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Possibilities of regression analysis in processing thermal conductivity measurement data

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ABSTRACT

When implementing energy saving measures, the correct choice of thermal insulation materials, the main characteristic of which is the thermal conductivity coefficient, is of key importance. Missing part of the data, which may occur during investigation of materials under natural conditions, can lead to incorrect determination of the corresponding characteristic, which negatively affects the effectiveness of the implemented measures and energy saving. Therefore, reconstruction of the missing data at the stage of preliminary processing of measured signals to obtain complete and accurate data when determining the thermal conductivity of thermal insulation materials will enable to avoid this situation. The article presents the results of regression analysis of data obtained during express control of thermal conductivity of thermal insulation materials based on the local thermal impact method. Regression models were built for signal reconstruction with 10%, 20% and 30% missing data, using which a relative error of determination the thermal conductivity coefficient of less than 8% was obtained. This is acceptable for express control of thermal conductivity and indicates the correctness of data restoration in this way. In addition, an algorithm is provided for determining signal stationarity, which enables to reasonably reduce the duration of each material with a given level of permissible error.

Keywords: thermal conductivity determination, insulation materials, regression analysis, missing data, data processing.

INTRODUCTION

Thermal insulation materials are widely used in various application areas, both in the implementation of energy saving measures and for thermal protection of various objects. The effectiveness of the application of these measures and the reliability of the operation of objects under supercritical conditions, which ultimately contributes to the saving of material, energy and environmental resources, depends on the correct choice of material. For example, to achieve good energy performance of a building, the correct choice of insulating materials for enclosing structures, which is determined by their thermophysical properties, is fundamental [1–2]. The main indicator that characterises the thermal insulation properties of materials is thermal conductivity. It is of great importance for identifying the mechanism of heat transfer in materials while developing modern thermal insulations and accurately designing thermal protection systems [3]. Tabulated thermal conductivity coefficient values of thermal insulation materials are often used, for example, in the construction sector when designing and renovating buildings, which leads to the fact that the actual characteristics of a building's enclosing structures differ from the design predictions with an increase in the building's energy consumption; thus, a greater risk of condensation and a decrease in the comfort of residents occur [4]. When calculating the thermal load of a building, probabilistic methods for assessing the characteristics of materials are used, data on which are obtained under laboratory conditions [5, 6]. Despite the high reliability of these methods, they are of little use for practical purposes due to the lack of such data that can be obtained under natural conditions [7, 8].

That is why it is important to determine the actual thermal conductivity coefficient values of thermal insulation materials. The most common are steady-state methods, which are implemented, as a rule, under laboratory conditions [9, 10]. The main advantage of these methods is precision, and the disadvantages include the significant duration of experimental studies (from 3–8 to 24 hours) [10, 11]. It should be noted that the thermal conductivity of thermal insulation materials depends on temperature, humidity and bulk density [12]. These factors have a significant impact on the storage and transportation of materials, so it is advisable to determine their characteristics under field conditions, for example, during incoming quality control at a construction site, and not be limited to data obtained under laboratory conditions.

Challenges in field research include power instability, changing environmental conditions, etc., which can cause signal transmission failure and loss of part of the data, in turn leading to incorrect determination of material characteristics.

Methods for restoring missing data, in particular, when monitoring various structural elements, are discussed in detail in [13]. The authors distinguish four main groups of such methods depending on the type of mathematical model that describes such characteristic features of the data as spatial and temporal distribution, in particular such methods as numerical analysis, optimisation, probability estimation and regression model. An important aspect when choosing a data restoration method is its accuracy, reliability, high computational efficiency, ease of implementation and simplicity. In [14], a correlation-based imputation method has been proposed for data restoration. This approach involves selecting a base set of complete instances, generating strongly correlated data segments using the base set and the remaining complete instances, and imputing each missing value by applying linear models to the identified data segments. Therefore, the aim of the work was to build a regression model for the reconstruction of missing data at the stage of pre-processing measured signals to obtain complete and accurate data on the example of determining the thermal conductivity coefficient of thermal insulation materials. In addition, changing environmental conditions in field tests directly affects the time of establishing a stationary measurement mode, in connection with which the authors propose an algorithm for assessing the entry into a conditionally stationary measurement mode based on the dynamics of changes in the obtained results.

