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Analysis and forecasting of the dynamics of fuel trade between Turkmenistan and China using the autoregressive integrated moving average (ARIMA) model

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Abstract
Energy resources are vital to determining geopolitical strategy and driving economic growth in the modern global environment. International fuel commerce is fundamental to political and economic relations between countries, and the connection between China and Turkmenistan is particularly significant in this regard. Turkmenistan is well-positioned to serve as a major energy provider to China, given its vast supplies of natural gas. This research uses the ARIMA technique to forecast trade dynamics using fuel trade data from 2005 to 2022. The findings provide valuable insights for strategic policymaking and promote cooperation within the energy industry.

Keywords: ARIMA method, historical data, forecasting, trade volume

Introduction

In addition, a number of statistical tests will be used to verify that the time series is stationary. A time series is said to be stationary if its statistical features, like mean and variance, hold steady over the course of the series. Non-stationary series often require transformations, such as differencing, to become suitable for analysis using ARIMA. These methods and tools will help more accurately determine the appropriate ARIMA model parameters for analyzing and forecasting the dynamics of fuel trade between Turkmenistan and China, ensuring the reliability and relevance of the research. To implement the chosen methodology, we will use the Python programming language in conjunction with the relevant libraries.

The importance of this study is due to the need for a thorough understanding of the political and economic ramifications of Turkmenistan and China's energy partnership. The research results can be used to shape strategies and policies in the field of energy cooperation and provide valuable insights for economists, policymakers, researchers, and the academic community interested in global energy and international trade.

Energy resources are vital to the modern global economy, impacting both national economic growth and geopolitical plans. Under these circumstances, the global fuel trade assumes a major role in international relations. Particular attention is drawn to the interactions between China and Turkmenistan, two significant players in the world energy market. China's "One Belt, One Road" initiative creates new opportunities to develop and expand relations with other countries, particularly in the energy sector [1]. Energy cooperation between China and Central Asian nations becomes even more important within this global project, acting as a fundamental component of the Silk Road Economic Belt strategy [2].

Strategically located in the center of the Eurasian continent, Central Asia is a strategic partner for China in the energy sector due to its vast reserves of coal, natural gas, oil, and other resources. China considers Central Asia to be an essential source of oil and gas, as the country is heavily reliant on imports of these resources. Building energy connections with Central Asian nations is vital for maintaining China's economic growth and energy security, given its goal to overtake the US as the largest economy in the world [3].

Due to the nation's rapid economic growth, China actively explores new sources of energy resources, particularly in the Central Asian region. In this regard, Turkmenistan, with 17.4%

of global natural gas reserves, emerges as an ideal partner for China. The crucial role that energy resources play in international relations and state management strategies underscores the significance of this collaboration by making energy security issues relevant on a global scale [4]. Top of Form The analysis of energy relations between China and Turkmenistan is not only of interest in the context of China's energy security but is also crucial for understanding its future role in 21st-century global politics [5]. As China becomes a key player in global energy security issues, it stimulates international competition for resources and contributes to the strengthening of international energy ties, making its policy in this sphere particularly significant [6]. Turkmenistan, endowed with substantial natural gas reserves, and China, one of the world's largest energy consumers, form unique trade relations that exert a significant influence on energy markets and regional policies.

Currently, with China actively expressing interest in the energy resources of Kazakhstan and Turkmenistan, with a primary focus on oil and gas extraction and the development of nuclear energy, it is essential to highlight Turkmenistan's recent achievements in this field. Special attention deserves the fact that by the end of 2021, Turkmenistan had reached a record level of natural gas production in its entire history, reaching a volume of 83 billion 772.9 million cubic meters.

This impressive success underscores Turkmenistan's status as one of the leading energy producers. Extensive natural gas reserves exceeding 20 trillion cubic meters and oil reserves of approximately 20 billion tons position Turkmenistan as a prominent player among the world's largest hydrocarbon producers. Moreover, in 2017, Turkmenistan solidified its status on the global stage by chairing the Energy Charter Conference, emphasizing its importance in the global energy landscape [7].

Taking into consideration the aforementioned facts, China's interest in Turkmenistan's energy resources becomes evident. This interest logically aligns with China's comprehensive strategy to strengthen its economic and political positions in Central Asia and on the global stage. Seeking sustainable economic growth and energy security, China views Turkmenistan as a reliable partner capable of meeting the country's growing needs for energy resources.

In the dynamic realm of global energy trade, interactions between energy-producing and consuming nations shape economic, geopolitical, and environmental landscapes. A significant example is the Turkmenistan-China partnership, which is garnering increasing attention. This research explores the multifaceted fuel trade between them, revealing underlying factors, trends, and implications. Natural gas from Turkmenistan satisfies China's rising energy needs as a result of economic expansion and the Belt and Road Initiative, leading to deeper engagement through pipelines, agreements, and infrastructure investments [1, 8, 9, 10].

The expanding momentum of bilateral relationships indicates that cooperation in the sphere of natural gas is the most prominent area of cooperation between Turkmenistan and China. China and Turkmenistan have held a number of significant meetings recently regarding their collaboration on natural gas. The Turkmenistan-Uzbekistan-Kazakhstan-China natural gas pipeline, which Turkmenistan's Minister of Education Mamedova dubbed the "project of the century" in 2013, is the foundation of cooperation. Beginning at the border between Turkmenistan and Uzbekistan, the pipeline crosses through Kazakhstan and Uzbekistan before entering China via its northwest border. It's about 10,000 kilometers long as of right now [11].

The purpose of this research is to use the autoregressive integrated moving average (ARIMA) method to forecast and analyze the dynamics of fuel trade between Turkmenistan and China. The statistical model known as ARIMA, or Autoregressive Integrated Moving Average, is used to forecast and analyze time series data. In the domains of meteorology, economics, finance, and other fields, it is one of the most widely used forecasting techniques.

The term "autoregressive" (AR) refers to a statistical technique that illustrates how a time series' past values and current values are related. The parameter p, which denotes the number of time lags (delays), determines this relationship. I (Integrated): Integrated: It shows how a time series is differentiated, which results in the series becoming stationary (that is, its statistical characteristics, like mean and variance, don't change over time). The parameter d indicates the order of integration, or the number of times the series must be differentiable to become stationary. Moving Average (MA): Moving Average describes the relationship between a time series' current value and its forecast errors as a result of a given time lag in the past. The parameter q indicates the total number of lag forecast errors in the model. This method was chosen for its ability to analyze and forecast time series, which is critically important for understanding and predicting trends in international fuel trade. Two ARIMA models were considered: ARIMA (1, 1, 1) and ARIMA (2, 1, 2), with ARIMA (2, 1, 2) selected as the more efficient one. The study covers the period from 2005 to 2022 and aims to identify key trends and potential changes in trade volumes in the coming years. Using this method, a forecast of fuel trade was made from 2023 to 2027. Several methods will be employed within the study to ensure the accuracy and reliability of the analysis. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are two important tools. These plots aid in identifying the most important lags (delays) for the model and whether there is temporal dependence in the data. ACF measures the correlation between time series observations at different time lags, allowing for the identification of overall autocorrelation in the data. PACF, on the other hand, measures the correlation between observations, taking into account the influence of intermediate lags, which is particularly important for determining the parameters of the AR component of the ARIMA model.

