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Analysis of the Impact of Clean Coal Technologies on the Share of Coal in Poland's Energy Mix

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Abstract: This article presents research results on the share of coal in the energy mix and the impact of clean coal technologies on Poland's energy mix. Two mathematical models were utilised: the Boltzmann sigmoidal curve and a supervised machine learning model that employs multiple regressions. Eight explanatory variables were incorporated into the model, the influence of which on the explained variable was confirmed by Student's *t*-test. The constructed models were verified using ex post errors and the Durbin–Watson and Shapiro–Wilk statistical tests. It was observed that the share of coal in the mix decreased more dynamically after 2015 compared to previous years. Furthermore, a simulation was conducted using the machine learning model, which confirmed the hypothesis on the influence of clean coal technologies on the level of coal share in the Poland energy production structure. As shown by the analysis and simulation, coal could be maintained in the energy mixes of EU countries, and even if the negative aspects of using this fuel were limited—primarily the emission of harmful substances—its share could even increase. It was noted that this share could be higher by 22% assuming a return to the interest in CCT levels from before 2015 and the reduction in CO_2 emissions using membrane techniques proposed by the authors. Clean coal technologies would enable diversification of the energy mix, which is an important aspect of energy security. They would also enable the gradual introduction of renewable energy sources or other energy sources, which would facilitate the transition stage on the way to a sustainable energy mix.

Keywords: coal demand; clean coal technologies; machine learning

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1. Introduction

Coal has always been the basis for Poland's energy mix. It has been mined in Silesia at least since the 17th century [1]. This is directly related to the rich coal deposits located in the geographical area of Poland. Coal constitutes the basis for Poland's energy security, which, in connection with the war in Ukraine, is one of the most important topics, in addition to the military security of the European Union. After more than three centuries of unchanging coal domination in the structure of Poland's energy carriers, the time for change has come. Hard coal has been recognised as a fuel with a critical impact on the natural environment due to its chemical properties, which results in the release of harmful gaseous substances and solid waste during the extraction and combustion of this fuel. However, in times of increasing global energy demand and limitations of other energy sources, such as renewable energy, it is necessary to consider the possibility of continuing to use coal while limiting its negative impact on the natural environment. This would make it possible to maintain energy security and at the same time implement the assumptions of sustainable development. To make this possible, it is necessary to use appropriate technological solutions that will enable clean combustion and also use all the waste generated in the coal combustion process. There is no doubt that changes in the structure of energy production are necessary due to the defects of the coal mining and combustion process. They have been known for many years, but currently, the main impulse accelerating the modification of the energy mix structure are the European Union guidelines, mainly the European Climate Law, European Green Deal and Fit for 55 [2,3].

The traditional way of burning coal emits large amounts of greenhouse gases. These are mainly carbon dioxide (CO_2), sulphur oxides (SOx), nitrogen oxides (NOx) and particulate matter [4]. Coal is responsible for 90% of SO_2 emissions, 70% of dust emissions, 67% of NOx emissions and 70% of CO_2 emissions [5]. These gases are some of the causes of global warming and climate change. Eliminating the negative impact of the use of coal in the economy requires decisive steps. As one of them, it is possible to completely abandon the use of coal. Most EU countries have chosen this option. It is also promoted in the EU and constitutes the basic assumption of the EU's decarbonisation process. However, this is a very complex task, especially for countries with economies heavily dependent on coal. These are primarily Poland, Germany and the Czech Republic [6]. Figure 1 presents the share of coal in the total primary energy consumption. It includes selected countries where the demand for coal exceeds 10%. The largest share was observed in Poland.

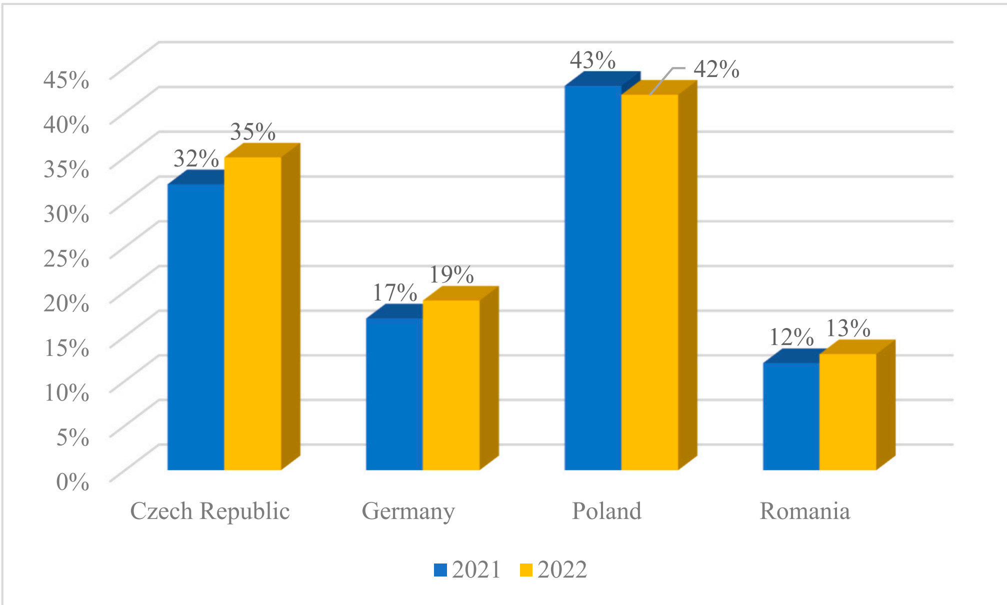

Figure 1. Primary energy consumption by fuel: coal, EJ [6].

In the case of electricity production, the share of coal is significant for 10 EU countries (Figure 2). Again, the highest level of dependence is typical primarily for Poland (at a level of 70%), but also for the Czech Republic, Germany and Bulgaria.

Therefore, coal dependence is still significant in EU. Additionally, changes in the level of demand for coal in the last two years are minor. In some countries, the share of coal has not decreased and has even increased slightly. This is the result of the war in Ukraine and the replacement of Russian natural gas with coal. The second way to reduce harmful gas emissions without giving up coal is to implement clean coal technologies (CCTs) that allow the continued use of coal without climate consequences.