MATERIALS AND METHODS

This work is based on the data from the study of samples of thermal insulation materials, which are described in [15]. The data were obtained during express thermal conductivity control based on the local thermal effect method using a portable device [16]. This method in the device is implemented according to a differential scheme, which assumes the presence of a sample signal. Structurally, this is implemented in the form of two probes, each of which contains identical heat flux and temperature sensors. One probe is the sample, the other is the measuring one, which additionally contains a heating element for a local thermal effect on the surface of the material under study. The sample probe is referred to a distance into the zone with an undisturbed thermal field. The main theoretical dependence is represented by an expression, based on which the thermal conductivity coefficient of the material under study is determined as a function of the ratio of the difference signals of the heat flux and temperature sensors:

$$\lambda = f\left(\frac{\Delta q}{\Delta T}\right) \tag{1}$$

where: Δq is the difference in heat flux values between the sample and measuring probes, ΔT is the difference in temperature values between the sample and measuring probes.

Theoretical calculations showed [17] that when measuring using the local thermal effect method, the measurement results on the samples made of materials with a thermal conductivity coefficient of more than 0.2 W/(m·K) are affected by contact thermal resistance. To reduce this effect, a thermally conductive grease was used.

One of the main operational characteristics of the device is the duration of the measurement process. This characteristic is especially important for the devices intended for express measurements. The above-mentioned relationship for the local thermal effect method is valid for the conditions of stationary heat exchange. In fact, from the beginning of the thermal effect on the material sample under study to the onset of the thermal mode, which will be conditionally considered stationary, a certain finite time passes – the time of exit from the stationary measurement mode. In addition, a certain period of time is required during which measurements are made (data recording). According to the standard procedure, the obtained data are averaged to reduce the influence of fluctuations in various mode parameters, for example, the convective heat transfer coefficient. The sum of these time periods determines the speed of the device. In this case, the following factors should considered:

- a constant temperature difference is maintained between the probes of the device (at a finite distance), and the temperature control system has a finite speed and limited power;
- there are parasitic thermal resistances between the probes of the device and the sample;
- there is convective-radiative heat exchange on the surface of the sample under study;
- the sample usually has finite dimensions compared to the distance between the probes.

As described in [16], when conducting measurements in the operating mode at the initial moment of time, the probes of the device are brought into contact with the material sample under study and the device is turned on. After the onset of stationary mode, which is achieved approximately after 25 minutes and is visually assessed according to the graph of changes in the measured signal, the temperature difference and the difference in heat flow are recorded for 5 minutes.

METHODS OF DATA RECONSTRUCTION

Reconstruction of missing data is one of the key tasks in data processing, since the absence of values can significantly affect the accuracy of the analysis, in particular the determination of the thermal conductivity coefficient. To solve this problem, it is important to create an accurate mathematical model and select appropriate algorithms. One of the methods for data restoration is regression analysis, which allows building a relationship between the input and output variables based on the available data. Regression can be of two types. Parametric regression relies on the assumption that the form of the relationship between the variables is known in advance and is described by a fixed function (for example, linear or polynomial). Nonparametric regression is used when the nature of the relationship is unknown. In this case, smoothing methods are used that allow obtaining a smooth estimate of the relationship while preserving the natural nature of the data.

To build an effective model, understanding of the temporal distribution of the data is required. These considerations are made before conducting an experiment, and they allow the experimenter to understand the goals of the experiment and, perhaps, to determine the suitable technique to achieve the goals [18]. If the results of engineering or scientific experiments reveal the periodic nature of a function, then orthogonal Fourier polynomials are best suited for approximating such functions [19–20]. This method enables to accurately represent the periodic components of the data as a sum of harmonic functions:

$$f(t) = a_0 + \sum_{i=1}^{K} (a_i \cdot \cos(iwt) + b_i \cdot \sin(iwt) \quad (2)$$

where: t is time, K – the number of harmonics (determines the complexity of the model), a_i and b_i – the coefficients that determine the amplitude of the harmonics.