The remaining article is organized as follows: following the introduction, there is a review of relevant literature, a detailed description of the research methodology, analysis of collected data, discussion of research results, and, in conclusion, findings and recommendations based on the conducted analysis.

Literature review

China and Turkmenistan have extensive economic and trade cooperation, particularly in the natural gas sector. China receives more than 90% of Turkmenistan's total gas exports [12]. The collapse of gas prices has influenced this trade relationship, causing Turkmenistan to experience a currency crisis. Turkmenistan's economic problems have reduced living standards and regime stability. China's role in Turkmenistan's economy is critical, as it is the primary creditor and recipient of Turkmen gas [13]. However, the terms of the Chinese-Turkmen contracts, which link gas prices to oil prices, have resulted in a drain of Turkmen resources and decreased foreign currency inflows [14].

Accurate price predictions are crucial because a variety of factors have an impact on China's carbon trading market. Artificial intelligence models, such as machine learning and neural network models, have become increasingly popular in this field. The ARIMA-LSTM hybrid model was found to have the best prediction effect, indicating significant fluctuations and instability in Shenzhen's carbon trading price over the next three years [15]. Nonetheless, the ARIMA model has demonstrated greater accuracy than the LSTM model in the short-term prediction of univariate time series data [16]. It is recommended that government regulations be tightened to control price fluctuations and enhance market liquidity in carbon emissions trading and that conventional statistical methods be combined with artificial intelligence algorithms to improve prediction ability [17].

The ARIMA method is a powerful time series analysis technique that can be used to model both stationary and non-stationary data [18]. An important part of modeling the autoregressive integrated moving average (ARIMA) model, which is widely used in forecasting, is parameter estimation. The ADF coefficient test is a fully parametric way to find a unit root in ARIMA models where the order is unknown [19]. In addition, the ARIMA parameter model is useful for analyzing and predicting electrical signals in plant environments, providing information on stability, and predicting short-term trends [20]. Additionally, a healthcare facility's incidence of acute respiratory infection (ARI) cases has been forecasted using the ARIMA methodology, yielding a forecast of 354 cases for 2019 using the 2.0,1 model [21].

China and Turkmenistan have established a robust partnership in the economic and trade sectors, particularly in the natural gas domain. Turkmenistan, Kazakhstan, and Uzbekistan hold significant importance for China and Japan regarding their reliance on natural gas imports [22]. The diplomatic and economic ties between China and Turkmenistan have gained considerable significance, particularly following the introduction of the "one belt, one road" strategy [23]. The pivotal role of China's National Oil Companies (CNOCs) has a significant impact on China's energy relations with Turkmenistan and Kazakhstan [24]. China's exclusive position as the sole recipient of Turkmenistan's gas exports has a significant impact on the complex dynamics of the fuel trade between those two countries [25]. The contracts between China and Turkmenistan, which establish a correlation between gas prices and oil prices, have resulted in the depletion of Turkmen resources and a decrease in the inflow of foreign currency [13]. It may be imperative for China to intervene to stabilize Turkmenistan's economy and prevent a potential collapse of the Turkmen state. According to the paper [14], China has gradually emerged as the primary consumer of natural gas from Turkmenistan, thereby indicating a dynamic fuel trade between the two nations.

The paper's primary focus is on Turkmenistan's energy trade policy and its strategic collaboration with neighboring nations and various political entities. It is worth noting, however, that the paper does not explicitly reference any research conducted on the intricacies of fuel trade dynamics between Turkmenistan and China.

Our investigation aims to employ the ARIMA methodology to scrutinize and predict the pat-terns of fuel trading between Turkmenistan and China.

Methods and Materials

Choice of Research Method

The time series analysis technique known as ARIMA (Autoregressive Integrated Moving Average) is frequently used to forecast future values based on historical observations. The choice of ARIMA is justifiable given its capacity to model intricate time dependencies and trends. Time series in fuel trade may contain various trends and seasonal fluctuations, which ARIMA captures effectively. ARIMA allows for data integration, which is particularly useful when dealing with non-stationary time series. ARIMA (Autoregressive Integrated Moving Average) is a statistical method used for the analysis and forecasting of time series. Let's delve into each component of the method:

Auto regression (AR): ARIMA utilizes the past values of a time series to forecast its current value. The formula for auto regression of order p is as follows:

$$Y_t=c+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+\cdots+\phi_p Y_{p-1}+\varepsilon_t \qquad (1)$$

Where:

Yt - current value of the series, c - constant, $\phi 1, \phi 2, \ldots, \phi p$ - autoregressive coefficients, εt - random error.

Integration (I): This component is responsible for the degree of differencing the time series to achieve stationarity. If the original series is non-stationary, differencing is applied.

The formula for integration of order d looks like the difference between the current and the previous values:

$$\nabla^d Y_t= (1-B)^d Y_t \qquad (2)$$

∇^d - differencing operator,

B - lag operator.

Moving Average (MA): This component considers the influence of previous forecast errors on the current value. The formula for moving average of order q looks as follows:

$$Y_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \qquad (3)$$

Where:

$\theta_1, \theta_2, \ldots, \theta_p$ - moving average coefficients.

Formula for ARIMA (p, d, q):

$$Y_t = c + \phi_1 \nabla^d Y_{t-1} + \cdots + \phi_p \nabla^d Y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_q\varepsilon_{t-q} \qquad (4)$$

Where p is the autoregressive order, d is the differencing order, q is the moving average order.

The model was chosen to ensure a comprehensive analysis of the time series of fuel trade between Turkmenistan and China, taking into account various types of dependencies between variables. Using this method, a forecast of fuel trade was made from 2023 to 2027. Various methods were employed, including autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as well as statistical tests for stationarity.

To implement the chosen methodology, we used the Python programming language along with relevant libraries.

Data Sources

The primary data sources include fuel trade statistics between Turkmenistan and China for the period from 2005 to 2022, as well as current data on energy production and imports in China. Before we proceed to the analysis of forecasts, let's briefly re-view the historical data on fuel trade between Turkmenistan and China. Below are key indicators of trade from 2005 to 2022:

Table 1: Bilateral trade between China and Turkmenistan in the period from 2005 to 2022 (in US dollars) in the field of fuels

Year	Trade in total	Exports from China to Turkmenistan	Imports from Turkmenistan to China
2005	4816	702	4114
2006	5820.92	906.22	4914.7
2007	24831.12	1880.92	22950.2
2008	35923,817	3,817	35920
2009	82932,434	2,434	82930
2010	998642.21	5396.06	993246.15
2011	4655490.46	3191.28	4652299.18
2012	8598769.99	3447.48	8595321.51
2013	8804221.2	2866.71	8801354.49
2014	9443997.13	2697.01	9441300.12
2015	7717069.17	648.45	7716420.72
2016	5481237.42	268.03	5480969.39
2017	6536959.15	922.72	6536036.43
2018	6338971,48	1793,31	6337178,17
2019	9561770.89	233,29	9561536,6
2020	8472277.44	91,21	8472186,23
2021	5479762,38	159,04	5479603,34
2022	10258577	633	10257944

From the table, it can be observed that the overall fuel trade gradually increased over time, reaching a value of 10.258 billion dollars in 2022. Fuel exports from China to Turkmenistan and imports from Turkmenistan to China also exhibit certain trends.

