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Prediction of strength of coal briquettes from Karakichi coal deposit using regression models

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***Abstract*:**

The purpose of this study was to predict the strength of fuel briquettes based on Karakichi coal using regression models. This study used experimental data obtained by varying the technological para meters of briquetting, including compaction pressure, compaction time, temperature, humidity, bentonite clay content, and the ash content of the initial mixture. A detailed pairwise correlation analysis was carried out to identify the factors having the greatest influence on briquette strength. This analysis examined the resulting index (strength) and nine technological variables, including pressing pressure, pressing time, temperature, mixture moisture, bentonite clay content, briquette thickness, fractional composition, and duration of natural drying. The analysis quantified the degree of correlation between each factor and briquette strength, identifying the most significant ones. The greatest strength of correlation was demonstrated by the variable ash content of coal raw material (X_9), with which briquette strength is positively and almost linearly related (correlation coefficient r = 0.9787). Based on these data, a one-factor linear regression model was constructed according to the least squares method, which helped to simplify the forecast calculations without significant loss of accuracy. According to the model, at 32% ash content in the mix, the predicted strength value is 5.56 MPa. The high coefficient of determination (R^2=0.9575) confirmed the reliability of the obtained model and its suitability for practical application. Thus, the proposed approach provided an objective and reproducible means of assessing the quality of briquettes, optimizing the production process and selecting technological parameters aimed at increasing the mechanical strength of fuel briquettes.

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1. Introduction

The problem of effective utilisation of fine brown coals containing a high percentage of ash is especially relevant for the fuel and energy complex of the Kyrgyz Republic. Coal from the Karakichi deposit, as well as other local low-quality coals, is characterised by high fines content (over 70%), which limits its direct use for industrial and household purposes. Under these conditions, the technology of coal dust briquetting using inorganic binders, such as bentonite clay, becomes a promising area. This enables the transformation of hard-to-use raw materials into a competitive fuel product with increased mechanical strength and stability during storage and transport.

Modern research in the field of fuel technology emphasises the need to use mathematical methods and econometric analysis to assess and predict the physical and mechanical characteristics of briquettes. This approach allows identifying key technological parameters affecting product quality, as well as generating optimum formulations of briquette mixtures based on local raw materials. The use of regression models and correlation analysis becomes crucial in conditions of varying technological regimes and limited resources, when rapid and accurate assessment of the influence of factors such as compaction pressure, compaction time, temperature, humidity, ash content, and binder content is required [1–4].

A series of modern studies has demonstrated the effectiveness of various approaches to utilise fine coal and increase the strength of coal briquettes, which is particularly relevant to the conditions of the Kyrgyz Republic. Tulepov *et al.* [5] proposed a technology for obtaining composite solid fuel based on non-standard coal using various additives, including organic binders, and conducted a comprehensive assessment of its physical and mechanical characteristics and suitability for industrial use.

The presented method improved the calorific value and strength of the briquettes, making their use in a wider industrial range possible. Shaidullaev *et al.* [6] considered the improvement of coal fuel properties by using organic and polymeric components as binders. The experiments confirmed that plant additives improved the formability and reduced the crumbling of briquettes. This approach proved to be particularly promising for localised production where access to expensive binders was limited.

Joldosheva *et al.* [7] demonstrated the application of mathematical planning of experiments for optimisation of coal briquette composition. The use of factor analysis helped determine the optimum proportions of bentonite and vegetable binder that provided maximum strength. This study confirmed the potential of using statistical models in managing fuel briquette formulation.

Mendekeyev and Karabaeva [8] focused on the development of cyclic-flow technologies of coal mining and processing in the Kyrgyz Republic. The researchers emphasised the significance of adapting logistic and technological schemes to the specific features of local deposits. Their findings confirmed that the effective organisation of technological processes contributed to the sustainable use of raw material resources.

Kabas *et al.* [9] developed predictive models of briquette strength based on ensemble machine learning algorithms. The researchers used physical and mechanical parameters as inputs for strain energy estimation. The resulting models had high accuracy and could be applied to predict the performance of briquettes under different conditions. Wang *et al.* [10] investigated the relationship between macroeconomic factors and coal prices by proposing models based on time series and influence factors. The results were found to be valuable for assessing the profitability of low-grade coal processing, especially under unstable market conditions. Their study reinforced the need to integrate economic models into strategic planning of fuel production.

Khan *et al.* [11] focused on the sustainable production of bio-waste briquettes, emphasising the environmental effect. The study proved that bio-based raw materials could serve as an effective binder component without compromising the strength properties. This opened new possibilities for combining coal dust with agrarian residues to reduce the cost of production.

Ossei-Bremang *et al.* [12] applied multivariate modelling for decision-making in the waste-based briquette formulation process. The model considered multiple criteria ranging from cost to durability and environmental risks. This approach was an example of applying engineering multi-criteria algorithms to real-world manufacturing problems.

Pawaree *et al.* [13] presented a method of multi-response optimisation based on the linear programming Technique for Order of Preference by Similarity to Ideal Solution and genetic algorithms. The researchers achieved a balanced tuning of pressing process and formulation parameters aimed at minimising waste and maximising quality. This hybrid method could be used in green economy systems, including small-scale manufacturing platforms.