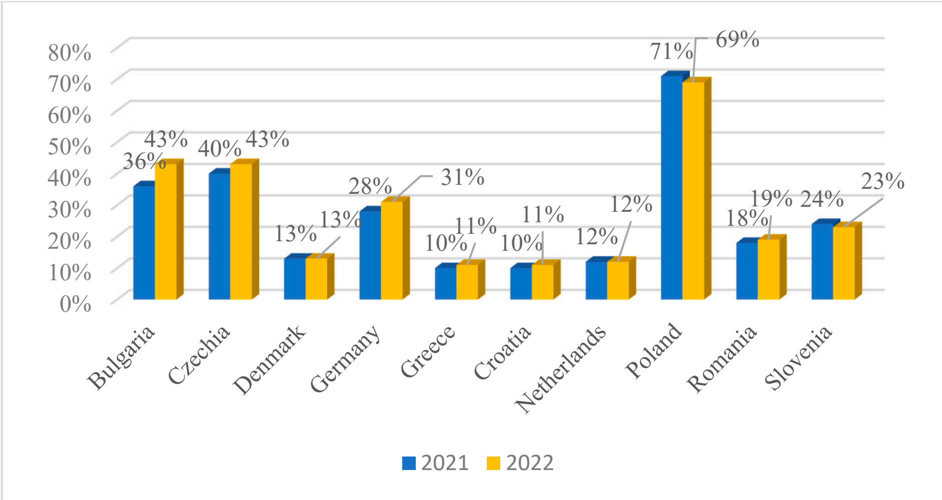

Figure 2. Production of electricity and derived heat by type of fuel (solid fossil fuels), [7].

Although the first solution is promoted in the European Union, clean coal technologies enjoy unwavering interest around the world. This is evidenced by the number of publications on clean coal technologies presented in Figure 3. The number of publications in ScienceDirect and Google Scholar was examined. In the period under study, that is, between 2000 and 2022, the number of publications increased sevenfold and fivefold, respectively. Therefore, the global interest in CCT is increasing, mainly in countries where coal is an important component of the energy mix, such as China, India, Australia, Russia and the USA [8].

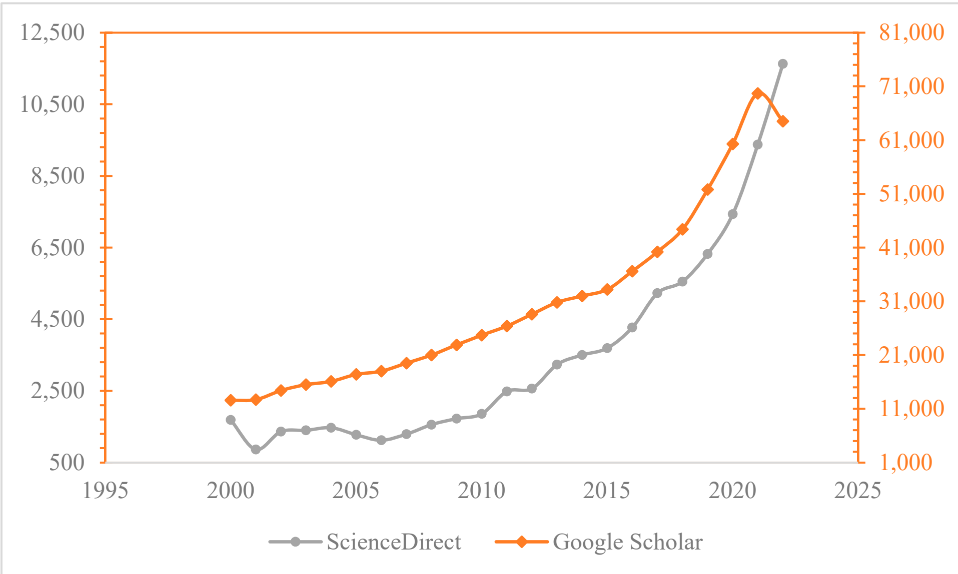

Figure 3. Number of publications on CCT in 2000–2022.

In Poland, interest in CCT decreased significantly since 2016, as evidenced by the number of patents submitted in years 2000–2019 and the number of publications (Figures 4 and 5).

Clean coal technologies include many different solutions used throughout the coal and energy distribution chain. Currently, EU countries use them in various variants, scopes and quantities. Some are mature technologies and others are in the development phase [10]. So, could clean coal technologies maintain coal in the energy mix? The authors conducted research aiming to verify the assumption that there is a relationship between the use of clean coal technologies and the demand for this fuel. If this assumption could be confirmed, it would mean that coal could still be the main source of energy and the basis of Poland's energy security.

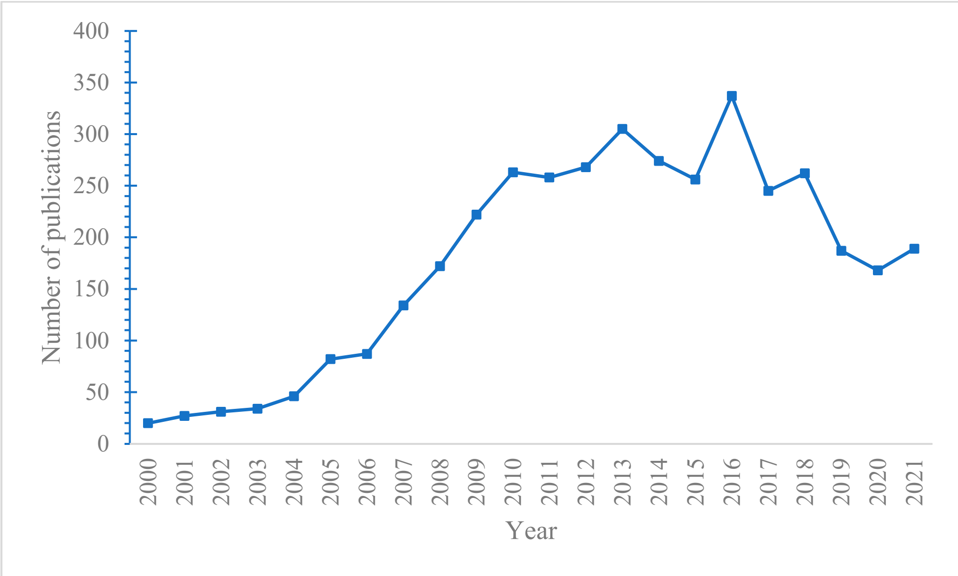

Figure 4. Number of publications on CCT in Polish, 2000–2022, Google Scholar.

