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Comparison of selected regression models in predicting railway traffic noise levels

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Abstract The aim of this study was to compare the effectiveness of selected regression methods in predicting the noise level generated by railway traffic. The analysis was based on measurement data collected at ten locations in Poland, taking into account technical and environmental parameters as well as train passage characteristics. Linear regression (OLS), Weighted Least Squares (WLS), LASSO, Ridge and Elastic Net were used in the modelling, and their effectiveness was assessed using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The results showed that the noise level depends primarily on train speed, passage time, and rolling stock type, while meteorological variables had a marginal impact. The best fit was obtained for the WLS model, with effectively solving the problem of heteroscedasticity. Regularized models made it possible to reduce the number of predictors without losing the quality of the fit. The study confirms that modern regression techniques can be a valuable tool for assessing the impact of railways on the acoustic environment.

Keywords: railway noise, noise prediction, regression models, environmental acoustics.

1. Introduction

Rail transport plays a significant role in the logistics system both in Europe and worldwide, providing an efficient means of transporting passengers and goods over medium and long distances. Its dynamic development in recent decades results not only from the growing demand for alternatives to road transport but also from environmental considerations, as railways generate a substantially smaller carbon footprint per transport unit. Despite numerous benefits, railway infrastructure entails a range of challenges, one of the most critical being noise emissions associated with train operations. Prolonged exposure to excessive sound levels can considerably deteriorate the quality of life of residents living in proximity to railway lines, leading to health issues and psychological discomfort [1, 2]. The multidimensional nature of noise generation makes its modeling a complex task, dependent on a variety of technical and environmental factors. Variability in operating conditions, rolling stock characteristics, and location means that effective noise prediction requires the application of advanced analytical methods, enabling both accurate representation of the phenomenon and simplification of overly complex models.

In the literature, railway noise has been extensively documented and analyzed from multiple perspectives [3–5]. However, the problem remains highly complex. The magnitude of sound emissions additionally depends on a range of environmental and technical factors such as the condition of track and rolling stock infrastructure, traffic volume, and terrain topography [3]. The large number of potential predictors translates into increased analytical model complexity and highlights the necessity of applying effective methods of variable selection and dimensionality reduction.

Traditionally, railway noise has been modeled for the purposes of spatial planning, infrastructure design, and the development of noise maps, particularly in the context of the requirements defined in Directive 2002/49/EC (END) [6]. This act obliges the Member States of the European Union to systematically assess and monitor noise levels and to prepare action plans for areas exposed to exceedances of permissible values. One of the first models applied for this purpose was the Dutch method RMR (Reken- en Meetvoorschrift Railverkeerslawaai) [7]. In Germany, the “Schall 03 2006” method was used [8]. To ensure consistency and comparability of results across the entire EU, the CNOSSOS-EU method (Common Noise Assessment Methods in Europe) was developed, which since 2017 has constituted the official methodology for environmental noise assessment [9].

Classical calculation models (RMR, CNOSSOS-EU, Schall 03) are of significant importance in regulatory and planning contexts, although their structure and intended use make them less suitable for empirical studies based on measurement data. Therefore, the present study focuses on a comparative analysis of regression models, which allow for the assessment of the influence of specific input variables on noise levels and for the evaluation of their predictive performance using metrics such as RMSE, MAE, and R^2.

2. Methods

2.1. Data collection

The objective of the conducted study was to determine the noise levels generated by passing trains, which represent one of the key indicators for assessing the acoustic conditions of the environment in the immediate vicinity of railway lines. The research focused not only on the noise level itself but also on the identification of factors that have a significant influence on its magnitude. To ensure a comprehensive representation of the phenomenon, additional parameters were recorded, including train speed, train passage time at the measurement cross-section, and the type of rolling stock. These data made it possible to link the value of noise emissions with the technical characteristics of rail vehicles and their dynamic operating parameters.

In total, 506 single train pass-bys were recorded. Measurements were carried out at ten selected locations across six voivodeships, as shown in Figure 1. This spatial distribution of research sites allowed for the inclusion of infrastructure variability across different regions of Poland. Each location was selected with regard to the presence of active railway lines and suitable conditions for conducting measurements in compliance with applicable standards.