Guo *et al.* [14] investigated the parameters of waste coal briquetting and tested the particle emissions during combustion. Their optimisation models resulted in significant improvements in the environmental and strength performance of the briquettes. These findings highlighted the significance of integrated analysis, from the pressing technology to the combustion behaviour of the fuel.

Despite a considerable number of studies, methods for simplified prediction of briquette strength based on one of the key factors, the ash content of the coal mixture, are still understudied. This variable has a complex influence on the mechanical properties of briquettes, their thermal stability, and their tendency to break during transport. Furthermore, most of the existing models require complex measurements and are not always suitable for rapid application in small and medium-sized operations. The purpose of the present study was to build a simplified regression model of the strength of coal briquettes from Karakichi coal using bentonite, based on the identification of key factors and calculation of the coefficient of determination.

2. Materials and methods

The study was based on the results of laboratory experiments conducted in the period from September to December 2024 with samples of briquettes made from coal fines from the Karakichi coal deposit with the addition of bentonite clay as an inorganic binder. Raw material for the experiment was obtained from the operating sites of the Karakichi coal basin, characterised by high ash content and fine fractions (up to 70%). The choice of this deposit was conditioned by its industrial significance, the availability of material, and the necessity of developing technologies for processing low-quality coal into solid fuel with increased strength.

Experimental modelling of briquette strength included variation of nine technological factors: compaction pressure (X_1), compaction time (X_2), mixture temperature (X_3), fractional composition (X_4), moisture content (X_5), bentonite concentration (X_6), briquette thickness (X_7), natural drying time (X_8), and ash content (X_9). Specifically, the compaction pressure varied within 10-80 MPa, the compaction time varied within 10-80 s, the mixture temperature varied within 0-70°C, the fractional composition varied from 0-1 mm to 0-8 mm, the moisture content varied within 0-35%, the bentonite concentration varied within 0-35%, the briquette thickness varied within 10-80 mm, the natural drying time varied from 2 hours (0.083 days) to 60 days, and the ash content of the coal feedstock varied within 0-35%. The compressive strength of the briquettes, expressed in megapascals

(MPa), was measured as the resulting index (Y). Measurements were performed using a force-controlled press with digital strain indicators, providing accuracy up to 0.01 MPa.

Correlation and regression analysis with the application of mathematical statistics methods was employed to build a predictive model. At the first stage, a pair correlation analysis was performed between each of the factors X_1-X_9 and the resulting indicator Y, which helped to determine the variables with the greatest influence on the strength of briquettes. Calculations were performed in the Microsoft Excel environment using inbuilt statistical functions and formulae for Pearson's coefficients. At the second stage, regression equations were constructed, including a simplified linear model of the dependence of briquette strength on ash content (X_9) as the most significant factor (r = 0.9787). The least squares method was employed to build the model, based on which the system of normal equations was solved (1):

$$\begin{cases} na_0 + \left(\sum X_9\right) a_1 = \sum Y \\ \left(\sum X_9\right) a_0 + \left(\sum X_9^2\right) a_1 = \sum X_9 Y \end{cases} \tag{1}$$

where Y is the briquette strength (MPa); X_9 is the coal ash content (%); a_0 is the free term; a_1 is the slope coefficient of the regression line; n is the number of observations.

To assess the quality of the obtained model, the coefficient of determination (R^2) was calculated, which characterises the proportion of variance of the dependent variable explained by the following model (2):

$$R^2 = \frac{\sum_{i=1}^{n}(\widetilde{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}. \tag{2}$$

Forecasting calculations were performed by substituting X_9 values into the regression equation obtained by the least squares method. Additionally, the study used the technique of building a prediction model with a subsequent comparison of the obtained values with the factual results of the experiment.

To improve the accuracy of the analysis and verification of the model, statistical methods such as mean square error, mean absolute error, and Fisher's criterion were applied to assess the its significance. Particular attention was paid to testing the hypothesis of excluding multicollinear factors, which ensured the stability of the model while reducing the number of variables. When optimising the model, constraints on the physical parameters of the briquetting process were considered, such as the minimum strength required for storage and transportation of briquettes (at least 5 MPa). The analytical part of the study was focused on the application of the obtained model in practical conditions at small and medium-sized enterprises processing low-quality coal. The results of modelling can be adapted to various production conditions with the possibility of adjustment to the characteristics of local raw materials and available binder material. The application of this methodology also allows optimising pressing parameters and reducing energy consumption in the production cycle.

3. Results and discussion

The analysis of experimental data helped to establish the nature of the influence of technological factors on the strength characteristics of fuel briquettes obtained from coal fines from the Karakichi coal deposit. The purpose of this stage of the study was to identify statistically significant relationships between the varying parameters of briquetting and the final strength of the product. The obtained results formed the basis of mathematical modelling and became the baseline for the development of a predictive regression model suitable for practical applications in the conditions of coal preparation and briquetting plants.

For each combination of parameters, the compressive strength of the briquettes was experimentally determined using a laboratory press and a precision digital force meter. The obtained data are presented in Table 1, where the values of all nine factors and their corresponding strength test results are systematised.

Table 1
Experimental data on the strength of briquettes.

