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Natural Gas Consumption Forecasting using Particle Swarm Optimization based Grey Model

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ABSTRACT

Natural gas is regarded as one of the most important nonrenewable energy sources in the world. Accurate prediction of the natural gas consumption plays a critical role in the energy policy of a country. In this study, firstly, GM(1,1) model with rolling mechanism is applied to predict the long-term natural gas consumption of Turkey. Then, in order to improve the forecasting performance of the original GM(1,1) model, particle swarm optimization algorithm is used to optimize the parameter value of this model. The experimental results show that the optimization of parameter value significantly increases the original GM (1,1) model's performance. The proposed particle swarm optimization based GM (1,1) model presents an efficient methodology for forecasting the natural gas consumption of Turkey.

Keywords: Grey Theory; Grey Prediction; Natural Gas Consumption; Particle Swarm Optimization; Turkey.

1. Introduction

Natural gas is a clean energy source that is used for electricity generation, industrial applications, residential heating and cooking. In Turkey, natural gas is the most widely used source among various energy sources for electricity generation. However, only a very small amount of total natural gas consumption was provided using indigenous sources. Due to limited amount of domestic natural gas production, Turkey is a country that is dependent on natural gas imports. At this point, forecasting of the natural gas consumption has a significant importance for providing efficient energy policy.

This study aims to forecast long-term natural gas consumption in Turkey by using original GM(1,1) model and particle swarm optimization based GM(1,1) model. The organization of this paper is organized as follows. Section 2 provides a literature review on the natural gas consumption prediction. Section 3 gives brief introduction about GM (1,1) model and GM (1,1) model optimized with particle swarm optimization. In section 4, an application of the proposed models for the prediction of annual natural gas consumption in Turkey is given. The results are discussed in Section 5.

2. Literature Review

In the literature, many studies were performed on natural gas consumption forecasting. These studies are summarized below:

Sarak and Satman (2003) proposed degree-day method study for the predictions of residential heating natural gas consumption in Turkey. Aras and Aras (2004) used autoregressive time series models to forecast residential monthly natural gas consumption in Turkey.

Gutierrez et al. (2005) applied a Gompertz-type innovation diffusion model to predict the natural gas consumption in Spain. The application result showed that the Gompertz model has a greater forecasting accuracy than other stochastic diffusion growth models such as logistic and log-normal models.

Ediger and Akar (2007) used autoregressive integrated moving average (ARIMA) model and seasonal moving average for long-term natural gas consumption forecasting in Turkey.

Vondracek (2008) presented a statistical approach based on nonlinear regression principles for estimation of the natural gas consumption of individual residential and small commercial customers.

Akkurt et al. (2010) predicted the natural gas consumption of Turkey in different time periods by using various time series methods such as exponential smoothing, winters' forecasting and seasonal ARIMA methods. The analysis results indicated that in the yearly data set, double exponential smoothing has a greater forecasting accuracy than the other forecasting models and in the monthly data set, seasonal ARIMA model outperforms the other models.

Erdogdu (2010) analyzed short and long term price and income elasticities of sectoral natural gas demand in Turkey. Also, in this study, future growth in Turkey's natural gas demand was estimated using ARIMA model.

Forouzanfar et al. (2010) developed a logistic based approach with nonlinear programming and genetic algorithm to predict the natural gas consumption for residential and commercial sectors in Iran. In this study, genetic algorithm and nonlinear programming were used to estimate the logistic parameters.

Kaynar et al. (2011) examined the weekly natural gas consumption of Turkey using ARIMA, artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) models. This research concluded that ANFIS has outperformed ANN and ARIMA models.

Soldo (2012) presented a state-of-the-art-survey of forecasting natural gas consumption. In this study, the literature studies in the area of forecasting natural gas consumption were classified according to applied area, forecasting horizon, forecasting method, input data and independent variables, on natural gas consumption forecasting,

Demirel et al. (2012) estimated short-term natural gas consumption for a region in Turkey by using neural network models, autoregressive moving average with exogenous variable (ARMAX) and multiple regression. The forecasting result showed that the neural network model with backpropagation outperforms multiple regression, the neural network model with the GA, and the ARMAX model for natural gas forecasting.

Dalfard et al. (2013) developed a combined model of fuzzy inference system and linear regression to forecast long term natural gas consumption when prices experience large increase. In this study, the applicability of the presented model was illustrated by using natural gas consumption data of Iran.

Taspınar et al. (2013) used seasonal autoregressive integrated moving average with exogenous input (SARIMA), artificial neural network with multilayer perceptron (ANN-MLP), artificial neural network with radial basis function (ANN-RBF) and ordinary least squares (OLS) regression models to forecast the daily natural gas consumption in regional level. The application results indicated that SARIMA model provides the better forecasting results than the other forecasting models.