Fig 1: Bilateral Trade in Fuels between China and Turkmenistan (2005-2022)

Analysis of historical data underscores the importance of using the ARIMA method to forecast the dynamics of fuel trade between Turkmenistan and China. In the following sections, we will delve into the results of applying the ARIMA method to these data and provide forecasts for the upcoming year

Model Training

Stationarity Check of Time Series

In this section, we used the Augmented Dickey-Fuller (ADF) test to verify the time series' stationarity. We chose the commodity's year and volume for the time series analysis (tab. 1). A statistical test called the ADF test is used to assess if a time series is stationary. The ADF statistic, p-value, and critical values are included in the test results. The p-value in my instance is 0.0599, and the ADF statistic is -2.79. We typically reject the null hypothesis that the series is non-stationary if the p-value is less than 0.05. Since the p-value in my instance is nearly 0.05, we are unable to declare the null hypothesis to be false with confidence.

```
ADF Statistic: -2.7885706574841014
p-value: 0.05992500604246004
Critical Values: {'1%': -4.331573, '5%': -3.23295, '10%': -2.7487}
```

Fig 2: ADF Result

This may suggest that the time series could be non-stationary, but sometimes such results are close to the significance level, and in some cases, stationarity can be tentatively accepted.

Determination of ARIMA Model Parameters

Parameter p (AR): This parameter determines the number of previous values in the time series used to forecast the next value. Too high values of p may consider random fluctuations as systematic trends, leading to an overestimation of the model. In-sufficient p values may fail to capture important patterns in the data.

Parameter d (I-Integrated): This parameter is responsible for the number of differences required to stabilize the time series and make it stationary. Too low values of d may make it impossible to remove trends and seasonal fluctuations from the data, leading to an underestimation of the model. Too high values of d can make the time series excessively stationary, removing too much information from the data.

Parameter q (MA, moving average): This parameter determines the number of previous model errors considered when forecasting the next value. Too high q values may include random noise as a systematic component, leading to an overestimation of the model. Insufficient q values may not account for the influence of previous errors on future values.

In time series analysis, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) are used to determine how much autocorrelation exists be-tween a time series and its lags. Autocorrelation Function, or ACF.
ACF measures the correlation between the current value of a time series and its previous values at different lags. For a given lag k, ACF is calculated as follows:

$$\mathbf{ACF(k)} = \frac{Cov(Y_t, Y_{t-k})}{Var(Y_t)} \quad (5)$$

Where Yt is the current value of the time series is, Yt-k is the value at lag k, Cov is co-variance, and Var is variance.

PACF (Partial Autocorrelation Function):
PACF measures the direct correlation between the current value of a time series and its previous values, excluding the influence of intermediate lags. For a given lag k, PACF is calculated as follows:

$$\mathrm{PACF(k)} = \frac{Cov(Y_t, Y_{t-k} \mid Other\ Lags)}{Var(Y_t)} \quad (6)$$

Where Cov(Yt,Yt-k│Other Lags)is the conditional covariance between Yt and Yt-k given other lags.
To construct an optimal ARIMA model, it is crucial to identify the values of the parameters "p," "d," and "q." This process involves the analysis of autocorrelation, partial autocorrelation function (PACF), and autocorrelation function (ACF) plots.
Understanding the relationship between time series values and their corresponding lags is possible with the help of the autocorrelation function (ACF) plot. In addition, the Partial Autocorrelation Function (PACF) plot, which eliminates the impact of intermediate lags, displays direct correlations between the values of time series and their lags. Analyzing these plots assists in determining the ARIMA model parameters:

- p (autoregressive order): The last significant lag on the PACF plot indicates the value for the "p" parameter.
- d (order of differencing): The number of differences required to achieve stationarity.
- q (Moving average order): The last significant lag on the ACF plot conveys the value for the "q" parameter.

These values will be used in building the ARIMA model for forecasting the time series of trade between Turkmenistan and China.
For the analysis of the trade time series between Turkmenistan and China, ACF and PACF plots were generated. The ACF plot provides information about the correlation between time values and their lags, while the PACF plot reveals a direct correlation, excluding the influence of intermediate lags.

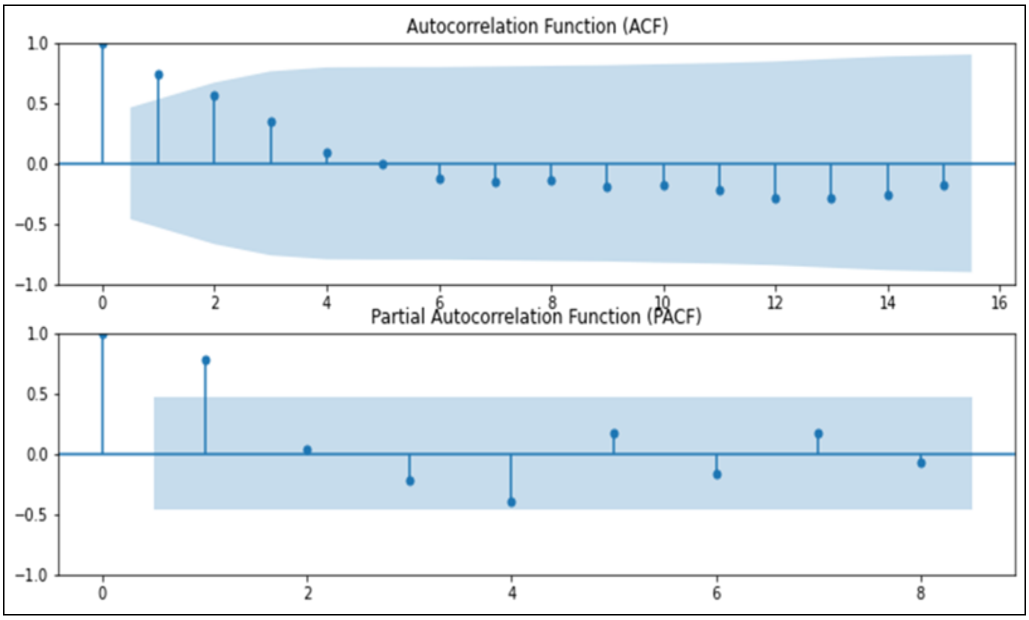

Fig 3: ACF and PACF

Analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF): ACF shows decaying correlations with increasing lags, indicating the presence of a trend in the data. PACF shows a significant correlation at initial lags. Based on these plots, we can hypothesize that the ARIMA model may have the following parameters: p (autoregressive lags): Since PACF has significant values at the first few lags, we can start with p = 1 or 2. d (order of differencing): Considering the p-value of the Dickey-Fuller test, d = 1 may be suitable to achieve stationarity. q (Moving average lags): ACF shows decaying correlations, suggesting q = 1 or 2.