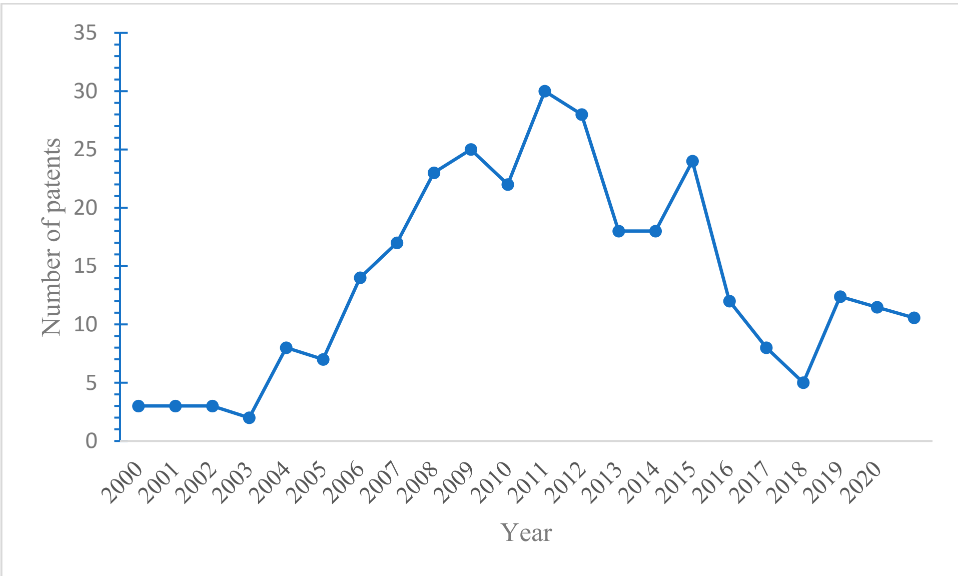

Figure 5. Number of patents related to CCT [9].

2. Clean Coal Technologies

Clean coal technologies (CCTs) are a group of solutions that affect the efficiency of the coal mining and combustion process. The purpose of using CCT is to reduce the impact of these processes on the environment and climate change [11]. These solutions can be divided into three main categories:

- Coal enrichment.
- Coal transformation, supercritical combustion and combustion in oxygen atmosphere.
- Exhaust gas treatment.

According to the place of application in the distribution chain, the technologies can be divided as used in the following stages:

- Operation and mechanical processing.

- In the combustion process.
- During the management of waste generated in earlier stages.

Coal processing makes it possible to clean the fuel, remove waste rock and separate impurities that may have mixed with the fuel during the exploitation process. The pre-treatment of fuel is used due to the emission of greenhouse gases, but also the efficiency of the fuel combustion process [12]. In Poland, depending on the grain size of the coal, various enrichment methods are used. For grains larger than 20 mm, these are mainly heavy liquid separators and pistonless jigs. For grains from 0.5 to 20 mm, fine jigs, spiral enrichers and cyclones with heavy liquid are used. Flotation machines are used to enrich grains smaller than 0.5 mm [13]. In the coal enrichment process, additional solutions can be used, such as averaging coal quality parameters, creating coal–lime mixtures, selective grinding, or deep coal enrichment [14]. It involves crushing the excavated material to release small elements of waste rock and pyrite. After the crushing process is completed, additional enrichment methods are used, such as flotation [15].

In addition to mechanical methods, such as separation and sorting, or chemical methods, such as flotation, biological methods can also be used to enrich coal, i.e., the use of living organisms to remove contaminants from coal [16]. They allow the sulphur and ash content in coal to be reduced by using microorganisms such as fungi and bacteria. All these methods and treatments aim to improve the calorific value of coal, reduce the content of substances that interfere with the combustion process, and thus influence the amount of greenhouse gas emissions.

Further steps to reduce the negative impact of coal on the natural environment should be taken at the stage of coal combustion. There are many technological solutions that can be used at this stage. These include, for example, power plants with fluidised bed boilers [17], oxy-combustion [18], or supercritical power plants with steam boilers [19]. It is also possible to use coal conversion processes, for example, gasification and underground gasification [20,21]. Exhaust gas purification methods are also used, e.g., pre-combustion, post-combustion or oxy-fuel combustion. The most popular techniques of cleansing exhaust gases are CCS (Carbon Capture and Storage), CCU-CO_2 (Capture and Utilisation) and CCUS-CO_2 (Capture, Utilisation and Sequestration) [22,23]; however, the use of CCS has a negative impact on fuel combustion efficiency. CCS requires additional energy, which increases the demand for coal [24]. It is assumed that the costs of building a power plant with a CCS installation may increase by up to 30%, and the costs of energy production by approximately 60% [25].

Another clean coal technology that can be used in the fuel combustion stage are membrane techniques [26]. They are an alternative to CCS methods but have additional advantages. First, the use of membranes is a process that does not require high energy input, and the membrane installation can be used in all power plants, both coal and gas, in those just under construction and those already existing [27]. Membranes do not affect the continuity of power plant operation. The membrane is a selective barrier that separates two phases and limits the transport of one of them [28]. The mixture of gases produced in the coal combustion process constitutes the feed solution, which, after passing through the membrane, is separated into permeate and retentate. Retentate is a mixture of greenhouse gases (mainly carbon oxides, but also sulphur and nitrogen oxides), which can be additionally separated in order to be captured, stored or further processed and used [29]. Despite numerous advantages, membranes also have disadvantages, mainly chemical and mechanical resistance, as well as the need to regenerate membranes [30].

