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Forecasting Natural Gas Consumption in Turkey using fractional nonlinear grey Bernoulli model optimized by Grey Wolf Optimization (GWO) Algorithm

Abstract

Natural gas stands as an indispensable energy source, integrated to the daily operations of countries worldwide, serving as a primary energy input for various industries, homes, and sectors. The predominant driver behind the escalating trend in natural gas consumption is rooted in its distinctive environmental profile, characterized by a relatively lower carbon emissions footprint. Recognized as the most environmentally friendly among fossil fuels, natural gas has become the preferred choice, reflecting a conscious effort to mitigate environmental impact and promote sustainability in energy consumption patterns in the world. Especially, in developing countries like Turkey, effective management of energy resources and the formulation of policies centred on the production and consumption of natural gas necessitate accurate forecasting. This study, thus, focuses on forecasting natural gas consumption in Turkey, employing the Fractional Nonlinear Grey Bernoulli Model (FANGBM(1,1)) optimized by Grey Wolf Optimizer (GWO). Firstly, the parameters are optimized by using GWO for an accurate forecasting to be used through the metaheuristic model FANGBM(1,1). After using GWO-FANGBM (1,1) model to forecast natural gas consumption in Turkey, a comparative study has been performed including GM(1,1) and GWO-GM(1,1). The predictive performance of these models is compared with ARIMA and linear regression. Notably, numerical results reveal that the proposed hybrid model GWO-FANGBM(1,1) model surpasses other grey models, such as GM(1,1) and GWO-GM(1,1), as well as statistical methods like ARIMA and linear regression. Numerical results show that the proposed hybrid model, GWO-FANGBM(1,1), achieves superior prediction accuracy with a MAPE of 5.82%, an RMSE of 3857.12, and an MAE of 3062.00, outperforming GM(1,1), GWO-GM(1,1), ARIMA, and LR. The originality of the study is supported by the fact that a hybrid approach named as GWO-FANGBM(1,1) has not been used in the literature to forecast natural gas consumption in Turkey with an accurate parameter optimisation.

Keywords: Natural Gas Consumption, Grey Forecasting, Fractional NGBM(1,1), Grey Wolf Optimizer, Parameter Optimization.

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1. Introduction

As natural gas has emerged as the primary energy resource fostering sustainable development, there has been a substantial and burgeoning global demand for this invaluable energy commodity (Liu et al., 2021). It is highlighted that natural gas consumption is presently one of the most vital and substantial energy sources worldwide, constituting one-fifth of global energy production, following coal and oil. The Global Gas Report (2024) projects that NGC will rise significantly, reaching 5,179 million tons of oil equivalent (Mtoe) by 2040 (Raza and Lin, 2023). The main reason about the increase of natural gas consumption can be stated as the fact that natural gas stands out for its relatively lower carbon emissions footprint, regarded as the most environmentally friendly among fossil fuels (Alam et al., 2024). In this context, it is argued that increasing the consumption of natural gas and renewable energy can reduce CO2 emissions. Specifically, a 1% increase in natural gas consumption is projected to decrease CO2 emissions by 0.1641%, while a 1% increase in renewable energy consumption is expected to reduce CO2 emissions by 0.2601% for the BRICS countries (Dong et al., 2017). Furthermore, natural gas has emerged as the swiftest expanding fossil fuel, boasting an annual growth rate of 1.9 percent. In contrast, coal, which is the slowest-growing fuel, is anticipated to be eclipsed by the ascendancy of natural gas by the year 2030 (Cesur et al., 2018; U.S. Energy Information Administration, 2023).

Contemporary environmental initiatives are increasingly pivoting towards energy sources characterized by reduced carbon emissions, placing natural gas at the forefront of this transition (Svoboda et al., 2021; Soldo, 2012). As an environmentally friendly energy source, the predominant utilization of natural gas occurs within urban centres, where it serves as a primary source for daily heating and electricity generation (Wei et al., 2019). On the other hand, in light of its myriad advantages, natural gas has found extensive application in diverse sectors including power generation, transportation, aviation and chemical engineering, emerging as a pivotal catalyst for social and economic development in recent years, playing a central role in advancing various facets of contemporary society. Consequently, ensuring the uninterrupted supply of natural gas poses inherent challenges to contemporary natural gas management practices (Wei et al., 2019; Soldo et al., 2014).

In upper-middle income countries, Turkey is recognized as one of the prominent emerging nations, demonstrating substantial economic growth and ranking as the 17th largest economy globally with a noteworthy gross domestic product (GDP) of $1.154 trillion in 2023 (World Bank, 2023; Beyca et al., 2019). Considering natural gas consumption and production, while Turkey possesses limited proven natural gas reserves, it strategically occupies an advantageous position within the natural gas market. Situated geographically between Europe and the energy-rich nations of Central Asia, Turkey emerges as a potential energy corridor facilitating the seamless transportation of natural gas between these two pivotal regions (Cetin and Oguz, 2018). However, the factual reality is that Turkey's rapidly expanding economy is actively striving to integrate into the European Union's economic framework, aiming to attain a level of economic growth that positions it in competition with certain EU member states(Saatçioğlu, 2020; Erat et al., 2021). This trajectory inevitably results in an escalation of Turkey's energy demand, a demand that cannot be fully satisfied by its domestic natural energy sources (Telli et al., 2021). Simultaneously, the significant political risks present in the region may also hinder the country from initiating new pipeline projects and exploring supply options, although they may also compel a preference for one option over another (Austvik and Rzayeva, 2017), implying that a substantial portion of the primary energy resources, encompassing oil, coal, natural gas, etc., is necessitated to be imported from external sources, prominently including Russia, Iran, Algeria, and Nigeria (Taşpınar et al., 2013; Melikoglu, 2013). Furthermore, Boran (2014) stated that Turkey is among the world's fastest-growing natural gas markets, driven by pipeline gas and liquefied natural gas (LNG) sales. The country has signed purchase contracts with the Russian Federation, Algeria, Nigeria, Iran, and Turkmenistan. However, Turkey has primarily relied on domestic and renewable resources to meet its energy needs, aiming to reduce energy imports, alleviate the economic burden of energy dependence, and ensure energy security. Recent studies indicate that fossil fuels, which account for about 85% of global energy consumption, are nearing depletion. As of 2018, the global reserve-to-production ratios for oil, natural gas, and coal indicate that existing reserves are sufficient for approximately 50, 51, and 132 years of current production, respectively (Eygu and Soğukpınar, 2023; Erat et al., 2021; Alola and Donve, 2021).

In this vein, the anticipated rise in natural gas demand in Turkey is underlined by the potential benefits associated with its usage, encompassing factors such as price competitiveness and environmental considerations. However, geopolitical events, such as regional conflicts and diplomatic relations, alongside international energy market dynamics, including fluctuations in global natural gas prices and supply chain disruptions, significantly influence natural gas consumption patterns in Turkey by affecting both availability and cost. Additionally, regulatory changes within Turkey, such as shifts in energy policy, subsidies, and environmental regulations, further shape domestic natural gas demand by altering the economic incentives and legal framework for energy use (Berk and Ediger, 2018; Biresselioglu et al., 2019). Accurate predictions of natural gas consumption, thus, assume paramount significance for energy policymakers, playing a pivotal role in informing strategic planning for future energy sources (Boran, 2014). In addition, it’s worth to note that the intricate interplay between a varied consumer base and the crucial constraints of the natural gas grid renders forecasting inherently complex and uncertain (Anagnostis et al., 2020).

In this study, we, thus, offer a novel framework by introducing a novel hybrid approach Fractional Nonlinear Grey Bernoulli Model (FANGBM (1,1)) optimized by Grey Wolf Optimizer (GWO) to forecast natural gas consumption in Turkey. This study provides not only a novel approach but also a comparison of the results of our proposed model and traditional grey Bernoulli models as well as linear regression and ARIMA models. Significantly, the numerical findings demonstrate that our hybrid GWO-FANGBM (1,1) model outperforms other grey models, including GM(1,1) and GWO-GM(1,1), as well as conventional statistical methods like ARIMA and linear regression. Given that this underscores its superior predictive accuracy in the given context. The originality of our novel hybrid approach is triggered by the fact that this method has not been used to forecast the natural gas consumption in Turkey.