The Fourier regression analysis coefficients are obtained using the inverse discrete Fourier transform [21]. Another method of nonparametric regression is approximation by using Gaussian curves:

$$f(t) = \sum_{i=1}^{K} a_i e^{-\left(\frac{t-b_i}{c_i}\right)^2} \quad (3)$$

where: a_i, b_i, c_i are the model parameters.

There are many cases that can be modelled using exponential functions

$$f(t) = \sum_{i=1}^{K} a_i e^{t_i} \quad (4)$$

One of the best known statistical indicators for assessing the quality of a constructed model is the coefficient of determination, known as R^2 [22]. It is also called the value of the approximation reliability and is determined by the formula:

$$R^2 = 1 - \frac{S_{res}}{S_{tot}} \tag{5}$$

where $S_{res} = \sum_{i=1}^{n} \left(f(t_i) - \hat{f}(t_i) \right)^2$ is the residual sum of squares, $S_{tot} = \sum_{i=1}^{n} \left(f(t_i) - \overline{f(t)} \right)^2$ – the total sum of squares, and $\overline{f(t)} = \frac{1}{n} \sum_{i=1}^{n} f(t_i)$ – the mean of the observed data.

However, this indicator is not always correct to use for evaluating nonlinear models. In [22] it is proposed to use the mean squared error (MSE) together with the correlation coefficient r for the observed and predicted values:

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(f(t_i) - \hat{f}(t_i) \right)^2 \tag{6}$$

$$r = \frac{\sum_{i=1}^{n} \left(\left(f(t_i) - \overline{f(t_i)} \right) \cdot \left(\hat{f}(t_i) - \overline{\hat{f}(t_i)} \right) \right)}{\sqrt{\sum_{i=1}^{n} \left(f(t_i) - \overline{f(t_i)} \right)^2} \cdot \sqrt{\sum_{i=1}^{n} \left(\hat{f}(t_i) - \overline{\hat{f}(t_i)} \right)^2}} \tag{7}$$

where: $f(t_i)$ and $\hat{f}(t_i)$ are the observed and predicted values, respectively, and n – the total number of predicted data.

The root mean squared error (RMSE) is the square root of the mean squared error [23]. It describes the standard deviation of residuals according to the formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(f(t_i) - \hat{f}(t_i) \right)^2} \tag{8}$$

To measure the effectiveness of regression the mean average percentage error (MAPE) is used [24]:

$$\mathrm{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{f(t_i) - \hat{f}(t_i)}{f(t_i)} \right| \cdot 100\% \tag{9}$$

The higher the MAPE value, the worse the model. MAPE measures the total loss [25].

RESULTS AND DISCUSSION

Processing thermal conductivity measurement data using regression analysis

On the basis of the measured data, the regression models were constructed for different amounts of missing data for the thermal conductivity coefficient of materials (extruded polystyrene (XPS), polyurethane and organic glass SOL). The article presents individual examples with different percentages of missing data. In the first case (Signal 1), 30 data units were missed, respectively, within the ranges 1–300 s, 300–600 s and 600–900 s, which is 10% of all the data. In the second case (Signal 2), 90 data units were missed within the range 1–300 s, which is 10% of all the data. In the third case (Signal 3), 90 data units were missed within the range 300–600 s, which is 10% of all the data. In the fourth case (Signal 4), 90 data units were missed within the range 600–900 s, which is 10% of all the data. In the fifth case (Signal 5), 60 data units were missed, respectively, within the ranges 1–300 s, 300–600 s and 600–900 s, which is 20% of all the data. In the sixth case (Signal 6), 90 data units were missed, respectively, within the ranges 1–300 s, 300–600 s and 600–900 s, which is 30% of all the data.The results for XPS are depicted in Figure 1.The metrics that assess the quality of the regression model for extruded polystyrene (XPS) are given in Table 1. The results for polyurethane are shown in Figure 2.

The metrics that assess the quality of the regression model for polyurethane are given in Table 2.