Sample No.	X_1 (MPa)	X_2 (s)	X_3 (°C)	X_4 (mm)	X_5 (%)	X_6 (%)	X_7 (mm)	X_8 (days)	X_9 (%)	Y (MPa)
1	10	10	0	0-1	0	2.6	10	0.083	0	2.6
2	10	20	10	0-1	5	2.9	20	1	5	3.4
3	20	20	20	0-3	10	3.5	30	10	10	3.8
4	30	30	30	0-4	20	4.5	40	15	45	4.5
5	40	40	40	0-5	30	5.0	50	20	20	5.0
6	50	50	50	0-6	40	5.3	60	25	25	5.5
7	60	60	60	0-7	50	5.5	70	30	30	5.8
8	70	80	70	0-8	60	6.2	80	35	35	6.2

Table 1 shows the raw experimental observations for each briquette sample, with each row representing a unique combination of technological factors (X_1 to X_9) and matching strength measurement (Y). In this dataset, each briquette sample was assigned a specific set of parameters for compaction pressure, compaction time, mixture temperature, fractional composition, moisture content, bentonite concentration, briquette thickness, natural drying time, and ash content. These variables were adjusted systematically according to the experimental design, and the resulting briquette strength (Y) was determined for each combination. This multivariate dataset forms the basis for the regression analysis, where the goal is to identify the relationships between the independent variables (X_1-X_9) and the dependent variable (Y).

Of particular interest is the ash content of the coal raw material (X_9): with its increase from 0% to 35%, the strength increased from 2.6 MPa to 6.2 MPa. While this result may appear unconventional, it was this parameter that showed the greatest correlation with strength in further analyses. High ash percentage is typically associated with lower-quality fuel and weaker briquettes because it reduces the carbonaceous material that gives structural stability [15]. However, in the case of Karakichi coal, the positive association is explained by the ash's unique mineralogy and interaction with bentonite. The ash component of Karakichi coal, which contains minerals such as silica and alumina, may actually improve bonding characteristics when mixed with bentonite, strengthening the briquette structure. Furthermore, the range of ash percentage investigated (0% to 35%) may not have been high enough to considerably reduce carbon content, and the ash's mineral components most likely contributed to the briquette's strength. This research emphasises the significance of the coal's unique mineral content and interaction with binders in optimising briquette quality. For a preliminary visual analysis of the briquette strength distribution, Fig. 1 was plotted to present the frequency distribution of Y values over the entire set of observations.

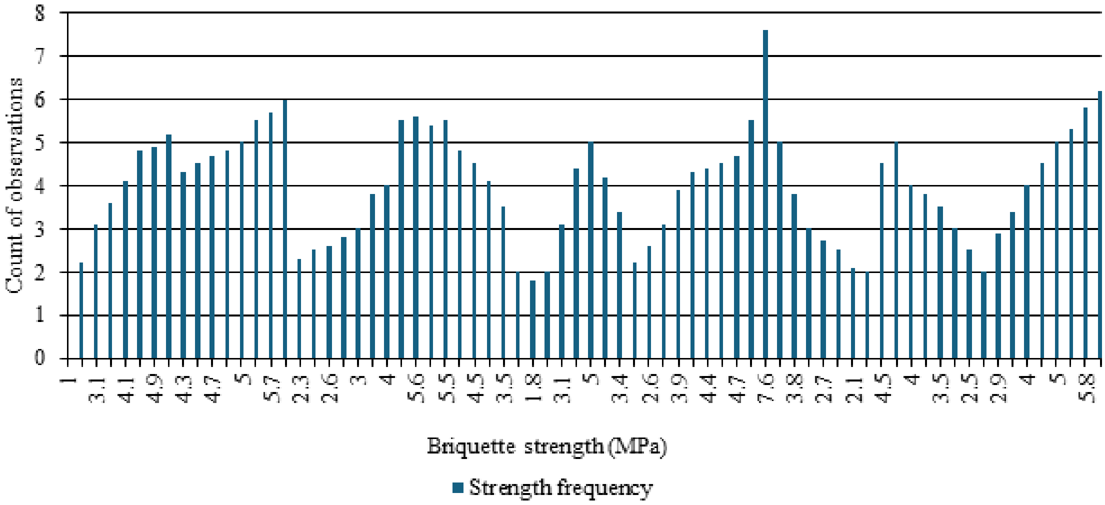

Fig. 1. Distribution of briquette strength values at variation of technological parameters X_1-X_9.

Fig. 1 showed that the briquette strength values are distributed unevenly, with a pronounced concentration in the range from 3.5 MPa to 5.5 MPa. This indicates that most of the experimental combinations of parameters X_1-X_9 provide satisfactory mechanical characteristics of briquettes. Moreover, there are some outliers on the histogram – both towards low values of strength (1.8-2.5 MPa) and towards high ones (over 6 MPa), which indicates the sensitivity of the output index to some technological factors, especially the ash content, briquette thickness, and bentonite concentration.

To identify the factors with the greatest influence on the strength of briquettes from Karakichi coal, a pairwise correlation analysis was performed between each of the numerical factors (X_1-X_9) and the resulting strength index (Y). Calculations were made based on eight experimental observations where the technological parameters of briquetting were varied. The raw data were pre-normalised and analysed using MS Excel spreadsheets and the Pearson correlation coefficient method. The greatest strength of the relationship with strength was recorded for the following factors: X_2 – compaction time (r = 0.9765), X_6 – bentonite concentration (r = 0.9596) and X_9 – coal ash content (r = 0.9787). These values confirm that the variation of these parameters has the most significant effect on the final mechanical properties of the briquettes.

