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Assessing the Influence of Mining Impacts on Buildings using SVM and MLR Method

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Abstract. The article presents research studies, the aim of which was to assess the influence of mining impacts in the form of surface deformation, as well as mining tremors, on technical wear of traditional residential development in a mining area. A group of 170 single-family masonry residential buildings located in the mining area of the *Legnica-Głogów Copper District* (*LGOM*) were analysed. The assessment was based on the model of technical wear, developed using *SVM* (*Support Vector Machine*) method in *ε-SVR* regression approach. In order to interpret the metrics describing the monotonicity of the nonlinear *ε-SVR* model and to confirm the established trends, they were confronted with the results obtained using a multiple linear regression model (*MLR - Multiple Linear Regression*). The results confirmed the view that it was the age of the masonry buildings located in the Copper District which had the dominant influence on their technical wear, while the influence of mining impacts was to be considered secondary, however, significant in the statistical sense.

1. Introduction

As far as development in mining areas is concerned, the effect of long-term impacts of continuous surface deformation, or possibly mining tremors, on the acceleration of the technical wear of buildings appears to be a major problem. This is not the case of the safety of a structure itself or its users, but lower comfort of its use as well as a reduction in its value. Technical wear s_z is material (physical) wear associated with the changes occurring in the matter of a building, interpreted as a decrease in performance or value of its individual elements. The dominant component of the technical wear s_z is natural wear, mainly related to the aging process of building materials in specific environmental and operating conditions [1]. The impacts of mining exploitation are an additional factor, random factor in the statistical sense, which might accelerate the process.

The research studies presented in the article aimed to assess the cumulative impact of mining factors (surface deformation and mining tremors) on technical wear of traditional residential development in the mining area.

Given the fact that the course of technical wear is described by the domain of various factors having a potential impact on its approximated value, and that this mapping is implicit and non-linear, the *SVM* (*Support Vector Machine*) method was adopted in *ε-SVR* regression approach. Additionally, in order to verify the obtained trends and to enable the interpretation of the metrics used at the stage of studying monotonicity of the *ε-SVR* model, the range of the analysis was extended by developing a multidimensional linear regression model (*MLR*).

A group of 170 single-family masonry residential buildings located in the mining area of the *Legnica-Głogów Copper District* (*LGOM*) were subjected to the research studies.

2. Research methodology

The study was based on the database containing information about 170 single-family residential buildings, with their age not exceeding 35 years (e.g. Figure 1), located in the same town, within the harmful impacts of the *Mining Plant of KGHM "PolskaMiedź"* S.A. (the mining area of *Legnica-Głogów Copper District*). All the buildings included in the analysis have the traditional masonry load-bearing structure and during the construction stage preventive measures were taken to protect them against mining impacts in the form of continuous surface deformation. The study comprised the structures which in recent years had not been subjected to major building interference such as complete renovation, refurbishment or reconstruction. Survey works were performed as part of the research studies carried out in recent years at the Department of Engineering Surveying and Civil Engineering of AGH University of Science and Technology. The degree of technical wear s_z was determined for each structure individually using the weighted average method. The method was based on the individual assessment of the degree of wear of particular components and then, by assigning appropriate weights, on the determination of the weighted average degree of the wear of the entire building [1].


Figure 1. Numerical model of the flyover Examples of building structures included in the analysis. Source: own work

3. Indices describing the impacts of mining exploitation on the studied development

Indices describing mining impacts were determined individually for each building, based on the data from the mine.

3.1. Risk index of continuous surface deformation

The subject of the study were buildings of traditional structure, up to 3 stories tall, and of a relatively small size of the horizontal projection. Therefore, in accordance with the current knowledge [2], specific horizontal deformations ε [mm/m] were adopted as a basic measure of the risk of continuous surface deformation [3].

At this point, attention should be paid to the study results of the relationship between technical wear and specific horizontal deformations, as presented in [4].

In this study, significant correlations were obtained with relatively large coefficients for the horizontal tensile strains $\varepsilon(+)$. They were much higher than those obtained for both ε_{max} and $\varepsilon(-)$, even though relative to the absolute value of the strain $\varepsilon(-)$, they were often larger than $\varepsilon(+)$. The results confirm the view that for this type of development, it is the tensile strain, and not the category of the land, which are the basic measure of the risk associated with the formation of a mining subsidence.