ARIMA (1, 1, 1) Model: The ARIMA (1, 1, 1) model consists of the following components: AR (autoregressive) order 1: Previous values of the time series influence the current value. This component accounts for autocorrelation in the data, which is crucial for identifying patterns in preceding periods. (Integrated) Order 1: One difference is applied to achieve stationarity in the time series. This step helps eliminate trends and seasonal fluctuations, simplifying data analysis. MA (moving average) order 1: Previous forecast errors influence the current value. This component accounts for the impact of random shocks, which is important for modeling random changes in the da-ta. The goal of taking into account both previous values and forecast errors, which can be crucial for time series with strong trends and noise, justifies choosing ARIMA (1, 1, 1).

ARIMA (2, 1, 2) Model: The ARIMA (2, 1, 2) model includes the following components: Two AR (autoregressive) components: Two previous values of the time series influence the current value. This allows for capturing more complex dependencies and changes in the data. One I (integrated) component: One difference is applied to ensure stationarity. This component helps remove trends and improve the adaptability of the model. Two MA (moving average) components: Two previous values of forecast errors influence the current value. These components account for random shocks and changes. The need for a more adaptable model that can accommodate a more complex time series structure justifies choosing ARIMA (2, 1, 2). Additional AR and MA components allow for more effective capture of both linear and nonlinear trends and structures in the data. Thus, we can start with either the ARIMA (1, 1, 1) or ARIMA (2, 1, 2) model and further adjust the parameters based on model diagnostics and performance.

Results and Discussion

Evaluation of the first ARIMA (1, 1, 1) model

Based on the analysis of ACF and PACF graphs, it was suggested that the ARIMA model could have initial parameters (p, d, q) equal to (1, 1, 1) or (2, 1, 2). Now, let's proceed to the model training.

In the table with the results of the ARIMA (1, 1, 1) model, key characteristics, coefficients, standard errors, z-test statistics, p-values, and confidence intervals, as well as the results of tests for autocorrelation (Ljung-Box), normality of residuals (Jarque-Bera), and heteroskedasticity, are presented. These results provide comprehensive information about the quality and adequacy of the model for the data.

Dep. Variable:	Trade_Total	**No. Observations:**	18
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-153.310
Date:	Fri, 19 Jan 2024	**AIC**	312.620
Time:	15:03:29	**BIC**	315.120
Sample:	0	**HQIC**	312.869
	- 18		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.4466	0.245	-1.825	0.068	-0.926	0.033
ma.L1	0.9995	0.359	2.782	0.005	0.295	1.704
sigma2	3.599e+06	9.98e-08	3.6e+13	0.000	3.6e+06	3.6e+06

Ljung-Box (L1) (Q):	0.30	**Jarque-Bera (JB):**	0.34
Prob(Q):	0.58	**Prob(JB):**	0.84
Heteroskedasticity (H):	3.58	**Skew:**	0.26
Prob(H) (two-sided):	0.15	**Kurtosis:**	2.55

Fig 4: Results of the ARIMA (1, 1, 1) model

Let's delve into each element in the results table more thoroughly:

The log likelihood is a measure of how likely the observed data is to be true when using a specific model. In the case of the ARIMA model, the log likelihood measures how well the model fits the time series data.

The formula for log likelihood is as follows:

$$\mathcal{LL} = \sum_{i=1}^{n} log f(x_i \mid \theta) \quad (7)$$

Where

$\mathcal{LL}$ is the log likelihood,

n is the number of observations in the time series,

xi are individual time series observations,

θ are the model parameters,

f(xi | θ) is the probability density function (or probability function) for an individual observation given the parameters.

The goal is to maximize the log likelihood. Maximizing the log likelihood means that the model better fits the data. Maximizing the log likelihood is the same as maximizing the likelihood function since the logarithm is a monotonic function. The log likelihood value in my instance is -153.310. The better the model fits the data, the closer this value is to zero or larger positive values.

Information criteria (AIC, BIC, and HQIC) are measures that assess the quality of a model, taking into account its complexity. Below are the formulas for each of these criteria:

AIC (Akaike Information Criterion): This criterion penalizes the model for complexity, aiming to strike a balance between the model's accuracy and its complexity. A model with a lower AIC is preferred, and a value of 312.620 indicates a relatively good fit to the data.

The formula for AIC is as follows:

$$AIC = -2 \cdot \mathcal{LL} + 2 \cdot k \quad (8)$$

Where:

$\mathcal{LL}$ is the log-likelihood of the model, and k is the number of parameters in the model.

BIC (Bayesian Information Criterion): Similar to AIC, this criterion penalizes the mod-el for complexity, but more strongly. BIC aims to avoid over fitting and is more prefer-able for choosing simpler models. The value of 315.120 might suggest that the model could be slightly more complex. The formula for BIC is expressed as follows:

$$BIC = -2 \cdot \mathcal{LL} + k \cdot log(n) \quad (9)$$

Where n is the number of observations.

HQIC (Hannan-Quinn Information Criterion): Similar to AIC, but it penalizes complexity more. The goal is also to minimize the value. The value of 312.869 indicates a good fit to the data considering the complexity of the model.

The formula for HQIC is defined as follows:

$$HQIC = -2 \cdot \mathcal{LL} + 2 \cdot k \cdot log(log(n)) \quad (10)$$

Where n is the number of observations

Covariance Type: The covariance type indicates the method used in estimating the co-variance matrix of the model parameters. In this case, "opg" (optimal parameter method) is specified.

Optimal Parameter Method (OPG): OPG is one of the methods used to estimate the covariance matrix of model parameters. It is based on the outer product of the gradient of the log-likelihood function (in this case, the log-likelihood of the ARIMA model) and is used to calculate the standard errors of model parameters.

OPG is employed as one of the covariance matrix estimation methods within the maximum likelihood estimation framework. Its use helps to assess the uncertainty of model parameters, providing information about how precise the parameter estimates might be.

Coefficients, Standard Errors, Z-Statistics, and P-Values: These are essential elements for assessing the significance and influence of each coefficient in the model.

Confidence Intervals: Confidence intervals represent ranges of values within which we can expect the true value of a parameter to lie with a certain probability. Confidence intervals [0.025, 0.975] typically correspond to a 95% confidence level. Confidence intervals help assess the level of uncertainty around the coefficient estimate, aiding re-searchers in understanding how confidently they can rely on the model predictions.