The remainder of the study is as follows. The next section of the study provides a background to investigate the existing literature related to natural gas consumption in the world and specifically in Turkey. Then, fractional nonlinear grey Bernoulli model and grey wolf optimization are described. In the fourth section, the developed hybrid GWO-FANGBM(1,1) model for prediction of the natural gas consumption are given. Followed by the fourth section, we present our data and our results to discuss our numerical findings integrated with the hybrid approach that we propose. Lastly, we proceed with the limitations and conclusion parts.

2. Literature Review

In the existing literature, a myriad of studies has been employed for energy demand forecasting, with a specific focus on natural gas consumption (Liu et al., 2021; Baldacci et al., 2016; Bai and Li, 2016; Szoplik et al., 2015; Ozcan et al., 2023) by using different techniques. However, as mentioned in the previous section, the originality of our study is underscored by

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the application of a hybrid approach, termed as GWO-FANGBM (1,1), a methodology that has not been previously utilized in the literature for the accurate prediction of natural gas consumption in Turkey, particularly with a focus on parameter optimization. As an overview, Figure 1 shows the distribution of natural gas consumption forecasting studies based on countries geographically (See the appendix for the complete bibliography)

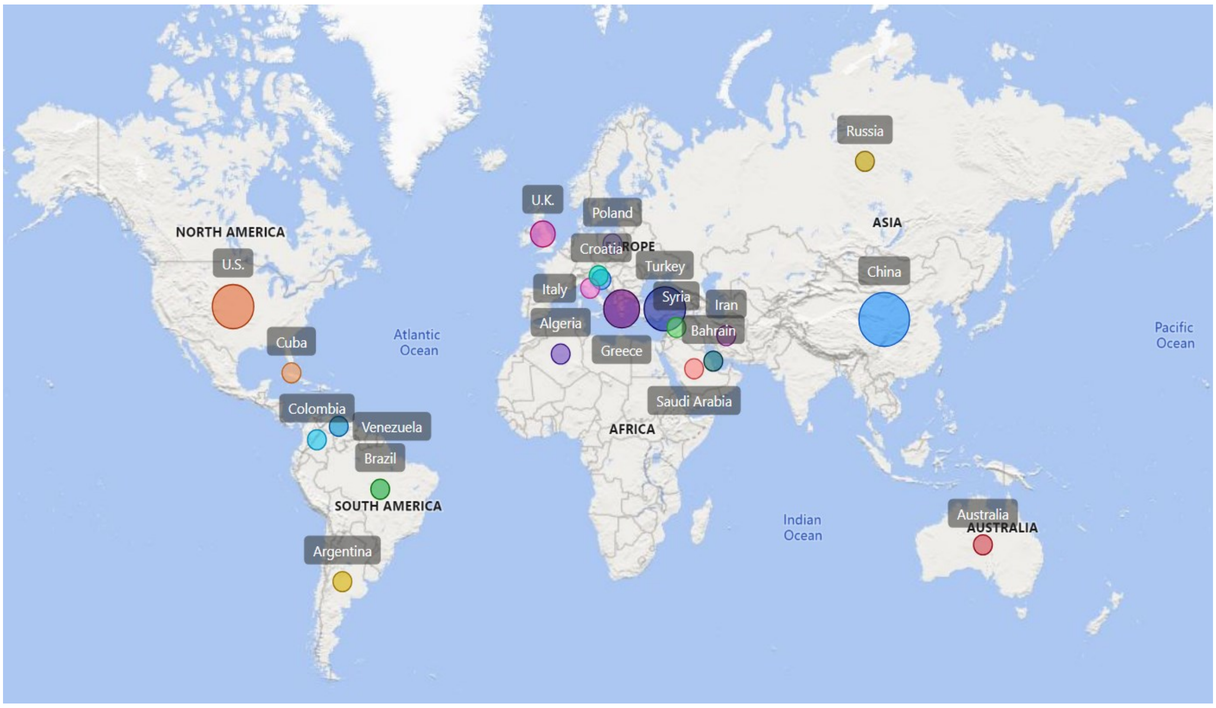

Figure 1. Map of the studies of natural gas consumption forecasting based on countries

Related to the literature review, the studies of natural gas consumption forecasting have been classified based on their methodologies. Figure 2 shows the distribution of methodologies used in natural gas consumption forecasting. Furthermore, the performance metrics used in the studies have been categorised and shown in Figure 3.