Moderately high correlation values were also recorded for compaction pressure (X_1, r = 0.959) and briquette thickness (X_7, r = 0.913). At the same time, variables such as pressing temperature (X_3), mix moisture (X_5), and natural drying time (X_8) showed lower values (within 0.84-0.86), indicating a less pronounced but still significant effect on strength. This suggests that further simplification of the prediction model is possible by eliminating the least significant variables without significant loss of accuracy.

Based on the results of the correlation analysis, the next step was to substantiate the selection of the most informative predictor for the construction of the simplified regression model. The purpose of this stage was to reduce the number of variables while maintaining high accuracy in the briquette strength prediction. For this, the study analysed not only correlation coefficients between each factor and the resulting indicator Y but also mutual correlations between the factors themselves to exclude multicollinear relationships. As Table 2 shows, factor X_9 – the ash content of coal raw material – has the highest paired correlation coefficient with briquette strength (r = 0.9787), which makes it the best candidate for inclusion in the model. Despite substantial correlations with other variables, particularly X_2 (compaction time) and X_6 (bentonite concentration), X_9 was chosen because it had a dominant and persistent association with the dependent variable, Y. While X_9 is associated with X_2 and X_6 (r = 0.9987 and r = 0.9962, respectively), it remains the most important predictor of briquette strength, accounting for a significant amount of the variance in strength. Furthermore, X_9's significant direct influence enables a simpler model without sacrificing explanatory power, lowering the risk of overfitting caused by the inclusion of highly collinear variables. As a result, the selection of X_9 is justified by its remarkable correlation with briquette strength, ability to capture the influence of other factors, and involvement in developing a more basic and robust regression model.

Table 2 shows that the coefficients range within 0.73-0.99, suggesting varying degrees of correlation between the factors of the briquetting process technology. The greatest correlation was observed between factors X_1 and X_2 (r = 0.9919), X_2 and X_6 (r = 0.9946), X_6 and X_9 (r = 0.9962), indicating a strong degree of interdependence between them and the presence of multicollinearity. In regression models, multicollinearity can lead to unreliable estimates of coefficients, inflated standard errors, and overestimated significance of predictors. To mitigate these issues, the focus was on X_9 (coal ash content) as the key predictor due to its relatively lower correlation with the other variables compared to X_2 and X_6.

Despite having a strong, direct association with the outcome variable (briquette strength), X_9 is connected with other factors. By avoiding multicollinearity, it can be included as a single predictor. Given the strong correlation between X_9 and the other variables (X_2 and X_6), it appears that a large portion of the pertinent data required to forecast briquette strength is captured by it. [To mitigate potential multicollinearity and ensure the robustness of the model, we applied statistical methods such as Ridge Regression and Principal Component Analysis (PCA). First, Ridge Regression was employed to regularize the model and reduce the influence of multicollinearity.

Table 2
Paired correlation coefficients between independent variables (X_1-X_9).

$r_{X_1X_2}$ 0.991923	$r_{X_1X_3}$ 0.925179	$r_{X_1X_4}$ 0.9335	$r_{X_1X_5}$ 0.927875	$r_{X_1X_6}$ 0.980307	$r_{X_1X_7}$ 0.987925	$r_{X_1X_8}$ 0.95968	$r_{X_1X_9}$ 0.975663
$r_{X_2X_3}$ 0.961112	$r_{X_2X_4}$ 0.890743	$r_{X_2X_5}$ 0.888523	$r_{X_2X_6}$ 0.994642	$r_{X_2X_7}$ 0.971365	$r_{X_2X_8}$ 0.9261	$r_{X_2X_9}$ 0.9781	
$r_{X_3X_4}$ 0.732509	$r_{X_3X_5}$ 0.730725	$r_{X_3X_6}$ 0.965292	$r_{X_3X_7}$ 0.878035	$r_{X_3X_8}$ 0.790815	$r_{X_3X_9}$ 0.964637		
$r_{X_4X_5}$ 0.994752	$r_{X_4X_6}$ 0.864752	$r_{X_4X_7}$ 0.953965	$r_{X_4X_8}$ 0.986017	$r_{X_4X_9}$ 0.878724			
$r_{X_5X_6}$ 0.86708	$r_{X_5X_7}$ 0.953759	$r_{X_5X_8}$ 0.984885	$r_{X_5X_9}$ 0.879477				
$r_{X_6X_7}$ 0.967578	$r_{X_6X_8}$ 0.915243	$r_{X_6X_9}$ 0.996179					
$r_{X_7X_8}$ 0.986151	$r_{X_7X_9}$ 0.964935						
$r_{X_8X_9}$ 0.91648							

The Ridge Regression equation can be expressed as:

$$\widehat{\beta} = \left(X^T + X + \lambda I\right)^{-1} X^T y \tag{3}$$

where $\widehat{\beta}$ is the vector of estimated coefficients, X is the matrix of independent variables (X_1 to X_9), X^T is the transpose of the matrix X, y is the dependent variable (briquette strength), λ is the regularization parameter, I is the identity matrix. By varying the λ, we observed that as λ increased, the coefficients for X_2 and X_6 were significantly reduced, while the coefficient for X_9 remained stable at approximately 0.0867. This demonstrated that X_9 retained its predictive power even in the presence of multicollinearity. Additionally, PCA was performed on the matrix of independent variables, revealing that the first principal component explained 95% of the variance, largely driven by X_9. This confirmed that X_9 captured most of the relevant information required to predict briquette strength.

