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Integrated application of ARIMA and Ridge Regression methods for forecasting hard coal production, imports, and exports under conditions of economic instability

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Abstract
This article examines the problem of forecasting coal production, imports, and exports under conditions of economic instability using a comprehensive approach that combines ARIMA methods and Ridge Regression. Coal remains a strategically important energy resource for many countries; however, its market dynamics are characterised by high volatility driven by geopolitical risks, structural transformations of energy systems, and changes in the macroeconomic environment. Using the cases of Ukraine, Poland, and China, the study analyses different models of coal sector functioning, ranging from countries with transition economies to a global leader with large-scale domestic production.
The forecasting framework is based on the integration of econometric time series analysis using ARIMA and regularised linear regression via Ridge Regression, which makes it possible to account for both the temporal dynamics of the indicators and the multicollinearity of macroeconomic and energy-related factors. To ensure forecast robustness, data preprocessing procedures, temporal validation, automatic ARIMA parameter selection, and heuristic optimisation of forecasting results are employed.
The obtained results indicate that the proposed hybrid approach provides higher forecasting accuracy and robustness compared with the use of individual models. Significant cross-country differences are identified: Ukraine exhibits a high dependence on imports; Poland demonstrates a managed contraction of the coal industry; and China maintains large-scale production with flexible utilisation of imports. The findings may be applied to scenario-based forecasting, decision-making support, and the formulation of energy security strategies.

Keywords
hard coal; forecasting; ARIMA; Ridge Regression; energy security; time series.

Introduction

Coal remains one of the key energy resources, playing a crucial role in supporting industrial production, electricity generation, and the foreign trade of many countries. The volumes of its production, imports, and exports have a significant impact on national economic stability, levels of energy security, and the functioning of both domestic and international markets. For countries such as Ukraine, Poland, and China, coal retains strategic importance while fulfilling different roles within national energy systems and external trade relations.

Under conditions of economic instability, heightened geopolitical risks, and structural changes in energy consumption, the dynamics of coal production, imports, and exports are characterised by high volatility and unpredictability. Ukraine faces instability in domestic production and an increasing dependence on imports; Poland combines substantial domestic production with a gradual transformation of the coal industry; and China, in turn, is the world's largest producer and consumer of coal, shaping global market trends. These factors complicate sectoral development planning and managerial decision-making processes.

A distinctive feature of the contemporary energy environment is the coexistence of cyclical macroeconomic instability with exogenous influences such as military conflicts, trade restrictions, and decarbonisation policies. For the coal sector, this implies that classical assumptions of stationarity and regularity in time series are violated, while structural breaks become a common occurrence. Consequently, the use of hybrid models capable of simultaneously capturing temporal inertia and adapting to changing economic conditions is critically important for producing realistic medium-term forecasts.

Under such conditions, traditional approaches to forecasting coal market indicators often fail to deliver sufficient accuracy, as they do not adequately account for the specific properties of time series data or the influence of multiple interrelated economic factors. This has increased the need for the application of modern econometric forecasting methods capable of adapting to unstable environments. ARIMA models enable effective analysis of the temporal dynamics of coal production, imports, and exports, while Ridge Regression allows for the incorporation of the combined effects of macroeconomic factors and the mitigation of multicollinearity issues.

The aim of this study is to develop forecasts of coal production, imports, and exports based on the integrated application of ARIMA and Ridge Regression methods under conditions of economic instability. An empirical analysis using the cases of Ukraine, Poland, and China enables a comparison of different models of coal market functioning – from countries with transition economies to a global industry leader – and an assessment of differences in the projected dynamics of the indicators.

The scientific novelty of this study lies in the application of an integrated approach to forecasting coal industry indicators through the combination of ARIMA and Ridge Regression within a unified methodological framework. In contrast to approaches that rely on individual forecasting methods, the proposed approach enhances the robustness and accuracy of forecasts across countries with differing structural characteristics of the coal market. The scientific hypothesis posits that the integrated application of these methods yields more reliable forecasts of coal production, imports, and exports than the use of a single method, particularly in the cases of Ukraine, Poland, and China.

Analysis of recent research and publications

Angelo M. D., et al. (2023) compared the performance of the ARIMA and Prophet algorithms in forecasting Bitcoin prices over the period from February 2019 to 2021 using daily, weekly, and monthly data. The study employed univariate models with two features for training, while the parameters of each model were selected through cross-validation and manual optimisation. The results indicated that Prophet performed best for daily and weekly data, whereas ARIMA achieved higher accuracy for monthly data. Model evaluation was conducted using MAE, MAPE, MSE, and RMSE, enabling an objective comparison of forecasting accuracy.

Sherly A., et al. (2025) examined the effectiveness of the univariate Prophet model and the multivariate VARIMA model for time series forecasting in the context of edge computing and the Internet of Things (IoT). The authors proposed a hybrid approach that integrates ARIMA and Prophet to improve forecasting accuracy by combining ARIMA's ability to capture linear relationships and short-term fluctuations with Prophet's effectiveness in modelling non-linear trends, seasonality, and holiday effects. Model performance was evaluated using RMSE and MAE, and the results demonstrated that the hybrid model consistently outperformed the individual models, particularly for complex time series containing both stationary and non-stationary components.

Reddy B. D., et al. (2025) conducted a methodological review of the application of the ARIMA model for time series forecasting across various domains, including energy, healthcare, supply chains, and consumer behaviour analysis. The authors highlight the high flexibility of ARIMA in identifying and modelling temporal patterns, while also emphasising its limitations, notably sensitivity to parameter selection, challenges in handling seasonality, and the inability to capture non-linear relationships.

Parreño S. J. E. (2022) investigated the application of ARIMA models for forecasting coal production and consumption in the Philippines. For production, the ARIMA(1,2,0) model was identified as the most appropriate, while ARIMA(0,2,1) was found to be optimal for consumption; both models were subjected to residual diagnostics and forecast accuracy assessment. The results indicated that coal production is expected to decline in the coming years, whereas consumption will increase, implying that the country will need to import approximately 133.2 million tonnes of coal over the period 2021-2025.

Jiang S., et al. (2018) applied ARIMA models to forecast coal consumption, prices, and investment in China's coal industry over the period 2016-2030. The authors selected the most appropriate models for each indicator and conducted an assessment of forecasting accuracy. The results indicated that the average annual rates of decline in coal consumption and investment would be substantial, while coal prices were expected to exhibit a fluctuating pattern throughout the forecast horizon.

Li S., et al. (2019) examined the forecasting of coal consumption in India up to 2030 using combined MGM-ARIMA and BP-ARIMA models based on a metabolic grey model and a backpropagation (BP) neural network. The models demonstrated low mean relative errors (1.42-2.28%) in reproducing data for the period 1995-2017. The forecast indicates that coal consumption in India will continue to increase at an average annual rate of approximately 2.5% over the period 2018-2030.

Ma M., et al. (2018) investigated the forecasting of coal consumption in South Africa over the period 2017-2030 using linear (Metabolic Grey Model), non-linear (Non-linear Grey Model), and combined (MGM-ARIMA) models. The combined model proved to be the most accurate, achieving a mean absolute forecasting error of 3.4%. The forecast indicated a gradual decline in coal consumption at an average annual rate of 1.9%, providing a basis for energy and coal policy planning.

Benalcazar P., et al. (2017) examined global coal consumption and its forecasting using a multilayer perceptron (MLP) neural network. The authors emphasise that the industrialisation of services, population growth, and economic development in Asia over the past 50 years have led to a substantial increase in global energy consumption. According to estimates by the U.S. Energy Information Administration, global energy consumption is projected to increase by 48% between 2012 and 2040, with growth of 71% expected in developing countries (China, India, and South Africa), compared with only 18% in OECD countries. In the twenty-first century, fossil fuels (coal, natural gas, and oil) remain the dominant sources of energy and are expected to account for approximately 78% of global energy consumption by 2040. The MLP model, trained on data for the period 1970-2016, forecasts a slowdown in the growth rate of global coal consumption during 2020-2030. The study highlights the continued importance of coal in the global energy balance, particularly in countries characterised by high levels of industrialisation and a strong dependence on fossil resources.

Gangwar A., et al. (2024) investigated the forecasting of coal production in India using time series analysis. The study applied component- and correlation-oriented models, including Naïve, Holt, and ARIMA, to data covering the period 1980-2022. As a result, the ARIMA(2,2,2) model, optimised using the AIC and BIC criteria, was selected for forecasting. Residual diagnostics were conducted to confirm model adequacy, followed by the generation of forecasts for the subsequent five years. The study highlights the practicality of ARIMA for assessing future trends in coal production in India and proposes new methodological approaches to energy resource forecasting.