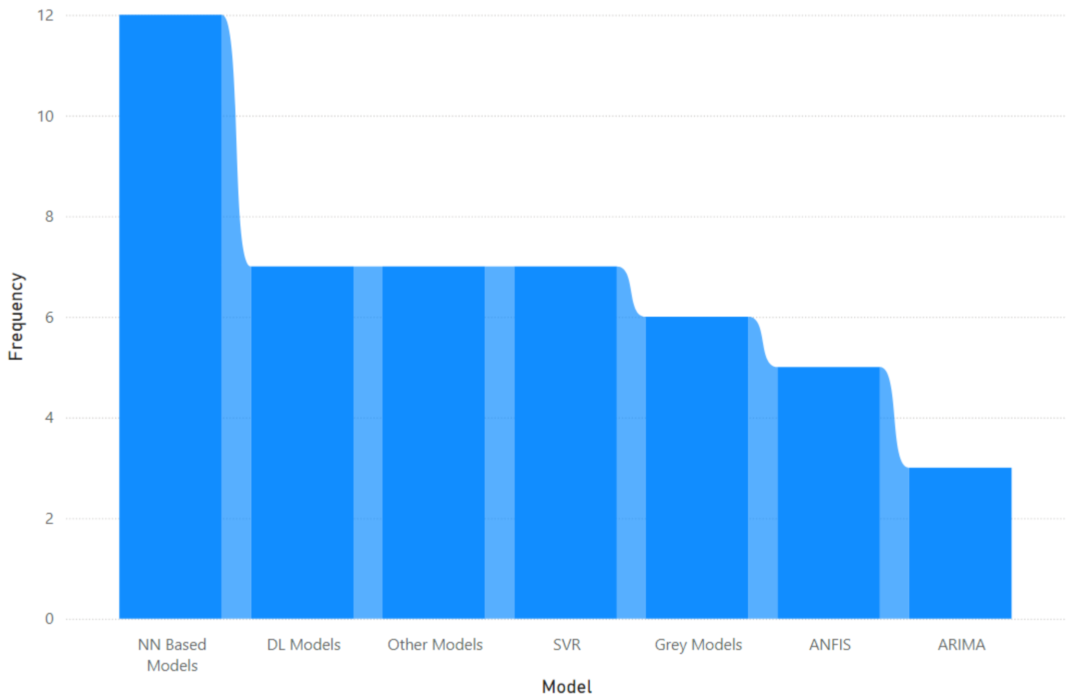

Figure 2. Distribution of the methods to forecast natural gas consumption

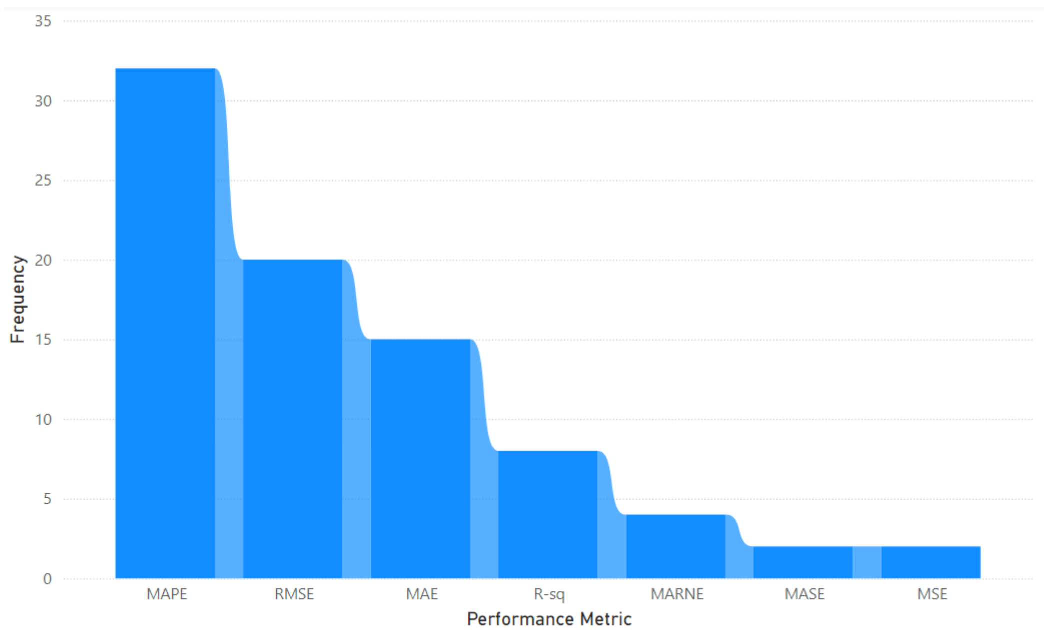

Figure 3. Distribution of the performance metrics used in the studies of forecasting natural gas consumption

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MAE: Mean Absolute Error, **MAPE:** Mean Absolute Percentage Error, **MARNE:** Mean Absolute Range Normalized Error, **MSE:** Mean Square Error, **MRSPE:** Mean relative simulation percentage error, **MRFPE:** Mean relative prediction percentage error

Various methodologies have been employed to specifically predict the natural gas consumption in Turkey, encompassing forecasts at both the national and provincial levels. Taşpınar et al. (2013) focused on modelling of residential natural gas consumption at a regional level in Turkey. Multiple computational methods were employed for this purpose, including Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) and two distinct Artificial Neural Network (ANN) models. These computational techniques were leveraged to analyse and predict patterns in residential natural gas consumption across different regions in Turkey. Melikoglu (2013) generated precise forecasts for Turkey's natural gas demand spanning the years 2013 to 2030. To achieve this goal, the author developed two semi-empirical models grounded in econometrics. These models were based on key indicators, specifically the gross domestic product (GDP) at purchasing power parity (PPP) per capita and demographic factors, specifically population change. The models were constructed using a combination of logistic and linear approaches to enhance accuracy in predicting Turkey's natural gas demand. Boran (2015) used a grey prediction with rolling mechanism (GPRM) approach to forecast natural gas consumption in Turkey. Beyca et al. (2019) presented a precise forecasting model for the natural gas consumption of Istanbul. They achieved this by employing three widely recognized machine learning tools, namely the Support Vector Regression (SVR) model with a polynomial cubic kernel function, and two Artificial Neural Network (ANN) models. These machine learning techniques were applied to enhance the accuracy of predicting natural gas consumption in Istanbul.

3. Methodology

In this section, we aim to provide a concise overview of FANGBM(1,1), Grey Wolf Optimization (GWO) and the proposed hybrid GWO-FANGBM(1,1) model, briefly. FANGBM (1,1) modelling has been described by Wu et al. (2019), which can be applied to engineering problems successfully for forecasting (Xie and Yu, 2020).

The main reason why we offer this hybrid approach to forecast natural gas consumption in Turkey can be stated the superiority of FANGBM(1,1) in terms of forecasting accuracy has been discussed compared to traditional grey models related to forecasting by several scholars in the existing literature (Yang and Wu, 2023; Şahin, 2021; Şahin 2020). At this outset, it's known that several scholars stated that the Grey Wolf Optimizer increases the searching efficiency and accuracy of the parameters when it's integrated with FANGBM(1,1) (Wang et al., 2022; Xie et al., 2021; Yin and Mao, 2023).

3.1. Grey Forecasting

Grey systems theory, initially developed by Deng (1982), is employed to address uncertainties arising from discrete data and incomplete information. The key advantages of grey systems theory lie in its ability to yield successful outcomes with relatively limited data under conditions of uncertainty (Xu et al., 2011; Kayacan et al., 2010). Moreover, it facilitates the analysis and modeling of systems with restricted or incomplete information. Grey systems theory encompasses five fundamental components: grey forecasting, grey relational analysis, grey decision making, grey programming, and grey control (Wei, 2011). Of these, grey forecasting plays a pivotal role in the current study (Ren et al., 2012).

It's worth to note that in comparison to traditional statistical prediction models, grey prediction models offer several advantages. However, these advantages are limited compared to FANBGM (1,1) models (Yang and Wu, 2023). These advantages related to grey prediction models can be as follows (Tsai, 2016; Ren et al., 2012).

1. Grey prediction models are particularly useful when the available data for traditional statistical methods is insufficient. These models require only small datasets to effectively describe system behavior. And knowledge of the distribution of sample populations is not obligatory.

2. The original data's noise is mitigated through the application of the Accumulated Generating Operation (AGO).

3. Grey prediction models involve straightforward calculations (Tsai, 2016).

3.2. The Fractional Nonlinear Grey Bernoulli Model (FANGBM(1,1))

The methodology of the FANGBM (1,1) model can be elucidated through the following sequential steps (Wu et al., 2019; Şahin and Şahin, 2020). Thus, step by step overview of FANGBM (1,1) model can be seen as follows:

Step 1: The original data sequence $X^{(0)}$ is formed as seen in the equation 1. ($\mathrm{r-AGO}$)

$$X^{(0)} = \left\{X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \dots\dots, X^{(0)}(n)\right\} \qquad (1)$$

Here, 'n' denotes the length of the sequence or the quantity of the original data.

Step 2: Transforming the $X^{(0)}$ to the $X^{(r)}$ involves the application of the rth Accumulated Generating Operation, donated as ($\mathrm{r-AGO}$) where 'r' represents a fractional order value greater than 0 as given in the equation (2)

$$X^{(r)}(k) = \sum_{i=1}^{k} X^{(r-1)}(i) \quad , k = 1,2,3 \dots, n \qquad (2)$$

And, $X^{(r)}$ can be also written in the matrix form as seen in the equation (3)

$$X^{(r)} = A^r X^{(0)} \qquad (3)$$

Here, one may note that A^r denotes the r-th order accumulated generating matrix, while A^{-r} represents the inverse accumulated generating operation matrix. In the matrix form, the forms of A^r and A^{-r} can be expressed through the following equations as given in (4) and (5) respectively.

$$A^r = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ r & 1 & 0 & \cdots & 0 \\ \frac{r(r+1)}{2!} & r & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ \frac{r(r+1)\cdots(r+n-2)}{(n-1)!} & \frac{r(r+1)\cdots(r+n-3)}{(n-2)!} & \frac{r(r+1)\cdots(r+n-3)}{(n-3)!} & \cdots & 1 \end{pmatrix} \qquad (4)$$

$$A^{-r} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ -r & 1 & 0 & \cdots & 0 \\ \frac{r(r-1)}{2!} & -r & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ \frac{r(r-1)\cdots(r-n+2)(-1)^{n-1}}{(n-1)!} & \frac{r(r-1)\cdots(r-n+3)(-1)^{n-2}}{(n-2)!} & \frac{r(r-1)\cdots(r-n+4)(-1)^{n-2}}{(n-3)!} & \cdots & 1 \end{pmatrix} \qquad (5)$$

When r is equal to 1, $X^{(r)}(k)$ transforms into the first-order accumulated generating operation (1-AGO) sequence of $X^{(0)}$, also denoted as $X^{(1)}(k)$. $X^{(1)}(k)$ is expressed as given in (6).