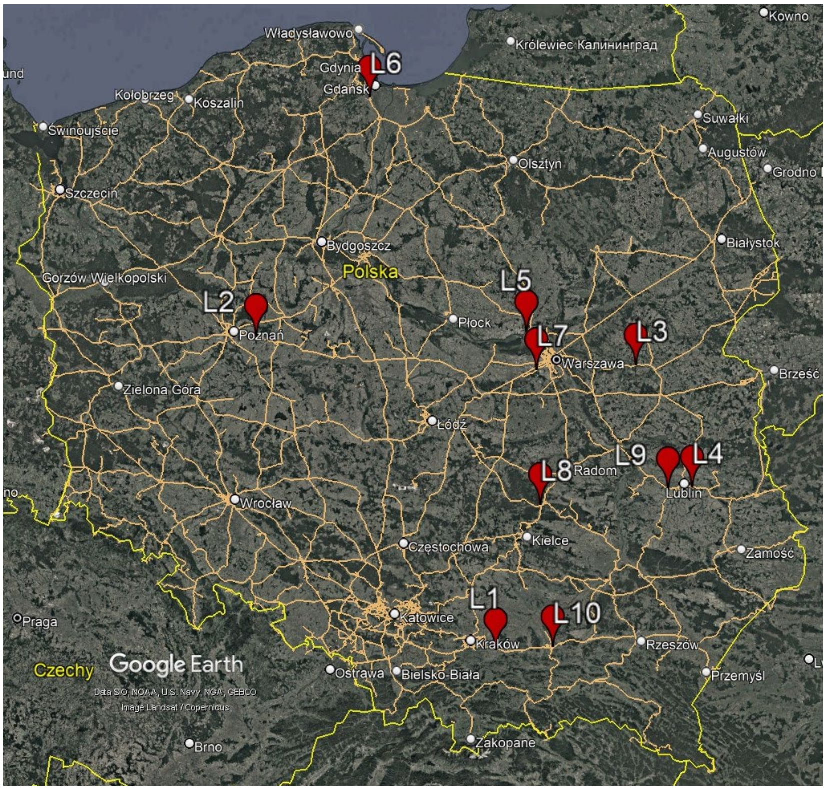

Figure 1. Location of measurement points in Poland.

All measurement sites were characterized by consistent track structure parameters, ensuring comparability of results. At each location, measurements were conducted on a double-track railway line equipped with 60 E1 rails corresponding to the UIC 60 standard, SB W1 fastening systems, PWE rail pads, and PB 85K sleepers compliant with the UIC 60 specification.

Measurement points were established in accordance with the PN-EN ISO 3095:2013-12 standard [10], taking into account the pass-by test procedure. Measurement microphones were positioned at a height of 1.2 m above the top of the rail and at a distance of 7.5 m from the track axis. During the study, simultaneous recording of meteorological conditions was also ensured.

2.2. Measurement data

In the analysis of railway noise, the individual assessment of train pass-bys is of key importance, as each train may be characterized by a different noise level. Therefore, for each recorded pass-by, the equivalent sound level is determined, calculated exclusively for the duration of the recorded acoustic event.

The A-weighted equivalent sound pressure level during a train pass-by is defined according to [10]:

$$L_{\mathrm{pAeqT_p}} = 10 \log\left(\frac{1}{T_2 - T_1}\int_{T_1}^{T_2} \frac{p_A^2(t)}{p_0^2}\, dt\right), \tag{1}$$

where L_{pAeqTp} is the equivalent sound level during the train pass-by in dB, $T_2 - T_1$ is the observation time of a single acoustic event in seconds, $p_A(t)$ is the instantaneous sound pressure corrected with the A-weighting frequency in Pa, p_0 is the reference sound pressure equal to $2 \cdot 10^{-5}$ Pa.

The same measurement procedure was applied in each of the selected research locations. This approach enabled the collection of a representative dataset of empirical measurements, from which the key variables for further statistical analysis were subsequently extracted. This dataset formed the basis for constructing regression models and for evaluating the influence of individual factors on the generated railway noise level. These variables, along with their interpretation, are presented below in Table 1.

Table 1. Summary of variables used in the regression analysis.

Variable symbol	Variable name	Description
Y	L_{AeqT}	A-weighted equivalent sound level of a single train pass-by [dB]
X1	Train speed	Train speed at the moment of pass-by (km/h)
X2	Passage time	Train passage time through the measurement cross-section [s]
X3	Train type	Rolling stock category (P_P, P_SN, P_SS, P_T, P_W, P_L, P_A)*
X4	Location	Measurement site (L_1 – L_10)
X5	Humidity	Relative air humidity on the measurement day [%]
X6	Temperature	Average air temperature on the measurement day [°C]
X7	Atmospheric pressure	Average air pressure on the measurement day [hPa]
X8	Wind speed	Average wind speed at the measurement site [m/s]

*Categories: high-speed train (P_P), self-propelled passenger train new type (P_SN), self-propelled passenger train old type (P_SS), freight train (P_T), passenger train with wagons (P_W), locomotive (P_L), railbus (P_A).

2.3. Selected Types of Regression

2.3.1. Linear Regression (OLS)

Linear regression is one of the fundamental methods of statistical analysis, used to model the relationship between a dependent (explained) variable and one or more independent (explanatory) variables. The objective of linear regression is to find the best-fitting line (or hyperplane in the case of multiple variables) that describes the relationship between these variables [11].