Suharsono A., et al. (2023) applied a combination of ARIMA and an asymmetric GARCH model to forecast the daily coal production of company "B" in Indonesia over the period 2021-2022. ARIMA was used to model short-term data fluctuations, while the EGARCH model captured heteroskedasticity and asymmetric effects in the residuals. The optimal ARIMA-EGARCH model demonstrated superior accuracy in terms of AIC, SBC, and RMSE compared with the baseline ARIMA model, while MAD remained similar for both approaches. The study confirms the effectiveness of hybrid methods for production forecasting under conditions of market instability and volatility.

Liu G., et al. (2023) proposed a dynamic optimisation method for production planning in open-pit coal mines, combining the forecasting of economic time series with the analysis of "fuzzy" structured elements of mine reserves. An ARIMA model was employed to predict future coal prices, enabling the determination of optimal extraction volumes and the maximisation of the net present value (NPV) of the production plan. A case study of the Baorishile mine in the Inner Mongolia Autonomous Region (China) demonstrated the effectiveness of this approach for dynamic production management under economic uncertainty and for supporting mine design decision-making.

Bai E., et al. (2025) investigated the application of "green" coal mining technologies and low-carbon production in China. The authors developed a model for assessing roof collapse and overburden degradation, enabling the identification of mechanisms and criteria for surface damage during underground mining. The study integrates concepts of source control, impact transfer management technologies, and water-conserving mining methods, while also analysing carbon emissions and the management of thermal hazards in mines. The work provides both a theoretical foundation and practical recommendations for the coordinated development of environmentally safe and low-carbon coal mining in China.

Jonek-Kowalska I., et al. (2025) investigated the post-reorganisation performance of Poland's hard coal mining industry. The authors found that the closure of unprofitable mines did not yield the expected results, and workforce reductions have proceeded slowly and inconsistently. Labour productivity per employee is declining, while wages are rising faster than inflation, resulting in high production costs for coal. The study indicates that without a radical improvement in productivity and efficiency, the coal sector faces the risk of elimination. The article also highlights the microeconomic determinants of productivity in coal mining enterprises and the consequences of ineffective restructuring measures.

Raza M., et al. (2025) examined global coal trends, including reserves, prices, electricity generation, carbon emissions, and coal phase-out plans. Using a SARIMAX model in Python with data from 1980-2022, the authors projected developments up to 2050. The results indicate that global coal reserves amount to 1.07 trillion tonnes, prices fluctuate between 130-206 USD/t, and coal-based electricity generation is expected to rise from 10,415 TWh in 2023 to 15,243 TWh in 2050, leading to increased CO_2 emissions. A phased coal phase-out is planned, with 75% reduction by 2030 and full elimination by 2040 in many countries to meet IPCC targets. The study emphasises the need for a transition to clean energy sources and a reduction in coal-based electricity production.

Wang J., et al. (2011) investigated coal production forecasting in China and low-carbon development policies. The authors employed three enhanced models based on Grey Systems Theory: the Discrete Grey Model (DGM), Rolling DGM (RDGM), and p-value RDGM, using coal production data from 1949-2005 to forecast the period 2006-2010. The p-value RDGM was identified as the most accurate model. Forecasts for 2011-2015 indicate an increase in coal production, underscoring the need for policies aimed at reducing carbon emissions and other pollutants. The study demonstrates the application of grey forecasting models for strategic energy planning.

Berk I. & Ediger V. Ş. (2016) investigated the forecasting of lignite production by TKI (Turkey) using Hubbert curve methodology, depletion curves, and decline curves. The results indicate that Turkey's largest deposits have entered a phase of declining production, with TKI's production peak occurring in 2018. The authors emphasise the importance of forecasting domestic energy production for sustainable energy planning and for reducing dependence on imports.

Aristizabal-H G., et al. (2023) examined the history and socio-economic consequences of coal industry closures in Germany and the potential lessons for Colombia. The authors emphasise the importance of gradual mine closures, structural regional transformations, and the use of mining revenues to strengthen regional economies.

Mao J., et al. (2024) investigated the forecasting of excess coal power capacity in China, considering political and industrial factors, using textual data and sentiment analysis, as well as scenarios under the "dual carbon" strategy. The authors identify the main drivers of excess capacity and demonstrate an expected increase in the scale of overcapacity up to 2060.

Liu X., et al. (2023) analysed the development of China's coal industry with a focus on the transition from production volume to product quality. The study employed statistical analysis of mine capacities, average production volumes, and the distribution of mines at provincial, municipal, and enterprise levels. It was found that 87% of coal is produced underground, while 13% is extracted via open-pit mining; a significant proportion of small-scale mines constrains the transition to a "green" coal industry. The study proposes measures for the closure of small mines, the elimination of outdated capacities, and the promotion of high-quality coal production development.

Makarov V., et al. (2024) analysed the technological state of Ukraine's coal industry and the role of coal in the country's energy balance. The study considers complex geological conditions, the low technical level of enterprises, the physical and moral ageing of equipment, limited investment resources, and inefficient management. It was found that 43% of longwalls in state-owned mines are equipped with modern technical complexes. The authors identified priorities for technological development and emphasised the necessity of modernising and reforming the sector to improve efficiency [20].

Haidai O., et al. (2022) analysed coal production in Western Donbas and its impact on Ukraine's energy security. Computational schemes for coal seam parameters were employed to effectively control rock pressure and enhance the safety of underground operations. The results demonstrated that the application of these technological solutions increases coal production, improves the stability of main transport routes, and generates additional economic benefits, thereby strengthening Ukraine's energy security.

Polishchuk V., et al. (2021) investigated the application of fuzzy information models for assessing the creditworthiness of enterprises in Ukraine's coal industry. The authors developed an enhanced fuzzy mathematical model comprising 11 criteria, divided into three groups: financial stability, profit and loss analysis, and enterprise management efficiency. The model accounts for uncertainty in input data, generates a normalised format for comparison, and evaluates the ability of enterprises to meet financial obligations on time. Testing on Lvivugol data demonstrated the model's effectiveness for decision-making and strategic planning in the sector. The study emphasises the importance of applying fuzzy models for analysing and forecasting the condition of coal enterprises, providing a potential framework for other countries.

Bijańska J. & Wodarski K. (2024) analysed hard coal mining in Poland in the context of EU climate and energy policies and the war in Ukraine. A business-risk assessment model was applied to evaluate investments aimed at maintaining or increasing coal production. The results indicate that, considering the embargo on Russian coal imports and reductions in coal production in other EU countries, Poland has the capacity to offset the deficit; however, maintaining or expanding production requires capital investment and risk management.

Gajdzik B., et al. (2024) investigated the issue of methane emissions from coal mines in Poland in the context of European climate policy. Strategic analyses of coal mines, the surrounding environment, and the macro-environment were employed to assess the dynamics of methane emissions and methane extraction projects. It was found that absolute methane emissions have decreased since 2008, while extraction volumes have consistently exceeded 300 million m³ per year since 2014. The study emphasises the role of government support, partnerships, and stakeholder engagement for the successful integration of methane extraction technologies and highlights the need for modernisation and efficiency improvements in methane capture and utilisation technologies.

Despite a substantial body of research devoted to forecasting coal production and consumption, studies differ in methodological approaches depending on country-specific characteristics and data availability. For instance, in China, most studies focus on ARIMA models and their combinations with other approaches (BP-ARIMA, MGM-ARIMA, ARIMA-EGARCH), reflecting the need to forecast large-scale coal production, price dynamics, and investment under conditions of high economic instability and rapid industrialisation. In Poland, emphasis is placed on strategic and socio-economic analyses, integrating business-risk assessment models and evaluating the impacts of restructuring, which allows for consideration of climate policy, mine closures, and regional structural transformations. In contrast, studies in Ukraine employ methods that combine ARIMA with regression models (Ridge Regression) to forecast coal production, imports, and exports, reflecting limited investment resources, ageing equipment, and the need to improve energy efficiency and security.

Therefore, differences in methodological choices reflect the specificities of national energy strategies: in China, the focus is on large-scale forecasting and dynamic management of coal production; in Poland, on the consideration of socio-economic and regional transformations; and in Ukraine, on the integration of ARIMA and regression models to enhance forecasting accuracy under complex economic conditions and to ensure energy security.

The review of previous studies indicates that most research either concentrates on purely time series models (ARIMA, SARIMA, GARCH) or employs advanced machine learning methods without clear economic interpretation of the influencing factors. At the same time, the approach in which energy flow forecasting is integrated with macroeconomic variables through regularised regression models remains insufficiently explored. It is precisely this gap between temporal and structural modelling that the proposed ARIMA-Ridge approach in the present study aims to address.

Methodology

The data pre-processing stage is designed to ensure structural consistency and integrity of the input time series used for building forecasting models for Ukraine, Poland, and China. It is implemented as a pipeline that includes feature normalisation, specification of variable configurations, and the reconstruction of missing values. The feature space is divided into vectors of endogenous variables Y and exogenous variables X. The vector of target indicators ($TARGETS$) comprises coal production, exports, and imports, while the regressor vector $\vec{X}$ encompasses macroeconomic and energy-related indicators.

