using several methods of data analysis, correlation curves were presented that combine the laboratory readouts of moisture of the samples prepared for the experiment gravimetrically with moisture evaluated by TDR applying different methods of signal interpretation (classical TDR and three machine learning methods). These relations achieved for sensors A and B are presented in Figures 5 and 6, respectively. From the diagrams, it is clearly visible that the traditional approach of TDR data analysis provides very good quality of moisture evaluation. Coefficient of determination of linear function is very high, equal to 0.9893. Also, the estimators of the function are confirming that TDR method provides very good accuracy, where the slope coefficient is equal to 0.9892 and y-intercept is 0.315. It ought to be noticed that two models obtained using the supporting vector machine (SVM) learning methods provide less satisfactory dependences with R^2 = 0.9592 for Coarse Gaussian method. Linear SVM provides better R^2 value than traditional TDR approach, on the other hand, estimators values are less satisfactory. Gaussian process regression must be mentioned here as the method that provides more satisfactory parameters in terms of the coefficient of

Table 2. Achieved regression models based on the diagrams presented in Figures 3 and 4

Sensor type	Regression model	Coefficient of determination
Sensor A	$W = -1.0382 \cdot \varepsilon^2 + 22.598 \cdot \varepsilon - 60.13$	0.9893
Sensor B	$W = -0.5716 \cdot \varepsilon^2 + 15.907 \cdot \varepsilon - 41.725$	0.992

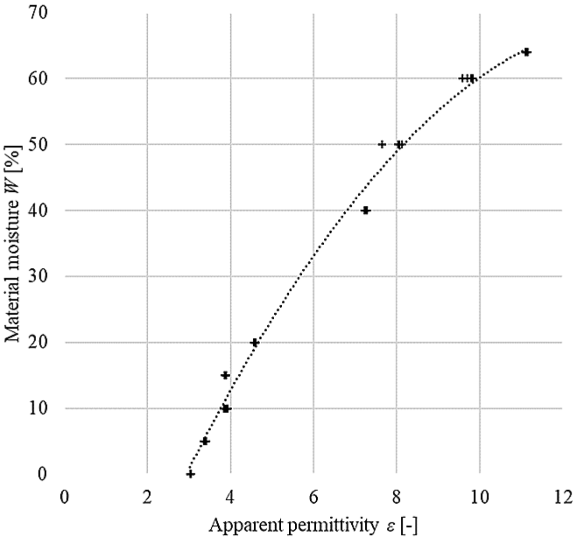

Figure 4. Calibration model developed for sensor B and examined aerated concrete

determination and the regression estimator values, which are equal nearly 1 for R^2 and slope estimator, and zero for y-intercept. A similar comparison was conducted for sensor B. Similarly, to sensor A it is visible that the traditional approach is still quite efficient. Coefficient of determination equals here to 0.992. Also, the estimators of the function are even better than in the case of sensor A. The models which utilise supporting vector machine learning methods are also worse in terms of coefficients of determination and linear function estimators, but Gaussian process regression provides more satisfactory parameters in terms of the coefficient of determination and the regression estimator values, which are equal nearly to 1 for R^2 and slope estimator, and zero for y-intercept. Additionally, data analysis was supplemented with root mean squared