Clean coal techniques should also be implemented in the stage of managing waste generated during the exploitation and combustion of coal. In the mining process, solid waste is generated, mainly rock waste, methane and CO_2 gases, as well as water generated during exploitation and coal processing [31–33]. This publication focuses on waste generated during coal combustion. Combustion process waste includes gases which, once separated thanks to the CCT used in the previous step, can be effectively cleaned and used. For example, in the case of CO_2, it can be used during the exploitation of natural gas and crude oil, in the production of beverages and food [34], animal feed, and the production of biofuels and their components [35]. Sulphur oxides, in turn, are used during the production of sulfuric acid or fertilisers [36]. Nitrogen oxides are used in the production of explosives and in the production of nitric acid and fertilisers [37].

Coal combustion also produces waste in the form of slag, mill waste and, to a large extent, fly ash. The disposal of the latter is a large problem. Coal ash storage involves high fees, dusting problems and environmental pollution with heavy metals [38]. So far, they have been used primarily in construction [39], backfilling mining excavations [40–42], ceramics and agriculture [43]. However, the fact that they are a source of rare earth elements (REEs), i.e., critical raw materials without which modern technology cannot develop, brings a new way of managing this waste in accordance with the principles of a circular economy [44]. So far, approximately 30% of fly ash generated in Poland is managed annually. Polish ashes contain mainly light REEs such as neodymium, praseodymium, cerium and lanthanum (up to 300 ppm), with heavy REEs in smaller amounts up to 150 ppm—mainly terbium, yttrium, ytterbium, lutetium, dysprosium, erbium and thul [45]. Currently, REEs are of great importance for the energy transformation because they are an indispensable element of wind turbines and are also used in the construction of energy storage facilities [46]. Considering their importance, price fluctuations and limited access to deposits of elements, the possibility of obtaining them from fly ash is an excellent solution. Rare earth elements can be obtained by using membrane techniques such as reverse osmosis [47], emulsification liquid membrane [48], nanofiltration [49], hollow fibre liquid membranes [50] and membrane methods.

The presented research aimed to verify the hypothesis about the existence of a relationship between the use of CCT and the share of coal in the Polish energy mix. For this purpose, two mathematical models and statistical tests were used to verify the correctness of the analysis. A description of these is presented in the Methods chapter.

3. Materials and Methods

The sigmoidal Boltzmann curve model was used to determine the forecast of coal demand until 2025. The model is characterised by the following equation [51].

$$f_i(x) = \frac{(a_1 - a_2)}{1 + e^{\frac{(x_i - x_0)}{dx}}} + a_2$$

where x is the independent variable (year), i are individual observations, a_1 is the horizontal asymptote of the function $f_i(x)$, a_2 is the horizontal asymptote of the function $f_i(x)$, x_0 is the middle value of the interval, x_i are the years and dx is the slope of the function.

The Boltzmann model is defined by a function that takes the shape of the letter s. The model parameter a_1, i.e., the upper asymptote, means the upper limit to which the function strives, and a_2 is the lower asymptote.

3.1. Machine Learning

One of the definitions of machine learning says that it is a subfield of artificial intelligence that represents a different way of programming. The sample data replace the program's rigid calculation rules of the programme. Learning methods or algorithms extract statistical regularities from the given sample data and present them in the form of models. Models can react to new, unknown data and classify them into categories or make predictions [52]. Machine learning is a subset of artificial intelligence. It allows for identifying patterns characterising a data set, classifying data and, on this basis, predicting the desired results [53].

There are many varieties and methods of machine learning. For the purposes of this research, supervised learning (SL) was used. Supervised learning allows expected responses to be introduced into the model, which are called labels [54]. In the analysed case, these are the values of the explained variable, i.e., the amount of demand for coal. With this solution, it was possible to analyse the relationship between the explanatory variables and the explained variable. The machine learning model is designed to identify the rules and relationships that connect variables. The machine learning algorithm involves training a model on a set of training data. The consequence of the training stage is to obtain a model ready for inference. The model is validated using test data set [55]. By comparing the actual results obtained with the expected values, the effectiveness of the model and the accuracy of the prediction process can be determined. Multiple linear regression was used to forecast the demand for coal. Due to this, it was possible to introduce a larger number of explanatory variables into the model [56]. The regression coefficients of the model characterise the contribution of the independent variable in the process of predicting the demand. The model used is described by the equation the following:

$$z = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i + \varepsilon \tag{1}$$

where x_i are the explanatory variables, ε is a random variable and β_i is the regression coefficient.

3.2. Methods of Variable Selection and Model Verification

In order to correctly select the set of explanatory variables, a Student's t-test was performed before introducing them into the regression model. This made it possible to verify the importance of the impact of each explanatory variable on the demand for hard coal. The test requires two hypotheses: H0, about the lack of statistical significance of the influence of the explanatory variable, and H1, which states that the independent variable influences the variable y and this influence is not accidental. The Student's *t*-test is performed according to the following formula [57]:

$$t = \frac{\overline{x} - \mu_0}{s/\sqrt{(n-1)}} \tag{2}$$

where n is the sample size, s is the standard deviation, μ_0 is the parameter value adopted within H0 and $\overline{x}$ is the sample average.

The Student's *t*-test statistics allows the p-value to be determined, i.e., the probability that the null hypothesis is false (small p-values). The p-value should be related to the level of significance. When p is less than the significance level α, it is necessary to reject hypothesis H0 in favour of hypothesis H1.

Before a time series can be used to build a mathematical model, it must be verified whether it is stationary. In a stationary series, the mean and variance are constant and do not change with the shift in the periods. Otherwise, a spurious regression phenomenon may occur. The Dickey–Fuller test [58] was used, whose statistics verifying the occurrence of a unit root are determined according to the following formula:

$$DF = \frac{\delta}{S(\delta)} \tag{3}$$

A stochastic process that does not contain a root that lies inside or on the periphery of the unit circle is a stationary process. The Dickey–Fuller test requires the formulation and verification of hypotheses:

H0: *there is a unit root in the time series,* $\delta = 0$.