A characteristic feature of economic time series is the presence of missing observations, which precludes the application of many machine learning algorithms, including ARIMA and Ridge Regression. To address this issue, a data reconstruction algorithm was developed and applied separately for each country. The algorithm consists of three sequential steps: linear interpolation, forward filling (*ffill*), and backward filling (*bfill*).

Linear interpolation is employed to impute missing values within a time series. If the values of a variable v are observed at time points t_aта t_b ($t_a < t < t_b$), but are missing at time t, the interpolated value v_t is calculated using the following formula.

$$v_t = v_{t_a} + (t - t_a)\frac{v_{t_b} - v_{t_a}}{t_b - t_a}, \tag{1}$$

where

v_{t_a}	the last observed value prior to the missing observation,
v_{t_b}	the first observed value following the missing observation,
$(t - t_a)$	the elapsed time from the last observed observation,
$\frac{v_{t_b} - v_{t_a}}{t_b - t_a}$	characterises the rate of change of the indicator over the interval $[t_a, t_b]$.

This approach preserves the overall trend between observed points, avoiding abrupt jumps that may arise when missing values are replaced with the mean or with zeros. As linear interpolation cannot recover values at the beginning or the end of a series in the absence of reference points, forward fill (*ffill*) and backward fill (*bfill*) methods are applied. The *ffill* method is used to impute missing values at the end of the series:

$$v_t = u_{t-k}, k = min\,\{i \in N \vee v_{t-i}\ exists\} \tag{2}$$

whereas the bfill method is used to impute missing values at the beginning of the time series:

$$v_t = u_{t+k}, k = min\,\{i \in N \vee v_{t+i}\ exists\} \quad (3)$$

The application of this combined approach ensures full continuity of the numerical time series for all variables across each country, thereby producing a valid dataset for the subsequent training of forecasting models.

The next stage involves modelling and validation, which are critical for assessing the forecasting system's ability to generalise the identified patterns to future periods. Given the relatively short length of the time series and the potential structural shifts characteristic of the data for Ukraine, Poland, and China, a hybrid architecture was selected, combining classical econometric methods (ARIMA), regularised linear regression (Ridge Regression), and parametric heuristic optimisation.

To assess the forecasting capability of the model, a temporal validation approach (Time Series Cross-Validation) was employed, factor in the chronological structure of the data. Random shuffling of observations is not feasible due to autocorrelative dependencies; therefore, the Last Block Validation method was applied. Let D denote the time-ordered set of observations for a given country, consisting of T periods:

$$D = \{(X_1, Y_1), (X_2, Y_2), \ldots, (X_T, Y_T)\}. \quad (4)$$

The training set comprises all historical data from the beginning of the observation period up to the time point $T - 1$:

$$D_{train} = \{(X_t, Y_t) \vee t = 1, \ldots, T - 1\}, \quad (5)$$

whereas the test set is formed from the data of the final year Ti and is used exclusively for the evaluation of performance metrics and the calibration of heuristic coefficients:

$$D_{test} = \{(X_T, Y_T)\}. \quad (6)$$

This approach, known as a "one-step-ahead forecast," replicates the real-world scenario of model application, where the forecast for the next year is generated based on all available historical information.

To forecast future values of the independent variables X, which serve as input for the primary model, the Auto-ARIMA (Autoregressive Integrated Moving Average) method is employed, as applied in the study by Arslan M. A. & Talan T. (2025). This approach allows for the automatic selection of optimal parameters (p, d, q) or each regressor $x_j \in X$ by minimizing the Akaike Information Criterion (AIC), thereby achieving a balance between fitting accuracy and model complexity.

The general form of the ARIMA model is described by the following equation:

$$(1 - \sum_{i=1}^{p} \phi_i L^i)(1 - L)^d x_t = (1 + \sum_{j=1}^{q} \theta_j L^j)\varepsilon_t, \quad (7)$$

where

L	lag operator, for which $L^k x_t = x_{t-k}$,
p	order of autoregression, representing the dependence of the current value on the previous p observations,
d	order of integration, which specifies the number of differencing transformations required to achieve stationarity in the series,
q	order of the moving average, which represents the influence of previous forecast errors on the current value,
ϕ_i, θ_j	model coefficients,
ε_t	white noise with zero mean and constant variance.

Thus, each regressor is forecasted individually, and the resulting future values $\hat{X}_{T+h}$ are used as inputs for the target variable model, ensuring the correct recursive generation of forecasts for all key indicators of coal production, export, and import.

To establish the relationship between the regressor vector X and the target variable vector Y linear regression with L_2 – regularization, known as Ridge Regression, is employed, as applied in the study by Khalid N., et al. (2025). This approach is particularly effective in conditions of multicollinearity, where the regressors are highly correlated, and when the sample size is limited, as it mitigates the risk of overfitting. Prior to training, all data are standardized, ensuring a uniform scale across variables and stabilizing the optimization process.

The training task consists of finding the weight coefficient matrix B, я that minimizes the loss function:

$$\hat{B} = arg\ min\ (\parallel Y - XB \parallel_2^2 + \alpha \parallel B \parallel_2^2), \quad (8)$$

where

$\parallel Y - XB \parallel_2^2$	residual sum of squares (RSS), which characterizes the goodness of fit of the model,
$\parallel B \parallel_2^2$	the penalty term, which regulates the magnitude of the coefficients,
α	the regularization hyperparameter.

Two regularization regimes were established depending on the country: a baseline regime with $\alpha = 1.5$ for Poland and Ukraine, providing a balanced trade-off between bias and variance, and a strengthened regularization with $\alpha = 10.0$ for China, which stabilizes the model on data with large absolute values and reduces the risk of errors due to minor fluctuations in the input variables.

As purely statistical methods do not always adequately account for sector-specific constraints, such as physical extraction limits or political quotas, the model is augmented with a layer of parametric heuristics. The purpose of this layer is to determine the optimal parameter vector Θ, which adjusts the Ridge model's forecast in order to minimize the error on the held-out test set D_{test}.

To determine the optimal values, the algorithm employed in Li M., et al. (2025) was used: L-BFGS-B (Limited-memory Broyden-Fletcher-Goldfarb-Shanno with Bounds), This quasi-Newton method allows for efficient incorporation of parameter constraints, which is essential for preserving the physical interpretability of the model (for example, a decay coefficient cannot be negative).

The objective function for the optimization is defined as the minimization of the mean squared error (MSE) on the test dataset:

$$\Theta = arg\ min \frac{1}{N}\sum_{i=1}^{N}(y_{test,i} - f_{model}(x_{test,i}, \Theta))^2, \tag{9}$$

where

$f_{\text{model}}(x_{\text{test},i}, \Theta)$	predicted value for the *i-th* observation for the current set of parameters Θ,
$y_{\text{test},i}$	the actual value of the target variable.

As a result of this procedure, an optimal set of parameters Θ, was obtained, which minimizes the discrepancy between the forecast and the actual data for the most recent year. These parameters are then fixed and integrated into the final model for generating forecasts for future periods, thereby accounting for sector-specific characteristics and enhancing the stability of predictions.

After completing the validation stage and determining the optimal parameters Θ, the system proceeds to generate the long-term forecast. The main challenge at this stage is the need to predict values over a horizon of $H = 7$ years, given that the future values of the regressors remain unknown. To address this challenge, a recursive multivariate forecasting method is employed, which combines the extrapolation of independent variables with iterative updating of the target indicators.

Before initiating the forecasting process, all components of the model are retrained on the full set of available data D, including the previously held-out test set D_{test}. First, the parameters for the regressors are updated: the ARIMA models (p, d, q) are retrained on the complete series X to obtain up-to-date estimates of the coefficients ϕ та θ. Subsequently, the Ridge Regression model is retrained, and the final coefficient matrix $\hat{B}$ is computed using the regularized normal equation:

$$\hat{B} = (X^T X + \alpha I)^{-1} X^T Y, \tag{10}$$

where

X	matrix of historical regressors,
Y	matrix of target variables,
α	regularization coefficient,
I	identity matrix.