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i)\,, k = 1,2,3,\ldots,n \quad X^{(0)}(i) \qquad (6)$$

Furthermore, the relationship between $X^{(0)}$ and $X^{(1)}$ is formulated as given in (7).

$$X^{(0)} = A^{-1} X^{(1)} \qquad (7)$$

Here,we note that A^{-1} is given as the inverse of the A matrix. The matrix forms of A and A^{-1} are illustrated as given in (8) and (9) respectively.

$$A = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 1 & 1 & 1 & \cdots & 1 \end{pmatrix} \qquad (8)$$

and,

$$A^{-1} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ -1 & 1 & 0 & \dots & 0 \\ 0 & -1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix} \qquad (9)$$

Additionally, $X^{(0)}$ can be obtained by the mathematical operations as given in the equation (10)

$$X^{(0)} = A^{-1}X^{(1)} = A^{-2}X^{(2)} = A^{-3}X^{(3)} = \cdots = A^{-r}X^{(r)} \qquad (10)$$

Step 3: Now, we can define the whitening equation and the grey differential equation by the equations given in (11) and (12).

$$\frac{dX^{(\mathrm{r})}(k)}{dt} + aX^{(\mathrm{r})}(k) = b\left(X^{(\mathrm{r})}(k)\right)^{\gamma}, r > 0 \qquad (11)$$

$$X^{(r)}(k) - X^{(r)}(k-1) + az^{(\mathrm{r})}(k) = b\left(z^{(\mathrm{r})}(k)\right)^{\gamma} \qquad (12)$$

Here, γ is indicated as the power index value. By taking into consideration of Eq. $(12), z^{(\mathrm{r})}(k)$ is stated as given in (13)

$$z^{(\mathrm{r})}(k) = \alpha * \left(X^{(\mathrm{r})}(k) + X^{(\mathrm{r})}(k-1)\right), k = 2,3,4 \dots n \qquad (13)$$

Step 4: The parameters a and b can be obtained by using the least squares method as given below in the equation (14)

$$[a \quad b]^{T} = [B^{T}B]^{-1}B^{T}Y \qquad (14)$$

where, B and Y are expressed as given below in (15) and (16)

$$B = \begin{bmatrix} -z^{(r)}(2) & \left(z^{(r)}(2)\right)^{\gamma} \\ -z^{(r)}(3) & \left(z^{(r)}(3)\right)^{\gamma} \\ -z^{(r)}(4) & \left(z^{(r)}(4)\right)^{\gamma} \\ \vdots & \vdots \\ \vdots & \vdots \\ -z^{(r)}(\mathrm{n}) & \left(z^{(r)}(n)\right)^{\gamma} \end{bmatrix} \quad (15)$$

and,

$$Y = \begin{bmatrix} X^{(r)}(2) - X^{(r)}(1) \\ X^{(r)}(3) - X^{(r)}(2) \\ X^{(r)}(4) - X^{(r)}(3) \\ \vdots \\ \vdots \\ X^{(r)}(n) - X^{(r)}(n-1) \end{bmatrix} \quad (16)$$

Step 5: Finally, the equation (17) gives the predicted values.

$$\begin{cases} \hat{X}^{(r)}(1) = X^{(0)}(1) \\ \hat{X}^{(r)}(k) = \left[\left(\left(\hat{X}^{(r)}(1)\right)^{1-\gamma} - \frac{b}{a}\right) e^{-a*(1-\gamma)(k-1)} + \frac{b}{a}\right]^{\frac{1}{1-\gamma}}, k = 2,3,\dots,n \end{cases} \quad (17)$$

3.3. Grey Wolf Optimizer (GWO)

The GWO algorithm has been firstly introduced by Mirjalili et al. (2014). The GWO algorithm draws inspiration from the collaborative hunting behaviour of grey wolves in nature, seeking to optimize the search for prey. Mimicking the hierarchical organization observed in wolf packs, the GWO algorithm assigns distinct roles to its members, aligning with the pack hierarchy (Rezaei et al., 2018). In GWO, the pack members are categorized into four groups, each fulfilling a specific role, thereby contributing to the collective advancement of the optimization process (Faris et al., 2018). To mathematically characterize the social hierarchy of wolves in the design of the Grey Wolf Optimizer (GWO), the fittest solution is designated as alpha (α). Subsequently, the second and third best solutions are denoted as beta (β) and delta

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(δ) respectively. The remaining candidate solutions are collectively referred to as omega (ω) (Emary et al., 2016). In the GWO algorithm, the optimization process is guided by the alpha, beta, and delta wolves, with the omega wolves following the lead of these three individuals (Mirjalili et al., 2014). The equations (18) and (19) give the mathematical formulation of omega wolves.

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_{\mathrm{p}}}(t) - \vec{X}(t)\right| \quad (18)$$

$$\vec{X}(t+1) = \overrightarrow{X_{\mathrm{p}}}(t) - \vec{A} \cdot \vec{D} \; (19)$$

Here, it's worth to note that 't' signifies the current iteration, while $\boldsymbol{\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1}\ \vec{a}, \vec{C} = 2 \cdot \overrightarrow{r_2}, \overrightarrow{X_{\mathrm{p}}}}$ expresses the position vector of the prey and , $\boldsymbol{\vec{X}}$ denotes the position vector of a grey wolf, $\boldsymbol{\vec{a}}$ linearly decreases from 2 to 0, and $\boldsymbol{r_1, r_2}$ are random vectors within the range [0, 1] (Mirjalili et al., 2014).

It is important to note that each omega wolf is obligated to update its position concurrently with respect to alpha, beta, and delta according to the following formula given in (20), (21), (22), (23), (24) and (25) (Mirjalili et al., 2014).

$$\boldsymbol{\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X}\right|} \qquad (20)$$

$$\boldsymbol{\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right|} \qquad (21)$$

$$\boldsymbol{\overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \cdot \left(\overrightarrow{D_\alpha}\right)} \quad (22)$$

$$\boldsymbol{\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta}\right)} \quad (23)$$

$$\boldsymbol{\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta}\right)} \quad (24)$$

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$$\vec{\boldsymbol{X}}(\boldsymbol{t}+\mathbf{1}) = \frac{\overrightarrow{\boldsymbol{X_1}} + \overrightarrow{\boldsymbol{X_2}} + \overrightarrow{\boldsymbol{X_3}}}{\mathbf{3}} \quad (25)$$

Miralili et al. (2018) argued that the parameters $\boldsymbol{A}$ and $\boldsymbol{C}$ play a crucial role in guiding the Grey Wolf Optimizer (GWO) algorithm to balance between exploration and exploitation of the search space. Specifically, half of the iterations are allocated to exploration (when $|\boldsymbol{A}| > \mathbf{1}$), and the remaining iterations are dedicated to exploitation (when $|\boldsymbol{A}| < \mathbf{1}$). Additionally, the parameter $\boldsymbol{C}$ undergoes random changes to address the issue of local optima stagnation during the optimization process.

3.4. Proposed Approach: GWO-FANGBM(1,1) Hybrid Model

In the proposed model, the Grey Wolf Optimization algorithm (GWO) is utilized to improve the prediction performance of fractional nonlinear grey Bernoulli model. FANGBM has three parameters such as production coefficient of the background value (α), power index (γ) and fractional order (*r*). At this point, the parameter optimization problem can be defined by Equations (26)-(29).

$$\min \ Z=\frac{1}{n}\sum_{k=1}^{n}(\hat{x}_0(k)-x_0(k))^2 \quad (26)$$

s.t.

$$0 \le \alpha \le 1 \quad (27)$$

$$r > 0 \quad (28)$$

$$\gamma \ne 1 \quad (29)$$

In this mathematical model, α, γ and r are decision variables and the objective function is to minimize the root mean squares error (RMSE). Also, in the equation (26), $x_0(k)$ shows the actual value, $\hat{x}_0(k)$ indicates the predicted value and n is the number of testing data.

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In the proposed approach, the data set is divided into two sets: training data and testing data. The training data is used to determine parameters, while the testing data is only used for performance evaluation of the prediction models. The pseudocode of the proposed hybrid GWO-FANGBM(1,1) model is presented in Table 2.