Therefore, basing on the information about mining exploitation carried in the studied areas, each building was assigned maximum values of specific horizontal tensile strains $\varepsilon(+)$ which occurred throughout the whole period of the building existence. This index was determined basing on the geometric and integral model of mining impacts.

3.2. Index of the impact of mining tremors

To study the impact of mining tremors on the technical wear, an index of dynamic influences a_{sg}, accelerating the technical wear of a building structure, was adopted. It was defined in [5]. It was demonstrated that the acceleration of the process of technical wear of building structures is significantly influenced by both the number and intensity of seismic phenomena affecting the structure during the entire period of its use. The index a_{sg} for a structure located in a position with the coordinates (x,y) is as follows - Eq. (1):

$$a_{sg}(x,y) = \sqrt{\sum_{k=1}^{n} a_{Hk}(x,y)^2} \quad ; \quad a_{Hk}(x,y) \tag{1}$$

where:
(x,y) - coordinates of the structure,
$a_{Hk}\,(x,y)$ - the peak value of the horizontal component of vibration acceleration in the frequency range of up to10 Hz for the k-th tremor, calculated at the point (x,y),
n - number of tremors that occurred during the use, and for which the peak value calculated at the point (x,y) was greater than the threshold value a_p,
a_p - according to [5], a predetermined threshold value $a_p = 0.12$ m/s^2.

A confirmation of the assumption of a significant influence of the number of tremor impacts on the technical wear of a building structure, even with relatively small peak values of acceleration, are the results of the study of relationships between the technical wear of buildings and mining tremors presented in [6]. As a measure of risk, in addition to a_{sg}, also a_{max} index was adopted, which is the maximum of the peak values of the horizontal component of the acceleration of vibrations. The yielded results are significant correlations of medium and high values of coefficients between the degree of technical wear and the index of dynamic influences a_{sg}. On the other hand, in the studies of dependence between the technical wear and a_{max} index, no significant correlation in any of the studied groups was obtained.

To assess the influence of tremors occurring over the period of thirty years of exploitation of copper deposits, seismic mining catalogues were used, as well as statistical relationships between the parameters of vibrations, the force of a tremor and the distance from the epicentre.

As a result, for all the studied buildings located in the mining area, peak values of a_H were calculated (of the horizontal component of vibration acceleration in the frequency range of up to 10 Hz), excited at the location of a structure, by all the tremors that occurred in the period from its construction until the day when survey works were performed, and then for each building a_{sg} index was determined.

4. Assessing the effect of mining impacts on the technical wear of masonry buildings located in *Legnica-Głogów Copper District*

To model the course of technical wear in time of the studied structures, the *SVM* (*Support Vector Machine*) method in *ε-SVR* regression approach and the method of multiple linear regression (*MLR)* were used.

In both approaches, parameters of the models described by the domain of the factors having a potential impact on its approximated value which can be interpreted in terms of monotonicity of approximators.

4.1. Research Methodology

4.1.1. Modelling technical wear using SVM in regression approach (ε-SVR). In the course of the search for a method allowing for the modelling of non-linear technical wear of buildings in multidimensional field of input variables, it was decided to apply the *SVM* method, which is a special type of *Artificial*

Neural Network (*ANN*). e.g. in [7, 8]. The regression approach of the *SVM* method, also known as *ε-SVR* (*Support Vector Regression*) [9, 10], in the context of the structure and operation of the fixed system, is very similar to neural networks with radial basis function *RBF* (*Radial Basis Function Neural Network* – [11, 12]. The difference is revealed in the process associated with learning such systems and determining their structure [13].

The main advantages of the *SVM* method, which resulted in the decision to use this method in the study, included [9, 10, 14]:

- a possibility to present the course of technical wear in the multidimensional domain of explanatory variables,
- a possibility to implement a non-linear mapping,
- no need to give a starting form of mapping,
- a possibility to conduct a sensitivity analysis with respect to the developed model.

The *SVM* method is a tool used both in solving the problems of classification and regression. Given the purpose of the research, regression approach called *ε-SVR* was used [15].

The main advantage of the *ε-SVR* method, in contrast to typical artificial neural networks, is the uniqueness of the optimization process. This process is brought to the problem of solving quadratic programming, thereby eliminating the problem of oscillation around local minima of cost function. An additional advantage resulting directly from a deterministic description of the *ε-SVR* approximator (Eq. (2)), which preserves the continuity and differentiability in the field of input variables, is a possibility to carry out a sensitivity analysis of the developed model.

$$y(\mathbf{x}) = \sum_{k=1}^{N_{SV}} \left(\alpha_k - \alpha_k^*\right) K(\mathbf{x}, \mathbf{x}_k) + b \tag{2}$$

where:
α_k, α_k^* - Lagrange multipliers,
$K(\mathbf{x}, \mathbf{x}_k)$ - is the kernel of the system (Chang and Lin 2011).

