Prediction of parameters of building structures using regression equations with independent action of variables and constancy of operating factors

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Abstract. In this article, the authors present a method for predicting the parameters of building structures and calculating the residual life using regression equations. The most commonly used regression equations were used: linear, polynomial, power, exponential, exponential, logarithmic, semilogarithmic, hyperbolic and logistic. The authors proposed to use one-factor regression equations, in which the variable is time, and the dependent value is the parameter of the building structure, the changes of which the researcher needs to determine. These equations are named by the author as the basic regression equations. Also, the authors in this article in the future, the basic equations are presented as multifactorial. This is achieved by replacing the coefficients of the main equation with regression equations, which are obtained after a series of tests are performed for various values of the selected input parameters (environmental conditions, material of construction, etc.), regression equations are obtained for each such state, as a result of which there are a number of values for the parameters of the basic regression equations. As a result, a repeated regression analysis is carried out and a regression equation is constructed for the coefficients of the main regression equation, which depends on the value of the specified parameters. Such equations are called secondary by the authors. Examples are given for conditional linear regression, where the author has demonstrated how the coefficients of the main regression equation are replaced and what final form the equation goes to after replacing the coefficients with secondary equations.

1. Introduction

Currently, the question of predicting changes in the parameters of building structures over time is becoming acute. Having the ability to predict the values of the parameters of building structures, it is possible to estimate their residual life, safety factors of bearing capacity, to determine the most optimal values of the parameters of the materials used, operating conditions, etc.

This is especially true when conducting a survey. But the existing survey methods give an assessment of the technical condition of buildings and structures only at the current time. They do not
give an idea of how long an object can still be operated in these conditions, having at the moment one or another category of technical condition. This is of great economic importance.

First, knowing how much more a building or structure will be used, you can calculate the required amount of deductions that will be received every month (quarter, year) for subsequent repairs. This will make it possible to evenly distribute the material load, which is beneficial not only for enterprises, but also for ordinary citizens who pay to the fund for capital repairs of housing.

Secondly, knowing how the parameters of building structures will change, it is possible to assess the feasibility of building a new building or structure to replace an existing one. For example, an estimate of the additional life of buildings that have served more than 50 years. The standard service life of these buildings is long gone. However, they are still in operation and it is necessary to make a forecast for changes in the parameters of their building structures.

This is important because in the context of limited funding for the demolition of old houses, it would be possible to estimate the additional service life of the building and identify priority objects for demolition (renovation). The same applies to buildings classified as hazardous housing. Thanks to the assessment of the change in the parameters of building structures in time for such buildings, it is possible to justify the need for urgent resettlement of people or to justify that this building will still be able to serve for some time, which is important when there are a lot of such objects, and little money is allocated for the construction of new housing for resettlement. This will make it possible to determine the priority objects for resettlement, based on the remaining service life.

It also matters when a building or structure has been or is constantly exposed to extreme factors (high temperature or fire, low temperatures, vibration, etc.).

2. Methods.

To solve this problem, the authors propose to use regression equations. The most commonly used multivariate regression equations are:

1) Multiple Linear Regression:

\[ y = a_0 + a_1 \cdot x_1 + \cdots + a_n \cdot x_n + \varepsilon \]  

A particular case is the paired Linear Regression:

\[ y = a_0 + a_1 \cdot x + \varepsilon \] (2)

2) Polynomial Regression:

\[ y = a_0 + a_{n,j} \cdot x_i^n + a_{n-1,j} \cdot x_i^{n-1} + \cdots + a_{j,j} \cdot x_i + \cdots + \varepsilon \] (3)

A particular case is the regression of n-th degree for one variable:

\[ y = a_0 + a_1 \cdot x + a_2 \cdot x^2 + \cdots + a_n \cdot x^n + \varepsilon \] (4)

3) Power regression:

\[ y = a_0 \cdot x_1^{a_1} \cdot \cdots \cdot x_n^{a_n} + \varepsilon \] (5)

4) Significant regression:

\[ y = a_0 \cdot x_1^{a_1} \cdot \cdots \cdot x_n^{a_n} + \varepsilon \] (6)

5) Exponential regression:

\[ y = e^{(a_0 + a_1 \cdot x_1 + \cdots + a_n \cdot x_n)} + \varepsilon \] (7)