Table 2. The pseudo-code of the proposed GWO-FANGBM(1,1) hybrid method

Load the dataset
Divide data into training and testing datasets
Initialize GWO parameters (the size of grey wolf population=40, the maximum iteration number is 500)
Define the α, γ and *r* parameters of initial grey wolves randomly
Set fitness function=$RMSE_i$
Calculate the fitness value for each wolf
Find the positions of alpha, beta, and delta wolves
Set t=1
While (t < max number of iterations)
    for each wolf
        Update the position (α, γ and *r* values) of current wolf
        Calculate $RMSE_i$ for current wolf
    end for
Update the positions of alpha, beta, and delta wolves
t=t+1
end while
return the best α, γ and *r* value and the best RMSE value
Build a FANGBM(1,1) model with finalized α, γ and *r* parameters
Calculate RMSE value of the testing data

4. Application

In our proposed methodology, we embark on a comprehensive analysis of historical natural gas consumption data in Turkey slated for forecasting. Subsequently, we employ the hybrid model GWO-FANGBM (1,1) for the forecasting, drawing comparisons with established models such as GM(1,1) and GWO-GM(1,1), as well as statistical methods like ARIMA and linear regression. Following the application of these models, their performance is rigorously evaluated by measuring the disparity between estimated values and actual consumption figures, utilizing metrics such as root mean squares error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE). These metrics can be calculated using Equation (30)-(32), respectively.

$$\text{RMSE}=\frac{1}{n}\sum_{k=1}^{n}(\hat{x}_0(k)-x_0(k))^2 \tag{30}$$

$$\text{MAPE}=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}_0(k)-x_0(k)}{x_0(k)}\right|\times 100\% \tag{31}$$

$$\text{MAE}=\frac{1}{n}\sum_{k=1}^{n}|\hat{x}_0(k)-x_0(k)| \tag{32}$$

4.1. Data Collection

At this outset, the dataset detailing natural gas consumption (in million m3) for Turkey spanning the years 2003–2022 is sourced from the Republic of Turkey Energy Market Regulatory Authority database. The specifics of this dataset are outlined in Table 3, and a visual representation is presented in Figure 4 (Republic of Turkey Energy Market Regulatory Authority, 2023).

Table 3. Annually natural gas consumption (million m^3) in Turkey from 2004 to 2022

Year	Consumption	Year	Consumption
2004	22273	2014	48717
2005	27348	2015	47999
2006	30982	2016	46395
2007	35395	2017	53857
2008	36865	2018	49329
2009	35219	2019	45285
2010	37411	2020	48261
2011	43697	2021	59854
2012	45242	2022	53255
2013	45918		

Özcan, T., Konyalioglu, A. K., & Apaydın, T. B. (2024). Forecasting natural gas consumption in Turkey using fractional non-linear grey Bernoulli model optimized by grey wolf optimization (GWO) algorithm. *Euro-Mediterranean Journal for Environmental Integration*. Advance online publication. https://doi.org/10.1007/s41207-024-00618-9

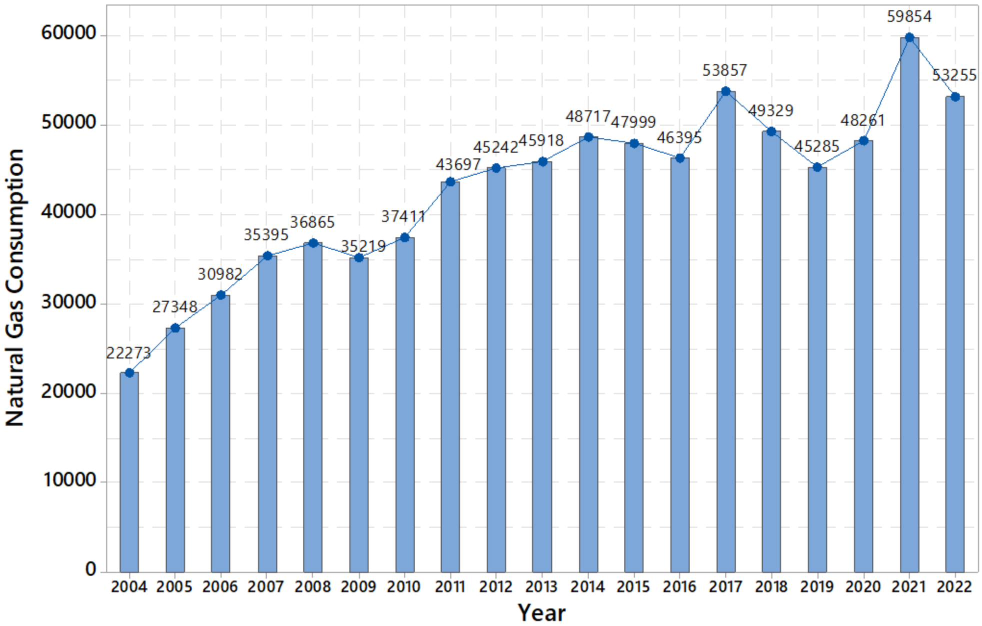

Figure 4. Natural gas consumption in Turkey from 2004 to 2022

4.2. Prediction of Natural Gas Consumption with Proposed Models

This study aims to predict the natural gas consumption by using a fractional nonlinear grey Bernoulli model optimized with grey wolf optimizer (GWO-FANGBM(1,1)) for the future years in Turkey. In this study, the consumption data spanning from 2004 to 2017, comprising 14 data points, is employed as the training dataset for model construction. Subsequently, consumption data from 2018 to 2022, amounting to 5 data points, is utilized in the testing stage for model validation. The construction of the prediction models involves the use of a rolling mechanism. In this mechanism, the predicted value for the year 2018 is calculated using the training dataset from 2004 to 2017 for each method we used including GM(1,1), GWO-GM(1,1), LR, ARIMA and our novel hybrid approach GWO-FANGBM(1,1).

Following the acquisition of the predicted value, the oldest data point (2004) is then removed from the training dataset, and the newly predicted data (2018) is added at the end of the training dataset. This iterative process is repeated until the size of the training dataset remains constant. The rolling mechanism ensures a dynamic adaptation of our hybrid model, named as GWO-FANGBM(1,1) as new data becomes available, allowing for continuous refinement and validation throughout the forecasting process.

In order to compare the results of forecasting natural gas consumption in Turkey, we, firstly, used traditional GM(1,1) and GWO-GM(1,1) as well as ARIMA and LR. Before applying traditional grey models to the data provided in the previous section, the grey wolf optimizer has been used for the parameter optimization in traditional grey models as suggested by some scholars in the existing literature (Gandomi et al., 2013; Gazi & Passino, 2004) to increase the efficiency of the current grey models.

In the parameter optimization model, root mean squared error (RMSE) is used as the fitness function. The size of grey wolf population is taken as 40 and the maximum number of iterations is taken as 500. In the GWO, MAPE converges very fast to a stationary point. The GWO-FANGBM(1,1), GWO-GM(1,1), GM(1,1), ARIMA and LR models are coded on MATLAB 2022a. Also, the p,d and q values of the ARIMA model are optimized. For the testing data, the prediction results and performance metrics of the proposed models are given in Table 4 and Figure 5.