The main problem during the model development stage in *ε-SVR* approach is to determine the optimal values of the parameters *C*, *ε* and γ. Parameter γ is a result of adopting radial basis function, and, according to the Eq. (3), for the developed approximator it defines its width [13].

$$K(\mathbf{x}_k, \mathbf{x}_j) = \exp\left(-\frac{(\mathbf{x}_k - \mathbf{x}_j)^2}{\gamma^2}\right) \overset{\sigma = \frac{1}{\gamma^2}}{=} \exp\left(-\sigma(\mathbf{x}_k - \mathbf{x}_j)^2\right) \tag{3}$$

On the other hand, the parameters *C* and *ε*, resulting from the formulation of the original problem to minimize the objective function Eq. (4), are respectively a regularization constant and a tolerance margin [14]:

$$\min_{\mathbf{w}, b, \xi_k^*, \xi_k} J(\mathbf{w}, \xi_k^*, \xi_k) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{k=1}^{N}\left(\xi_k^* + \xi_k\right),\ k = 1 \ldots N \tag{4}$$

With inequality limitations of the function:

$$\begin{cases} y_k - \mathbf{w}^T\varphi(\mathbf{x}_k) - b \le \varepsilon + \xi_k \\ \mathbf{w}^T\varphi(\mathbf{x}_k) + b - y_k \le \varepsilon + \xi_k^* \\ \xi_k, \xi_k^* \ge 0 \end{cases} \tag{5}$$

where:
w - vector of weights,
ξ_k^*, ξ_k–positive slack coefficients,
C - regularization constant, *ε* - width of the margin of tolerance, *b* - free term.

An attempt to determine the sought parameters, hereinafter referred to as *hyperparameters*, was made in [16] where, basing on the concept of *Meta-SVM* [17], the measure of the *FPE* error (*Final Prediction Error*) [18] was additionally used. In the further course of the research, however, the author decided to apply a more efficient method based on the concept described in (Chang and Lin 2011). The ultimate stage of this method is the *n-fold cross-validation* carried out on the pre-prepared sets: training and testing ones. For each iteration of the validation, a certain range of the examined parameters C, ε and γ is assumed, expressed on a logarithmic scale. Then, according to the proposed optimization algorithm grid search, minimization of the objective function is performed, adopted as *MSE* (*Mean Squared Error*), averaged from all n testing sets used in the validation. As a result, an optimal with respect to the strategy set of the sought *hyperparameters* C, ε and γ is obtained. The grid search algorithm is a gradient method of global minimization [19]. However, it has a certain drawback which concerns a necessity to provide ranges for the sought area and giving a starting point. Therefore, in this work, instead of the grid search algorithm, the optimization method was used, which is based on genetic algorithm. The applied method is also a gradientless algorithm that allows to specify the global minimum. A description of genetic algorithms used in minimization of the function of several variables can be found in [20, 21].

4.1.2. Sensitivity analysis using SVM model. The study used a two-stage methodology for evaluating the effect of individual input variables on the course of the approximated value of the technical wear of building structures.

The first stage studied how the basic measures of fitting the model changed in relation to the reference data when the subsequent input variables were excluded from its description. To assess model sensitivity for the removal of subsequent input variables (i) from its description, an auxiliary measure was introduced, described by the following formula - Eq. (6):

$$W_i^{corr} = \left(1 - \frac{R_i}{R_{zup}}\right) \cdot 100 \quad [\%] \tag{6}$$

where:

R_i - coefficient of linear correlation between the model prediction and the reference data, when the i-th input variable has been removed from the approximator description,

R_{zup} - coefficient of linear correlation between the model prediction and the reference data, when all the input variables are active.

Auxiliary measure W_i^{corr} determines the relative degree of worsened fitting quality – the higher the value of W_i^{corr}, the more important the variable which has been removed, for the description of the modeled phenomenon.