6) Logarithmic regression:

\[ y = a_0 + a_1 \cdot \ln x_1 + \cdots + a_n \cdot \ln x_n + \varepsilon \] (8)

\[ y = a_0 + a_1 \cdot \lg x_1 + \cdots + a_n \cdot \lg x_n + \varepsilon \] (9)
7) **Semilogarithmic regression:**

\[ y = \alpha_0 + \alpha_1 \cdot \log x_1 + \cdots + \alpha_n \cdot \log x_n + \varepsilon \]  

(10)

8) **Hyperbolic Regression:**

\[ y = \frac{\alpha_0}{x_1} + \frac{\alpha_1}{x_1} + \cdots + \frac{\alpha_n}{x_n} + \varepsilon \]  

(11)

\[ y = \frac{1}{\alpha_0 + \alpha_1 x_1 + \cdots + \alpha_n x_n} + \varepsilon \]  

(12)

9) **Logistic regression:**

\[ y = \frac{1}{1 + e^{\left(\alpha_0 + \alpha_1 x_1 + \cdots + \alpha_n x_n\right)}} + \varepsilon \]  

(13)

where:
- \(\alpha_0, \alpha_1, \ldots, \alpha_n\) — coefficients of the regression equation;
- \(x_0, x_1, \ldots, x_n\) — independent variables;
- \(\varepsilon\) — residual (error) of approximation;
- \(y\) — dependent variable, which is found by the regression equation.

These equations are widely used in studies of both foreign and Russian scientists [1-20] due to their versatility. These equations can be applied to any operating conditions, even extreme ones, for any building structures with various amounts of physical wear.

**3. Results and Discussion.**

To solve the forecasting problem, we will use one-factor regression equations. Time will be used as a variable \(t\). Since we do not know the true value of the parameters, therefore, the magnitude of the error is also unknown to us. Therefore, we will assume that \(\varepsilon = 0\). Then the equations will take the form:

1) **Linear Regression:**

\[ R = \alpha_0 + \alpha_1 \cdot t \]  

(14)

2) **Polynomial Regression:**

\[ R = \alpha_0 + \alpha_1 \cdot t + \alpha_2 \cdot t^2 + \cdots + \alpha_n \cdot t^n \]  

(15)

3) **Power regression:**

\[ R = \alpha_0 \cdot t^{\alpha_1} \]  

(16)

4) **Exponential regression:**

\[ R = \alpha_0 \cdot \alpha_1^t \]  

(17)

5) **Exponential regression:**

\[ R = e^{(\alpha_0 + \alpha_1 t)} \]  

(18)

\[ R = \alpha_0 \cdot e^{(\alpha_1 t)} \]  

(19)

6) **Logarithmic regression:**

\[ R = \alpha_0 + \alpha_1 \cdot \ln t \]  

(20)

\[ R = \alpha_0 + \alpha_1 \cdot \lg t \]  

(21)

7) **Semilogarithmic regression:**

\[ y = \alpha_0 + \alpha_1 \cdot \log t \]  

(22)

8) **Hyperbolic Regression:**
Logistic regression:

\[ R = \frac{1}{1 + e^{(a_0 + a_1 t)}} \]  

9) Logistic regression:

\[ R = \frac{1}{a_0 + a_1 t} \]

\[ R = \alpha_0 + \alpha_1 \frac{t}{t} \]  

\[ R = \frac{1}{\alpha_0 + \alpha_1 \cdot t} \]

**Logistic regression:**

\[ R = \frac{1}{1 + e^{(a_0 + a_1 t)}} \]

\[ R - \text{predicted parameter (dependent variable)}; \]
\[ t - \text{time (independent variable)}; \]
\[ a_0, a_1, ..., a_n - \text{parameters of the regression equation.} \]

The resulting equations will be called the **basic** regression equations.

These equations can be represented as multifactorial.

The reason why these equations, despite the fact that only one parameter is measured, can be presented as multifactorial, lies in the fact that in the experiment the researcher inevitably encounters the influence of other factors (parameters). These factors are always present as external and internal conditions of the environment in which the experiment is carried out. Some of them are specially created by the experimenter, others are always present and the only thing that can be done is to vary their value.

For example, when testing wood materials for strength, the experimenter can add a factor such as ultraviolet radiation or remove it by conducting the experiment in a room where the effect of radiation is negligible.

Therefore, taking these parameters into account will make it possible to better predict the change in the quantities of interest to us, if we additionally take into account these parameters in the basic equations.