At this stage, the optimized heuristics Θ, are fixed and subsequently used to adjust the forecasts. The forecasting process is implemented as an iterative cycle, since the value of the target variable at each step depends on the system's state in the previous period. For each step $h \in \{1,2, \ldots, H\}$ the following operations are performed. First, the regressors are extrapolated:

$$\hat{x}_{T+h} = f_{\text{ARIMA}}(x_{T+h-1}), \tag{11}$$

This allows the estimation of the values of external factors for the forecast year. Next, the baseline forecast of the target indicators is generated using the Ridge model:

$$\hat{y}_{T+h}^{\text{base}} = \hat{B} \cdot \hat{x}_{T+h}, \tag{12}$$

where $\hat{y}_{T+h}^{\text{base}}$ contains the baseline estimates of coal production, export, and import. To prevent the accumulation of statistical errors and to account for industry-specific characteristics (e.g., mine closures in Poland or the volatility of Ukraine's energy system), the baseline forecast is adjusted using the optimized heuristics Θ through a multiplicative model:

$$\hat{y}_{T+h}^{\text{final}} = \hat{y}_{T+h}^{\text{base}} \cdot \prod_{i=1}^{h} \Theta_{k,i}, \tag{13}$$

where

$\theta_{k,i}$	a specific coefficient for the *k-th* variable, which determines its rate of growth or decay,
h	reflecting the cumulative effect of the heuristic over time.

Since the forecast is recursive, any error at step h increases the uncertainty at the subsequent step $h + 1$. To quantify this uncertainty, an error propagation method is employed, initially defining the baseline model variance based on the residuals from the training set:

$$\sigma^2 = \frac{\sum_{t=1}^{T}(y_t - \hat{x}_t)^2}{T - k}, \tag{14}$$

where

$(y_t - \hat{x}_t)$	the difference between the actual and modelled value (residual),
k	the degrees of freedom considered when estimating the variance.

The final stage of modelling involves the post-processing of the obtained results and their systematization for subsequent use. At this stage, the numerical arrays generated during both the analysis of historical data and the forecasting procedure are aggregated, enabling the creation of a unified information space that is convenient for analytical purposes and visualization.

After generating the forecast over the horizon of H years, it becomes necessary to restore the continuity of the time series by merging historical observations with the forecasted values. The concatenation procedure is performed along the temporal axis; formally, the resulting data array D is defined as an ordered set of tuples:

$$D = D_{\text{hist}} + D_{\text{forecast}}, \tag{15}$$

where

D_{hist}	contains all available historical observations,
D_{forecast}	forecasted values of the target variables over the horizon H.

Such a structure ensures the continuity of the time series for subsequent processing and analysis. For visualization, the matplotlib library was employed, enabling a clear representation of the indicator dynamics while accounting for forecast uncertainty. For each target variable $y \in Y$ a graph $G(t)$, is constructed, comprising three key components:

- the historical period ($t \in D_{\text{hist}}$) is represented by a solid line, illustrating the actual observed dynamics;
- the forecast period ($t \in D_{\text{forecast}}$) is shown as a dashed line with markers, highlighting the probabilistic nature of the projected values;
- to enhance interpretability, numerical labels are added for the forecasted years, allowing direct assessment of key indicators without the need to refer to tabular data.

This approach to post-processing and visualization ensures a clear and integrated presentation of the modelling results, combining historical data and forecasts within a unified analytical framework.

A key advantage of using Ridge Regression in this context lies not only in its ability to mitigate multicollinearity but also in preserving the interpretability of model coefficients. Unlike “black-box” methods such as neural networks, regularized linear regression allows for a direct assessment of both the direction and magnitude of the influence of individual macroeconomic and energy-related factors on coal production, imports, and exports. This interpretability is crucial for applying the modelling results in governmental and corporate strategic planning.

Results

For the empirical component of the study, open international databases are utilized, allowing for the comparison of time series of macroeconomic and energy indicators across different countries. Data from World Bank Open Data provide a comprehensive set of economic development indicators, among which the key variable for this study is gross domestic product (GDP). The World Bank offers standardized data series for over 200 economies worldwide, enabling the analysis of long-term trends in economic growth.

For the analysis of energy structures and changes in the shares of different energy sources, the Ember Electricity Data dataset is employed. It contains annual and monthly indicators of electricity generation, the shares of renewables and coal, and total demand and supply for most countries worldwide. Ember specializes in open datasets for monitoring the energy transition, including detailed metrics on the generation shares of coal, gas, and renewables, which are critical for assessing trends in the energy sector within the context of transformational dynamics.

In addition to general energy and macroeconomic indicators, the study also integrates industrial production indices as proxies for assessing domestic energy demand. Data on the industrial production index for Poland are available from CountryEconomy.com, which collects official statistics and aggregates them into time series for economic analysis. For China and Ukraine, economic calendars and national indices are used, accessible via the platforms Investing.com and Index.Minfin.com.ua, providing monthly and annual data on industrial sector activity. The integration of these indicators enables an assessment of the relationship between industrial activity and energy demand, particularly in the context of coal production, imports, and exports.

Ukraine. Over the past decade, Ukraine's coal sector has undergone significant structural transformations driven by a combination of economic, geopolitical, and security factors. Since 2014, the loss of coal deposits in the eastern regions of the country, the destruction of production infrastructure, and disruptions to logistics chains have led to a sharp decline in domestic coal production. Concurrently, the energy system's dependence on imported supplies has increased, substantially affecting the country's external trade balance and energy security.

An additional destabilizing factor was the full-scale military aggression in 2022, which resulted in the temporary loss of control over part of the production capacities, a decline in industrial demand, and a transformation of the energy consumption structure. Under these conditions, forecasting coal production, exports, and imports assumes particular importance for assessing the prospects for industrial sector recovery and for shaping Ukraine's medium-term energy policy.

The dynamics of coal production in Ukraine over the period 2013-2030 exhibit a distinct phase of sharp decline, followed by attempts at partial stabilization. Prior to 2013, Ukraine maintained substantial domestic production volumes; however, by 2014-2015, production had fallen by more than half. In subsequent years, production displays a fluctuating pattern on a low base, reflecting both the limited potential for industry recovery and the instability of industrial demand.

Forecasted values for the period 2024-2030 indicate a moderate increase in coal production, which may be associated with the adaptation of production processes to new conditions, partial modernization of mines, and a focus on domestic consumption. At the same time, these volumes remain significantly below pre-war levels, reflecting the long-term nature of structural changes in the coal sector.

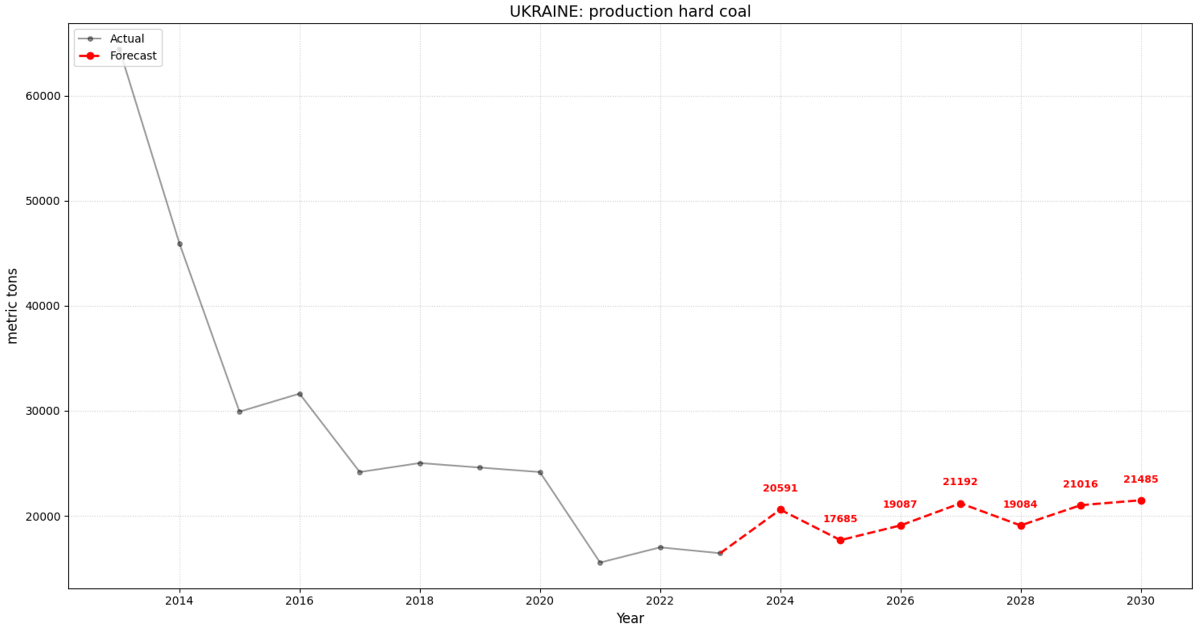

Fig. 1. Coal Production in Ukraine, 2013-2030.

Ukraine's coal exports have experienced a sharp and virtually irreversible decline since 2014. While export volumes exceeded 8 million tonnes in 2013, they fell to minimal levels by 2015, and after 2018, exports have effectively lost their economic significance. This trend is attributable both to the decline in domestic production and to the reallocation of produced coal to meet internal demand.