H1: *the time series is stationary,* $\delta < 0$ [59].

The built model should be verified to check whether the model correctly describes the analysed phenomenon. For this purpose, the expired forecasts and model residuals are first determined. Then, ex post-forecast errors such as the Root-Mean-Square Error (*RMSE*) and the mean absolute percentage error (*MAPE*) should be calculated [60–63]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_t^2}{n}} \tag{4}$$

$$MAPE = \frac{\sum_{i=1}^{n} |e_t / y_t|}{n} \tag{5}$$

where y_t is the value of the explained variable in period t, n is the number of observations and e_t is the forecast error.

The determined residuals of the model, i.e., the differences between empirical and theoretical variables, were also examined. It was verified whether the model residuals were normally distributed and free of autocorrelation. For this purpose, the Shapiro–Wilk and Durbin–Watson tests were used, respectively [64]. The Shapiro–Wilk test was used to verify the hypothesis:

H0: the distribution of the random component of the model is normal;

H1: the random component of the model has a non-normal distribution.

The test statistics were determined according to the following formula [65]:

$$w = \frac{\sum_{i=1}^{[\frac{n}{2}]} a_{n,i} (e_{n-i+1} - e_i)^2}{\sum_{i=1}^{n} (e_i - \bar{e})^2} \tag{6}$$

where a_{ni} is a constant depending on n and k, e_i are model residuals sorted in ascending order, W^* is a critical value taken from Shapiro–Wilk test tables and $W > W^*$ is the hypothesis that the normality of distribution should be maintained [66].

The H0 hypothesis about the lack of autocorrelation of the model residuals was confirmed by the Durbin–Watson test. The autocorrelation of residuals indicates an incorrectly selected model or failure to take into account patterns occurring in the time series in the model:

$$DW = \frac{\sum_{i=2}^{T} (e_i - e_{i-1})^2}{\sum_{i=1}^{T} e_i^2} \tag{7}$$

where e_n is the rest of the model and T is the length of the sequence of residuals.

4. Results

The authors aimed to verify the hypothesis that the use of clean coal technologies could influence the share of coal in Poland's energy mix. For this purpose, it was first necessary to determine measures and explanatory variables that would make it possible to verify the existence of such a relationship. Based on the authors' experience [27,29] and literature review [2,3,5,6,9,10,12,25,34,45], the set of indicators presented in Table 1 was adopted for analysis.

When examining the impact of clean coal technologies on the volume of demand for coal, it was necessary to focus on measures that would take into account the demand for electricity and heat, the development and support for CCT and alternative energy sources (RES), prices of the energy carrier and, most importantly, the EU energy policy.

Table 1. Explanatory variables used to build forecast models.

Variables	Source	Type of Variable
Coal sales, Mg	Industrial Development Agency [67]	target
Gross electricity production (toe)	Eurostat [7]	Features
Energy consumption from renewable energy sources, EJ	Energy Institute [6]	
Number of patents	IRENA [9]	
Public investments in renewable energy, USD mil	IRENA	
Heat from coal, TJ	IRENA	
Heat from renewable energy sources, TJ	IRENA	
Greenhouse gas emissions intensity of energy consumption, 2000 = 100	Eurostat	
Coal price, PLN/Mg	Industrial Development Agency	

This set included the number of patents related to CCT, which indicates progress in this field. Regulatory policy related to greenhouse gas emissions will affect the attractiveness of coal as an energy source. The amount of CO_2 emissions was chosen as the measure in this respect. For the most part, the decision on the energy source used is also dictated by the prices of raw materials. Therefore, the coal price was also used as an explanatory variable. State support for alternative energy sources means that even sources that are unprofitable compared to coal can compete with it and reduce the demand for coal. The explanatory variable in this case was public investment in renewable energy sources. The availability of alternative energy sources is also important. Since, in the future, the role of coal will be largely taken over by renewable energy sources and the European Union is focusing on their development, they were the reference point when selecting explanatory variables. Therefore, the amount of electricity and heat produced from renewable energy sources and coal was adopted as a measure. The volume of fuel sales was used as an indicator of the demand for coal.

The MLT 1.0 programme was written and used to perform all analyses necessary to conduct the presented research. The programme was written in Java. The structure of the model classes is presented in Figure 6. The programme can use two types of mathematical models, i.e., the Boltzmann sigmoidal curve and machine learning using regression. These models were initially selected by the authors based on visual analysis of the coal demand time series. Additionally, the programme is equipped with tools to analyse input data and verify the statistical significance of variables and the stationarity of the time series. If the time series turns out to be nonstationary, the Data Differencing class includes code that allows it to be reduced to a stationary form by differentiating the time series. In the Forecast class, it is possible to obtain expired forecasts and forecasts for a selected number of periods ahead, and determine model residuals and *MAE*, *RMSE* and *MAPE* errors. In the Residuals autocorrelation and distribution normality class, the hypotheses about normality and lack of autocorrelation of residuals are verified.

Apache libraries were used to build the tools used. Apache Spark is a unified analytics engine for data processing. Spark provides a framework for data analysis, including machine learning, via the MLib module [68].

First, an analysis of changes in the time series of demand for coal in Poland was carried out in the years 2000–2022. A mathematical model was built in which the time variable was used as the only independent variable. The Boltzmann sigmoidal curve model was used.

The *MAPE* error was less than 5%, which indicates its high accuracy. Figure 7 presents empirical and theoretical variables and the forecast until 2025.