Let \( n \) experiments be carried out. In this case, it is assumed that the number of samples in each experiment was large enough so that subsequent experiments would make it possible to obtain coefficient values that slightly differ from each other under the same accepted conditions of each experiment. Each experiment corresponds to its own value of the parameters, which the researcher stipulated in advance in the experimental procedure. The parameters themselves, as well as their composition, do not change, only their values change with a certain step, which is stipulated in advance in the experimental procedure.

As a result of processing the experimental data, \( n \) regression equations were obtained.

**Linear Regression:**

\[ R_1 = \alpha_{01} + \alpha_{11} t \]  

\[ R_2 = \alpha_{02} + \alpha_{12} t \]  

\[ ..................... \]

\[ R_n = \alpha_{0n} + \alpha_{1n} t \]

Regression equations of other types for each test result are similarly composed.

Consider first a case with one determining factor. We will assume that the effect of other factors is negligible.

According to the test results, series of values of the regression coefficients were obtained depending on the determining factor (see Fig. 1).
Based on the results of the regression analysis, equations for the regression coefficients were obtained. These equations will be called secondary regression equations.

1) Linear Regression:

\[ a_i = \beta_{0i} + \beta_{1i} \cdot P \]  (29)

2) Polynomial Regression:

\[ a_i = \beta_{0i} + \beta_{1i} \cdot P + \beta_{2i} \cdot P^2 + \cdots + \beta_{ni} \cdot P^n \]  (30)

3) Power regression:

\[ a_i = \beta_{0i} \cdot P^{\beta_{1i}} \]  (31)

4) Exponential regression:

\[ a_i = \beta_{0i} \cdot e^{\beta_{1i} \cdot P} \]  (32)

5) Exponential regression:

\[ a_i = e^{(\beta_{0i} + \beta_{1i} \cdot P)} \]  (33)

\[ a_i = \beta_{0i} \cdot e^{(\beta_{1i} \cdot P)} \]  (34)

6) Logarithmic regression:

\[ a_i = \beta_{0i} + \beta_{1i} \cdot \ln P \]  (35)

\[ a_i = \beta_{0i} + \beta_{1i} \cdot \log P \]  (36)

7) Semilogarithmic regression:

\[ a_i = \beta_{0i} + \beta_{1i} \cdot \log P \]  (37)

8) Hyperbolic Regression:

\[ a_i = \beta_0 + \frac{\beta_{1i}}{P} \]  (38)

\[ a_i = \frac{1}{\beta_0 + \beta_{1i} \cdot P} \]  (39)

9) Logistic regression:

\[ a_i = \frac{1}{1 + e^{(\beta_{0i} + \beta_{1i} \cdot P)}} \]  (40)

\( a_i \) - i-th coefficient of the main regression equation;

Fig. 1. Values of the i-th coefficient from the i-th parameter value.
P – parameter, the effect of which is considered during testing;
\( \beta_{0i}, \beta_{1i}, \ldots, \beta_{ni} \) – i-th coefficients of the secondary regression equation.

Since there can be several equations that would satisfy the reliability requirements for the approximation (the coefficient of determination must be greater than or equal to 0.85), then, in the general case, each coefficient of the basic regression equation will be a system of equations.

\[
a_i = f_i(x) = \begin{cases} 
  a_i = \beta_{0i} + \beta_{1i} \cdot P \\
  a_i = \beta_{0i} + \beta_{1i} \cdot P + \beta_{2i} \cdot P^2 + \cdots + \beta_{ni} \cdot P^n \\
  a_i = \beta_{0i} \cdot \beta_{1i}^p \\
  a_i = e^{(\beta_{0i} + \beta_{1i} \cdot P)} \\
  a_i = \beta_{1i} \cdot e^{(\beta_{1i} \cdot P)} \\
  a_i = \beta_{0i} + \beta_{1i} \cdot \ln P \\
  a_i = \beta_{0i} + \beta_{1i} \cdot \lg P \\
  a_i = \beta_{0i} + \beta_{1i} \cdot \log P \\
  a_i = \beta_{0i} + \beta_{1i} \cdot \frac{1}{P} \\
  a_i = \beta_{0i} + \beta_{1i} \cdot P \\
  a_i = \frac{1}{1 + e^{(\beta_{0i} + \beta_{1i} \cdot P)}} \\
\end{cases} \geq 0.85
\]

Since only one equation is sufficient for practical purposes, it is advisable to use the equation with the highest coefficient of determination.

\[
a_i = f_i(x) \rightarrow \max D^2
\]

\( D^2 \) – coefficient of determination.