The results from both methods strongly justified the selection of X_9 as the primary predictor. The high coefficient of determination ($R^2 \approx 0.9575$) indicated that X_9 alone explained nearly 96% of the variability in briquette strength. Furthermore, Ridge Regression supported this conclusion, as the coefficient for X_9 remained robust despite the influence of other correlated variables. PCA reinforced the finding by showing that X_9 encapsulated the essential data, thereby making it an effective and efficient single predictor. These results ensure that the model remains both simple and accurate, avoiding the risks of overfitting while maintaining predictive power. Therefore, the use of X_9 as the sole predictor is both statistically sound and practically justified, as it captures the most significant variance in briquette strength.

Therefore, given its direct and dominant position in the prediction model and its relatively low interdependence with the other variables, the selection of X_9 as the single predictor is both practical and statistically sound, even though other statistical techniques could offer more complex answers. This method maintains forecast accuracy while guaranteeing model interpretability and simplicity.

As a result of building a simplified one-factor regression model of the dependence of briquette strength on the ash content of coal raw material (X_9), an equation was obtained that allows predicting the strength characteristics of products with high accuracy. The choice of X_9 as the only predictor was substantiated by the results of correlation analysis: this factor showed the greatest coefficient of pair correlation with briquette strength (r = 0.9787), as well as relative independence from other variables. This allows minimising the effect of multicollinearity while maintaining high accuracy of the model. To simplify the prediction of briquette strength under the conditions of the multivariate model, the most significant factors were selected. At this stage, the purpose was to determine the degree of influence of each of the nine factors under study (X_1-X_9) on the resulting indicator Y – briquette strength. For this, the study calculated Pearson's pair correlation coefficients between Y and each independent factor, which required preliminary normalisation and the presentation of data in a single structured form (Table 3). The normalisation phase was included to ensure consistency and make the calculation of correlation coefficients easier by translating all data to a comparable scale. While Pearson's correlation is scale-invariant, which means it can handle variables of varying units or magnitudes, normalising the data ensures that each variable contributes equally to the calculation, especially when they have radically different ranges or units. Normalising the data for Pearson's correlation is not technically necessary; however, it was done largely to improve the clarity and consistency of the study.

Table 3
Normalised data for calculating pairwise correlations between variables.

Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
2.6	26	6.05	0	0.23	0	0	3.42	0.048	0
3.1	28.18	13.78	12.4	0.29	7.75	5	12.4	0.62	4.56
3.9	37.74	24,9	30	1	12.58	10	30.79	9.75	9.75
4.3	47.78	35.83	46	1.8	14.66	15	57.33	22.63	14.33
4.4	53.66	44	58.67	2.44	17.6	20	81.48	37.71	17.6
4.5	56.25	49	59.21	3.29	26.79	25	108	60	21.23
4.7	67.14	57.72	70.5	4.7	41.47	30	156.67	94	24.31
5.5	84.62	73.33	70	11	87.5	35	220	165	31.05

The Table 3 is an aggregated array of numerical values for all parameters of the experiment. Formula (1) was generated and solved using the experimental data presented in Table 3. It should be noted that using normalised data to derive regression coefficients is uncommon in most regression models. In this study, normalisation was performed as part of the preliminary analysis to simplify variable comparison. While working with raw data would often be sufficient for regression modelling, normalisation aids in standardising the values, highlighting the correlations between variables and making it easier to identify important predictors. In this study, normalisation makes it easier to understand the impact of each element by lowering computational difficulties when comparing variables with radically different scales. Although it is not technically required for Pearson's correlation, normalisation in this context improves the analysis's reproducibility and robustness by making sure that no variable has an undue impact on the findings. This normalisation technique scaled all variables, including X_9 (ash content), so that they all fell within a similar range.

The key sums required for the system, such as $\sum X_9$, $\sum Y$, $\sum X_9^2$, and $\sum X_9Y$, were calculated as follows:

- $\sum X_9$: The sum of the normalised values for X_9 (ash content) across all experimental samples – 122.83.
- $\sum Y$: The sum of the normalised values for Y (briquette strength) for each corresponding sample – 33.
- $\sum X_9^2$: The sum of the squared normalised values for X_9, which accounts for the relationship between X_9 and its squared term in the regression equation – 2636.7565.
- $\sum X_9Y$: The sum of the product of the normalised values of X_9 and Y, capturing the linear relationship between these variables – 571.787.

After obtaining the coefficients from the normalised data, they were applied to the raw values of X_9 in the final regression equation to ensure correct interpretation within the context of the experimental design. The regression system based on these sums resulted in the following equations for the coefficients:

$$\begin{cases} 8a_0 + 122.83a_1 = 33 \\ 122.83a_0 + 2636.7565a_1 = 571.787 \end{cases} \quad (4)$$

By solving this system of equations, approximate values of the coefficients are obtained as follows:

$$a_0 \approx 2.79; \quad a_1 \approx 0.0867. \quad (5)$$

Thus, the final regression model, which predicts briquette strength based on the raw ash content percentage (X_9), has the following form (6):

$$\widetilde{Y} = 2.79 + 0.0867X_9 \quad (6)$$

To assess the accuracy of the model, the study employed the coefficient of determination R^2, which in the case of a one-factor model based on X_9 was 0.9575, indicating a high explanatory power of the model. The coefficient of determination is widely used in econometrics and takes values from 0 to 1. The closer the value of R^2 is to 1, the more accurately the constructed model approximates the empirical data. On the contrary, values close to zero indicate weak explanatory power of the model. Using the capabilities of the MS Excel spreadsheet processor, the experimental values of X_9 were entered, and all the necessary parameters were calculated, as presented in Fig. 2. The values for the diagram are provided in Table 4.