Ljung-Box Test: The Ljung-Box test is used to determine whether autocorrelation is present in the model's residuals. This test's null hypothesis states that the residuals at the given lags show no statistically significant autocorrelation. Formula for Calculating the Q-Statistic in the Ljung-Box Test:

$$Q = n \cdot (n+2) \cdot \sum_{k=1}^{h} \frac{\hat{\rho}_k^2}{n-k} \quad (11)$$

Where n is the number of observations, h is the number of lags, and $\hat{\rho}_k^2$ is the estimated autocorrelation at lag k.

The Jarque-Bera test checks whether the residuals of the model follow a normal distribution. The null hypothesis asserts that the residuals are normally distributed.

Formula for the JB statistic:

$$B = \frac{n}{6}(S^2 + \frac{1}{4}(K^2 - 3)) \quad (12)$$

Where:

- n is the number of observations,
- S is the skewness coefficient,
- K is the kurtosis coefficient.

Low p-values for Q and JB may indicate the presence of autocorrelation in the residuals or a departure from the normal distribution. If p-values are significantly lower than the chosen significance level, the null hypothesis (no autocorrelation or normal distribution) is rejected.

The test for heteroskedasticity is used to examine variability in the model residuals, which may suggest instability in variance. The null hypothesis of this test asserts the absence of heteroskedasticity in the residuals.

H (heteroskedasticity): This value is the statistic for the test of heteroskedasticity. The value of 3.58 may indicate the presence of heteroskedasticity, but assessing its significance requires analyzing the p-value.

Prob (H) (P-value): The p-value for the heteroskedasticity test is as follows: The value of 0.15 does not meet the standard significance level of 0.05. It is not possible to rule out the null hypothesis that there is no heteroskedasticity because of a high p-value. Therefore, there isn't any statistically significant proof of heteroskedasticity according to this test.

Skewness (Skew): The value of 0.26 indicates that the data has a slight positive skew-ness.

Kurtosis: The value of 2.55 indicates that the data's kurtosis is relatively high.

Evaluation of the Second ARIMA (2, 1, 2) Model

Based on the analysis of ACF and PACF plots, it was assumed that the ARIMA model could have initial parameters (p, d, q) equal to (1, 1, 1) or (2, 1, 2). Now, we will analyse the second model (2, 1, 2).

The log likelihood is -151.135. This value is used to evaluate how well the model fits the data. In this case, the closer the value is to zero or larger positive values, the better.

AIC (Akaike Information Criterion): 312.271. This criterion balances the accuracy of the model with its complexity. A model with a lower AIC value is preferable.

BIC (Bayesian Information Criterion): 316.437. Similar to AIC, BIC evaluates the model's quality considering its complexity. A model with a lower BIC value is considered better.

HQIC (Hannan-Quinn Information Criterion): 312.685. Similar to AIC and BIC, HQIC helps choose a model considering both quality and complexity. A lower value is preferable.

Coefficients (Coef): Represent the values of the coefficients for each of the ARIMA (2, 1, 2) model parameters.

Standard Errors (Std Err): Indicate the estimated standard deviation for each coefficient.

Dep. Variable:	Trade_Total	No. Observations:	18
Model:	ARIMA(2, 1, 2)	Log Likelihood	-151.135
Date:	Fri, 19 Jan 2024	AIC	312.271
Time:	15:08:48	BIC	316.437
Sample:	0	HQIC	312.685
	- 18		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-1.3088	1.361	-0.961	0.336	-3.977	1.359
ar.L2	-0.7428	0.809	-0.918	0.359	-2.329	0.844
ma.L1	1.9560	1.172	1.668	0.095	-0.342	4.254
ma.L2	0.9903	2.156	0.459	0.646	-3.236	5.216
sigma2	2.188e+06	1.41e-06	1.56e+12	0.000	2.19e+06	2.19e+06

Ljung-Box (L1) (Q):	0.16	Jarque-Bera (JB):	0.07
Prob(Q):	0.69	Prob(JB):	0.97
Heteroskedasticity (H):	1.71	Skew:	-0.14
Prob(H) (two-sided):	0.53	Kurtosis:	2.86

Fig 5: Results of the ARIMA Model (2, 1, 2)

z-Statistics (z): Values of z-statistics to test the significance of each coefficient.
P>|z| (P-values): Probabilities that the corresponding coefficient is not significant (null hypothesis rejected).
Confidence Intervals (0.025, 0.975): Intervals within which the true value of the coefficient is expected with a certain probability.
sigma2: Estimate of the variance of model errors.
Ljung-Box Test (L1) (Q): Value 0.16 - Q statistic for the first lag in the Ljung-Box test. The P-value of 0.69 is above the standard significance level of 0.05, providing no grounds to reject the null hypothesis of no statistically significant autocorrelation in the residuals.
Jarque-Bera Test (JB): Value 0.07, a Jarque-Bera statistic for testing the normality of the residual distribution. The P-value of 0.97 is also above the standard significance level of 0.05, providing no grounds to reject the null hypothesis of a normal distribution of residuals.
Heteroskedasticity Test (H): Value: 1.71 with a p-value of 0.53. A low p-value would reject the null hypothesis of no heteroskedasticity. In this case, the hypothesis is not rejected.
Skew (Skew): 0.14 - a measure of asymmetry in the data.
Kurtosis (Excess): 2.86, a measure of excess in the data.

Model Comparison and Selection
In this section, a comparison is made between two ARIMA models, ARIMA (1, 1, 1) and ARIMA (2, 1, 2), for forecasting trade data between China and Turkmenistan. The analysis results are presented in the previous sections, and in this section, we will conduct a comprehensive comparison and make a decision regarding the model selection.
Mean Squared Error (MSE) is a metric used to measure the average squared difference between actual and predicted values in a dataset. It provides the average magnitude of prediction errors, where each error is squared before computing the average. The MSE formula looks like this:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad (13)$$

Where:
n is the number of observations, Yi is the actual value, and $\hat{Y}_i$ is the predicted value.
The smaller the MSE value, the more accurate the model. MSE is widely used in assessing the performance of forecasting models, such as time series and regression models.