The results for organic glass SOL are plotted in Figure 3. The metrics that assess the quality of the regression model for organic glass SOL are given in Table 3. A comparison of the results of thermal conductivity determination (for all investigated materials) calculated according to the standard procedure [10, 15], (without missing data, marked as λ_0) with the results of thermal conductivity determination based on regression analysis in the case of missing data using the express method (marked as λ_{calc}), is given in Table 4.

The results in Table 4 show that the greatest error is obtained at 30% of missing data for all materials. For organic glass SOL the relative error is most influenced by data missing in the range

Table 1. Estimates of regression models for extruded polystyrene (XPS)

Signals	r	MAPE, %	RMSE
Signal 1_{XPS}	0.86	0.74	0.00021
Signal 2_{XPS}	0.71	0.88	0.00041
Signal 3_{XPS}	0.79	0.77	0.00034
Signal 4_{XPS}	0.78	0.79	0.00034
Signal 5_{XPS}	0.77	0.78	0.00035
Signal 6_{XPS}	0.70	0.88	0.00041

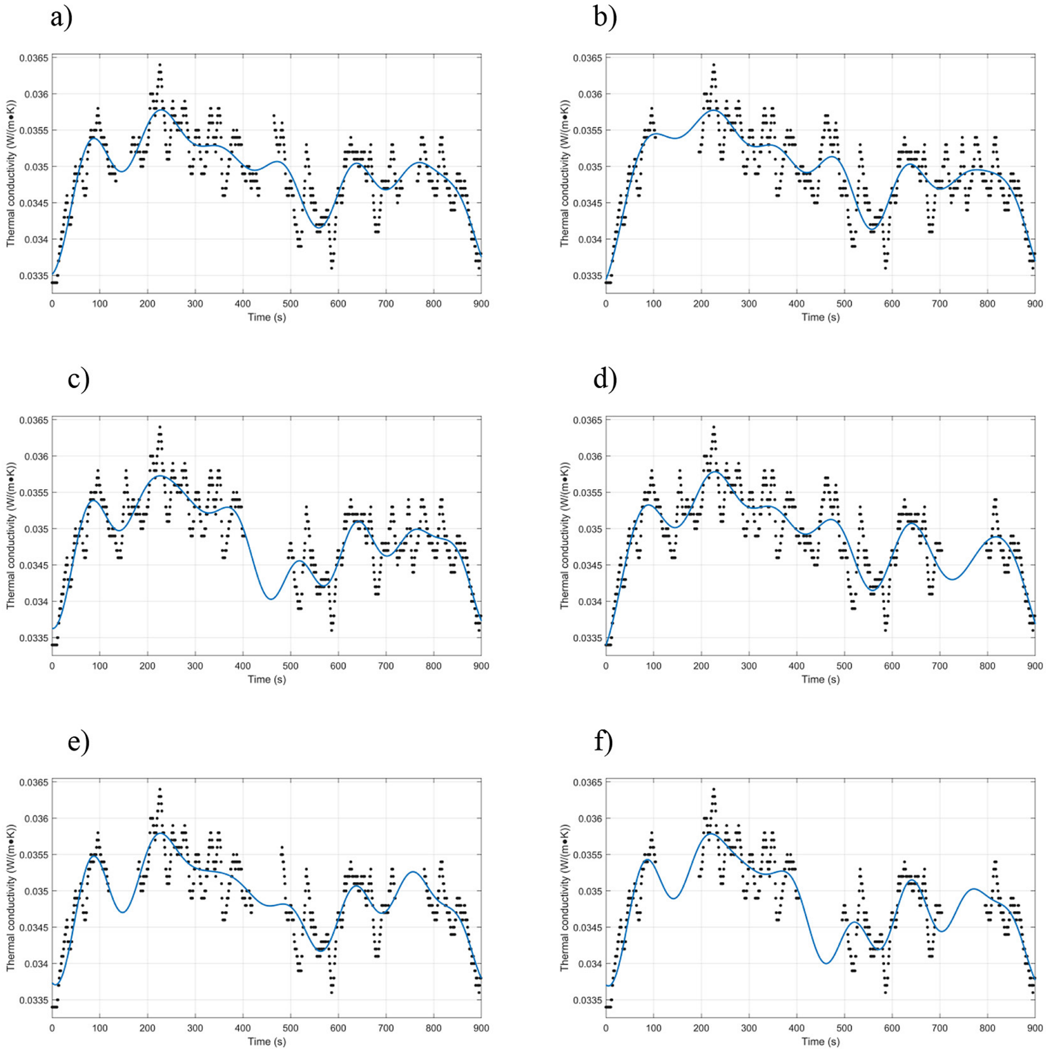

Figure 1. Thermal conductivity of extruded polystyrene (XPS) for measured values (black dots) and regression line (marked in blue) for signal 1 $_{XPS}$ (a), signal 2 $_{XPS}$ (b), signal 3 $_{XPS}$ (c), signal 4 $_{XPS}$ (d), signal 5 $_{XPS}$ (e) and signal 6 $_{XPS}$ (f)