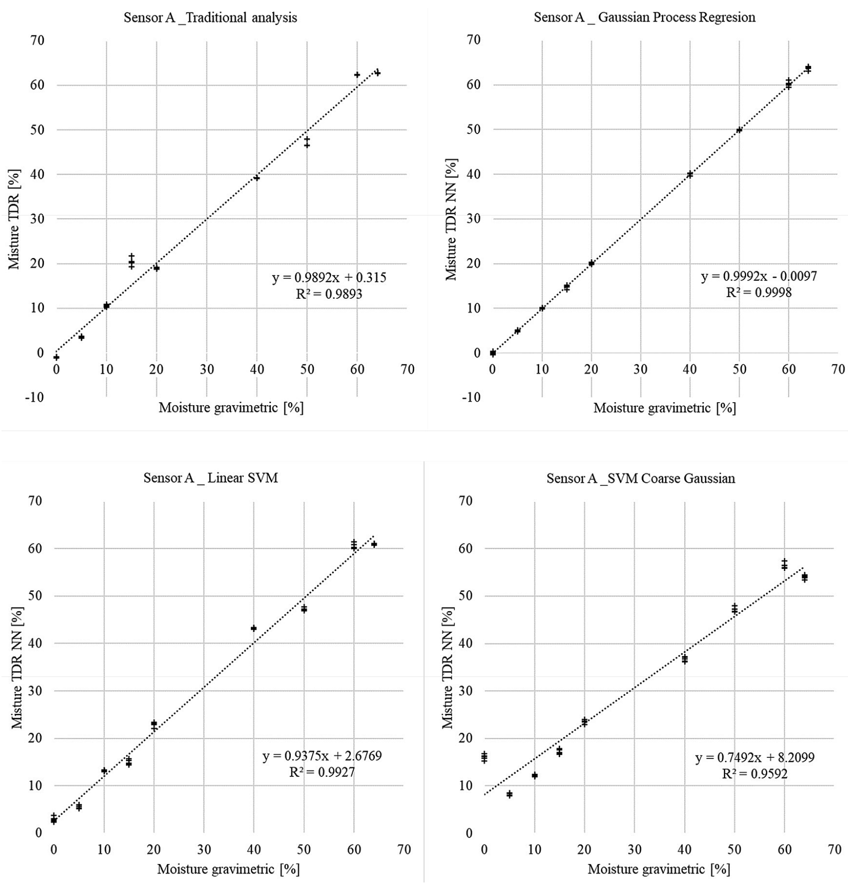

Figure 5. Dependences between moisture determined gravimetrically and determined using sensor A and several methods of data analysis

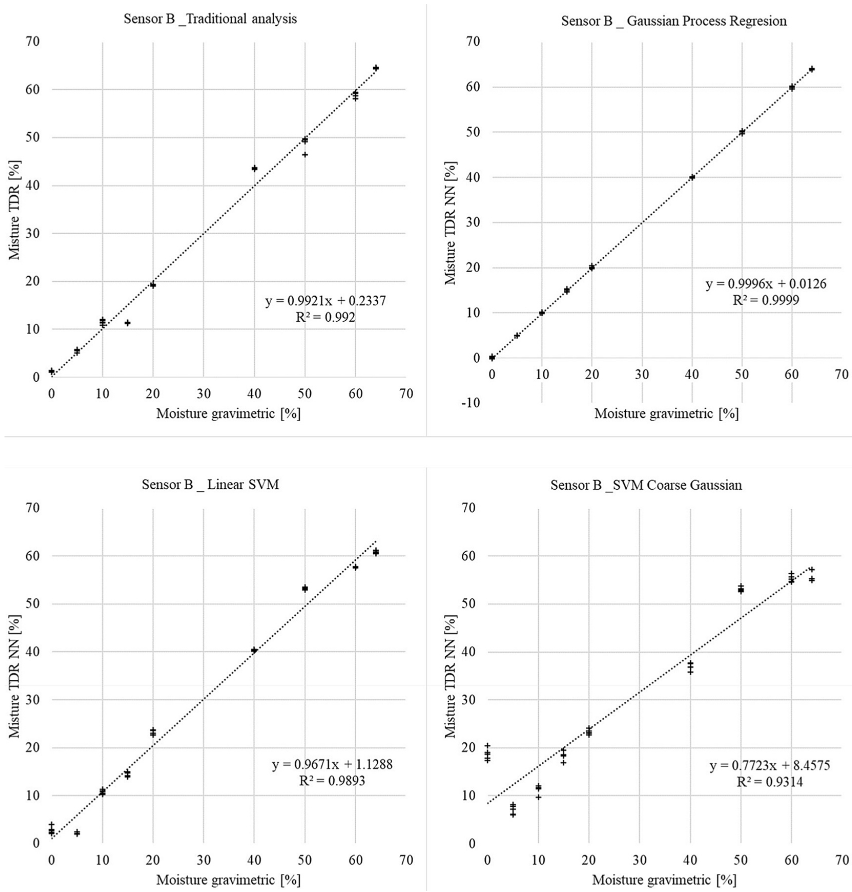

Figure 6. Dependences between moisture determined gravimetrically and determined using sensor B and several methods of data analysis

error analysis in order to compare the measuring errors of all techniques of data analysis. All RMSE values are presented in Table 3.