Table 4. The performance metrics and predicted values of the prediction models

Year	Actual Value	Prediction Values				
		GWO-FANGBM(1,1)	GWO-GM(1,1)	GM(1,1)	ARIMA(2,0,1)	LR
2018	49329	46319.30	53983.96	55968.17	53461.23	55437.04
2019	45285	48385.81	55373.99	57935.29	52243.72	57520.86
2020	48261	50269.19	56812.49	60098.14	54100.71	59604.67
2021	59854	52665.06	58501.67	62740.85	53927.55	61688.49
2022	53255	53252.62	60176.9	65532.35	54341.95	63772.31
RMSE		**3857.12**	**7018.92**	**10032.88**	**5213.55**	**9270.19**
MAE		**3062.00**	**6313.93**	**9258.16**	**4788.81**	**8407.87**
MAPE (%)		**5.82%**	**12.94%**	**18.76%**	**9.56%**	**17.14%**

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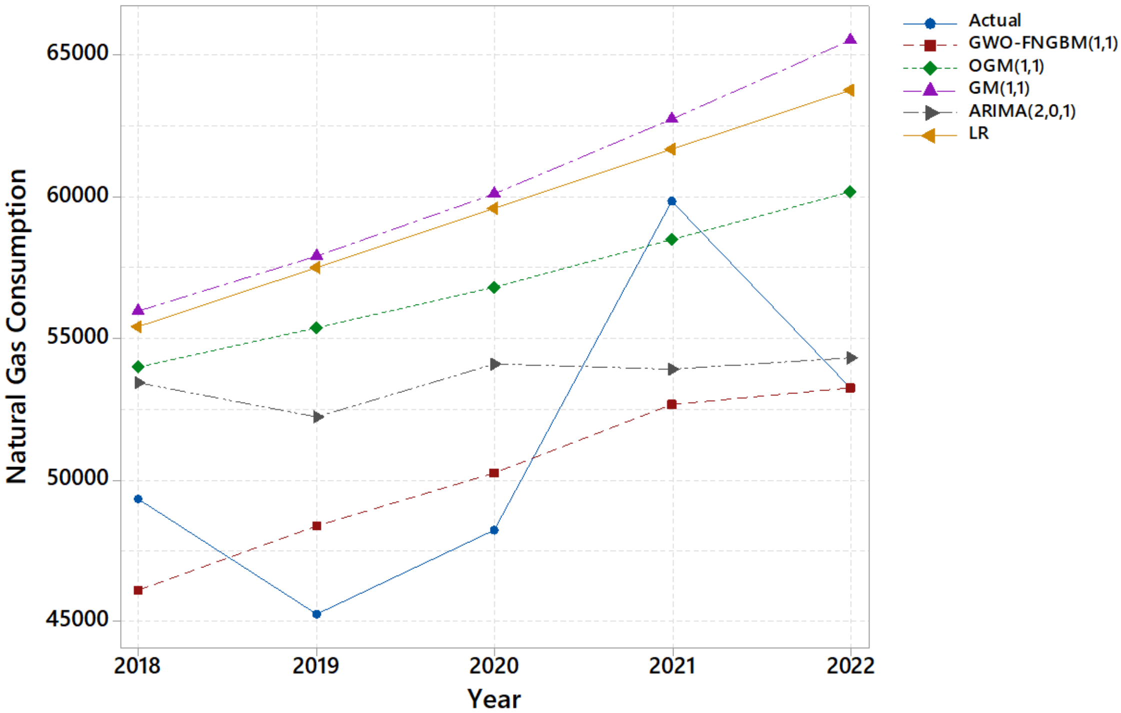

Figure 5. The predicted values of the proposed models for the testing data

In the proposed GWO-FANGBM(1,1) model, the minimum MAPE (5.82%), α=0, γ=-1.6859 and r=1.0124 are determined by using grey wolf optimizer. Similarly, the minimum MAPE (12.94%) and α=1 is found with the parameter optimization in the GWO-GM(1,1) model. In the optimized ARIMA model, the order of the autoregressive component (p), the number of regular differences (d) and the order of the moving averages component (q) parameters are optimized by using GWO. In this model, the optimum p, d and q values are obtained as 2, 0 and 1, respectively.

According to the results in Table 4, the proposed GWO-FANGBM(1,1) hybrid model achieves the lowest RMSE, MAPE and MAE values compared with the other proposed models. The GWO-FANGBM(1,1) has the minimum MAPE value of 5.82% whereas linear regression model has the highest MAPE value of 17.14%. The numerical results also indicate that parameter optimization and rolling strategy improves the forecasting accuracy of GM(1,1) and

FANGBM(1,1) models. The proposed GWO-FANGBM(1,1) hybrid model provides an efficient model for predicting the natural gas consumption of Turkey.

4.3. Sensitivity Analysis

In this study, sensitivity analysis is conducted to validate the robustness of the proposed forecasting models. In the GM(1,1) model, sensitivity analysis is performed by changing the production coefficient α from 0.0 to 1.0, as in the study by Tan et al. (2015). Figure 6 presents mean absolute percentage error (MAPE) values for different values of α in the GM(1,1) model. As can be seen in Figure 6, the GM(1,1) model is sensitive to parameter settings for natural gas consumption prediction.

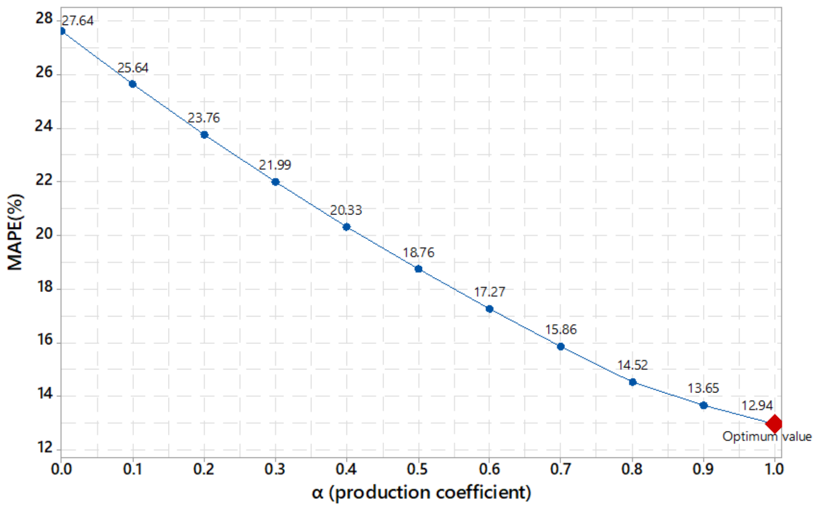

Figure 6. Prediction error for different α (production coefficient) values in the GM(1,1) model

In the FANGBM(1,1) model, sensitivity analysis is performed by changing the production coefficient (α), power index (γ) and fractional degree (r) parameters of this model.

In sensitivity analysis of each parameter, the optimum values of the other two parameters calculated by the GWO algorithm are used.

Figures 7-9 show the change of prediction error for different values of α, γ and r parameters, respectively. In these figures, the x-axis indicates the parameter value and the y-axis shows the calculated MAPE. As can be seen from Figures 7-9, the prediction performance of the FANBGM (1,1) model is sensitive to the adjustment of all three parameters. Additionally, it can be stated that the MAPE value of the FANBGM(1,1) model is most sensitive to the fractional order (r) parameter.

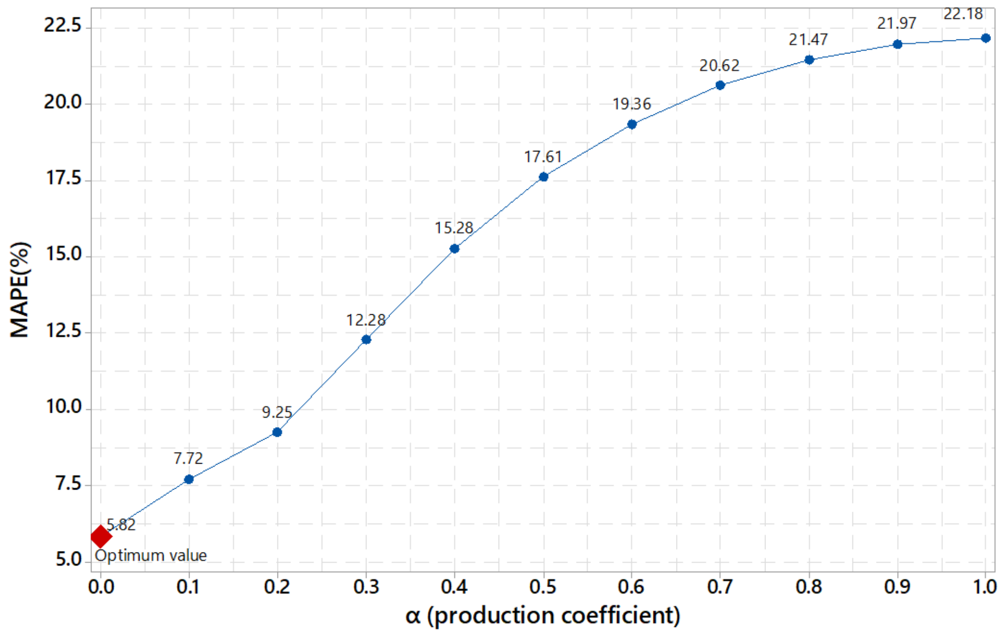

Figure 7. Prediction error for different α (production coefficient) values in the FANGBM(1,1) model