of 300–600 s, and for polyurethane and extruded polystyrene (XPS) – in the ranges of 100–300 s and 600–900 s, respectively. The relative error of determination the thermal conductivity coefficient for the described regression models did not exceed the 8% allowable for express control of thermal conductivity [16].

Table 2. Estimates of regression models for polyurethane

Signals	*r*	MAPE	RMSE
Signal 1 $_{PU}$	0.78	1.15	0.00032
Signal 2 $_{PU}$	0.71	1.31	0.00038
Signal 3 $_{PU}$	0.76	1.17	0.00032
Signal 4 $_{PU}$	0.73	1.19	0.00032
Signal 5 $_{PU}$	0.71	1.24	0.00040
Signal 6 $_{PU}$	0.70	1.58	0.00045

Determining the stationary mode of the signal

As mentioned above, the onset of a stationary mode according to the standard procedure is carried out on the basis of a visual assessment of the graph of the measured signal. If the fixation

Table 3. Estimates of regression models for organic glass SOL

Signals	*r*	MAPE, %	RMSE
Signal 1 $_{OG}$	0.86	0.74	0.00021
Signal 2 $_{OG}$	0.79	0.77	0.00034
Signal 3 $_{OG}$	0.71	0.88	0.00041
Signal 4 $_{OG}$	0.78	0.79	0.00034
Signal 5 $_{OG}$	0.77	0.78	0.00035
Signal 6 $_{OG}$	0.70	0.88	0.00041