Multiple linear regression extends simple regression to the case where more than one independent variable is included. In matrix notation, the model is expressed as:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{2}$$

where **Y** is the vector of observations of the dependent variable (n × 1), **X** is the input data matrix containing the independent variables and a column of ones (n × (p+1)), **β** is the vector of parameters to be estimated (p+1) × 1), **ε** is the vector of random error terms (n × 1).

2.3.2. LASSO Regression (Least Absolute Shrinkage and Selection Operator)

LASSO regression (Least Absolute Shrinkage and Selection Operator) is a statistical method that extends classical linear regression. Its objective is the simultaneous selection of variables and estimation of regression model parameters. LASSO is particularly useful when the number of predictors is large or when strong multicollinearity among them is present [12].

The LASSO estimator is obtained as the solution to the following optimization problem [13]:

$$\hat{\beta}_{lasso} = \arg_{\beta} \min \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}, \tag{3}$$

where y_i is the value of the dependent variable, x_{ij} is the value of the j-th independent variable in the i-th observation, β_0 is the intercept, β_j is the regression coefficient, λ is the regularization parameter (selected, for example, through cross-validation).

2.3.3. Ridge Regression

Ridge regression is a modified version of the classical Ordinary Least Squares (OLS) method, developed to reduce the impact of multicollinearity among independent variables.

Ridge regression is based on the minimization of the following objective function:

$$\hat{\beta}_{ridge} = \arg\min \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} {\beta_j}^2 \right\}, \tag{4}$$

where y_i is the value of the dependent variable, x_{ij} is the value of the j-th independent variable in the i-th observation, β_0 is the intercept, β_j is the regression coefficient, λ is the regularization parameter.

2.3.4. Elastic Net Regression

Elastic Net regression is a method of regression analysis that combines the properties of Ridge regression and LASSO regression. This approach enables simultaneous mitigation of multicollinearity and variable selection.

The objective function of the Elastic Net estimator is defined as:

$$\hat{\beta}_{EN} = \arg\min \left\{ \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \left(\alpha \sum_{j=1}^{p} |\beta_j| \right) + (1-\alpha) \sum_{j=1}^{p} {\beta_j}^2 \right\}, \tag{5}$$

where y_i is the value of the dependent variable, x_{ij} is the value of the j-th independent variable in the i-th observation, β_0 is the intercept, β_j is the regression coefficient, λ is the regularization parameter, α is the mixing parameter controlling the balance between the LASSO and Ridge penalties.

2.3.5. Weighted least squares regression (WLS)

Weighted Least Squares regression (WLS) is an extension of the classical Ordinary Least Squares (OLS) method, applied in situations where the assumption of constant variance of the error term (homoscedasticity) is violated. In regression models with heteroscedasticity, the variance of the errors is not constant, which may lead to inefficient and biased statistical inference.

To obtain efficient estimators of the parameters β, the weighted sum of squared residuals is minimized:

$$\hat{\beta}_{WLS} = \arg_{\beta} \min \left\{ \sum_{i=1}^{n} w_i (y_i - \mathbf{x}_i \cdot \boldsymbol{\beta})^2 \right\}, \tag{6}$$

where w_i is the weight assigned to the i-th observation, $\mathbf{x}_i$ is the vector of predictors in the i-th observation.

3. Results

3.1. Descriptive statistics

Before constructing the regression models, an analysis of descriptive statistics of the numerical variables was carried out. Its purpose was to provide an initial assessment of the distributions, value ranges, and potential deviations from normality, which may influence the selection and performance of the applied models.

Table 2 presents a summary of the basic statistical measures (mean, standard deviation, median, minimum, maximum) for the dependent variable Y and the independent variables X1, X2, X5, X6, X7 and X8. Variables X3 (Train type) and X4 (Location) were excluded since they are categorical and textual in nature, for which typical descriptive measures are not meaningful in terms of interpretation.

Additionally, to provide a visual representation of the distributions, Figure 2 shows the histograms of all numerical variables, allowing for a quick assessment of symmetry, the presence of outliers, and the overall structure of the data.

Table 2. Descriptive statistics for numerical variables (n = 506).