The second stage of the study assessed the influence of individual variables in the context of monotonicity of the *ε-SVR* model. For this purpose, analogy with radial neural networks (*RBF – Radial Basis Function Neural Networks*) and the procedure proposed, e.g. in [22, 23] were used. By simulating the model, the course of its derivatives was analyzed, which were calculated relative to the various input factors. In order to assess the effect of each factor on the modelled course of technical wear, an auxiliary measure M_{sens} was introduced. This measure is a vector with a number of components equal to the number of analyzed factors, and its individual components are values of partial derivatives, averaged from all simulated cases. A reference diagram for developing components of the vector M_{sens} is presented in Table 1.

It should be noted that the results of the first stage reflect the influence of a given factor on explaining the variability of the modelled process, contained in the observed data.

On the other hand, the second stage of the study is focused on a qualitative assessment of the influence of a given variable on the course of a modelled phenomenon, which is reduction or increase in the value of technical wear.

Table 1. Calculation scheme for component determination for the measure M_{sens}

	Variable x_1	*Variable* x_2	...	*Variable* x_i	...	*Variable* x_K
M_{sens}	$\frac{\sum_{n=1}^{N}\left(\left(\frac{df^{\varepsilon-SVM}}{dx_1}\right)_n\right)}{N}$	$\frac{\sum_{n=1}^{N}\left(\left(\frac{df^{\varepsilon-SVM}}{dx_2}\right)_n\right)}{N}$	...	$\frac{\sum_{n=1}^{N}\left(\left(\frac{df^{\varepsilon-SVM}}{dx_i}\right)_n\right)}{N}$	...	$\frac{\sum_{n=1}^{N}\left(\left(\frac{df^{\varepsilon-SVM}}{dx_K}\right)_n\right)}{N}$

4.1.3. Study results. The primary database was divided into a training data set (120 cases) and a testing set (50 cases). Tables 2 and 3 illustrate a comparison of the main characteristics of the model as well as the values of the errors for the training and testing data sets.

Table 2. Comparison of the main characteristics of the model

Model parameters			
Regularization parameter *C*	Width of kernel functions *σ*	Width of tolerance band *ε*	Number of support vectors
5.88	0.27	0.11	35

Table 3. Comparison of errors and coefficients of linear correlation between model prediction and references for training and testing data sets

Results of linear correlation	Training data set (N = 120)	Testing data set (N = 50)
MSE	0.0181	0.0142
Coefficient of correlation *R*	0.819	0.786

The results contained in Table 2 illustrate that spontaneous expansion of the *ε-SVR* model resulted in the reduction in the size of its structure (the number of *Support Vectors nSV* = 35) by 60% compared to the size of the training data set (120 cases). This is a result of regularization, which occurs in this type of approach.

On the other hand, the values of *MSE* (*Mean Square Errors*) and the values of the coefficient of linear correlation between the model prediction and the data observed for the training and testing data sets contained in Table 3, exhibit high accuracy of the model relative to the observed data, as well as good regularization properties.

The analysis of the significance of input variables of the model of technical wear, developed for the building structures of traditional construction, located in the mining area, was carried out in two stages, according to the methodology described in section 4.1. Results of the first test stage have been summarized in Tables 4 and 5, and the effects of the second stage in Table 6.

Analysis of the results contained in Tables 4 and 5 allows to conclude that the age of the building t has the greatest influence on the variability of the model, whereas both mining factors have a definitely lower impact intensity, both at a similar level.

The research results contained in Table 6 illustrate that the increase of each of the analyzed variables entails the increase of the approximated value of the degree of technical wear, however, for the mining factors, the variable a_{sg} is accompanied by a more intense increase.

Table 4. Comparison of the values of the coefficient of linear correlation Rafter the removal of individual variables

Coefficient of linear correlation R between model prediction and given references [%]	Input variables		
	Age of the building structure t	Maximum horizontal strain ε_{max}	Index of dynamic Influences a_{sg}
21,55	inactive	active	active
81,59	active	inactive	active
79,98	active	active	inactive
81,96	active	active	active

Table 5. Comparison of the values of the W_i^{corr} index

	Input variables		
	Age of the building structure t	Maximum horizontal strain ε_{max}	Index of dynamic Influences a_{sg}
W_i^{corr} [%]	73.71	0.41	2.42

Table 6. Comparison of the values of the M_{sens} index

	Input variables		
	Age of the building structure t	Maximum horizontal strain ε_{max}	Index of dynamic Influences a_{sg}
M_{sens}	0.78	0.0178	0.20

4.2. Modeling the course of technical wear using multiple linear regression (MLR)

4.2.1. Research methodology. The model of the phenomenon developed using multiple regression allows, just like the *ε-SVR* method, to examine the cumulative effect of the factors determining a given process on the course of this process. The *MLR* method allows for a linear mapping of the process, specifying the strength of the individual factors in determining its monotonicity. Studies of the technical wear performed by the *MLR* method have been discussed in detail in [4] In this paper, the *MLR* model is a comparative basis for the results obtained by the *ε-SVR* method.