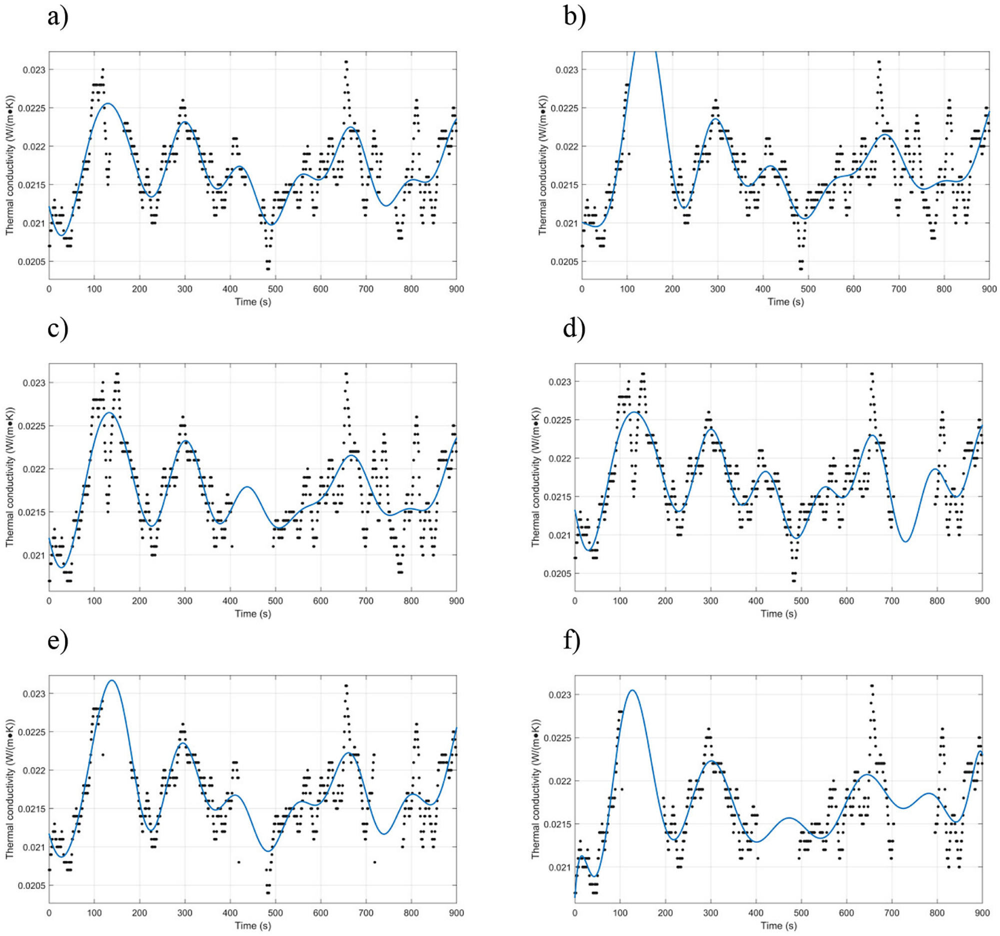

Figure 2. Thermal conductivity of polyurethane for measured values (black dots) and regression line (marked in blue) for signal 1 $_{PU}$ (a), signal 2 $_{PU}$ (b), signal 3 $_{PU}$ (c), signal 4 $_{PU}$ (d), signal 5 $_{PU}$ (e) and signal 6 $_{PU}$ (f)

Table 4. Results of thermal conductivity calculated according to the standard procedure and using regression analysis (with missing data).

Material	λ_0, W/(m·K) [1, 15]	λ_{cal_c}, W/(m·K)	Signals	Relative error, %
Organic glass SOL	0.1960	0.2091	Signal 1 $_{OG}$	6.683
		0.2095	Signal 2 $_{OG}$	6.887
		0.2096	Signal 3 $_{OG}$	6.938
		0.2090	Signal 4 $_{OG}$	6.632
		0.2095	Signal 5 $_{OG}$	6.887
		0.2098	Signal 6 $_{OG}$	7.041
Polyurethane	0.0227	0.0217	Signal 1 $_{PU}$	4.405
		0.0218	Signal 2 $_{PU}$	3.965
		0.0217	Signal 3 $_{PU}$	4.405
		0.0217	Signal 4 $_{PU}$	4.405
		0.0217	Signal 5 $_{PU}$	4.405
		0.0216	Signal 6 $_{PU}$	4.846
Extruded polystyrene (XPS)	0.0340	0.0348	Signal 1 $_{XPS}$	2.235
		0.0349	Signal 2 $_{XPS}$	2.265
		0.0348	Signal 3 $_{XPS}$	2.235
		0.0349	Signal 4 $_{XPS}$	2.265
		0.0348	Signal 5 $_{XPS}$	2.235
		0.0350	Signal 6 $_{XPS}$	2.941