Variable symbol	Unit	Mean	Standard deviation	Median	Min–Max
Y	dB	84.75	5.22	84.0	68–99.7
X1	km/h	76.89	26.84	77.0	19–161
X2	s	13.77	13.26	8.0	4–99
X5	%	20.89	5.19	21.0	4–31
X6	°C	57.79	9.96	58.0	40–83
X7	hPa	1014.52	5.59	1014.8	1001.3–1023
X8	m/s	3.65	0.91	3.9	0.8–4.8

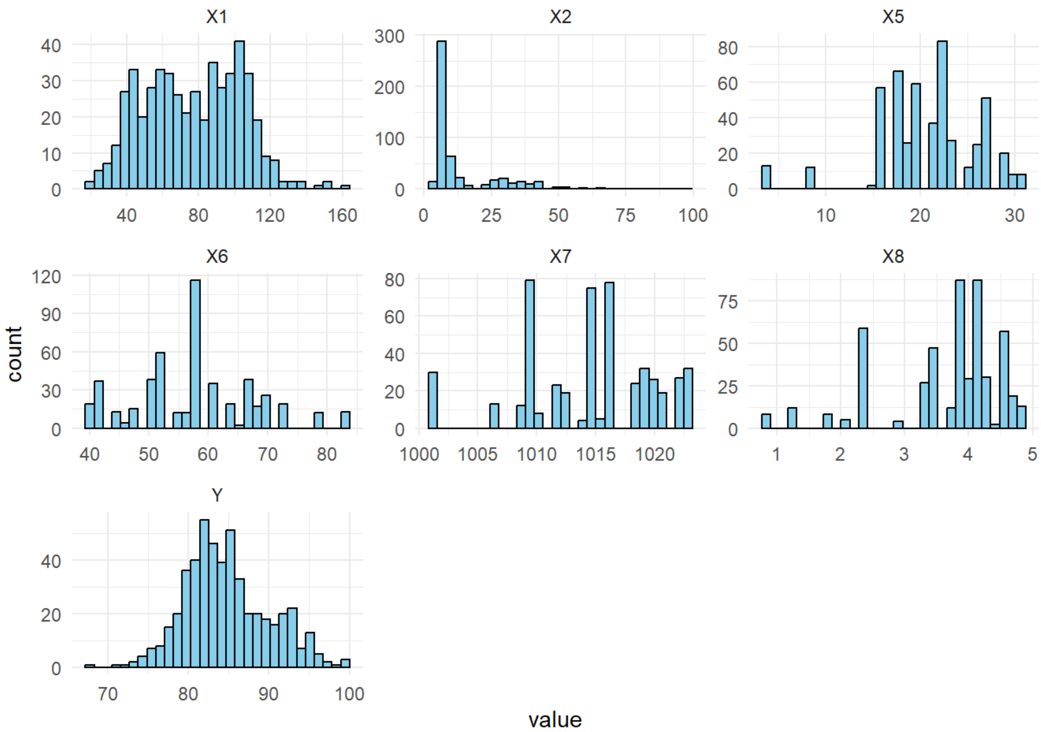

Figure 2. Histograms of the distributions of numerical variables (Y, X1, X2, X5–X8) used in the regression analysis.

To investigate the relationships between noise level (Y) and the remaining variables, a scatterplot matrix was constructed and is presented in Figure 3. These plots display all pairs of quantitative variables (Y, X1, X2, X5, X6, X7, X8) in a coordinate system, allowing for the identification of nonlinear dependencies, data clusters, and potential outliers. The most noticeable relationships are observed between the dependent variable and train speed (X1) as well as passage time (X2), which confirms the existence of strong physical links between vehicle movement and the level of generated noise.

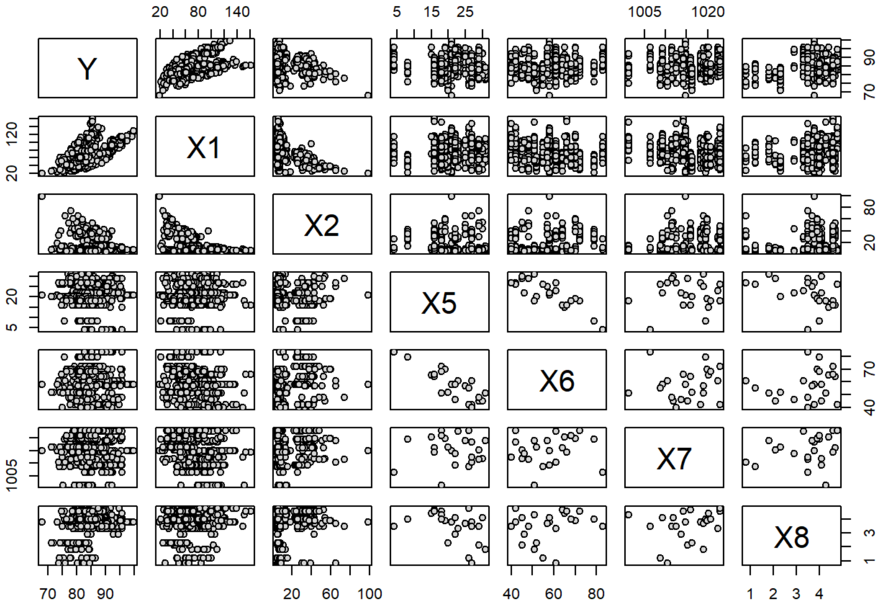

Figure 3. Scatterplot matrix between the dependent variable Y (noise level) and the independent variables (X1, X2, X5–X8).