As a result of the multiple regression analysis, we obtain coefficients of multiple correlation R and determination R^2, regression coefficients (B) and standardized regression coefficients ($BETA$). The values of $BETA$ coefficient allow to compare relative contribution that each independent variable brings in the prediction of the dependent variable. The results also present the significance level p for the determined parameters of the model (B), which justifies if a given variable should be included in the model description as statistically significant. Additionally, F-test is calculated, which refers to the entire model and verifies the significance of the slopes (B), the coefficient of determination and the significance of the overall linear relationship between the dependent variable and the input variables.

4.2.2. Study results. According to the adopted assumptions, using multiple regression, an analysis of the influence of three independent variables: age of the building t, index of horizontal tensile strain $\varepsilon(+)$, and index of the impact of mining tremors a_{sg}, on the degree of technical wear s_z was performed. The results of the analysis are contained in Table 7.

Table 7. Study results of the dependence between technical wear s_z and the age of a building t, indices of mining impacts $\varepsilon(+)$ and a_{sg}, using multiple regression analysis

Factor (independent variable)	Standardized regression coefficient *BETA*	Coefficient of the independent variable *B*	Significance level *p*	Correlation coefficient *R*	Coefficient of determination R^2
t	0.741	0.754	0.000	0.812	0.660
$\varepsilon(+)$	0.162	3.372	0.001		
a_{sg}	0.134	2.595	0.000		
Free term	-	-5.759	-		

The presented results demonstrate that the effect of the analyzed factors explains in total about 66% of the variability of technical wear of the studied development.

On the other hand, the values of standardized regression coefficients (*BETA*) point to time (the age of the buildings t) as dominantly affecting the technical wear of the studied development, which is at the level of 74.1%. The effect of mining impacts, compared to the age, must be considered secondary (16.2% and 13.4%, respectively), but statistically justified, as proven by significance levels p determined for the parameters describing mining impacts. A relatively greater influence of specific horizontal tensile strains $\varepsilon(+)$ on the degree of wear was identified, compared to mining tremors represented by a_{sg}.

5. Conclusion

The analysis described in the article aimed to assess the influence of mining impacts on the technical wear of 170 masonry residential buildings, with their age not exceeding 35 years.

The study was based on the *SVM* method in *ε-SVR* regression approach, as well as the method of multiple linear regression (*MLR*). Additionally, in order to identify the measures specifying the contributions of the individual factors to the course of the modelled phenomenon, a sensitivity analysis of the model was performed in the *ε-SVR* method. These analyzes were carried out in the context of variability and monotonicity of the approximator, expressed with *ε-SVR*.

Both developed models are characterized by similar levels of accuracy. Additionally, in the case of the *ε-SVR* method, no effects of overfitting were observed, and therefore this model can be considered correct in terms of generalization of the acquired knowledge.

Results of the analyzes performed both by the *ε-SVR* and *MLR* methods, identified the age of the building as having the dominant effect on the technical wear of masonry residential buildings located in *Legnica-Głogów Copper District* (*LGOM*). The influence of this factor explains the variability contained in the raw data at the level of 74% (see: Tab. 5), which makes the contribution of mining factors of secondary importance.

Moreover, due to the monotonicity of the modelled process, the sensitivity analysis of the *ε-SVR* model revealed a clear effect of ground vibrations, expressed by the index a_{sg} (see: Tab. 6). This result is not confirmed by the tests using multiple linear regression. This may be a confirmation of the alleged non-linear nature of the phenomenon described by the domain of mining factors.

These results should be treated as an assessment of the phenomenon on a global scale. Determining the influence of mining impacts on the technical wear of a single building structure requires individual assessment procedure.

The effects of the presented studies demonstrate the usefulness of the *SVM* method in analysing technical condition of complex building structures in the presence of a variety of input variables. Such studies, however, require relatively numerous databases. It is planned that further research will take into account the construction factors, such as repairs and preventive protection against mining impacts.

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