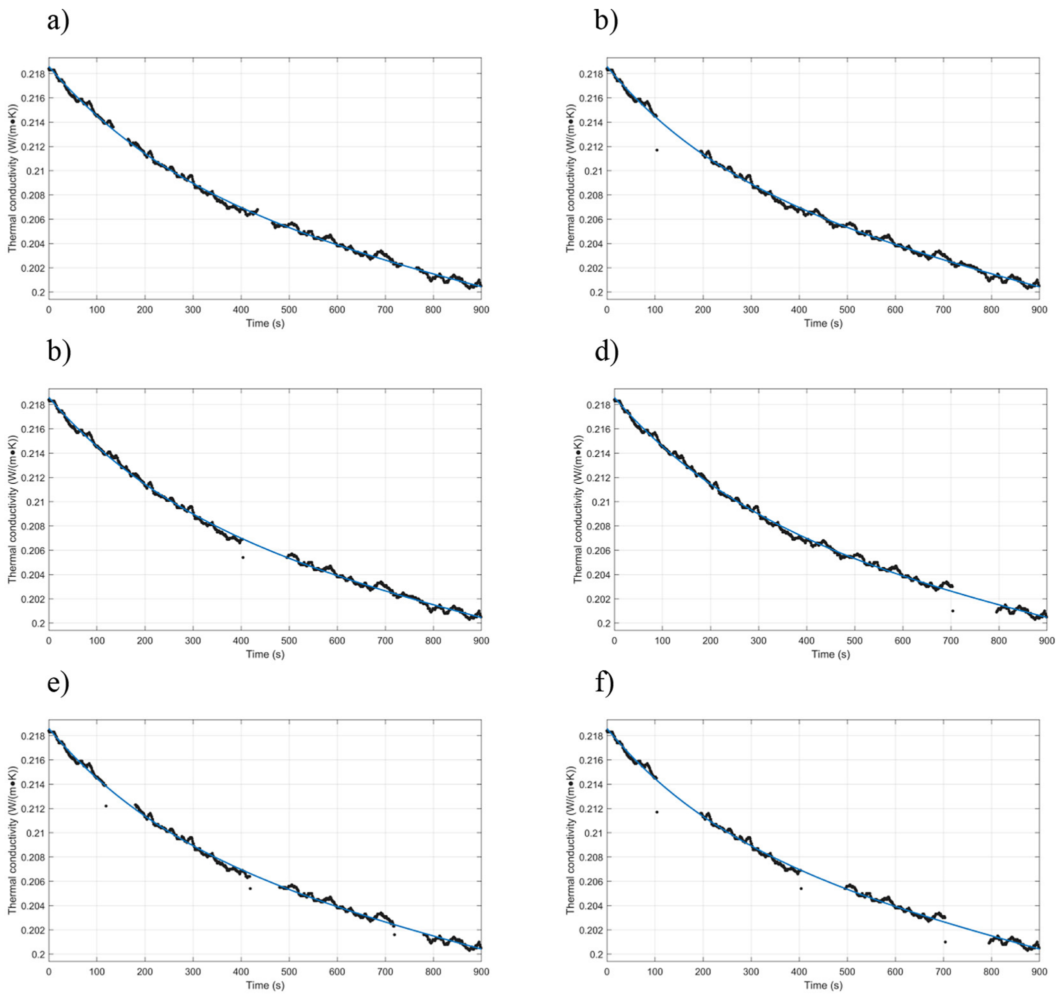

Figure 3. Thermal conductivity of organic glass SOL for measured values (black dots) and regression line (marked in blue) for signal 1 OG (a), signal 2 OG (b), signal 3 OG (c), signal 4 OG (d), signal 5 OG (e) and signal 6 OG (f)

of the signal stationarity is implemented programmatically, then the duration of the study can be reasonably adjusted (usually shortened) for specific materials with a given level of permissible error.

To determine the moment of stationarity of the measurement signal, a step-by-step analysis of the data was conducted.

On the basis of the preliminary analysis of the signal, the thermal conductivity coefficient in the first step lasting 5 minutes was determined. For the obtained data, the standard deviation and the slope of the trend line were calculated.

The maximum likelihood estimation (MLE) of the slope of the trend line is calculated by formula [26]:

$$m = \frac{\sum_{i=1}^{n}\left(t_i \cdot f(t_i)\right) - n\bar{t} \cdot \overline{f(t)}}{\sum_{i=1}^{n} t_i^2 - n \cdot \bar{t}^2} = \frac{n\sum_{i=1}^{n}\left(t_i \cdot f(t_i)\right) - \sum_{i=1}^{n} t_i \cdot \sum_{i=1}^{n} f(t)}{n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2} \quad (10)$$

where: $\bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i$, $\overline{f(t)} = \frac{1}{n}\sum_{i=1}^{n} f(t_i)$ are the mean values of the predictor and response variables, relatively.

The slope of the trend line reflects the direction of the relationship between variables. A positive slope means that the response variable increases along with the predictor variable. Conversely, a negative slope means that as the predictor variable increases, the response variable decreases. A zero slope implies the absence of a linear relationship between the two variables. The larger the slope value, the greater the overall tendency of the data series to increase or decrease. The smaller the slope value, the greater the tendency for the signal to transition to a stationary mode.