Table 2: Comparison of two models

Model Parameters	ARIMA (1,1,1)	ARIMA (2,1,2)
Selected Parameters	(p, d, q) = (1,1,1).	(p, d, q) = (2,1,2).
Model Coefficients	AR.L1:-0.4466 MA.L1: 0.9995	AR.L1: -1.3088, AR.L2: -0.7428, MA.L1: 1.9560, MA.L2: 0.9903
Log Likelihood	-153.310	151.135
AIC	312.620	312.271
BIC	315.120	316.437
HQIC	312.869	312.685
Sigma^2 (sigma2)	3.599e+06	2.188e+06
Performance Evaluation	MSE: 3,599,000	MSE: 2,710,048.8
Ljung-Box Statistics	Q-statistic (L1): 0.30, P-value: 0.58	Q-statistic (L1): 0.16, P-value: 0.69
Jarque-Bera Test	JB-statistic: 0.34, P-value: 0.84	JB-statistic: 0.07, P-value: 0.97
Heteroskedasticity	H: 3.58, P-value: 0.15	H: 1.71, P-value: 0.53
Skewness (Skew)	0.26	-0.14
Kurtosis	2.55	2.86

The ARIMA (1, 1, 1) model is characterized by the following parameters: AR. L1 = -0.4466, MA. L1 = 0.9995. The mean squared error (MSE) for this model is 3,599,000. The ARIMA (2, 1, 2) model has parameters: AR. L1 = -1.3088, AR. L2 = -0.7428, MA. L1 = 1.9560, MA. L2 = 0.9903, with an MSE of 2,710,048.8:

The Ljung-Box test was conducted for both models, showing Q-statistics and P-values. For ARIMA (1, 1, 1), the P-value is 0.58, indicating no autocorrelation in the residuals. Similarly, for ARIMA (2, 1, 2), the P-value is 0.69. The Jarque-Bera test confirms the normality of residuals for both models, with P-values above 0.05. Heteroskedasticity values, skewness, and kurtosis parameters were also considered.

The comparison was based on the mean squared error (MSE). ARIMA (2, 1, 2) demonstrated better performance with an MSE of 2,710,048.8 compared to the MSE of 3,599,000 for ARIMA (1, 1, 1). Based on the analysis and comparison of model performance, ARIMA (2, 1, 2) is chosen for further use due to its lower mean squared error. Future plans involve using this model for time series forecasting.

Forecasting and Discussion

In this section, the process of forecasting fuel trade dynamics between Turkmenistan and China based on the ARIMA (2, 1, 2) model is presented. This model was selected for predicting future trends in trade based on historical data from 2005 to 2022. The application of the ARIMA method allows not only the analysis of past data but also the creation of informed forecasts about the future, which is crucial for understanding changing trends in international fuel trade.

To assess the accuracy of the forecast, standard metrics, including Mean Squared Error (MSE), were used, allowing an evaluation of the model's effectiveness in predicting future trends. Forecasts obtained using the ARIMA (2, 1, 2) model indicate the expected trade volumes between China and Turkmenistan in the fuel sector (in billions of US dollars) for the period from 2023 to 2027:

The smaller the MSE value, the more accurate the model. MSE is widely used in assessing the performance of forecasting models, such as time series and regression models.

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Table 3: Forecasted numbers for the period from 2023 to 2027(in billions of US dollars)

Year	Bilateral Trade Forecast in Fuels
2023	9,427.77
2024	8,351.87
2025	10,377.11
2026	8,525.63
2027	9,444.55

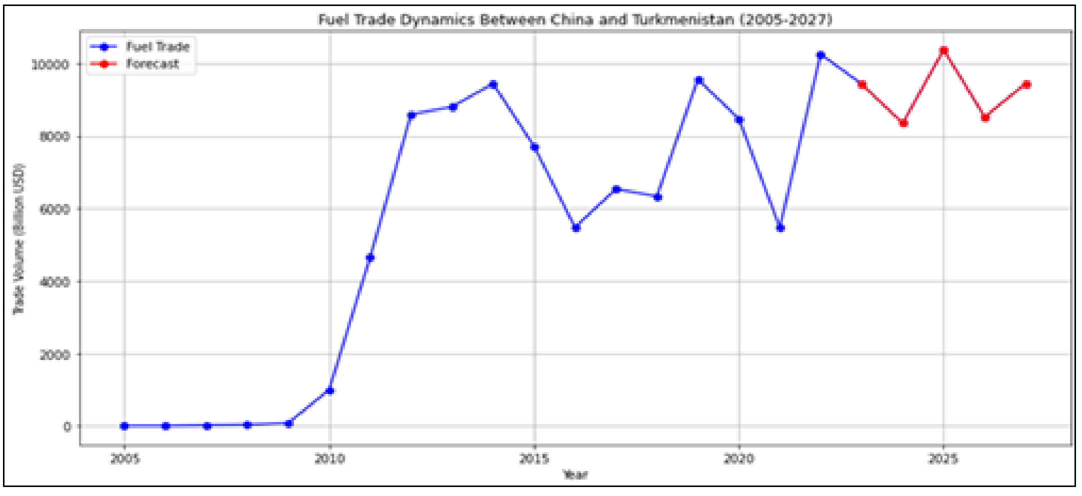

Fig 6: Fuel Trade Dynamics between China and Turkmenistan (2005-2027)

These forecasts reflect expected trends based on the analysis of time series and historical data. It is important to note that actual trade values may differ due to various factors, including economic, political, and global events, which may not always be possible to account for within the ARIMA model.

Analyzing the factors influencing the forecasts, the following aspects can be highlighted

Economic Growth and Consumption: China's increasing demand for natural gas is a direct result of its rapid economic growth and industrialization. This growing demand significantly influences the global natural gas market, particularly in terms of trade relations and cooperation between exporting countries and China. On one hand, China aims to ensure energy security and stability in its economic growth, requiring a reliable and consistent natural gas supply. On the other hand, countries with substantial gas reserves, such as Turkmenistan, see the increasing Chinese demand as an opportunity to expand their exports and strengthen economic ties. Furthermore, China views natural gas as a greener energy source than conventional fossil fuels like coal and oil, in keeping with worldwide environmental trends and the nation's commitment to reducing carbon emissions. This quickens the switch to more environmentally friendly energy sources and increases demand for natural gas. Therefore, China's increasing demand for natural gas and its initiatives to expand trade and collaboration in the gas industry are vital in determining the nation's energy strategy and have a big impact on global energy markets.

Geopolitical Stability: Geopolitical stability plays a critically important role in the development and success of gas projects, especially in the relations between Turkmenistan and China. Stability in the region and strong bilateral relations between these countries create a favorable environment for implementing large-scale energy initiatives and investments. Turkmenistan and China maintain long-term, stable political relations, providing a reliable foundation for energy cooperation. The significance of political stability cannot be underestimated, as it reduces risks for long-term investment projects such as the construction of gas pipelines. The economic interests of both countries converge in the energy sector. China, as one of the world's largest consumers of energy resources, seeks reliable supply sources, while Turkmenistan, with substantial natural gas reserves, aims to expand its exports. These mutual interests contribute to the strengthening of economic ties. The enhancement of the strategic partnership between China and Turkmenistan encompasses not only energy resource trade but also joint projects in infrastructure development and technologies. This partnership builds trust and cooperation on a broader geopolitical level. Stability in the Central Asian region is crucial for the unimpeded implementation of gas projects. The security of gas pipelines and other infrastructure from external threats and regional conflicts is a key factor in ensuring continuous gas supply. The development and signing of international agreements and agreements between Turkmenistan, China, and other regional countries contribute to establishing a legal framework for gas projects, thereby reducing political and legal risks. These aspects of geopolitical stability directly impact the success of gas projects, such as pipeline construction, field exploitation, and the expansion of trade networks. By guaranteeing stability and predictability, they provide the necessary conditions for attracting investments, risk management, and effective planning of long-term energy strategies [26].

