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Grey Forecasting Models Optimized by Firefly Algorithm for Natural Gas Consumption Prediction in Turkey

ÖZCAN T.[1], KONYALIOĞLU A. K[1,2,*], BELDEK T.[1,]

[1]Istanbul Technical University, Faculty of Management, Management Engineering Department, Istanbul-Turkey
[2]Strathclyde Business School, University of Strathclyde, 199 Cathedral Street, Glasgow, The United Kingdom

*corresponding author:
e-mail: aziz.konyalioglu@strath.ac.uk

Abstract Natural Gas is assumed to have a vital role as an energy source in all countries, serving as the primary fuel for industries, homes, and various sectors. The forecasting of natural gas consumption is very crucial for efficient energy management and the formulation of appropriate policies related to its production and usage, accurately. Forecasting has significant economic implications as it enables the implementation of cost-effective strategies based on reliable predictions of natural gas usage. This research focuses on predicting the consumption of natural gas in Turkey by employing Grey Forecasting Models (GF) Optimized by the Firefly Algorithm. The Firefly Algorithm optimizes the model parameters, while the GF models, namely GM (1,1) and NGBM (1,1), estimate the natural gas consumption in Turkey. The performance of these grey forecasting models is evaluated by comparing them with ARIMA and linear regression models. The calculations illustrate that the proposed NGBM (1,1) model, based on the Firefly Algorithm, surpasses other grey models such as OGM(1,1), GM(1,1) as well as statistical methods like ARIMA and linear regression, in terms of prediction accuracy.

Keywords: Natural gas consumption; Grey forecasting; Parameter optimization; Firefly algorithm

1. Introduction

Natural gas are always recognized as a clean and reliable energy resource for heating and industrial purposes (Taşpınar et al., 2013). Consequently, to ensure environmental sustainability, natural gas is still considered as the second-largest energy option in Turkey (Boran, 2015). Given Turkey's status as one of the world's largest emerging economies, the demand for natural gas is anticipated to rise due to increased production, population growth, and power generation (Beyca et al., 2019). The interplay between economic growth and energy consumption highlights Turkey's significant role in global natural gas demand and supply (Kum et al., 2012). Consequently, accurate forecasting and planning of natural gas consumption are crucial to sustain this economic growth.

Although Turkey has limited natural gas reserves, it heavily relies on imports from other countries (Melikoğlu, 2013). Additionally, natural gas consumption in Turkey exhibits seasonal variations, with peak demand occurring during winter and significant decreases in summer (Es, 2020). Consequently, the improvements in gas pipelines and economic planning for adequate natural gas supply in Turkey is based on consumption data, enabling more efficient optimization of natural gas resources (Yucesan et al., 2021). Therefore, estimating natural gas consumption in Turkey is of utmost importance for effective management of industrial operations, heating, and services.

This study mainly proposes to forecast the consumption of in Turkey by utilizing GF Models Optimized by the Firefly Algorithm. The Firefly Algorithm is utilized to have the model parameters optimized by Firefly algorithm, while Grey Forecasting models such as GM(1,1) and NGBM (1,1) are employed to estimate natural gas consumption in Turkey. To evaluate the performance of the grey forecasting models, a comparison is made with ARIMA and linear regression models. The integration of these models will provide an effective forecasting tool for managing Turkey's energy policies.

2. Background

According to literature, there are several studies concerning the estimation of natural gas consumption in various countries. However, there is a deficit in forecasting Turkey's natural gas consumption. Soldo (2012) first conducted an extensive literature search on predictive studies on natural gas consumption. Furthermore, an evaluation of the efficiency in a natural gas prediction study is performed by Liu et al. (2021). In Turkey, to estimate natural gas demand, Erdoğdu (2010) used a mathematical model to assess the elasticity of natural gas consumption from an economic perspective. In the same year, Toksari (2010) integrated economic indicators to forecast natural gas demand in Turkey through a simulation approach involving linear regression. There also exist several neural network approaches for estimating the consumption of natural gas in Turkey in the literature (Akpinar et al., 2017; Sen et al., 2017; Szoplik, 2015). In addition, algorithms based on machine learning and metaheuristics have also been used to forecast natural gas consumption in Turkey (Arık, 2019; Karadede et al., 2019; Ozturk and Ozturk, 2018).