Forecasts for 2024-2030 indicate that export volumes will remain extremely low, confirming Ukraine's transformation from a net exporter to a country primarily focused on domestic coal consumption. Accordingly, the export component is not considered a strategically significant element of sector development in the medium term.

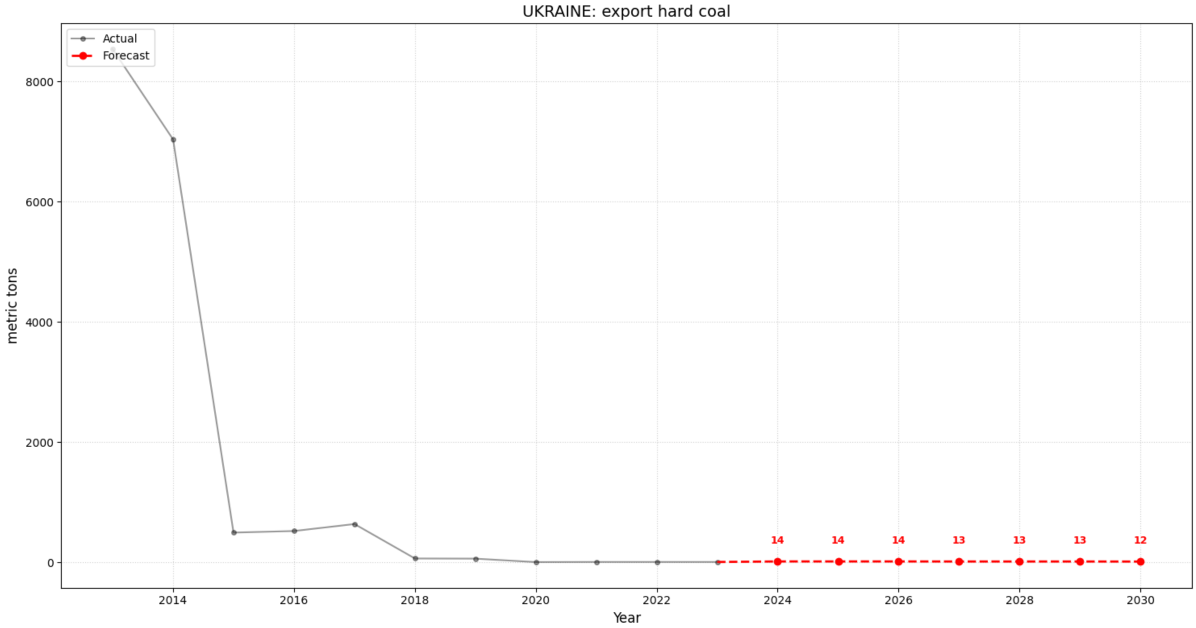

Fig. 2. Coal Exports from Ukraine, 2013-2030

Coal imports have played a key role in maintaining Ukraine's energy balance since 2014. The sharp decline in domestic production led to an increase in imports, which reached peak levels during 2017-2019. In 2022-2023, imports decreased due to reduced industrial activity and shifts in the energy consumption structure.

Forecast calculations for the period up to 2030 indicate a gradual decline in import volumes, which may be associated with the adaptation of the energy system, the growing role of alternative energy sources, and the partial recovery of domestic production. Nevertheless, imports remain an important instrument for balancing the energy market under conditions of instability.

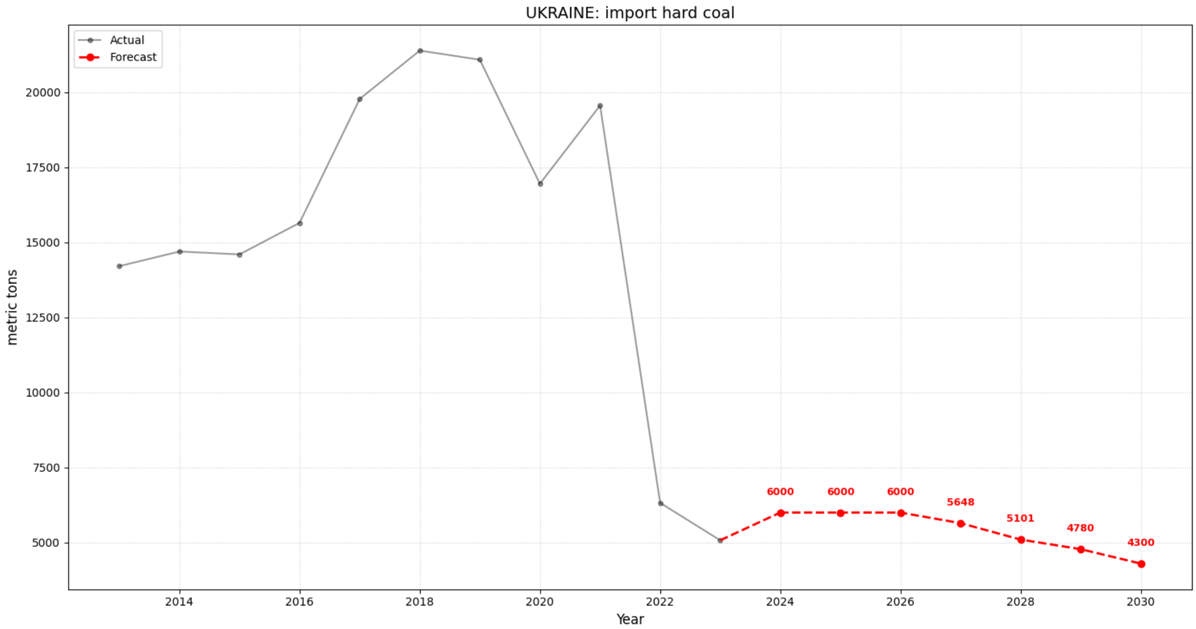

Fig. 3. Coal Imports into Ukraine, 2013-2030

To ensure comparability of indicators and facilitate cross-country analysis, data on coal production, exports, and imports were standardised with respect to time intervals and units of measurement. The aggregated values of production, exports, and imports are presented in Table 1, enabling a simultaneous assessment of changes in domestic output and external trade flows, and serving as a basis for scenario-based forecasting.

Table 1. Coal Production, Exports, and Imports in Ukraine, 2013-2030

Year	Export hard coal *metric t*	Import hard coal *metric t*	Production hard coal *metric t*
2013	8537	14208	64427
2014	7034	14695	45932
2015	494	14598	29917
2016	520	15648	31631
2017	636	19778	24167
2018	63	21387	25026
2019	60.7	21082.3	24595.5
2020	3	16951	24168
2021	5	19558.2	15553
2022	5	6323	17000
2023	5	5076.251	16439
2024	14.17	6000.00	20591.15
2025	13.85	6000.00	18713.57
2026	13.54	6000.00	19368.08
2027	13.22	5648.02	21531.56
2028	12.91	5100.88	19751.44
2029	12.59	4779.71	21145.33
2030	12.28	4299.87	21888.27

Table 1 indicates that Ukraine's coal sector is undergoing a prolonged structural transformation. Domestic production has declined substantially compared to the pre-war period and, even under optimistic forecasts, does not return to previous levels. Coal exports have lost their strategic significance, whereas imports remain an important mechanism for compensating for the shortfall in domestic production. The results obtained underscore the appropriateness of a scenario-based approach for forecasting the development of Ukraine's coal sector, considering the high level of external risks and uncertainty.

Poland. Poland's coal sector has traditionally played an important role in shaping the energy balance and supporting industrial production; however, over the past decade, it has been undergoing a gradual structural transformation. The main drivers of change include the implementation of European Union climate policy, the strengthening of environmental standards, and the economic feasibility of coal extraction in the context of rising production costs and competition from imported resources. Since 2013, Poland's coal sector has exhibited a stable trend of declining domestic production while maintaining substantial demand from the energy and industrial sectors.

An additional factor affecting the sector has been the need to adapt to external energy imbalances, in particular changes in the European energy market and the restructuring of logistics chains in 2021-2022. Under these conditions, the balance between domestic production, imports, and exports of hard coal becomes crucial for assessing the stability of Poland's energy system and for shaping a long-term strategy for phasing out carbon-intensive energy sources.

The dynamics of coal production in Poland over the period 2013-2030 exhibit a clearly defined downward trajectory. While production volumes exceeded 76 million tonnes in 2013, they fell to approximately 48 million tonnes by 2023. During the forecast period 2024-2030, further declines are expected, reaching around 26 million tonnes, reflecting the gradual phase-out of coal-fired generation and the closure of unprofitable mines. This trend indicates a systemic transformation of the sector rather than temporary fluctuations.