Consider the case with two determining factors in a similar way.

According to the test results, series of values of the regression coefficients were obtained depending on two determining factors (see Fig. 2).

![Fig. 2. Values of the i-th coefficient from the k-th and j-th parameter values.](image)

Based on the results of the regression analysis, the following equations for the regression coefficients were obtained.

1) Linear Regression:
\[ a_i = \beta_{0kj} + \beta_{1kj} \cdot P_1 + \beta_{2kj} \cdot P_2 \]  \hspace{1cm} (42)

2) Polynomial Regression:
\[ a_i = \beta_{0kj} + \beta_{1,n,kj} \cdot P_1 + \beta_{1,n-1,kj} \cdot P_1^{n-1} + \beta_{11,kj} \cdot P_1 + \cdots + \beta_{2n,kj} \cdot P_2^n + \beta_{2,n-1,kj} \cdot P_2^{n-1} + \cdots + \beta_{21,kj} \cdot P_2 \]  \hspace{1cm} (43)

3) Power regression:
\[ a_i = \beta_{0kj} \cdot P_1^{\beta_{1kj}} \cdot P_2^{\beta_{2kj}} \]  \hspace{1cm} (44)

4) Exponential regression:
\[ a_i = \beta_{0kj} \cdot P_1^{\beta_{1kj}} \cdot P_2^{\beta_{2kj}} \]  \hspace{1cm} (45)

5) Exponential regression:
\[ a_i = e^{(\beta_{0kj} + \beta_{1kj} \cdot P_1 + \beta_{2kj} \cdot P_2)} \]  \hspace{1cm} (46)

6) Logarithmic regression:
\[ a_i = \beta_{0kj} + \beta_{1kj} \cdot \ln P_1 + \beta_{2kj} \cdot \ln P_2 \]  \hspace{1cm} (47)
\[ a_i = \beta_{0kj} + \beta_{1kj} \cdot \log P_1 + \beta_{2kj} \cdot \log P_2 \]  \hspace{1cm} (48)

7) Semilogarithmic regression:
\[ a_i = \beta_{0kj} + \beta_{1kj} \cdot \log P_1 + \beta_{2kj} \cdot \log P_2 \]  \hspace{1cm} (49)

8) Hyperbolic Regression:
\[ a_i = \beta_{0kj} + \frac{\beta_{1kj}}{P_1} + \frac{\beta_{1kj}}{P_2} \]  \hspace{1cm} (50)
\[ a_i = \frac{1}{\beta_{0kj} + \beta_{1kj} \cdot P_1 + \beta_{1kj} \cdot P_2} \]  \hspace{1cm} (51)

9) Logistic regression:
\[ a_i = \frac{1}{1 + e^{(\beta_{0kj} + \beta_{1kj} \cdot P_1 + \beta_{1kj} \cdot P_2)}} \]  \hspace{1cm} (52)

Since there can be several equations that would satisfy the reliability requirements for the approximation (the coefficient of determination must be greater than or equal to 0.85), then, in the general case, each coefficient of the basic regression equation will be a system of equations.

Since only one equation is sufficient for practical purposes, in what follows we will use the equation with the highest coefficient of determination.

Similar reasoning can be made for the general case.

In this case, the equations will take the form:

1) Linear Regression:
\[ a_i = \beta_0 + \beta_1 \cdot P_1 + \cdots + \beta_n \cdot P_n \]  \hspace{1cm} (53)

2) Polynomial Regression:
\[ a_i = \beta_0 + \beta_{n,i} \cdot P_1^n + \beta_{n-1,i} \cdot P_1^{n-1} + \cdots + \beta_{1,i} \cdot P_1 \]  \hspace{1cm} (54)

3) Power regression:
\[ a_i = \beta_0 \cdot P_1^{\beta_1} \cdots P_n^{\beta_n} \]  \hspace{1cm} (55)

4) Exponential regression:
5) Exponential regression:
\[ a_i = \beta_0 \cdot \beta_1^{P_1} \cdot \ldots \cdot \beta_n^{P_n} \]  

(56)