In the next step, an analysis of the interdependencies among the numerical variables was performed by constructing a Pearson linear correlation matrix. The purpose of this analysis was to identify potential relationships between the dependent variable (Y) and the predictors, as well as to detect possible multicollinearity among the independent variables that could affect the stability of the regression models. The results are presented in Figure 4 in the form of a correlation matrix indicating the strength and direction of the relationships.

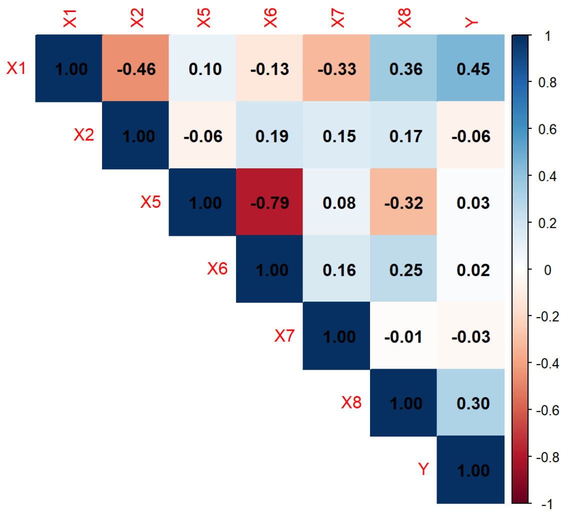

Figure 4. Pearson linear correlation matrix for numerical variables (X1, X2, X5–X8, Y).

The strongest positive relationship was observed between the dependent variable Y (noise level) and X1 (train speed), with a correlation coefficient of 0.45, which may indicate a moderate relationship: the higher the speed, the higher the level of emitted noise. A noticeable but weaker association was also found for *X8* (wind speed), with a correlation of 0.30, which may suggest that meteorological conditions partially influence the results of acoustic measurements.

In contrast, a strong negative correlation was observed between X5 (humidity) and X6 (temperature), reaching a value of −0.79. This may reflect a typical climatic phenomenon in which higher temperatures are usually associated with lower air humidity. The remaining correlations are weak or very weak ($|r| < 0.3$), suggesting relative independence of most variables and a low risk of multicollinearity.

3.2. Analysis of categorical variables

After analyzing the distributions of numerical variables and their interrelationships, the next step was to assess the impact of categorical variables: train type (X3) and measurement location (X4), on the noise level (Y). Since these variables are discrete, nonparametric analysis of variance methods were applied, allowing for comparison of measurement distributions across different groups. Figure 5 presents a boxplot illustrating the distribution of the equivalent sound pressure level depending on the type of rolling stock.

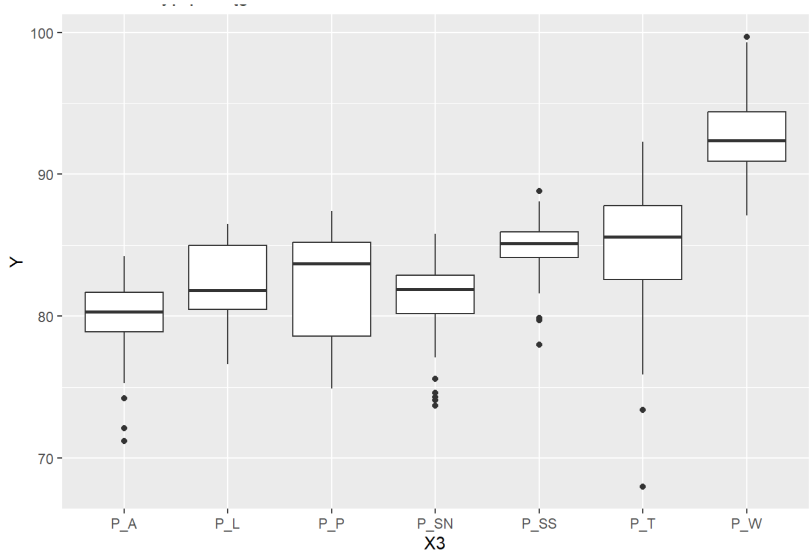

Figure 5. Variation in noise level (*Y*) depending on train type (*X3*).

Significant differences in median values and dispersion are visible between the categories. The highest noise levels were recorded for category P_W (passenger trains with wagons) and P_T (freight trains), while the lowest values were observed for P_A (railbuses) and P_SN (self-propelled passenger trains of the new type). This indicates a significant influence of the type of rolling stock on the generated noise. Figure 6 presents the variation in noise levels across individual measurement locations.