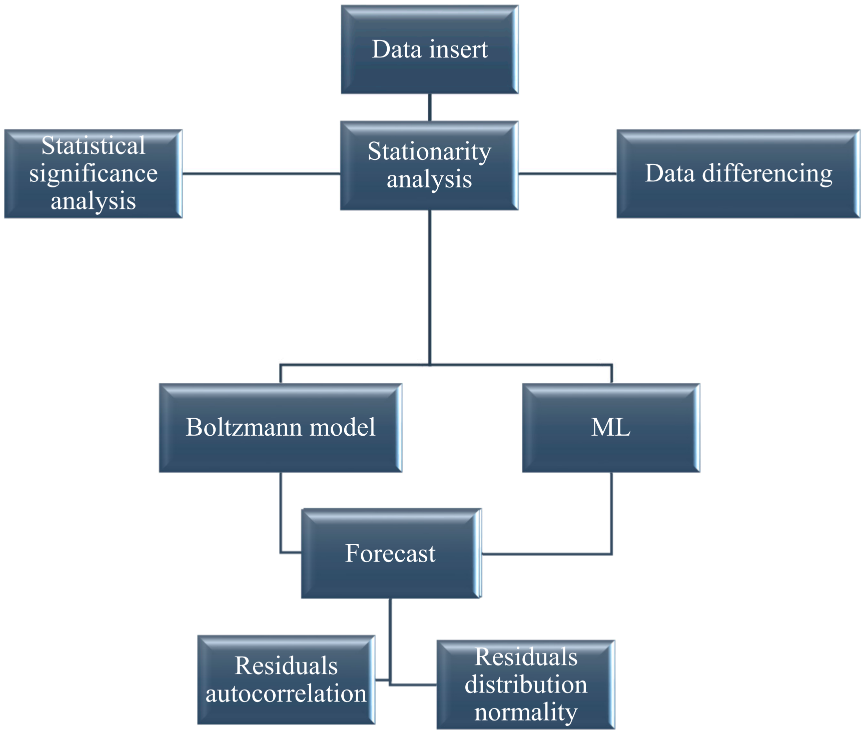

Figure 6. Structure of the MLT 1.0. program.

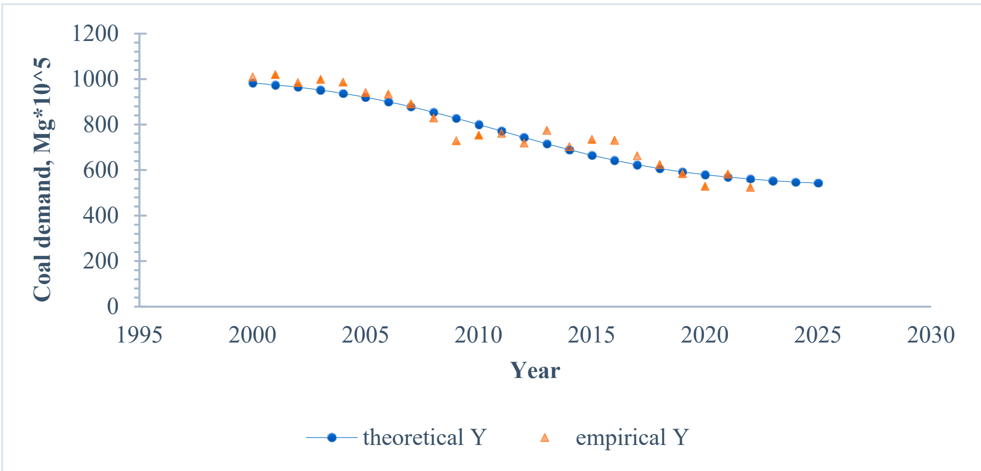

Figure 7. Coal demand volume, actual values, expired forecasts and forecast until 2025.

The residuals of the model were normally distributed, but they showed a first-order autocorrelation. This result indicates that the model was not able to describe all the regularities that characterise the time series of demand for coal. Therefore, in the next step, a multiple regression model was built that took into account a larger number of explanatory variables. The stationarity of the time series was confirmed by the Dicket–Fuller test.

A supervised machine learning model was built. A multiple regression algorithm was used. The input data were divided into two sets: training and testing. The analysis concerned a time series, so the sequence of subsequent values was important. Therefore, the chronology of the input data was preserved. 70% of the data was placed in the training set and 30% in the testing set.

The amount of data used to train the model has a large impact on its quality. More training data allow for a better understanding of the complexities and patterns that shape the data set. The longer the time series, the more training data can be used to build the model. Long time series can reveal more complex patterns and trends in the data. In the case of the analysed data with a one-year sampling period, the largest possible amount of data on the analysed phenomenon was collected. The limitation was that data on renewable energy sources, which developed in Poland after 2000, were used as explanatory variables.

Data that were to be used to build a multiple regression model were verified for statistical significance. Student's *t*-test was used. Ultimately, eight independent variables were used to build the model, in which case the test indicated the influence of the independent variable on the demand for coal. In all cases, the *p*-value was lower than the assumed significance level of alpha = 0.01; therefore, the test indicated the statistical significance of the analysed variables. The highest *p*-value occurred in the case of heat from renewable energy sources and amounted to 5.40×10^{-17}. Several optimisation algorithms were used to train the model. The Gradient Descent (GD) and Limited-memory GFGS (L-BFGS) algorithms were used. These algorithms are often used in numerical optimisation for machine learning. L-BFGS is a quasi-Newtonian algorithm with limited memory that allows for finding linear regression parameters. GD is the simplest method that allows for finding the local minimum of a function by iteratively improving the model parameters. Both algorithms produced very similar results, but L-BFGS was ultimately chosen.

Figure 8 presents empirical and theoretical data as well as the forecast until 2025. It can be seen that the model reflects the regularities of the time series of the explained variable much more accurately. The average *MAPE* error for the created model was 9%. For the training set, it was about 2.6%, and for the test set, it was 21%, which means that the forecast can be considered acceptable.