3. Materials and Methods

3.1. Grey Forecasting

GM(1,N), GM(1,1), NGBM(1,1) are considered as the three primary gray forecasting models, with recent studies showing a preference for GF models due to their improved prediction accuracy. These models incorporate optimization techniques to enhance the model parameters, with the Firefly algorithm utilized in this study for parameter optimization.

Gray system theory, introduced by Deng (1982), addresses the challenge of uncertainty arising from discrete data and incomplete information. The strengths of Gray system theory lie in its capability to handle uncertainty with limited data and to analyze and model systems with incomplete or restricted information. It consists of five main components: Gray prediction, Gray relationship analysis, Gray decision making, Gray programming, and Gray control (Wei, 2011). This study focuses on Gray prediction, which is a crucial element of Gray theory.

Compared to traditional statistical prediction models, gray prediction models offer several advantages (Zhou, 2006; Feng et al., 2012):

Gray prediction models are suitable when data is insufficient for traditional statistical methods, as they require minimal data to capture system behavior.
Knowledge of the sample population distribution is not necessary.
The Accumulate Operation (AGO) reduces noise in the original data.
The data required for gray prediction is typically easily obtainable, resulting in significant time and cost savings compared to other methods.

3.2. Firefly Algorithm

The Firefly optimization algorithm encompasses two crucial factors: variations in light intensity and the concept of attraction (Gandomi et al., 2013). In this context, the attractiveness of fireflies is primarily determined by their brightness, often referred to as light intensity, which is associated with their lens function (Gazi & Passino, 2004). The perception of firefly attractiveness is typically based on visual evaluation, as the intensity of their light diminishes with distance from the light source due to absorption within the medium (Gandomi et al., 2013).

4. Application

This study aims to employ an optimized gray model to forecast the forthcoming years about the utilization of natural gas in Turkey, annually. The natural gas consumption data (measured in million m3) for Turkey during the period spanning 2003 to 2022 is obtained from the Turkey Energy Market Database provided by the Regulatory Authority, as illustrated in Table 1 and Figure 1 (refer to https://www.epdk.gov.tr/).

Table 1. Annual consumption of natural gas (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		

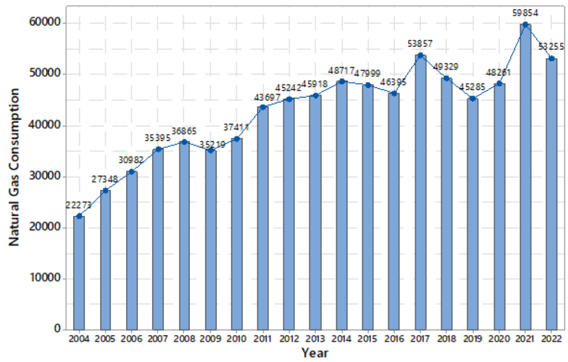

Figure 1. Natural gas consumption in Turkey from 2004 to 2022

In In this study, the consumption data spanning from 2004 to 2017, comprising 14 data points, is utilized as the training dataset for model development. The consumption data from 2018 to 2022, consisting of 5 data points, is employed for the testing phase to validate the proposed predictive model using the rolling method. The rolling method involves calculating predictions for the year 2018 using the training dataset (2004-2017). Once the predictions are obtained, the oldest data point (year 2004) is removed from the training dataset, and the newly predicted data (2018 forecast) is appended to the end. This process is repeated until the desired training data size is achieved.