6) Logarithmic regression:
\[ a_i = e^{(\beta_0 + \beta_1 \cdot P_1 + \ldots + \beta_n \cdot P_n)} \]  

(57)

7) Semilogarithmic regression:
\[ a_i = \beta_0 + \beta_1 \cdot \ln P_1 + \ldots + \beta_n \cdot \ln P_n \]  

(58)

\[ a_i = \beta_0 + \beta_1 \cdot \lg P_1 + \ldots + \beta_n \cdot \lg P_n \]  

(59)

8) Hyperbolic Regression:
\[ a_i = \frac{1}{\beta_0 + \beta_1 \cdot P_1 + \ldots + \beta_n \cdot P_n} \]  

(60)

9) Logistic regression:
\[ a_i = \frac{1}{1 + e^{(\beta_0 + \beta_1 \cdot P_1 + \ldots + \beta_n \cdot P_n)}} \]  

(61)

Let us illustrate with an example how it will look in practical implementation. Let’s consider cases for one, two and n-th number of factors. Suppose that in all cases the linear regression has the highest coefficient of determination. Let’s look at her example. First, we write down the basic regression equation, then replace the regression coefficients with the corresponding equations.

For one factor:
\[ R = \alpha_0 + \alpha_1 \cdot t = \beta_{01} + \beta_{11} \cdot P + (\beta_{02} + \beta_{12} \cdot P) \cdot t \]  

(62)

For two factors:
\[ R = \beta_{011} + \beta_{111} \cdot P_1 + \beta_{211} \cdot P_2 + (\beta_{022} + \beta_{122} \cdot P_1 + \beta_{222} \cdot P_2) \cdot t \]  

(63)

For n factors:
\[ R = \beta_0 + \beta_1 \cdot P_1 + \ldots + \beta_n \cdot P_n + (\beta_0 + \beta_1 \cdot P_1 + \ldots + \beta_n \cdot P_n) \cdot t \]  

(64)

4. Conclusions
In the presented article, the case was considered when the action of factors is constant in time and is independent, i.e. the mutual influence of factors is excluded.

The advantages of this method.

Versatility. It can be applied to any structure, under any operating conditions and with any physical wear.

Any parameters can be applied. Since these equations initially use dimensionless variables, the researcher himself chooses the parameter he needs. Moreover, he is not limited by anything in his choice.

Simplicity of calculation. There are software tools that allow you to quickly carry out regression, correlation and variance analysis.

Disadvantages of this method.

The complexity of practical implementation. In practice, it becomes problematic to implement this approach already with two parameters, and with an increase in their number it becomes almost unrealistic. Therefore, for practical purposes, the application of this method is, in fact, limited to two to three parameters.
The problem of physical justification or physical interpretation. These equations do not make it possible to understand the reason for the change in the parameter, since the obtained coefficients in physical terms may differ from the currently accepted characteristics of building structures.

In conclusion, I would like to note that the use of this method for predicting the parameters of building structures can significantly help in the description of those processes or phenomena that have not yet received proper justification, and for those who are engaged in the design and operation of building objects.