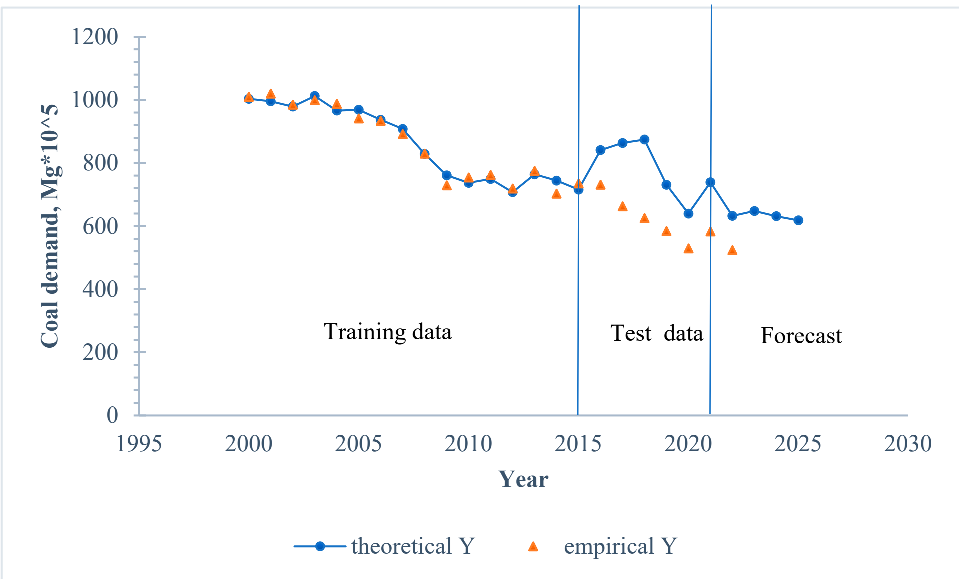

Figure 8. Multiple regression model, divided into training and test data sets, and forecast until 2025.

The *p*-value for the Shapiro–Wilk test is 0.70, so there are no grounds to reject the null hypothesis—the distribution is normal. The Durbin–Watson test statistic is 1.78, which means that there is no autocorrelation of first-order residuals.

Test set error values: *MAPE*: 20.72, *MAE* 1.28×10^{7} and *RMSE*: 2.04×10^{14}.

The error values of the training set: *MAPE* 2.64, *MAE*: 2201036.98 and *RMSE*: 1.07×10^{13}.

Figure 9 presents a model that was built without dividing it into a training and testing set. The *MAPE* error in this case is below 1%.

The Durbin–Watson statistic in this case is 1.83, which means that there is no first-order autocorrelation. The *p*-value for the Shapiro–Wilk test is 0.68, so there are no grounds to reject the null hypothesis, and the distribution of residuals is normal.

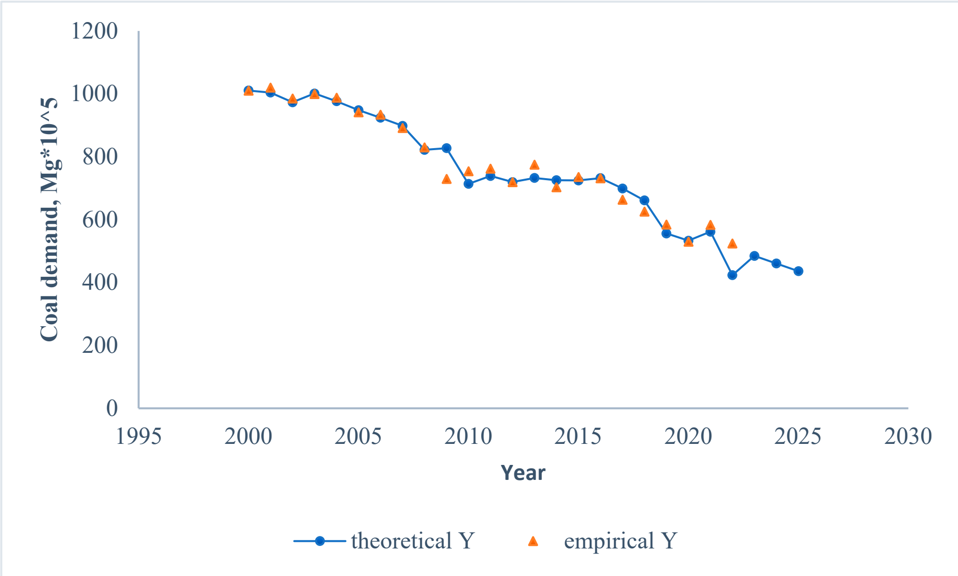

Figure 9. Multiple regression model and forecast until 2025.

Using the second ML model, the impact of the use of CCT on the demand for coal was simulated. The changes were made to the explanatory variables directly related to the CCT, i.e., the number of patents and the CO_2 emissions to reduce. Since 2016, the use of CCT resulted in a decrease in CO_2 emissions by 70%. This level of emission reduction was determined during the research on CO_2-selective membranes conducted by the authors [69]. The number of CCT patents maintained the trend that shaped this time series until 2015. Figure 10 presents the simulation results, as well as the trend line equations for the forecasted demand and that obtained as a result of the simulation. Not only is the share of coal in the mix higher for the data obtained during the simulation, but the slope of the time series of these values indicates a slower rate of decline in demand for coal. These changes resulted in an increase in demand for coal in the years 2017–2025 by an average of 22%.

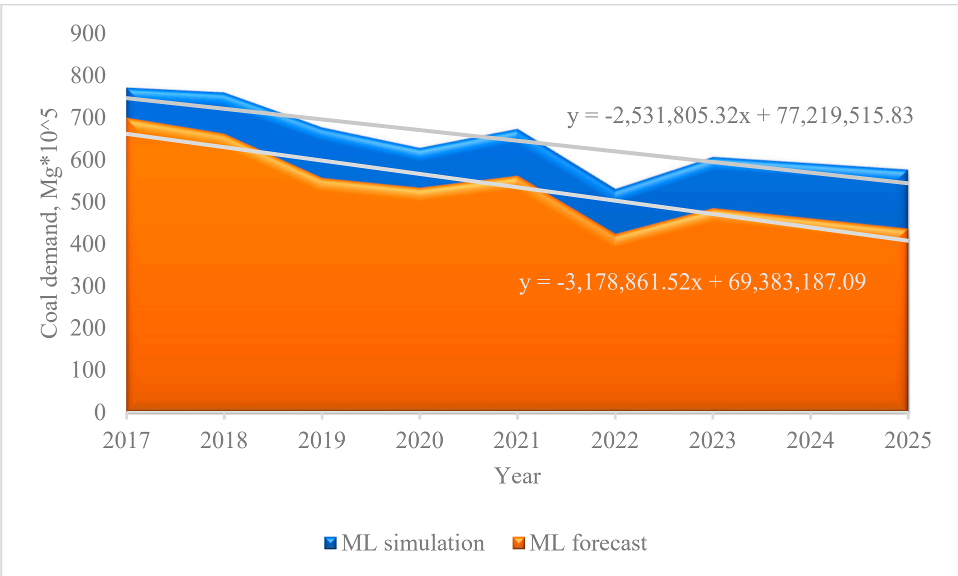

Figure 10. Results of the simulation of the coal share in Poland’s energy mix.