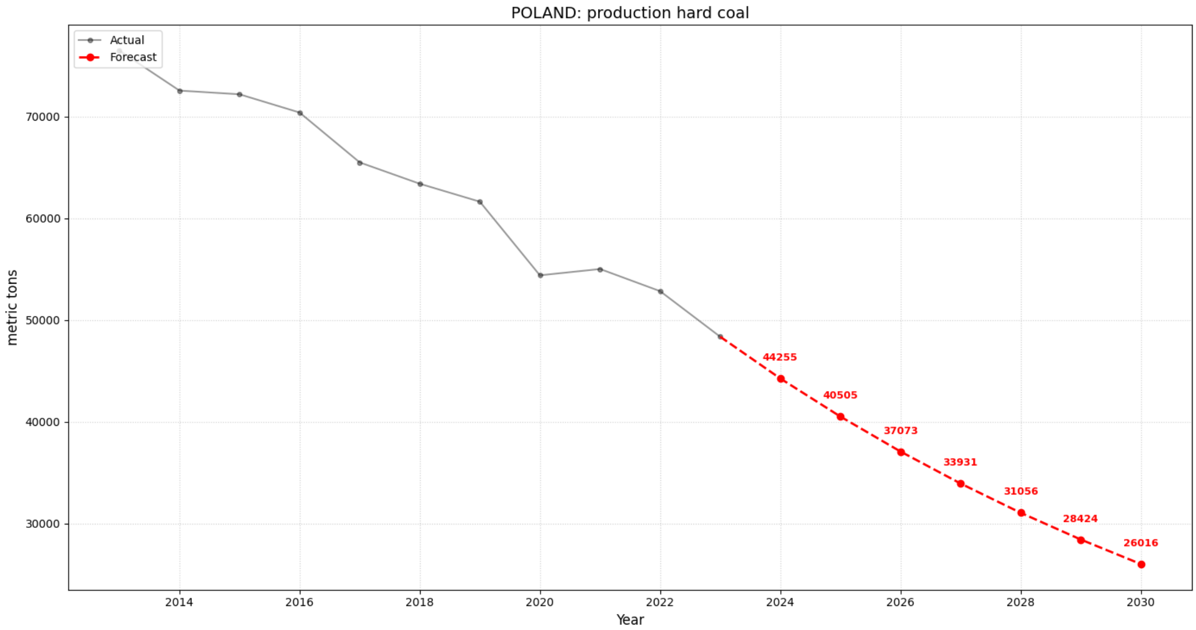

Fig. 4. Hard coal production in Poland in 2013-2030.

Hard coal production in Poland in 2013-2030Poland's coal exports exhibit a consistent declining trend throughout the analyzed period. After 2013, when export volumes exceeded 10 million tones, a gradual decrease is observed, reaching approximately 4.3 million tones by 2023. Forecasts up to 2030 indicate a further decline to around 1.4 million tones, reflecting the loss of an export orientation in the coal sector and the reallocation of resources to domestic consumption.

Accordingly, coal exports are not considered a strategically significant element of sector development in the medium term, with their role limited to providing a supplementary function during periods of domestic market imbalance.

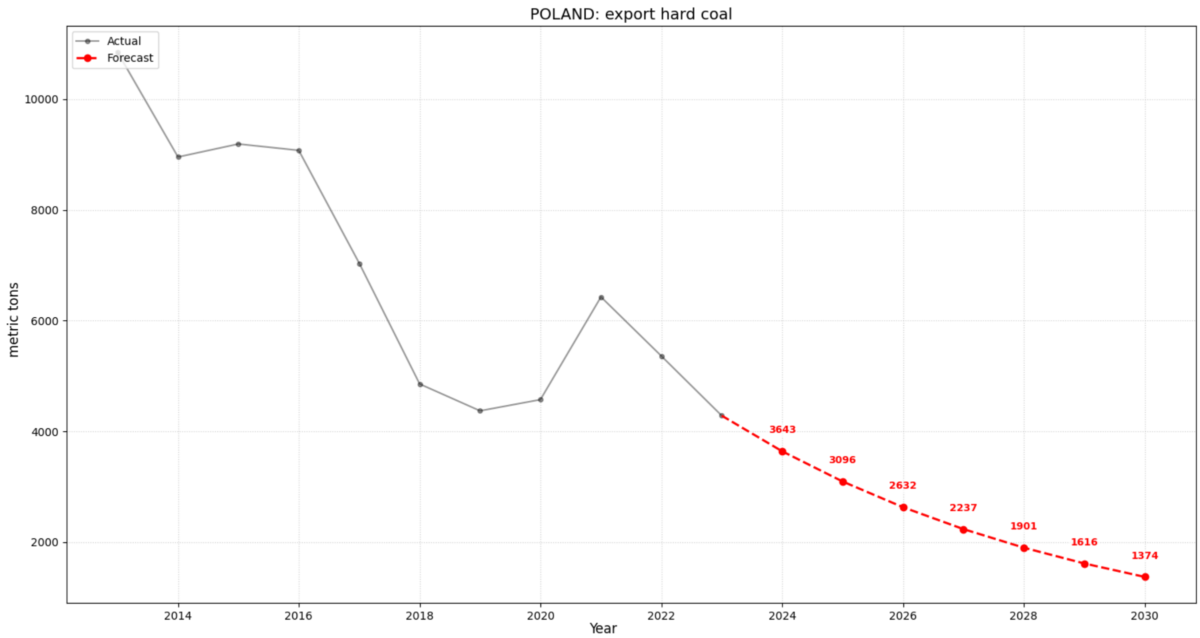

Fig. 5. Export of Hard Coal from Poland in 2013-2030

Coal imports play an increasingly important role in meeting Poland's energy needs amid declining domestic production. During 2017-2019 and in 2022, import volumes increased substantially, reflecting the need to compensate for the shortfall in domestic output and to respond to rising demand from the energy sector. In 2023, imports remain at a high level, exceeding 16 million tones.

Forecasts for the period up to 2030 indicate a gradual, though slow, decline in import volumes, associated with an expected reduction in overall coal consumption and the growing share of alternative energy sources. Nevertheless, imports remain a key mechanism for balancing Poland's energy market during the transitional period.

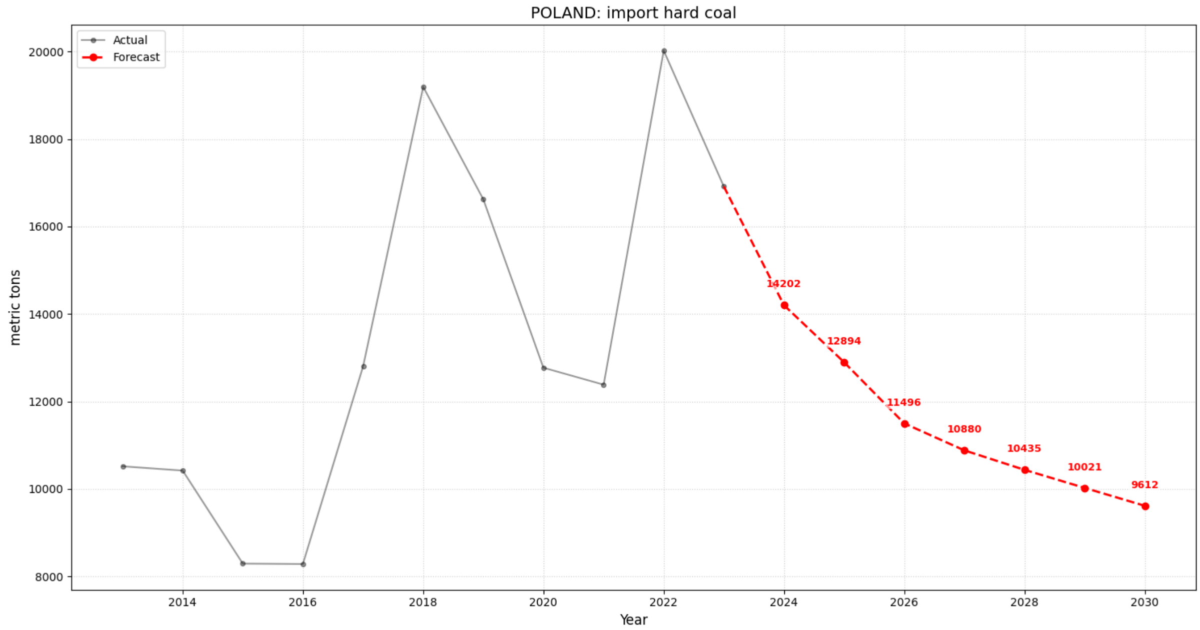

Fig. 6. Import of Hard Coal into Poland in 2013-2030

To ensure consistency of the time series and enable subsequent comparative analysis with other countries, data on coal production, exports, and imports were standardized with respect to the temporal horizon and units of measurement. The aggregated indicators are presented in Table 2, which allows for a comprehensive assessment of the transformation of Poland's coal sector and serves as a basis for scenario-based forecasting of the industry's development in the context of the energy transition.