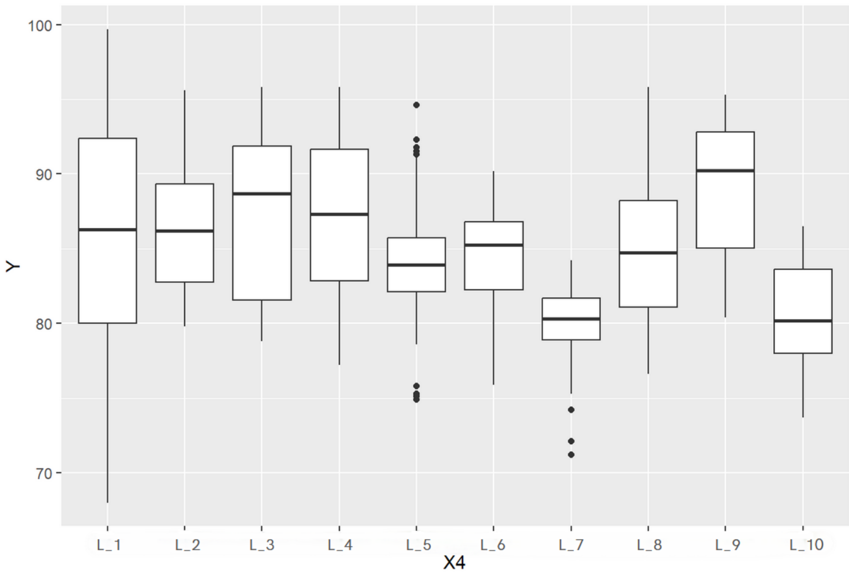

Figure 6. Variation in noise level (Y) across measurement locations (X4).

Here as well, substantial differences are noticeable. In some locations (e.g., L_1, L_3) sound levels exceeded 90 dB, whereas in others (L_6, L_7, L_10) the noise was considerably lower. This may result from local terrain conditions, track type, or lower train speeds.

To statistically verify the differences between groups, the Kruskal–Wallis test, a nonparametric equivalent of analysis of variance, was applied. In both cases, very low p-values were obtained, allowing the rejection of the hypothesis of distribution homogeneity:

- Train type (X3): χ^2 = 318.69, df = 6, p-value < 2.2^{-16}
- Location (X4): χ^2 = 125.37, df = 9, p-value < 2.2^{-16}

These results confirm that both train type and measurement location have a significant impact on noise levels. Therefore, variables X3 and X4 should be considered valuable predictors in further regression modeling.

3.3. Predictive Models

3.3.1. Analysis of Model Properties

The first stage of modeling was classical linear regression, aimed at estimating the impact of individual explanatory variables on the noise level generated by passing trains. All independent variables, both numerical and categorical (encoded using dummy variables), were included in the model, and the estimation was carried out using the least squares method.

The obtained model demonstrated very good fit and stability despite the inclusion of multiple predictors. The high value of the F-statistic (F = 224.1, p < 0.001) confirms the significance of the entire model.

During the analysis, variable X4L_7 was automatically excluded from the model due to perfect multicollinearity with other variables, a phenomenon referred to as singularity. This resulted from the fact that in location L_7 only railbus (P_A) pass-bys were recorded, which did not occur in any other measurement site. Such a one-to-one relationship between location and train type made it impossible to estimate a separate effect of this variable, which consequently led to its removal.

Moreover, the meteorological variables humidity (X5), temperature (X6), atmospheric pressure (X7), and wind speed (X8) did not exhibit a statistically significant effect on noise level when controlling for the other predictors, although they are potentially important from the perspective of the physics of sound propagation. For this reason, they were omitted in the subsequent stages of analysis, which allowed the model to be simplified and irrelevant variables to be eliminated.

After parameter estimation, a diagnostic analysis was performed to verify the compliance of residuals with the basic assumptions of regression, including the assessment of normality, homoscedasticity, and lack of autocorrelation. The obtained results are presented in Table 3.

Table 3. Results of tests for residual normality, homoscedasticity, and autocorrelation.

Test category	Test name	Statistic	p-value
Normality	Shapiro–Wilk	W = 0.9692	8.2^{-09}
	Anderson–Darling	A = 3.311	2.7^{-08}
	Lilliefors (Kolmogorow)	D = 0.0639	4.0^{-05}
	Jarque–Bera	X^2 = 130.2	< 2.2^{-16}
Homoscedasticity	Breusch–Pagan	BP = 97.24, df = 20	3.9^{-12}
	Goldfeld–Quandt	GQ = 2.85	3.5^{-15}
	Non-constant Variance	χ^2 = 1.43, df = 1	0.231
Autocorrelation	Durbin–Watson	DW = 1.91	0.761

Based on the conducted statistical tests, the null hypothesis was rejected in favor of the alternative hypothesis, according to which the distribution of residuals deviates from normality. This result does not disqualify the model, although it may affect the accuracy of confidence intervals and the reliability of parameter significance tests.