5. Discussion

A machine learning model using multiple regression built on training data showed a higher demand for coal than the empirical data after 2015. This is how the demand for coal should develop after introducing real explanatory variables, but the additional steps taken to remove coal from the energy mix resulted in a sharper-than-expected decline in fuel demand. This change was initiated by the European Union's climate policy, which aims to decarbonise the energy sector of member states. This is mainly regulated by the European Green Deal, which assumes that EU countries will achieve climate neutrality by 2050. The Green Deal emphasises EU countries investing in renewable energy sources, which are to take over the role of coal. The RED directives also specify the desired share of renewable energy sources in energy consumption in the EU.

Therefore, the main focus was placed on replacing fossil fuels with ecological alternatives such as wind or solar energy. The conducted research confirmed the hypothesis about the impact of the use of CCT on the share of coal in Poland's energy mix. As shown by analysis and simulation, coal could be maintained in the energy mixes of EU countries that have so far relied on it, and even if the negative aspects of using this fuel were limited—primarily the emission of harmful substances—its share could have been higher in the years 2017–2025 by an average of 22%. Due to the complicated political situation in the EU and the military threat that has been present for two years, assumptions regarding the method of decarbonisation of the energy sectors of the member states should be reconsidered. In addition to coal, EU countries also use other fossil fuels with a similar impact on the natural environment, especially crude oil, but also natural gas. The proposed technological solutions can be used for all fossil fuels. Research on CCT may also lead to innovative technological solutions that can be used not only in the energy industry, but also in other branches of the economy.

It should also be remembered that the renewable energy technology thanks to which we can use ecological energy sources is mainly created in China, or the components used to build renewable energy installations come from there. Firstly, the high level of dependence on one supplier raises problems related to energy security, and secondly, fossil fuels are used during the production of renewable energy technologies. Relying solely on renewable energy may therefore be another pitfall, not to mention problems related to the stability of the energy system. Additionally, the European Union should consider whether it will be able to compete with other countries, such as China or India. Removing coal from the energy mixes of member states may result in an increase in the prices of goods and services in the EU, which will cause the economy to have problems with competition from countries that do not approach the issue of decarbonisation so rigorously. Furthermore, it should be remembered that the EU is responsible for only 6% of global greenhouse gas emissions. Even if it completely eliminates its emissions, it will not matter on a global scale. As NASA research shows, the movements of air masses also cause these gases to be moved over Europe from other parts of the planet. Additionally, it may lead to a threat to the EU's energy security and, consequently, to its military security.

The results obtained may translate into the development of a sustainable energy strategy. This is especially important in the case of countries that have been relying on coal for years. The strategy of changes introduced to the energy mixes of individual member states should be adapted to their history, needs and capabilities. Countries deciding to use CCT should take into account a number of elements in their strategy that will enable sustainable energy production while limiting the negative impact on the environment. Governments and the private sector should invest in the development of clean coal technologies that will help reduce greenhouse gas emissions. Modernisation of the energy infrastructure will enable the integration of current and new energy sources, improving efficiency and increasing the reliability of energy supplies. International cooperation will also be necessary, which will enable the exchange of knowledge and experiences. It will also promote common goals for greenhouse gas reduction and sustainable development.

Implementing such an energy strategy will make it possible to keep coal in the energy mix while achieving the EU's climate goals.

Further research should focus on identifying potential barriers and challenges related to the implementation of clean coal technologies and developing strategies to overcome them. It will also be necessary to appropriately shape public opinion about CCTs and the benefits that may flow from their use, which will contribute to support for an energy policy based on the sustainable use of coal.

6. Conclusions

The research conducted describes the impact of clean coal technologies on coal demand. Factors that can be used to measure this impact have been identified. They were used to build a supervised machine learning model using multiple regression. Research has shown that after 2017, the demand for coal began to decline more intensely than previous historical data showed. An additional stimulus in this regard was Directive 2018/2001 promoting renewable energy sources. It introduced new goals regarding the share of renewable energy sources in energy mixes, as well as financial support mechanisms for renewable energy sources. Only then could renewable energy sources start to compete with coal, especially in the case of individual consumers. This resulted in changes in the structure of energy production in Poland in favour of renewable energy sources. However, especially in the case of EU countries, such as Poland, which still rely on coal, the energy transition may be complicated and unfavourable in terms of energy security. Summarising:

- Completely eliminating coal from the energy mixes of member states may increase energy prices in the EU and hamper economic competitiveness.
- The implementation of clean coal technologies can stabilise the share of coal in the energy mixes of member states.
- The European Union should continue to promote the diversification of energy sources. CCTs provide an opportunity to keep fossil fuels in the energy mixes of EU countries. This applies in particular to coal, which, as a fuel available in large quantities in the European Union, guarantees the EU's energy security.
- It is necessary to develop an energy transformation strategy adapted to the needs and capabilities of individual Member States.
- It will be necessary for the EU to cooperate with other countries such as the USA and China in order to exchange best practices regarding CCT and joint action for climate protection and the development of clean coal technologies.
- Public awareness of CCT should also be increased in order to build social acceptance for these types of solutions and rebuild a positive perception of coal.
- The use of clean coal technologies can contribute to achieving EU goals related to the reduction in greenhouse gas emissions. At the same time, it will enable a sustainable and safe energy transition.

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