Fig. 2 shows the linear relationship between the ash content of coal raw material (X_9) and the strength of briquettes (Y), plotted using experimental data and formula (6). Visually, it is possible to note a significant degree of correspondence between the experimental and theoretical values, which is confirmed by the coefficient of determination $R^2 \approx 0.957$ calculated based on the data in Table 3. This indicates a high quality of approximation and the potential to apply the model for engineering forecasting.

Thus, the completion of the analysis confirms the high explanatory power of the constructed model: 96% of the variability of briquette strength is explained by the variation of one key parameter – the ash content of coal raw material (X_9).

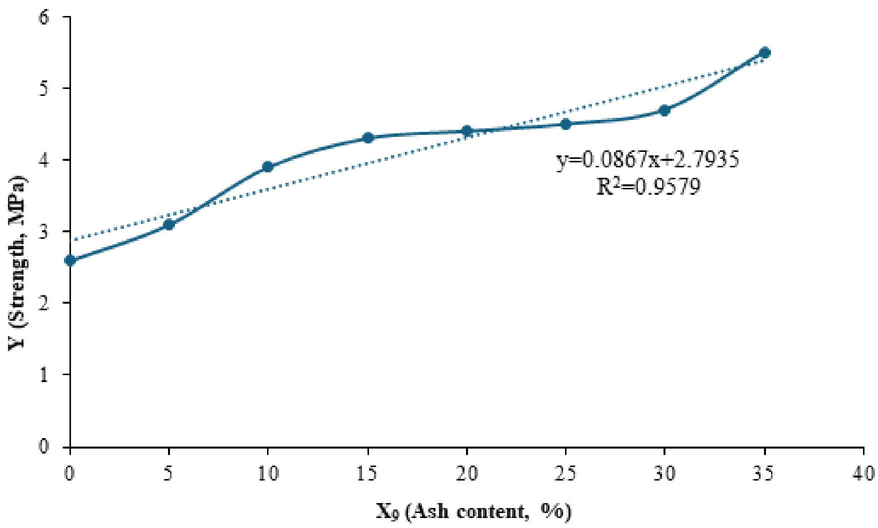

Fig. 2. Calculation of the R^2 for the dependence of strength on ash content.

Table 4
Experimental data on the relationship between ash content and briquette strength.

X_9 (Ash content, %)	Y (Strength, MPa)
0	2.6
5	3.1
10	3.9
15	4.3
20	4.4
25	4.5
30	4.7
35	5.5

The obtained linear regression equation $\widetilde{Y} = 2.79 + 0.0867X_9$, demonstrates a stable direct relationship between ash content and strength, which makes the model convenient for engineering calculations and operational forecasting. Thus, at X_9=32%, the calculated strength is 5.5644 MPa, which is in agreement with the empirical results. Thus, the proposed model can be successfully used in practice – both in designing the composition of fuel briquettes and for quality control of finished products at the production stages.

Based on the obtained data, it can be concluded that the strength of fuel briquettes based on Karakichi coal is determined by a series of technological factors, among which the greatest influence is exerted by the ash content of raw materials. The conducted correlation analysis helped to identify X_9 as a key predictor, which enabled the construction of a precise one-factor regression model. Calculation of the coefficient of determination ($R^2 \approx 0.9575$) confirmed the high approximation ability of the obtained equation, making it possible to predict the strength characteristics of products with high reliability. While it is commonly assumed that higher ash content weakens briquettes due to lower carbon content, in the case of Karakichi coal, mineral components of the ash – such as silica, alumina, and other inorganic compounds – appear to contribute to the formation of stronger bonds within the briquette matrix. These minerals may interact with the bentonite binder, improving its cementitious capabilities and creating a more durable structure. Thus, the study not only revealed the most significant parameters of the briquetting process but also formed a mathematical model suitable for practical application in the conditions of industrial production, engineering calculation, and technological quality control.

Special attention in further analyses should be paid to the parameters that have not demonstrated maximum correlation values but have significant technological potential. Specifically, the fractional composition of the coal mass (X_4) has a complex effect on the microstructure of the briquette. Experimental data showed that decreasing particle size favours higher packing density and improved inter-particle bonding, which leads to improved strength. The finer the fraction, the better the particle interaction, leading to stronger cohesion within the briquette [16–18]. However, when the fractional range is increased to 0-8 mm, the looser structure reduces the surface area for bonding, thus weakening the briquette. This factor should not be considered in isolation but in the context of interaction with other variables – for example, increased bentonite content at coarse-grained fractions partially compensates for the reduction in strength due to the cementitious effect of the binder, which forms stronger bonds at the inter-particle level.