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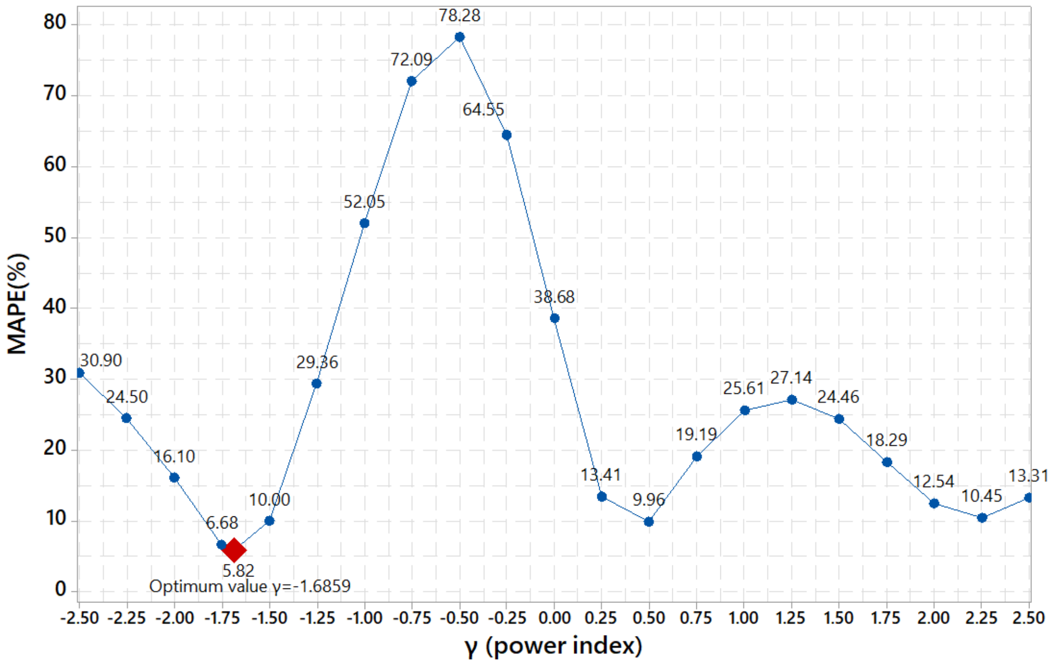
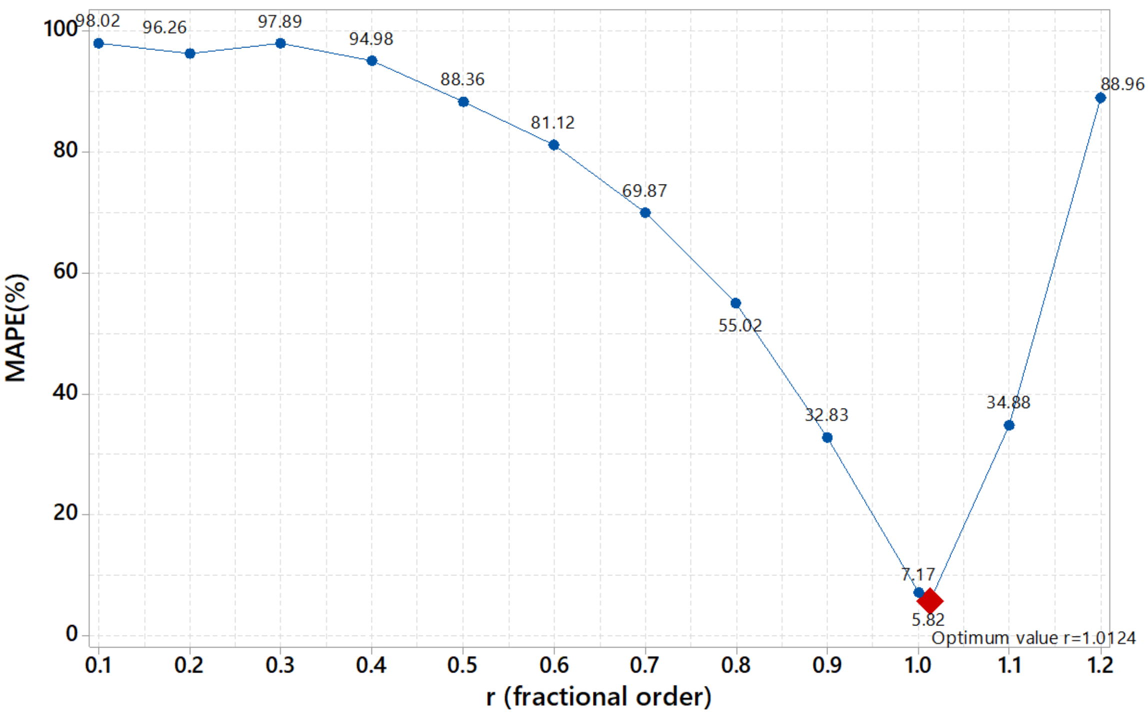


Figure 8. Prediction error for different γ (power index) values in the FANGBM(1,1) model



Özcan, T., Konyalioglu, A. K., & Apaydın, T. B. (2024). Forecasting natural gas consumption in Turkey using fractional non-linear grey Bernoulli model optimized by grey wolf optimization (GWO) algorithm. *Euro-Mediterranean Journal for Environmental Integration*. Advance online publication. https://doi.org/10.1007/s41207-024-00618-9

Figure 9. Prediction error for different *r* (fractional order) values in the FANGBM(1,1) model

The numerical results of sensitivity analysis demonstrate the effectiveness of the GWO algorithm for determining optimum parameter values and the robustness of the proposed GWO-FANGBM(1,1) algorithm.

5. Further Research and Limitations

While the comprehensive analysis employing diverse analytical techniques for forecasting natural gas consumption in Turkey yielded significant insights, several limitations merit consideration. Firstly, the study did not account for the COVID-19 pandemic's impact on natural gas demand dynamics from 2021 to 2023. The pandemic introduced substantial economic volatility globally, influencing energy consumption patterns (Cihan, 2022). The exclusion of COVID-19 data was primarily due to data unavailability during the study period, which restricted the ability to incorporate its effects into the analysis. Future studies could explore methods to address this limitation, potentially through scenario analysis or alternative data sources.

Secondly, although the study achieved a minimum MAPE of 5.82% using specific parameters optimized by GWO in the GWO-FANGBM(1,1) model, and identified a minimum MAPE of 12.94% with parameters $\alpha=0$, $\gamma=-1.6859$, and $r=1.0124$ in the GWO-GM(1,1) model, alternative optimization techniques for parameters α, γ, and r were not explored. Future investigations could benefit from exploring methodologies such as ant colony optimization or artificial bee colony algorithms, as identified in prior literature (Fidanova and Fidanova, 2021; Wang and Han, 2021; Kaya et al., 2022; Wu et al., 2020), which might enhance the accuracy of forecasting outcomes.