In two out of the three applied tests, heteroscedasticity was identified (BP, GQ), indicating variability of residual variance depending on the fitted values, which potentially reduces the efficiency of OLS estimators. In contrast, the Durbin–Watson test provided no grounds for rejecting the null hypothesis of no residual autocorrelation.

Attempts at data transformation aimed at achieving normality and variance homogeneity did not yield the expected results. Therefore, alternative regression techniques less sensitive to violations of these assumptions were applied.

In the LASSO regression model, the meteorological variables X5 (humidity) and X8 (wind speed) were found to be insignificant and were eliminated by reducing their coefficients to zero. Variables X6 (temperature) and X7 (atmospheric pressure) showed only marginal effects, which is consistent with earlier observations from classical linear regression.

Ridge regression, as a modified version of linear regression, effectively reduced the problem of multicollinearity and the risk of model overfitting. Unlike LASSO, this method retained all predictors while adjusting only the magnitude of their coefficients.

The Elastic Net model, which combines features of both approaches, eliminated four variables (X5–X8) that did not provide additional informational value. This method produced a more balanced solution compared with the exclusive use of either LASSO or Ridge, particularly in the context of correlated variables and a larger number of predictors.

Additionally, in response to the detected heteroscedasticity in the OLS model, Weighted Least Squares (WLS) regression was applied. Weights were defined as the inverse of the squared fitted values, based on the assumption of proportional variance growth with respect to the dependent variable. The analysis demonstrated a clear improvement in the residual structure, particularly in terms of variance stability. This was confirmed by statistical tests: the Breusch–Pagan test provided no grounds for rejecting the null hypothesis of homoscedasticity ($p = 1$), and the ncvTest result also did not indicate a dependence of variance on the fitted values. It should be noted, however, that the normality tests continued to confirm deviations of residuals from the normal distribution. Nevertheless, the improvement in variance homogeneity allows for more reliable statistical inference.

3.3.2. Comparison of the Effectiveness of Regression Models

The detailed estimation results of the individual regression models were compiled into a comparative summary. The analysis included five approaches: classical linear regression (LM), weighted least squares regression (WLS), and regularized regressions LASSO, Ridge, and Elastic Net.

The evaluation of model effectiveness was carried out based on three key goodness-of-fit metrics: the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). This comparison allows for a direct assessment of the performance of individual methods using the same dataset. The results are presented in Figure 7.

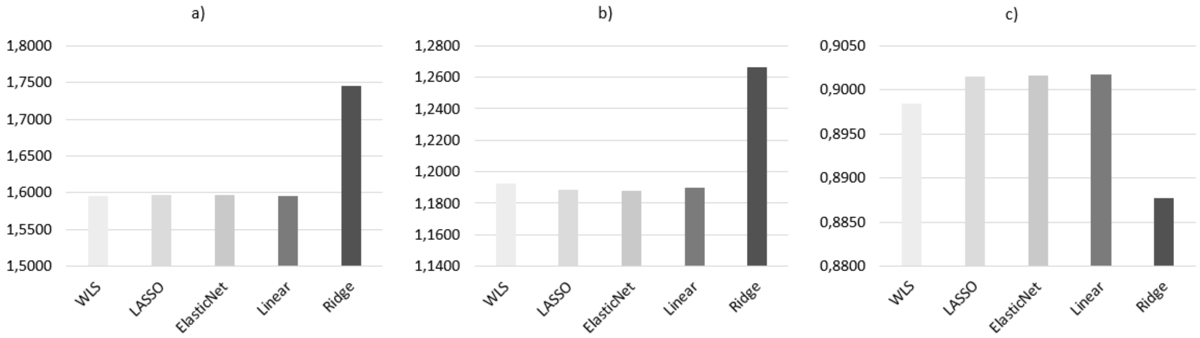

Figure 7. Comparison of regression models using: a) RMSE, b) MAE, c) R^2.

The values are very similar across all models, which confirms the consistency of results regardless of the applied regression method. The largest deviations are observed only for Ridge regression, where RMSE and MAE are noticeably higher and R^2 slightly lower.

4. Discussion and conclusions

Within the conducted analysis, five different regression approaches were compared: classical linear regression (LM), weighted least squares regression (WLS), LASSO regression, Ridge regression, and Elastic Net regression. Each model was tested on a reduced dataset that was cleaned of insignificant environmental predictors and the problematic location L_7, in order to improve consistency and stability of parameter estimation.