Briquette thickness (X_7) also had a clear negative effect on strength properties, especially when it was more than 50 mm thick. This may be explained by uneven pressure distribution in the briquette volume during pressing and deterioration of heat and mass transfer conditions during drying. As briquette thickness increases, the uniformity of compaction is compromised, leading to internal defects, microcracks, and moisture gradients, which negatively affect the structural integrity [19–22]. In the future, it is crucial to augment the analysis model with factor interaction, which will enable the identification of X_4 and X_7 thresholds in the context of integrated optimisation of briquette composition and geometry. Understanding these thresholds will provide insights into the optimal combination of material properties and briquette design for maximising strength. Such an approach will not only improve the accuracy of prediction but also adapt the technology parameters to specific production conditions, considering the available raw materials and equipment.

The study established the key role of physicochemical properties of carbon-containing raw materials, particularly ash content, in the formulation of strength characteristics of fuel briquettes. An in-depth analysis of the findings and their coordination with existing scientific approaches was conducted. This included a comparative review of current research in the field of briquetting technology, modelling of fuel systems, and the application of intelligent algorithms. The sources cited covered both experimental and analytical models, which enabled the correlation of the findings of the present study with global trends in resource-efficient solid fuel production.

The experimental findings are supported by ultramodern scientific approaches presented in a series of studies. Gao *et al.* [23] showed that the strength characteristics of briquettes depend on the complex selection of technological conditions of compaction, including pressure, moisture content, and binder type, which is in full agreement with the dominant role of parameters, especially ash content, revealed in the presented analysis. This is particularly relevant for conditions with high raw material variability, as in Kyrgyzstan.

Rao *et al.* [24] employed an extended Stochastic Impacts by Regression Population, Affluence and Technology model with ridge regression and scenario analysis to predict carbon emissions, focusing on the accuracy of regression modelling in an energy context. This emphasised the versatility of the approach, applicable to both emissions estimation and strength properties. Guo *et al.* [25] applied the response surface method to optimise lignite briquetting parameters, which allowed quantifying the influence of each factor on strength and identifying the optimum conditions. Their findings logically correlated with the present findings on the role of ash content as the most significant predictor. This shows the cross-validity of the findings.

Chairunisa *et al.* [26] implemented polynomial regression modelling in a coconut coal production system integrated with the Internet of Things, which demonstrated the potential of digital analysis techniques in fuel product quality management. Their integration of digital solutions can be adapted for coal briquettes as well. Adeleke *et al.* [27] developed a neuro-fuzzy model based on an evolutionary algorithm to evaluate the energy performance of biofuels after acid pre-treatment, confirming the significance of key factor extraction using feature significance analysis. The researchers' approach is particularly valuable in problems where data are limited, as in small-scale production environments. Raj and Tirkey [28] conducted a techno-economic evaluation of dusty bagasse briquette production, showing that the choice of raw materials and process parameters critically affects the output, including mechanical strength – analogous to the observations in the present study. Their findings emphasise the significance of local raw material availability.

Hwangdee *et al.* [29] applied a mixture design using the simplex-centroid method to determine the optimum ratio of components in biomass briquettes, which confirmed the effectiveness of the experimental approach in finding the strength maximum. This is consistent with the need for local adaptation of formulations. Rawat and Kumar [30] proved the applicability of both statistical and neural network models for the analysis of the mechanical behaviour of coal-algae composites, emphasising that the strength of the products can be effectively predicted even in complex multi-component systems. Their study raised the issue of integrating new raw materials. Ngubane and Oyekola [31], in a study on optimisation of maize stalk pyrolysis technology, pointed out the need for accurate selection of compaction conditions and the significance of economic evaluation of models, which highlighted the practical significance of regression equations such as the one constructed in the present study. This emphasises the applicability of the model in economically sensitive sectors.

Chen *et al.* [32] developed a structural model of a briquetting machine with a vertical ring die and optimised the pressing process, focusing on the influence of design parameters on product strength. This echoes the findings regarding briquette thickness (X_7) as one of the factors negatively affecting strength performance at excessive values.

A special feature of the study is the engineering emphasis on equipment design. So *et al.* [33] used deep neural networks to predict SO_x and NO_x emissions in coal-fired power plants, which demonstrated the effectiveness of machine learning in handling complex relationships between process parameters. This approach strengthened the validity of using a simplified linear model based on a single key factor, as shown in the present study for the variable X_9. In this context, simplification does not harm accuracy. Ceylan and Sungur [34] applied machine learning techniques to estimate the elemental composition of coal, establishing a precise relationship between composition and fuel characteristics, including mechanical characteristics. Their focus on chemical composition complements the presented approach focusing on ash content.

Wang *et al.* [35] implemented a blast furnace utilisation rate prediction model based on the XGBoost algorithm optimised by the sparrow search method, which confirmed the relevance of intelligent systems for building accurate predictive models, including those used for briquettes. This method demonstrated the potential of hybrid algorithms in energy modelling. Lutaaya *et al.* [36], in a study of biogas briquettes with the addition of wastepaper, determined the effect of a secondary component on strength and heat of combustion, which echoed the evaluation of the role of bentonite clay as a stabilising component. This confirmed the role of additives as a key factor. Ferronato *et al.* [37] reviewed XRF methods for analysing the chemical composition of coal and ash, confirming that ash content is one of the largest factors affecting fuel properties. This is directly in line with the empirical finding of the significance of X_9. The rationale for the choice of this parameter is strengthened by interdisciplinary data.