Table 2. Hard Coal Production, Export and Import in Poland in 2013-2030

Year	Export hard coal *metric t*	Import hard coal *metric t*	Production hard coal *metric t*
2013	10846	10515	76466
2014	8956	10417	72540
2015	9191	8289	72176
2016	9076	8279	70385
2017	7036.153	12803.095	65479.946
2018	4857.136	19194.73	63384.045
2019	4372.585	16623.23	61623.387
2020	4574.746	12770.745	54385.927
2021	6429.315	12382.309	55006.381
2022	5362.426	20024.979	52829.352
2023	4285.358	16917.515	48352.644
2024	3642.55	14201.86	44255.29
2025	3096.17	13171.05	40505.14
2026	2631.75	12046.76	37072.77
2027	2236.98	11641.40	33931.26
2028	1901.44	11344.17	31055.96
2029	1616.22	11025.83	28424.31
2030	1373.79	10672.55	26015.66

Table 2 confirms that Poland's coal sector is undergoing a controlled yet irreversible contraction. Domestic production is declining systematically, exports are losing their economic significance, while imports remain an important instrument for maintaining the energy balance. The results obtained underscore the appropriateness of a scenario-based approach for assessing the future development of Poland's coal sector, taking cognizance of long-term climate and economic constraints.

China. China's coal sector constitutes a fundamental element of the national economy and a key component of the country's energy balance. Throughout the analyzed period, China remains the world's largest producer and consumer of hard coal, driven by the scale of industrial production, the high energy intensity of the economy, and the need to ensure energy security. Despite active implementation of renewable energy development programmed, coal continues to play a dominant role in the structure of primary energy consumption.

At the same time, China's coal sector is undergoing gradual transformation under the influence of environmental constraints, international climate commitments, and domestic decarbonization policies. Government regulation focuses not on the rapid reduction of production volumes, but on improving production efficiency, consolidating the industry, and reducing environmental impact. Under these conditions, analyzing the dynamics of coal production, exports, and imports allows for an assessment of the actual pace and nature of structural changes within China's energy system.

The dynamics of coal production in China over the period 2013-2030 exhibit an overall upward trend, interspersed with phases of temporary slowdown. Production volumes remain consistently high throughout the period, exceeding 3.9 billion tones in 2013 and increasing to over 4.9 billion tones by the forecasted 2030. Temporary declines in production during the middle of the analyzed period reflect the impact of regulatory constraints and policies aimed at reducing excess capacity; however, in the long term, industrial and energy sector demand drives the resumption of growth.

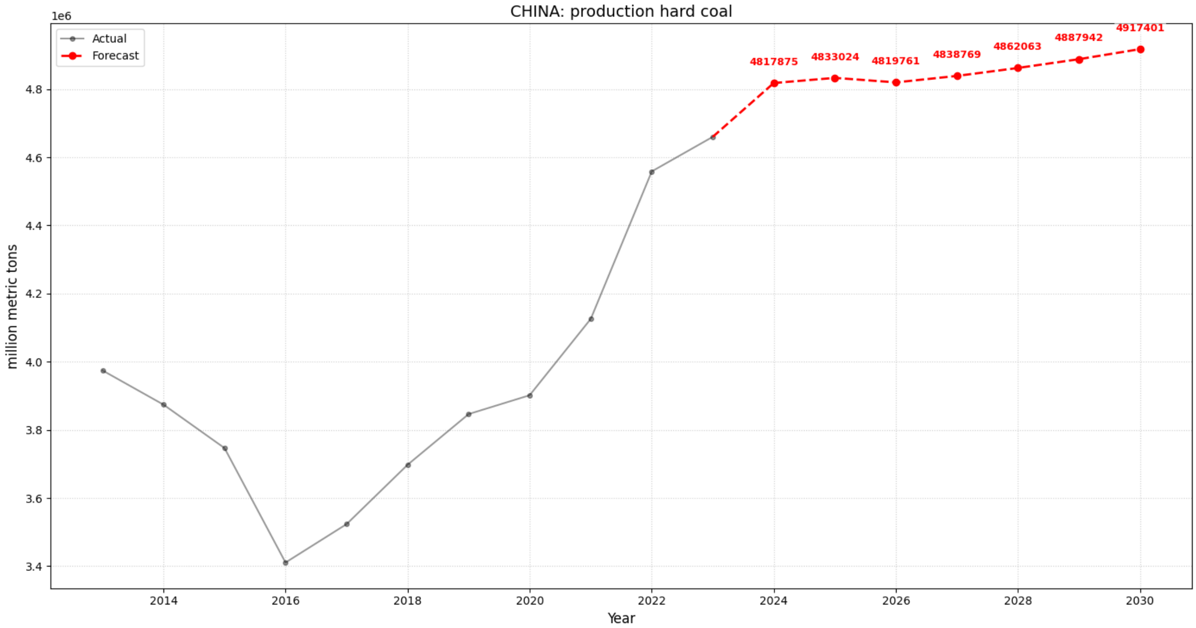

Fig. 7. Hard Coal Production in China in 2013-2030

China's coal exports exhibit a declining trend throughout the analyzed period and do not play a decisive role in the functioning of the sector. Relatively modest export volumes between 2013 and 2019 gradually decrease, reaching minimal levels in the forecast period after 2024. This trend reflects the sector's focus on meeting domestic demand and the limitation of external supplies in line with state energy policy.

In the medium term, coal exports are not considered a strategic direction for sectoral development; their volumes remain residual and are contingent on situational changes in regional markets.

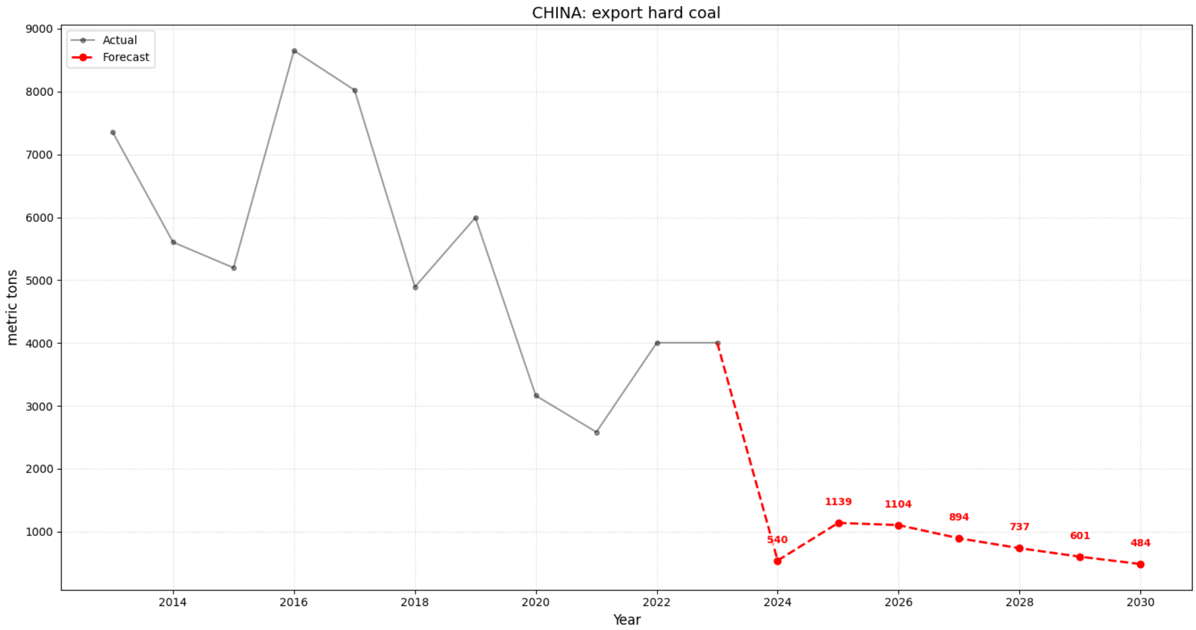

Fig. 8. Export of Hard Coal from China in 2013-2030

Despite its substantial domestic production, coal imports constitute an important component of China's energy strategy. Significant import volumes are driven by the need to diversify supply sources, ensure price stability, and meet peak industrial demand. Between 2013 and 2023, imports show a general upward trend, reaching peak levels during periods of active industrial recovery.

Forecast data for the period up to 2030 indicate that imports will remain at a high level with moderate growth, reflecting China's pragmatic approach to maintaining energy balance even in the context of dominant domestic production.