If the condition $|m| > \varepsilon$ (where ε is chosen according to the investigation aim) is met, then the measurement at the next step is continued.

Table 5. Results of thermal conductivity determination

Material	λ_0, W/(m·K) [1,15]	λ_{calc}, W/(m·K)	*t*, min	Relative error, %
Organic glass SOL	0.1960	0.2011	11	2.640
Polyurethane	0.0227	0.0219	5	3.326
Extruded polystyrene (XPS)	0.0340	0.0348	5	2.352

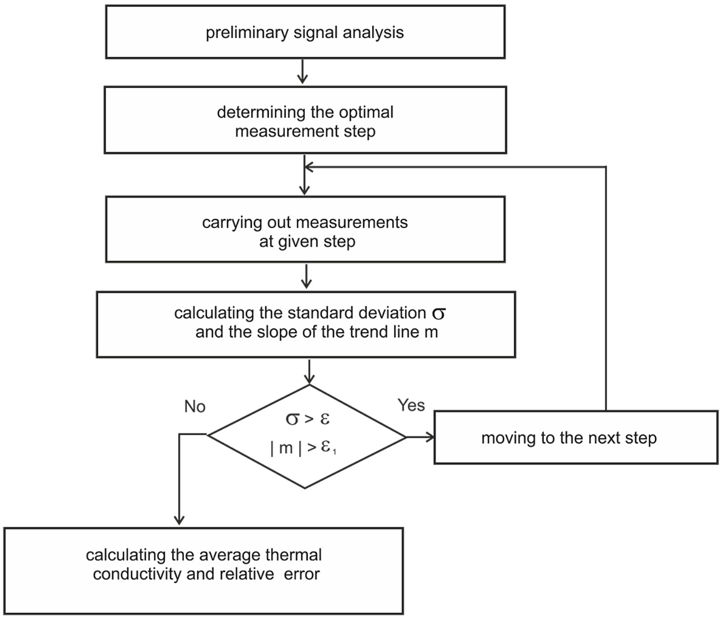

Figure 4. Flow chart of the algorithm for determining the stationary of the measurement signal

If the condition $|m| < \varepsilon$ is met, then it can be assumed that the signal has entered a stationary mode and the average value of thermal conductivity for a given step and the relative error can be calculated. The block diagram of the algorithm is shown in Figure 4. A comparison of the results of thermal conductivity measurements for all investigated materials processed according to the standard procedure [10, 15], with the results obtained using the proposed algorithm are given in Table 5.

The proposed algorithm allowed reducing the measurement time comparing with [16] to 700 s (11 min), 300 s (5 min) and 300 s (5 min) for organic glass SOL, for polyurethane and extruded polystyrene (XPS), respectively; and reducing the relative error to 2.64%, 3.326% and 2.352% for organic glass SOL, for polyurethane and extruded polystyrene (XPS), respectively.

CONCLUSIONS

The paper presents a regression model for the reconstruction of missing data at the stage of signal preprocessing using the example of determining the thermal conductivity coefficient of thermal insulation materials under natural conditions. The data obtained on samples of polyurethane and extruded polystyrene (XPS), which are the most common thermal insulation materials, were processed, and also organic glass SOL, which has stable values of the thermal conductivity coefficient, were taken as reference material.

The best results of signal modelling were obtained for polyurethane and extruded polystyrene (XPS) using orthogonal Fourier polynomials with K=8, and for organic glass SOL using exponential functions with K=2. The relative error of determination the thermal conductivity coefficient coefficient for the described regression models did not exceed the 8% allowable for express control of thermal conductivity.

In this way, regression models can reconstruct missing values and handle anomalies, which is often a problem in data analysis. This allows for more accurate modelling and forecasting of data.

In order to automate the determination of the start time of recording measurement data during express thermal conductivity control, an algorithm for determining signal stationarity was proposed. This algorithm allowed reducing the measurement time at least twice for organic glass and 4 times for polyurethane and extruded polystyrene, as well as reducing measurement error.

The obtained results are interesting for a reasonable duration of measurements and obtaining an error of a given level that does not exceed predetermined values.

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