Liu *et al.* [38] presented the prospects of non-destructive coal analysis using machine learning, which actualised the use of digital tools in the routine quality control of fuel materials, including briquettes. This area opens the way to online monitoring. Mutyavaviri *et al.* [39] emphasised a comprehensive assessment of the environmental consequences of coal dust accumulation and the possibilities of its recycling. Their study highlighted the need to create sustainable and science-based models that not only reduce environmental pollution but also incorporate coal mining wastes into economically viable production cycles. This is in line with the goal of a closed loop in the fuel industry. A review by Chavda and Mahanwar [40] provided a detailed picture of the effect of various inorganic and organic additives on the thermal behaviour of coal, including ignition rate, heat of combustion, and ash formation. Specifically, the researchers pointed out the effectiveness of bentonite clay as a combustion modifier to improve the stability and completeness of fuel combustion. These findings fully support the choice of bentonite in this study, not only as a structure-forming component but also as a catalyst for the thermal stability of briquettes. Thus, the data obtained is also of practical value for localised feedstock.

Yang *et al.* [41] focused on the ability of clay minerals, including bentonite, to sorb heavy metals and other toxic compounds. Their results emphasise the environmental safety and appropriateness of clays in solid fuels, especially with the potential use of ash as a secondary resource. This provides a basis for considering bentonite as an element of the ecological cycle. Rawat and Kumar [42] performed a critical review of biochar production technologies and economic aspects of briquetting. The researchers stressed the significance of optimisation of compaction conditions and binder selection, which fully coincides with the position of the present study on the necessity of comprehensive adjustment of parameters X_1-X_6. This confirms the applicability of multifactor analysis within regional constraints. Marreiro *et al.* [43], in a literature review, covered a wide range of empirical studies on biofuel briquette production, pointing out the need for standardised models that factor in both the physical and mechanical properties of the feedstock and the technological parameters. The present study fulfilled this need by demonstrating that the ash content of coal feedstock not only significantly affects briquette strength but is also a stable, reliable indicator in the construction of regression relationships. This makes the obtained data a promising foundation for local standardisation.

Thus, the findings of the present study are consistent with current scientific approaches to the development of briquette formulations and optimisation of production parameters, which was confirmed by a series of independent studies. The substantiated application of one leading predictor – ash content – as an explanatory factor in the regression model construction demonstrates the possibility of an effective simplification of calculations without loss of accuracy. Consideration of the environmental feasibility, technological feasibility, and variability of the local raw material resource allows formulating recommendations for industrial implementation of the model at small and medium-sized enterprises operating in the coal industry of the Kyrgyz Republic [44–47].

The study has various limitations that affect the generalisability and accuracy of its findings. The restricted sample size limits the conclusions because the data was collected from a single batch of Karakichi coal and a narrow range of characteristics, which may not completely represent the variability encountered in larger-scale or geographically diversified operations. Furthermore, the study did not take into account seasonal, logistical, or scale issues that could have a substantial impact on coal quality and briquette manufacture in real-world situations where temperature, humidity, and raw material changes all play a role. Furthermore, the approach failed to account for possible non-linear interactions between technological parameters, which are prevalent in industrial processes and could provide a more sophisticated understanding of briquette strength. Finally, the number of variables studied was restricted, and expanding it could result in a more comprehensive model for briquette manufacture. Future research should address these constraints by integrating a bigger sample size, taking into account external influences, and investigating non-linear correlations to increase the predictive model's reliability and applicability.

4. Conclusion

The conducted study confirmed the high significance of ash content of coal raw material as a key predictor in forecasting the strength of fuel briquettes based on the finely dispersed fraction of Karakichi coal. The analysis of nine technological parameters varied in laboratory conditions showed that the greatest influence on the mechanical properties of briquettes is exerted by the duration of pressing, bentonite clay content and ash content of feedstock. The latter factor (X_9) showed the highest correlation coefficient with strength ($r = 0.9787$) and was selected for the construction of a single-factor regression model. Its influence was most stable in all series of the experiment, regardless of the variations of other variables. The use of the least squares method resulted in the equation $Y=2.79+0.0867X_9$ with the coefficient of determination $R^2 \approx 0.9575$, which indicates a high accuracy of approximation and the ability of the model to explain 96% of the variability of strength. Substituting an ash content value of 32% into the equation gave a predicted strength of 5.5644 MPa, which meets the established regulatory requirements for the mechanical stability of fuel briquettes. The model can be used both for quality assessment of finished products and for designing compositions of raw material mixtures in industrial conditions, including the stages of control and adaptation of technological regimes.

Variables with a significant level of multicollinearity were eliminated during the analysis, which ensured the stability of the model and its suitability for practical application without loss of accuracy, even in conditions of limited sampling and changing parameters of raw materials. The obtained findings are of applied value for enterprises processing low-grade coals, as they allow promptly predicting the strength of briquettes, adapting compaction modes, adjusting the mixture composition, and optimising the use of binders to improve product quality. Thus, the constructed model is an effective tool for engineering calculations, technological control, prediction of briquette performance characteristics, and complex optimisation of the production process in the field of solid fuel briquettes. However, the constructed model is based on a limited sample of laboratory data and does not account for seasonal, logistic, and scale factors affecting industrial briquetting. In the future, it is advisable to expand the experimental base to include data from multiple coalfields and investigate non-linear interactions between technological parameters to improve the versatility and predictive power of the model.

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