Technological Cooperation: Technological cooperation between Turkmenistan and China plays a key role in strengthening their energy relations. This aspect involves the exchange of advanced technologies and joint efforts in developing gas fields, leading to a significant improvement in production processes and overall efficiency. Turkmenistan can benefit from advanced Chinese technologies in the gas industry, allowing the country to modernize its infrastructure and enhance the efficiency of natural gas extraction. In turn, China gains access to Turkmenistan's vast natural gas reserves, securing its energy needs. Joint projects for gas field development contribute to the exchange of knowledge and experience between the two countries, reinforcing their technical expertise. Such projects may include collaborative research, the development of new gas extraction methods, and the use of advanced technologies to increase production. The application of cutting-edge technologies helps improve the efficiency of production processes, reduce resource losses, and mitigate environmental impact. This also involves refining resource management techniques and enhancing extraction safety. Technological cooperation between countries promotes economic growth, job creation, and the development of local communities. It also strengthens trade relations between the nations, making their economies more interdependent and resilient. Such collaboration not only strengthens bilateral relations between Turkmenistan and China but also makes a significant contribution to regional and international energy security. By jointly working on technological innovations and developments, both countries contribute to the stability and sustainable development of the global energy market.

Ecological Requirements: Ecological requirements play a key role in the collaboration between Turkmenistan and China in the energy sector. Both states recognize the importance of sustainable and environmentally friendly development in energy-related projects. The following are more detailed aspects of the impact of ecological requirements on cooperation between Turkmenistan and China:

Both countries place significant importance on reducing emissions of natural gas into the atmosphere during its extraction and processing. Effective gas purification and combustion systems contribute to reducing environmental impacts.

Environmentally friendly technologies include the use of renewable energy sources, such as solar and wind energy, leading to a reduced dependency on fossil fuels and a decrease in greenhouse gas emissions.

Both nations adhere to strategies for increasing energy efficiency in industrial processes and everyday life. This involves improving the energy efficiency of equipment and infrastructure.

National and international ecological standards and regulations are followed in the cooperation between Turkmenistan and China, ensuring compliance with high ecological requirements during project implementation.

Both states invest in research and development aimed at creating more environmentally friendly technologies in the energy sector, fostering the emergence of new solutions to reduce environmental impact.
Collaboration in the field of environmentally friendly technologies and sustainable development may include joint projects for the development and implementation of environmentally effective solutions in the energy sector. Overall, ecological requirements are becoming increasingly important and shaping the future collaboration between Turkmenistan and China in the energy sector, advocating for more sustainable and environmentally friendly practices in this strategically vital area.

World Gas Market Dynamics: Changes and competition in the world gas market can significantly impact gas pricing and supply conditions between Turkmenistan and China. Fluctuations in gas prices and changes in demand globally can affect the profitability of trade and the selection of transit routes.

Trade and Economic Agreements: Mutual commitments and strategic partnerships between Turkmenistan and China play a key role in determining the long-term perspective of trade relations. Agreements and contracts between the countries may include supply volumes, prices, terms, and other conditions that can vary depending on the current situation.

Energy Security: Ensuring energy security is important for both countries. For Turkmenistan and China, this may involve diversifying energy sources, a variety of transit routes, and strengthening cooperation in the energy sector. Ensuring reliable supplies and minimizing risks are priorities for the energy security of both nations.

Current Trends in the Turkmenistan-China Gas Trade

According to the data from China's General Customs Administration, Turkmenistan maintains its leading position in pipeline gas supplies to China from January to May 2023. The total trade volume of fuel between the two countries during this period amounted to $4.25 billion, reflecting a growth of approximately 13.5% compared to the same period the previous year. This indicates the stable and promising nature of trade relations between Turkmenistan and China in the energy sector. These figures affirm the significance of Turkmen gas for China's energy security and the longevity of cooperation between the two countries. Turkmenistan remains a key supplier of natural gas to China, fulfilling a substantial portion of its energy needs. In February 2022, a crucial agreement was reached on the construction of the fourth gas pipeline connecting Turkmenistan and China. This significant development marks a new stage in the energy cooperation between the two countries. The construction of the fourth gas pipeline is expected to increase annual gas supplies from Turkmenistan to China to an impressive volume of 65 billion cubic meters. This step demonstrates Turkmenistan's intention to strengthen its role as a reliable supplier of natural gas to China. In 2021, Turkmenistan had already exported around 34 billion cubic meters of natural gas to China. However, according to China's General Customs Administration, from January to November 2023, the volume of Turkmen pipeline gas deliveries to China amounted to $8.82 billion, slightly less than the $9.28 billion for the same period the previous year. Following Turkmenistan in the list of leading gas suppliers to China are Russia, Myanmar, and Kazakhstan. Uzbekistan ranks fifth, with its gas deliveries nearly halved, reaching $509.03 million. After the commissioning of a pipeline that China built through Uzbekistan and Kazakhstan, the first gas deliveries from Turkmenistan to China started in December 2009.
China also imports liquefied natural gas (LNG), with Australia being the largest supplier in this category. However, despite the diversity of sources, Turkmen gas remains a priority for China. Experts claim that Beijing aims to secure reliable and stable supplies of natural gas and protect itself from potential fluctuations in the LNG market. To achieve this, China is preparing to implement the construction project of the fourth branch (D) of the pipeline through Uzbekistan, Tajikistan, and Kyrgyzstan, significantly increasing the volume of Turkmen gas supplies from the current 40 billion cubic meters to 65 billion cubic meters annually.

Conclusion

During this study, an analysis and forecast of fuel trade dynamics between Turkmenistan and China were conducted using the ARIMA method. To forecast trade between China and Turkmenistan in the fuel sector, two ARIMA models were considered: ARIMA (1, 1, 1) and ARIMA (2, 1, 2), and it was decided to choose ARIMA (2, 1, 2) as more efficient. The study covered the period from 2005 to 2022 and aimed to identify key trends and potential changes in trade volumes in the coming years. Using this method, a forecast of fuel trade was made from 2023 to 2027. Several methods were applied within the study to ensure the accuracy and reliability of the analysis. Plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) were two important tools. These plots assisted in identifying the most important lags (delays) for the model and whether the data exhibit temporal dependence. ACF measured the correlation between time series observations at different time lags, allowing the determination of the overall degree of autocorrelation in the data. In contrast, PACF measured the correlation between observations while accounting for the impact of intermediate lags, which is crucial when figuring out the parameters of the AR component of the ARIMA model.
In addition, a number of statistical tests were performed to confirm that the time series were stationary. A time series is said to be stationary if its statistical features, like mean and variance, hold steady over the course of the series. Non-stationary series often require transformations, such as differencing, to become suitable for analysis using ARIMA.
These tools and methods made it easier to find the right ARIMA model parameters for studying and predicting how fuel trade between Turkmenistan and China would change over time. This made sure that the research was reliable and useful. The Python programming language, along with relevant libraries, was used to implement the chosen methodology.
In the "Results and Discussion" section, the estimates of both models were compared, and it was revealed that ARIMA (2, 1, 2) has a smaller mean squared error (MSE), making it more accurate for forecasting. Based on the selected model, projections for the following five years were given. The study emphasized the importance of the two

nations' energy cooperation in light of global energy trends and economic growth. Based on the analysis of time series and historical data, forecasts were formulated, indicating sustainable growth in fuel trade from 2023 to 2027.