The final choice of the best model was not based solely on goodness-of-fit metrics. Model interpretability, compliance with statistical assumptions, robustness to disturbances, and applicability in environmental practice were also of key importance.

The regularized models (LASSO, Ridge, Elastic Net) did not provide significant improvement in predictive quality compared with classical regression. Moreover, Ridge regression yielded slightly weaker fit ($R^2 = 0.8877$, RMSE = 1.7447), while LASSO and Elastic Net, despite their ability to eliminate irrelevant variables, retained most predictors already included in the linear model. In this sense, these models did not contribute additional information, and their interpretation was more complex.

The weighted least squares model (WLS), on the other hand, proved to be the best alternative. It was introduced in response to the heteroscedasticity problem revealed in the analysis of the classical model. The improvement in variance structure in the WLS model was substantial. The Breusch–Pagan test provided no grounds for rejecting the hypothesis of homoscedastic residuals, which makes this model statistically superior.

For these reasons, weighted least squares regression (WLS) was selected as the final model, as it combines high quality of fit with better compliance with statistical assumptions, while maintaining full interpretability of the coefficients. This model can be applied to predict railway noise levels based on a set of key technical and locational variables. The final form of the weighted least squares regression model (WLS) is as follows:

$$\begin{aligned} Y = \ & 72.61 + 0.1346 \cdot X1 - 0.0568 \cdot X2 - 4.82 \cdot X3P\_P - 3.99 \cdot X3P\_SN - 0.61 \cdot X3P\_SS + 6.56 \\ & \cdot X3P\_T + 7.82 \cdot X3P\_W + 0.18 \cdot X4L\_2 + 1.62 \cdot X4L\_3 + 0.73 \cdot X4L\_4 + 0.48 \\ & \cdot X4L\_5 + 0.19 \cdot X4L\_6 + 0.88 \cdot X4L\_8 + 1.28 \cdot X4L\_9 + 0.67 \cdot X4L\_10, \end{aligned} \tag{7}$$

where X1 is train speed in km/h, X2 is passage time in seconds, X3P_ are binary variables representing train types (P – high-speed Pendolino, SN – self-propelled passenger new type, SS – self-propelled passenger old type, T – freight, W – passenger with wagons), X4L_ are binary variables for location (with L_1 as the reference category, and the others representing relative effects with respect to it).

Additional information

The author declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

References

1. M. Wrótny, J. Bohatkiewicz; Impact of Railway Noise on People Based on Strategic Acoustic Maps; Sustainability, 2020, 12(14), 5637; DOI: 10.3390/su12145637
2. M. Wrótny, J. Bohatkiewicz; Traffic noise and inhabitant health—a comparison of road and rail noise; Sustainability, 2021, 13(13), 7340; DOI: 10.3390/su13137340
3. D. Thompson; Railway Noise and Vibration: Mechanisms, Modelling and Means of Control; Elsevier, 2008
4. N. Craven, et al.; Railway Noise in Europe – State of the Art Report; European Commission, 2016
5. P.J. Remington; Wheel/rail noise – Part I: Characterization of the wheel/rail dynamic system; Journal of Sound and Vibration, 1976, 46(3), 359–379
6. Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the assessment and management of environmental noise; Official Journal of the European Communities, 2002, L 189/12
7. Ministerie van Volkshuisvesting; Reken- en Meetvoorschrift Railverkeerslawaai '96 (in Dutch); The Netherlands, 1996
8. Deutsche Bundesbahn; Richtlinie zur Berechnung der Schallimmissionen von Schienenwegen, Schall 03/Akustik 03 (in German); München, 2006
9. S. Kephalopoulos, M. Paviotti, F. Anfosso-Lédée; Common Noise Assessment Methods in Europe (CNOSSOS-EU); Publications Office of the European Union, 2012
10. Polish Committee for Standardization; PN-EN ISO 3095:2013-12 – Railway applications – Acoustics – Measurement of noise emitted by railbound vehicles, 2013
11. A.R. Nur, A.K. Jaya, S. Siswanto; Comparative Analysis of Ridge, LASSO, and Elastic Net Regularization Approaches in Handling Multicollinearity for Infant Mortality Data in South Sulawesi; Jurnal Matematika Statistika dan Komputasi, 2023, 20(2), 311–319; DOI: 10.20956/j.v20i2.31632
12. J. Ranstam, J.A. Cook; LASSO regression; British Journal of Surgery, 2018, 105(10), 1348; DOI: 10.1002/bjs.10895
13. R. Tibshirani; Regression Shrinkage and Selection via the Lasso; Journal of the Royal Statistical Society: Series B (Methodological), 1996, 58(1), 267–288; DOI: 10.1111/j.2517-6161.1996.tb02080.x