To enhance the prediction accuracy of the original GM(1,1) and NGBM(1,1) models, parameter optimization is conducted using the Firefly algorithm. The GM(1,1) model encompasses a single parameter, the background value (α), while the NGBM(1,1) model involves two parameters, namely the background value (α) and the power index (γ). The fitness function employed in the parameter optimization model is the mean absolute error in percent (MAPE).

The MATLAB 2022a software was utilized to implement the proposed gray model and parameter optimization approach. The outcomes of the predictive model, along with the corresponding mean absolute percentage error (MAPE) measurements, are presented in Table 1. The Firefly algorithm exhibits rapid convergence of MAPE to a stable point. The predictions and MAPE measurements derived from the proposed model are displayed in Table 2.

Table 2.predicted values and MAPE of the proposed prediction models

Year	Actual Value	ONGBM(1,1)		OGM(1,1)	
		Pred.	Error	Pred.	Error
2018	49329	46447.94	5.84%	53983.96	9.44%
2019	45285	48635.28	7.40%	55373.99	22.28%
2020	48261	50418.31	4.47%	56812.49	17.72%
2021	59854	52683.34	11.98%	58501.67	2.26%
2022	53255	53253.36	0.00%	60176.9	13.00%
MAPE			**5.94%**		**12.94%**

GM(1,1)		ARIMA(2,0,1)		Linear Regression	
Pred.	Error	Pred.	Error	Pred.	Error
55968.17	13.46%	53461.23	8.38%	55437.04	12.38%
57935.29	27.93%	52243.72	15.37%	57520.86	27.02%
60098.14	24.53%	54100.71	12.10%	59604.67	23.50%
62740.85	4.82%	53927.55	9.90%	61688.49	3.06%
65532.35	23.05%	54341.95	2.04%	63772.31	19.75%
MAPE	**18.76%**		**9.56%**		**17.14%**

5. Conclusions

Table 1 indicates that ONGBM(1,1) yields the most favorable outcomes, with the MAPE of the initial GM(1,1) model incorporating a rolling mechanism being 18.76%. By employing the firefly algorithm, the optimized GM(1,1) model with a rolling mechanism (OGM(1,1)) achieves a minimum MAPE of 12.94% and an optimal parameter value of α=1. Similarly, for the optimized NGBM(1,1) model with a rolling mechanism (ONGBM(1,1)), we attain a minimum MAPE of 5.94% with optimal parameter values of α=0 and γ=-1.6.

We also compare the prediction performance of the proposed gray models with statistical methods, we incorporate optimized ARIMA (p,d,q) and linear regression models in this study. The optimized ARIMA model involves parameter optimization for the autoregressive component order (p), the number of regular differences (d), and the moving averages component order (q). The optimal values obtained for this model are p=2, d=0, and q=1. The MAPE values for the optimized ARIMA and linear regression models are 9.56% and 17.14%, respectively.

Numerical findings highlight that the proposed ONGBM(1,1) model based on the Firefly algorithm exhibits superior prediction accuracy compared to other Gray models such as GM(1,1), OGM(1,1), as well as statistical models like ARIMA and linear regression. The parameter optimization and rolling procedure significantly enhance the predictive accuracy of the proposed model. Consequently, the proposed optimized ONGBM(1,1) model represents an efficient approach for forecasting natural gas consumption in Turkey.

References

Akpinar, M., Adak, M. F., & Yumusak, N. (2017). Day-ahead natural gas demand forecasting using optimized ABC-based neural network with sliding window technique: The case study of regional basis in Turkey. Energies, 10(6), 781.

Akpinar, M., & Yumusak, N. (2013, October). Forecasting household natural gas consumption with ARIMA model: A case study of removing cycle. In 2013 7th international conference on application of information and communication technologies (pp. 1-6). IEEE.

Arık, O. A. (2019). Artificial bee colony algorithm to forecast natural gas consumption of Turkey. SN Applied Sciences, 1(10), 1138.

Beyca, O. F., Ervural, B. C., Tatoglu, E., Ozuyar, P. G., & Zaim, S. (2019). Using machine learning tools for forecasting natural gas consumption in the province of Istanbul. Energy Economics, 80, 937-949.