Findings

Model Selection and Forecasting Accuracy

The ARIMA (2, 1, 2) model demonstrated superior forecasting accuracy, as evidenced by a lower mean squared error (MSE) compared to ARIMA (1, 1, 1).

Autocorrelation and partial autocorrelation analyses played a crucial role in identifying temporal dependencies and determining significant lags for the model.

Trade Dynamics and Historical Trends

Historical data from 2005 to 2022 revealed consistent growth in fuel trade volumes between Turkmenistan and China.

The sustained importance of energy cooperation between the two nations was highlighted, reflecting a robust and enduring partnership.

Potential Future Trends

Forecasts based on the ARIMA (2, 1, 2) model indicated a stable growth trajectory in fuel trade from 2023 to 2027.

The findings suggest a positive outlook for the energy partnership, aligning with global energy trends and economic development.

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References

1. Amineh MP, Van Driel M. China's Statist Energy Relations with Turkmenistan and Kazakhstan. African and Asian Studies. 2018;17(1-2):63-89. https://doi.org/10.1163/15692108-12341401
2. Annameredova L. A Study on the Trade Competitiveness of Agricultural Products in Turkmenistan and China. Science Innovation. 2017;5(1):27. https://doi.org/10.11648/j.si.20170501.15
3. Bandyopadhyay G. Gold Price Forecasting Using ARIMA Model. Journal of Advanced Management Science. 2016;4(2):117-121. https://doi.org/10.12720/joams.4.2.117-121
4. Callula Salsabillah. Regional Challenges and Competition in the Application of Public Diplomacy in East Asian Countries Year 2008. Journal of Social Science. 2021;2(1):11-19. https://doi.org/10.46799/jsss.v2i1.81
5. Erkan AÇ. The West Alternative in Turkmenistan's Energy Security. MANAS Sosyal Araştırmalar Dergisi. 2023;12(2):691-715. https://doi.org/10.33206/mjss.1230579
6. Eu R, Times E. Европейская энергетическая безопасность и Туркменистан; c2023. p. 61-64.
7. Hassan S, Jaafar J, Belhaouari BS, Khosravi A. A new genetic fuzzy system approach for parameter estimation of ARIMA model. AIP Conference Proceedings. 2012;1482:455-459. https://doi.org/10.1063/1.4757513
8. Herranz-surrallés A. Handbook of Energy Governance in Europe. Handbook of Energy Governance in Europe. 2020. https://doi.org/10.1007/978-3-319-73526-9
9. Hoh A. China's Belt and Road Initiative in Central Asia and the Middle East. Digest of Middle East Studies. 2019;28(2):241-276. https://doi.org/10.1111/dome.12191
10. Jakub J, Marszewski M. Crisis in Turkmenistan. A test for China's policy in the region. OSW Commentary. 2018;284:1-6. https://www.osw.waw.pl/sites/default/files/commentary_284_0.pdf
11. Yan J, Han W. Opportunities and risks in trade between China and Turkmenistan and prevention and control measures that should be taken. Economic Systems Research. 2022;35(3):354-375. https://doi.org/10.1080/09535314.2023.2174002
12. Ovezdyrdyyev K, Zhang B. Research on Economic and Trade Cooperation Problems and Countermeasures between China and Turkmenistan. Open Journal of Business and Management. 2020;8(01):357-368. https://doi.org/10.4236/ojbm.2020.81022
13. Saputra MF, Rizky M. Forecasting Number of Cases of Acute Respiratory Infection (ARI) in 2019 Using ARIMA Method. Jurnal Biometrika Dan Kependudukan; c2019 May. p. 138-145.
14. Sun Y, Tian L, Li M, Liu Z, Liu J, Liu C. Research on ARIMA Parameter Model Analysis Method Based on Plant Electrical Signal. 2021 7th International Conference on Control, Automation and Robotics, ICCAR 2021; c2021. p. 256-260. https://doi.org/10.1109/ICCAR52225.2021.9463471
15. Vepayev A, Deniz O. Production and Consumption Trends of Natural Gas of Turkmenistan the Years from 2009 to 2019. Health Sciences Quarterly. 2020;4(4):237-244. https://doi.org/10.26900/jsp.4.020
16. Wang W, Fan LW, Zhou P. Evolution of global fossil fuel trade dependencies. Energy. 2022;238:121924. https://doi.org/10.1016/j.energy.2021.121924
17. Xiao Z, Phillips PCB. An ADF coefficient test for a unit root in ARMA models of unknown order with empirical applications to the US economy. The Econometrics Journal. 1998;1(2):27-43. https://doi.org/10.1111/1368-423x.12016
18. Yang Z, Huang D, Wang Y. Measuring the Bilateral Energy Security Cooperation Sustainability between China and Its Neighboring Countries Based on the National Energy Security Level. Sustainability. 2023;15(2):1339. https://doi.org/10.3390/su15021339
19. Zhao H, Guo S. Carbon Trading Price Prediction of Three Carbon Trading Markets in China Based on a Hybrid Model Combining CEEMDAN, SE, ISSA, and MKELM. Mathematics. 2023;11(10). https://doi.org/10.3390/math11102319
20. Zhao Y, Zhao H, Li B, Wu B, Guo S. Point and interval forecasting for carbon trading price: a case of 8 carbon trading markets in China. In Environmental Science and Pollution Research. 2023;30(17). https://doi.org/10.1007/s11356-023-25151-0
21. Великий Шелковый путь история и современностьодитель. 2017.
22. ЭКОНОМИЧЕСКАЯ ПОЛИТИКА КИТАЯ В ПОСТСОВЕТСКОЙ ЦЕНТРАЛЬНОЙ АЗИИ; c2018. p. 86-95.
23. International Energy Agency. Natural Gas Information

2021; c2021. Available from: https://www.iea.org/reports/natural-gas-information-2021
24. Ministry of Energy of Turkmenistan. Turkmenistan's Energy Strategy; c2022. Available from: http://www.energy.gov.tm/en/
25. Xinhua. China-Turkmenistan gas pipeline to further boost energy cooperation; c2023. Available from: http://www.xinhuanet.com/english/2023-01/11/c_139657158.htm