From the readouts presented in Table 3 it can be noticed that the standard approach to TDR data analysis is still efficient and offers good accuracy of moisture estimation. Values oscillating around 2% are still satisfactory for the measured material. It must be mentioned here that they are comparable or better to those presented in many literature sources, where the Topp et al. [10] provided RMSE value for his calibration model in a range between 1% and 6.6%, depending on material. Malicki et al. [11] valuated his model for RMSE value at the level of 3%. It must be underlined here that those values are achieved for invasive TDR probes, but are representative for universal formulas of calibration and moisture is measured in volumetric water content value, which may be different from mass moisture depending on material bulk density. Comparing the RMSE for universal formulas available in literature, it must be noticed that the values achieved here using standard TDR analysis are worse from other scientific results – for example Domingues-Nino et al. [33] achieved RMSE values between 0.5% and 1% and Udawatta et al. [34] achieved from 0.8% to 3.4%. Additionally, it is worth mentioning here that the RMSE values achieved in this research using the standard processing methods are comparable to the values achieved by the co-authors of this paper,

Table 3. Root mean squared error values achieved for both types of sensors and different methods of TDR signal analysis

Method	RMSE for Sensor A [%]	RMSE for Sensor B [%]
TDR (standard approach)	2.391	2.061
Coarse gaussian SVM model	6.860	7.366
Linear SVM model	2.500	2.451
Gaussian process regression	0.313	0.181

presented in the following articles [3, 22] where RMSE values varied between 2% and 3% for similar probes and tested material.

By applying the machine learning methods, it is possible to increase the quality of measurement and improve the calibration of TDR techniques, but it requires applying the suitable method of data analysis. Applying the supporting vector machine learning methods gives no advantage over traditional TDR signal processing. In the case of Coarse Gaussian SVM model, the achieved values were worse and achieved RMSE values about 7%, which means that they should not be applied for TDR data analysis. By applying the linear SVM model, it is possible to achieve similar quality of measurement to the classical approach or worse, which still makes this method not applicable. This is mainly due to the fact that the processed raw TDR signal was a series of voltage changes over time, only one for each measurement. SVM methods cope better with multidimensional data and in the case of the analysed signal this feature was not used, while the Gaussian process regression learning method is more flexible and universal for one-dimensional data [35] and allows to achieve the highest possible accuracy of readings with RMSE values equal 0.181% for sensor B and 0.313% for sensor A. This is many times better from the other learning methods and standard TDR data interpretation.

CONCLUSIONS

Within this study, it was confirmed that machine learning methods could be utilised to assess the moisture of porous materials using time domain reflectometry method. The most important benefit of this work is that it is possible to find the appropriate model with a higher accuracy than that of the empirical models with a traditional approach and thus more reliably determine the moisture content of the material. According to the investigation of time domain reflectometry raw signal analyses using various machine learning methods, the following conclusions may be formulated: standard approach to TDR data analysis for two applied sensors still provides satisfactory quality of measurement, which can be estimated in RMSE values between 2.0% and 2.4% depending on sensor type. Many machine learning methods still provide worse results comparing to the traditional TDR method. Gaussian process regression learning method provided the best quality of moisture evaluation reaching the level of 0.2–0.3% of RMSE value, which is about 10 times lower from the traditional approach. It needs emphasising that this study is only limited to moisture assessment and only one type of porous material. Time domain reflectometry can be also utilised to measure moisture of various building materials that differ in structure and density, like bricks, concretes etc. which needs more advanced techniques of data analysing. Additionally, this method could be utilised to evaluate salinity of different porous materials that is an exploitation problem of many buildings. These two topics seem to be interesting from the point of method development and are the subject of the future research, together with machine learning application.

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