Boran, F. E. (2015). Forecasting natural gas consumption in Turkey using grey prediction. Energy Sources, Part B: Economics, Planning, and Policy, 10(2), 208-213.

Deng, J. L. (1982). Control problems of grey systems. Systems and Control Letters 1.

Duan, Y., Wang, H., Wei, M., Tan, L., & Yue, T. (2022). Application of ARIMA-RTS optimal smoothing algorithm in gas well production prediction. Petroleum, 8(2), 270-277.

Ediger, V. Ş., Akar, S., & Uğurlu, B. (2006). Forecasting production of fossil fuel sources in Turkey using a comparative regression and ARIMA model. Energy Policy, 34(18), 3836-3846.

Erdogdu, E. (2010). Natural gas demand in Turkey. Applied Energy, 87(1), 211-219.

Es, H. A. (2021). Monthly natural gas demand forecasting by adjusted seasonal grey forecasting model. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 43(1), 54-69.

Feng, S. J., Ma, Y. D., Song, Z. L., & Ying, J. (2012). Forecasting the energy consumption of China by the grey prediction model. Energy Sources, Part B: Economics, Planning, and Policy, 7(4), 376-389

Gandomi, A. H., Yang, X. S., Talatahari, S., & Alavi, A. H. (2013). Firefly algorithm with chaos. Communications in

Nonlinear Science and Numerical Simulation, 18(1), 89-98.

Gazi, V., & Passino, K. M. (2004). A class of attractions/repulsion functions for stable swarm aggregations. International Journal of Control, 77(18), 1567-1579.

Karadede, Y., Ozdemir, G., & Aydemir, E. (2017). Breeder hybrid algorithm approach for natural gas demand forecasting model. Energy, 141, 1269-1284.

Kum, H., Ocal, O., & Aslan, A. (2012). The relationship among natural gas energy consumption, capital and economic growth: Bootstrap-corrected causality tests from G-7 countries. Renewable and Sustainable Energy Reviews, 16(5), 2361-2365.

Liu, J., Wang, S., Wei, N., Chen, X., Xie, H., & Wang, J. (2021). Natural gas consumption forecasting: A discussion on forecasting history and future challenges. Journal of Natural Gas Science and Engineering, 90, 103930.

Melikoglu, M. (2013). Vision 2023: Forecasting Turkey's natural gas demand between 2013 and 2030. Renewable and Sustainable Energy Reviews, 22, 393-400.

Ozturk, S., & Ozturk, F. (2018). Forecasting energy consumption of Turkey by Arima model. Journal of Asian Scientific Research, 8(2), 52-60.

Ren, J., Manzardo, A., Zuliani, F., & Scipioni, A. (2012). An improved grey relation analysis for technologies selection based on life cycle sustainability. What is sustainable technology? The role of life cycle-based methods in addressing the challenges of sustainability assessment of technologies, 75.

Sen, D., Günay, M. E., & Tunç, K. M. (2019). Forecasting annual natural gas consumption using socio-economic indicators for making future policies. Energy, 173, 1106-1118.

Soldo, B. (2012). Forecasting natural gas consumption. Applied energy, 92, 26-37.

Szoplik, J. (2015). Forecasting of natural gas consumption with artificial neural networks. Energy, 85, 208-220.

Taşpınar, F., Celebi, N., & Tutkun, N. (2013). Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods. Energy and Buildings, 56, 23-31.

Toksari, M. (2010). Predicting the natural gas demand based on economic indicators: Case of Turkey. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 32(6), 559-566.

Yucesan, M., Pekel, E., Celik, E., Gul, M., & Serin, F. (2021). Forecasting daily natural gas consumption with regression, time series and machine learning based methods. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 1-16.

Zhou, P. A. B. W., Ang, B. W., & Poh, K. L. (2006). A trigonometric grey prediction approach to forecasting electricity demand. Energy, 31(14), 2839-2847.