References
[1] Klippel, M., Frangi, A., Fontana, M. Influence of the adhesive on the load-carrying capacity of glued laminated timber members in fire. DOI: 10.3801/IAFSS.FSS.10-12.
[2] Arima, T., Hayamura, S., Maruyama, N. Schematic Representation for Evaluating Adhesive Strength of Wood Component. DOI: 10.2472/jsms.41.528.
[3] Kim, K.-H., Kim, S.-J., Yang, S.-Y., Yeo, H., Eom, C.-D., Shim, K. Bonding performance of adhesives with lamina in structural glulam manufactured by high frequency heating system. DOI: 10.5658/WOOD.2015.43.5.682.
[4] Aven, T.: Interpretations of alternative uncertainty representations in a reliability and risk analysis context. Reliability Engineering and System Safety, 96(3), 353–360 (2011). DOI: 10.1016/j.ress.2010.11.004.
[5] Aven, T., Zio, E.: Some considerations on the treatment of uncertainties in risk assessment for practical decision making. In Reliability Engineering and System Safety, 96, 64–74 (2011). DOI: 10.1016/j.ress.2010.06.001.
[6] Suo, B., Zeng, C., Cheng, Y. S., Li, J.: An evidence theory-based algorithm for system reliability evaluation under mixed Aleatory and epistemic uncertainties. International Journal of Nonlinear Sciences and Numerical Simulation, 15(3–4), 189–196 (2014). DOI: 10.1515/ijnsns-2012-0050.
[7] Jiang, C., Zhang, Z., Han, X., Liu, J.: A novel evidence-theory-based reliability analysis method for structures with epistemic uncertainty. Computers and Structures, 129, 1–12 (2013). DOI: 10.1016/j.compstruc.2013.08.007.
[8] Li, H., Nie, X.: Structural reliability analysis with fuzzy random variables using error principle. Engineering Applications of Artificial Intelligence, 67, 91–99 (2018). DOI: 10.1016/j.engappai.2017.08.015.
[9] Xiao, N. C., Huang, H. Z., Li, Y. F., Wang, Z., Zhang, X. L.: Non-probabilistic reliability sensitivity analysis of the model of structural systems with s interval variables whose state of dependence is determined by constraints. Proceedings of the Institution of Mechanical Engineers, Part 06: Journal of Risk and Reliability, 227(5), 491–498 (2013). DOI: 10.1177/1748006X13480742.
[10] Wang, Y.: Imprecise probabilities based on generalized intervals for system reliability assessment. International Journal of Reliability and Safety, 4(4), 319–342 (2010). DOI: 10.1504/IJRS.2010.035572.
[11] Krejca, M., Janas, P., & Krejca, V.: Structural reliability analysis using DOProC method. In Procedia Engineering, 142, 34–41 (2016). DOI: 10.1016/j.proeng.2016.02.010.
[12] Caspeele, R., Sykora, M., Taeber, L.: Influence of quality control of concrete on structural reliability: assessment using a Bayesian approach. Materials and Structures/Materiaux et Constructions, 47(1–2), 105–116 (2014). DOI: 10.1617/s11527-013-0048-y.
[13] Köhler, Jochen (2006) Reliability of timber structures Doctoral thesis, Technische Wissenschaften, Eidgenössische Technische Hochschule ETH Zürich, Nr. 16378, 2006. DOI: 10.3929 / ETHZ-a-005164254.
[14] Simon Hannouz. Développement d’indicateurs pour la caractérisation mécanique et la durabilité des bois traités thermiquement. Mécanique des matériaux [physics.class-ph]. Ecole nationale
supérieure d'arts et métiers - ENSAM, 2014. Français. (NNT: 2014ENAM0047). (tel-01127400)

[15] Mounir Chaouch (2011). Effet de l'intensité du traitement sur la composition élémentaire et la durabilité du bois traité thermiquement : développement d'un marqueur de prédiction de la résistance aux champignons basidiomycètes. Autre. Université Henri Poincaré - Nancy 1, 2011. Français.

[16] Younes Faydi, Loïc Brancher, Guillaume Pot, Robert Collet. Prediction of Oak Wood Mechanical Properties Based on the Statistical Exploitation of Vibrational Response. Bioresources, North Carolina State University, 2017, 12 (3), pp.5913-5927 DOI: 10.15376/biores.12.3.5913-5927.

[17] Gravit, M.V., Serdjuks, D., Bardin, A.V., Prusakov, V., Buka-Vaivade, K. Fire Design Methods for Structures with Timber Framework. Magazine of Civil Engineering. 2019. 85(1). Pp. 92–106. DOI: 10.18720/MCE.85.8.

[18] Marina Gravit, Ivan Dmitriev and Alexander Ishkov. Quality control of fireproof coatings for reinforced concrete structures. IOP Conference Series: Earth and Environmental Science, Volume 90, conference 1. EMMFT 2017. IOP Conf. Series: Earth and Environmental Science (2017) 012226 DOI: 10.1088/1755-1315/90/1/012226.

[19] Marina Gravit, Oleg Nedryshkin, Andrey Zhuravlev. Negative use of finishing materials on Sorel’s cement. International Science Conference SPbWOSCE-2016 “SMART City”. St. Petersburg, Russia, November 15-17, 2016. MATEC Web of Conferences Volume 106 (2017). Published online: 23 May 2017 DOI: https://doi.org/10.1051/matecconf/201710603029.

[20] Gravit, M., Antonov, S., Nedryshkin, O. Research Features of Tunnel Linings with Innovations Fireproof Panels. 2016 Procedia Engineering. https://doi.org/10.1016/j.proeng.2016.11.906.