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Thirdly, as further researches, the analysis did not incorporate multivariate grey models (GM(1,N)) that could integrate additional variables such as the count of pipelines in Turkey, population growth rates, and electricity consumption levels. The inclusion of these variables could potentially enrich the predictive capabilities and comprehensiveness of future forecasting models (Chen et al., 2020; Ding et al., 2021; Xie et al., 2021). Furthermore, the optimisation of pipelines has not been considered in this research. It is suggested that future scholars compare the results with different grey models such as Fractional Hausdorff Grey models, adaptive discrete grey models, fractional non-homogenous grey models, or multivariate grey models (Chen et al., 2020; Ding et al., 2021; Xie et al., 2021) to further validate and expand upon the findings. Aligned with these models, hybrid models such as ANN or machine learning optimised by genetic algorithm, grey wolf optimiser or grid search can be used to enhance the quality of comparison.

Addressing these limitations in future research endeavors could further refine the reliability and applicability of natural gas consumption forecasts in the Turkish context. Future studies could also explore the inclusion of COVID-19 data, if available, to assess its impact on energy consumption patterns and enhance the robustness of predictive models.

6. Conclusions

In this study, the objective is to present not only a novel approach but also a comparative analysis of the results obtained from our proposed model against traditional grey Bernoulli models, linear regression, and ARIMA models as well as sensitivity analysis. Importantly, the numerical outcomes illustrate that our hybrid GWO-FANGBM(1,1) model surpasses other grey models, including GM(1,1) and GWO-GM(1,1), as well as conventional statistical methods such as ARIMA and linear regression. This highlights its superior predictive accuracy within the specified context. The uniqueness of our novel hybrid approach stems from the fact that it has not been previously applied to forecast natural gas consumption in Turkey. Numerical results indicate that the proposed hybrid model, GWO-FANGBM(1,1), demonstrates superior prediction accuracy, achieving a MAPE of 5.82%, RMSE of 3857.12, and MAE of 3062.00 compared to other techniques. This performance surpasses that of GM(1,1), GWO-GM(1,1), ARIMA, and LR models in terms of performance metrics. The sensitivity analysis results also underscore the efficacy of the GWO algorithm in identifying optimal parameter values, as well as the robustness of the proposed GWO-FANGBM(1,1) algorithm.

In our perspective, it is proposed that regulatory bodies overseeing natural gas in Turkey should prioritize industries, households, and transportation entities for the utilization of natural gas. Specifically, regulatory bodies could consider implementing tax incentives for companies that adopt natural gas as their primary energy source. Subsidies for research and development in natural gas technologies, particularly those that enhance efficiency and reduce emissions, would also be beneficial. Additionally, offering grants or low-interest loans to small and medium-sized enterprises (SMEs) for converting their systems to natural gas could accelerate adoption.

Furthermore, policies encouraging public transportation systems to transition to natural gas vehicles, coupled with subsidies for households installing natural gas heating systems, could significantly increase the utilization of natural gas. To optimize the use of these resources in Turkey, regulatory bodies should also consider introducing carbon credits for businesses that switch to natural gas, thus providing a financial incentive for reducing greenhouse gas emissions. However, these suggestions will also affect natural gas consumption amount in Turkey.

The influencing factors required by forecasting models have evolved significantly, from using minimal data with low dimensions to utilizing extensive datasets with higher dimensions. Generally, long-term forecasts are primarily influenced by production, population, and economic variables. To enhance the precision of these findings to forecast annually, future research efforts should incorporate more accurate data for forecasting natural gas demand and supply in Turkey and explore different hybrid models. Additionally, the analysis of storage capacity and the optimization of pipelines for natural gas transfer in Turkey could be refined by employing various techniques, such as advanced data analytics and machine learning, thereby facilitating the implementation of more effective forecasting instruments.

Authors contribution

TO: initial draft, modelling, coding
AKK: literature review, final draft, methodology
TBA: methodology, literature review, revising

Funding: There is no funding for this research

Data availability: Data can be shared on request.

Declarations

A part of this study has been presented in CEST 2023 conference and selected as special issue to be published in Euro-Mediterranean Journal for Environmental Integration.

Ethics approval and consent to participate: Not applicable.

Competing interests: The authors declare no competing interests.

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Appendix: Sources for Literature Review Figures

Reference	Method	Country	Performance Metric
Xu and Wang (2010)	PCMACP	China	MAPE
Azadeh et al. (2011)	ANFIS-SFA	Bahrain Saudi Arabia Syria	MAPE

Kaynar et al. (2011)	MLP ANFIS	Turkey	MAPE
Demirel et al. (2012)	BPNN	Turkey	MAPE RMSE MAD
Azadeh et al. (2013)	ANFIS-DEA-FDEA	Argentina Brazil Colombia Venezuela Cuba	MAPE RMSE R^2
Taşpınar et al. (2013)	ANN-MLP, SARIMAX	Turkey	MAPE RMSE R^2
Akpinar and Yumusak (2013)	ARIMA	Turkey	MAPE

Soldo et al. (2014)	MLP, SVM	Croatia	MAPE R^2
Yu and Xu (2014)	CCMGA-BPNN	China	MAE MAPE RMSE
Azadeh et al. (2015)	ELFIS	Iran	MAPE NMSE Time
Szoplik (2015)	MLP	Poland	MAPE RMSE
Zhu et al. (2015)	SVR-false neighbors filtered	U.K.	MAPE MAE
Bai and Li (2016)	SC-SVR	China	MAPE RMSE
Merkel et al. (2017)	DNN based on RBM	U.S.	-
Panapakidis and Dagoumas (2017)	WT-GA-ANFIS-FFNN	Greece	MARNE

Özmen et al. (2018)	Multivariate adaptive regression spline Conic multivariate adaptive regression spline	Turkey	MAE MAPE RMSE R^2
Merkel et al. (2018)	DNN Large DNN	U.S.	Average WMAPE
Fan et al. (2018)	GM-S-SIGM-GA	China	MAPE RMSE MAE
Wei et al. (2019)	LSTM-PCCA	China Greece	MAPE MARNE
Wei et al. (2019)	ISSA-LSTM	U.K. Australia China Greece	MAPE MARNE
Wei et al. (2019)	FSA-LGA-SVR	Greece	MAPE MARNE
Laib et al. (2019)	FM-MLP	Algerian	MAPE RMSE MAE
Beyca et al. (2019)	SVR	Turkey	MAPE MSE

Su et al. (2019)	WT-GA-RNN	U.S.	MAE MRE RMSE
Wang and Jiang (2019)	NMGM-ARIMA ARIMA-ANN	U.S.	MAPE RMSE
Hafezi et al. (2019)	ANN-GA	World	MAE MAPE MBE RMSE R^2
Lu et al. (2019)	CF-SA-FFOA-SVM	China	MAPE MSE RMSE
Hribar et al. (2019)	RNN	Slovenia	MAPE MAE
Qiao et al. (2019)	IWOA-RVM	China	MAPE MAE RMSE

Marziali et al. (2019)	Gaussian Process	Italy	Average MAE Average RMSE
Meira et al., 2022	Bagging and MEB	European Union	MASE sMAPE MAPE RMSE
Ozcan et al., 2023	Grey Forecasting Models including GM (1,1) NGBM (1,1)	Turkey	MAPE
Ma et al., 2023	Wavelet-Kernel based grey system	China	MAE MAPE MASE RMSE MedAe R^2 U1 U2 TIC IA
Gao et al., 2023	Holt-Winters model, long short term memory neural network with grey wolf optimizer	U.S.	MAE MAPE RMSE
Tong et al., 2023	Grey prediction model Self-adaptive time-varying grey Bernoulli prediction model	China U.S. Russia	APE RMSE MAPE MAE RMSPE

Singh et al., 2023	SVM-ANN	U.S.	MAPE
Liu et al., 2023	Gaussian correlation mixed clustering (GCMC)	Greece	MAE MAPE MARNE R^2
Ding et al., 2023	Dual Convolution with Seasonal Decomposition Network	China	RE RMSE R^2
Wang and Zhang, 2023	Fractional reverse accumulation method FGRM (1,1)	Commonwealth of Independent States (CIS)	MRSPE MRFPE

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