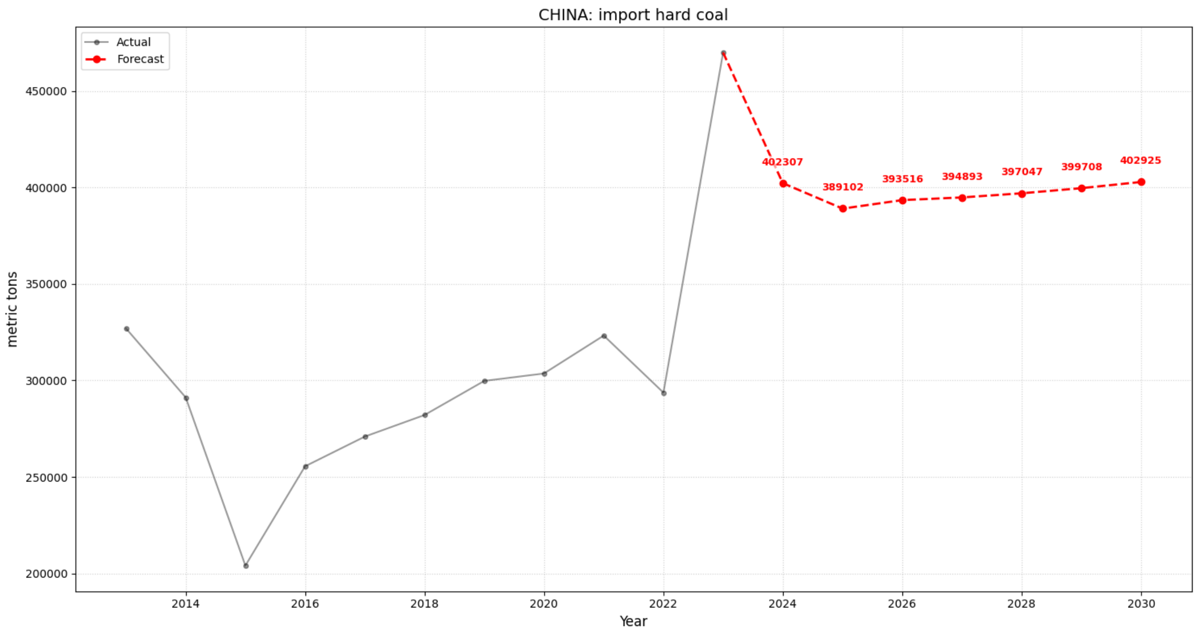

Fig. 9. Import of Hard Coal into China in 2013-2030

To ensure comparability of results and enable subsequent cross-country analysis, data on coal production, exports, and imports were standardized in terms of temporal coverage and measurement units. The aggregated indicators are presented in Table 3, which provides a comprehensive overview of the scale and characteristics of China's coal sector development within the context of global energy transitions.

Table 3. Hard Coal Production, Export and Import in China in 2013-2030

Year	Export hard coal *metric t*	Import hard coal *metric t*	Production hard coal *metric t*
2013	7354	326963.1	3974322
2014	5604.15	291182.35	3873919
2015	5197.35	204012.92	3746542
2016	8651.36	255497.07	3410604
2017	8023.84	270920.9	3523562
2018	4892.72	282097.9	3697735.8
2019	5995	299770	3846330
2020	3163.2	303610	3901580
2021	2583.5	323273.8	4125834
2022	4005	293703.6	4558552.9
2023	4005	470000	4660000
2024	580.23	402307.38	4817874.87
2025	1226.43	389210.44	4832364.73
2026	1189.12	393723.17	4818375.87
2027	962.02	395064.28	4837420.38
2028	792.61	397173.53	4860935.00
2029	646.79	399810.93	4886985.08
2030	521.16	403006.82	4916611.04

Table 3 demonstrates that China's coal sector follows a fundamentally different development model compared with Ukraine and Poland. Unlike countries exhibiting a trend of declining production, China maintains and expands output, employing imports as a tool for flexible balancing of the domestic market. The results confirm that the transformation of China's coal sector is evolutionary rather than reductive, driven by the scale of the economy and strategic energy security priorities.

The forecasted trajectories clearly reflect structural differences in coal sector development models. Ukraine exhibits a deficit-driven, import-dependent model; Poland follows a controlled contraction model; whereas China implements a large-scale, domestically self-sufficient model, using imports strategically to optimise prices and manage risks. Thus, even under an identical forecasting methodology, the results reveal distinct economic logics underpinning the functioning of the coal industry.

A comparative analysis of coal production, export, and import dynamics in Ukraine, Poland, and China reveals fundamentally different pathways of sectoral transformation, shaped by the scale of the economy, institutional capacity, and energy policy priorities. Ukraine exhibits a sharp structural decline in domestic production, an almost complete loss of export potential, and persistent import dependence, reflecting the high vulnerability of its energy system to external shocks. Poland implements a controlled contraction of its coal sector in line with EU climate policy, combining a gradual reduction in production with imports as a short-term stabilization mechanism. In contrast, China maintains large-scale domestic production and flexibly regulates imports and exports to support industrial growth and energy security. These findings confirm that coal sector transformation is highly context-dependent and necessitates scenario-based planning, energy source diversification, and coordinated regulatory measures to balance energy security, economic stability, and decarbonization objectives.

Discussion

The study results support the scientific hypothesis: the integrated application of ARIMA and Ridge Regression provides more accurate forecasts of coal production, import, and export volumes compared to the use of individual models. For Ukraine, Poland, and China, the hybrid approach allows the simultaneous consideration of temporal patterns and multicollinearity among macroeconomic and energy indicators, which is particularly important under conditions of economic instability and structural market changes.

The analysis of national characteristics revealed differing dynamics in the coal markets. Ukraine is marked by instability in domestic production and a growing dependence on imports, highlighting the need for modernization of production capacities and improvements in energy efficiency. Poland combines substantial domestic production with ongoing sectoral transformation and the influence of EU climate policy, creating a need for strategic planning and business-risk assessment. China, as the world's largest producer and consumer of coal, exerts significant influence on global markets, and large-scale forecasting using hybrid models supports effective management of production and investment decisions.

Despite the confirmation of the hypothesis, the study has several limitations:

1. Temporal data limitations. The model is based on statistics from the period 2013-2023, whereas the most significant changes in the coal sectors of Ukraine, Poland, and China occurred after 2020. Some of these changes are only partially captured through scenario-based adjust.
2. Lack of spatial granularity. Regional differences in resource distribution, infrastructure development, and levels of damage were not considered, which may affect the accuracy of national-level forecasts, particularly for Ukraine.
3. Ignoring extreme events. Sudden shocks – such as targeted attacks on energy infrastructure, sharp fluctuations in import and export, natural disasters, or rapid deployment of reserve technologies – were not incorporated into the model, which may limit its predictive reliability under crisis conditions.
4. Limited consideration of political and regulatory changes. Sudden shifts in legislation, environmental regulations, or market interventions can significantly affect production volumes and trade flows, yet the current model does not dynamically capture these rapid changes.

These limitations indicate that, although the model is reliable for capturing medium-term trends, its application for crisis management or localized planning requires caution.

Comparisons with alternative approaches confirm the practical significance of the hybrid method. The results are consistent with other studies demonstrating that combined models consistently outperform standalone ARIMA or Prophet models in forecasting complex time series. For Ukraine and Poland, the obtained forecasts can serve as a basis for energy security planning and the assessment of restructuring effectiveness, whereas for China they support the optimization of coal production and the management of investment flows in the global market.

In the future, it would be appropriate to extend the model by integrating spatial analysis and regional resource data, as well as incorporating extreme events, such as energy supply crises or political disruptions. Furthermore, the application of hybrid models incorporating neural networks or Prophet would allow for more accurate accounting of non-linear and seasonal effects, thereby enhancing forecasting precision over the long term.

Consequently, the proposed approach demonstrates high efficacy for forecasting the coal market under varying national economic structures and may serve as a reliable tool for supporting managerial decision-making and strategic planning.

Conclusion

The integrated application of ARIMA and Ridge Regression models ensures highly accurate forecasting of coal production, imports, and exports in countries with diverse economic conditions. This approach accounts for both temporal patterns and the multicollinearity of macroeconomic factors, significantly enhancing forecast accuracy compared with the use of individual methods.

Ukraine exhibits forecasts characterized by a high degree of volatility and reliance on imports, emphasizing the need for adaptive planning and modernization of the sector.

Poland presents results reflecting a stable level of production accompanied by a gradual transformation of the sector, with particular emphasis on socio-economic and regional aspects.

The forecasts for China indicate the large-scale nature of both production and consumption, necessitating stabilization through regulatory and technological constraints.

ARIMA enables the modelling of temporal dynamics in time series, while Ridge Regression accounts for the combined influence of macroeconomic indicators, thereby reducing the risk of overfitting and providing robust forecasts under conditions of economic instability. The developed integrated forecasting approach allows for the construction of well-founded scenarios for the development of the coal market in different countries and supports strategic decision-making in the coal sector.

It is advisable to integrate additional macroeconomic and environmental indicators, extend the time series, and apply hybrid machine learning approaches to enhance forecast accuracy, as well as to assess the impact of political and regulatory changes on the resilience of the coal market.

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