Bianco et al. (2014) utilized a linear logarithmic function for nonresidential natural gas consumption in Italy. In this function, gross domestic product per capita, average annual minimum temperature and gas price were used as explanatory variables.

Cetin and Yuksel (2014) analyzed the relationship between energy dependence and consumption in Turkish natural gas market by using a simultaneous co-integration model. The research results showed that energy dependence significantly affects the long-term gas consumption.

Potocnik et al. (2014) examined the performance of various forecasting models such as linear models, neural network models, and support vector regression models for the daily natural gas demand forecasting. This performance analysis of the proposed models was presented with two data sets taken from an individual house and a local distribution company.

Azadeh et al. (2015) suggested an integrated approach based on emotional learning based fuzzy inference system (ELFIS), ANN and ANFIS for long-term natural gas consumption of Iran in noisy and uncertain environments. In this approach, national income, customer price index, gross domestic product and population were used as independent variables. The results indicated that ELFIS has a better prediction performance than the other models.

Boran (2015) proposed a GM (1,1) model with rolling mechanism for Turkey's natural gas consumption forecasting. Additionally, in this study, the future projections were performed for next five years.

Szoplik (2015) developed artificial neural networks with multilayer perceptrons to forecast hourly natural gas consumption in residential and commercial sector in Poland. The forecasting results with different numbers of hidden layer and different size of training data were presented.

3. Methodology

3.1. Original GM (1,1) Model

Grey Theory, extremely high mathematical analysis of the systems that are partly known and partly unknown and defined as ''weak knowledge'' and ''insufficient data'', was first introduced by Deng (1982). The grey theory consists of five parts: grey prediction, grey relational analysis, grey decisionmaking, grey programming and grey control. Grey prediction is one of the important parts of the grey theory.

At this point, GM (1, 1) model is the basic grey prediction model. GM (1,1) indicates the first-order one-variable grey prediction model. The calculation steps of GM (1,1) model are described as follows (Tseng et al., 2001; Cui et al., 2013):

Step 1: Let X^0 be an original time series data.

$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(i), \ldots, x^{(0)}(n)\} \tag{1}$$

where $x^0(i)$ corresponds to the time series data at time i and n is the sample size of time series data.

Step 2: A new sequence $X^{(1)}$ is constructed by using accumulated generating operation (AGO) technique.

$$X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(i), \ldots, x^{(1)}(n)\} \tag{2}$$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \quad k = 1,2,\ldots,n \tag{3}$$

Step 3: A sequence $Z^{(1)}$ is obtained by consecutive values of sequence $X^{(1)}$.

$$Z^{(1)} = \{z^{(1)}(2), \ldots, z^{(1)}(i), \ldots, z^{(1)}(n)\} \tag{4}$$

$$z^{(1)}(\mathrm{k}) = \alpha x^{(1)}(\mathrm{k}) + (1-\alpha)x^{(1)}(\mathrm{k}-1), \qquad \forall k = 2,3,\ldots,n, \;\; 0 \le \alpha \le 1 \tag{5}$$

where α is the generating coefficient. This coefficient is taken as 0.5 in most problems.

Step 4: The first order –one variable grey differential equation of GM(1,1) is constructed as follows.

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{6}$$

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(\mathrm{t}) = b \tag{7}$$

In these Equation (6) and (7), a is developing coefficient and b is grey input. The values of parameter a and b can be calculated as follows by using the least square method.

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{8}$$

where

$$Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{9}$$

$$B=\begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ -z^{(1)}(4) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{10}$$

Step 5: The predicted values of the accumulated sequence are calculated using Equation (11).

$$\hat{x}^{(1)}(k+1)=(x^{(0)}(1)-\frac{b}{a})\,\mathrm{e}^{-ak}+\frac{b}{a}, \qquad k=1,2,\ldots,n \tag{11}$$

Step 6: The predicted values of the original sequence are obtained by using the inverse accumulated generating operation (IAGO).

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k), \qquad k=1,2,\ldots,n \tag{12}$$

3.2. Particle Swarm Optimization based Grey Model (PSO-GM(1,1))

Traditional GM(1,1) model usually sets the parameter α to 0.5. This value is not optimal for all data sets. Therefore, in this study, in order to improve the forecast performance of the original GM (1,1) model, particle swarm optimization algorithm can be used to optimize the parameter value of this model. The problem of parameter optimization can be formulated as the following optimization problem where the decision variable is generating coefficient (α) and the objective function is to minimize mean absolute percentage error (MAPE):

$$\min \quad Z=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}_0(k)-x_0(k)}{x_0(k)}\right| \mathrm{x}100\% \tag{13}$$

s.t.

$$0 \le \alpha \le 1 \tag{14}$$

where $x_0(k)$ is actual value, $\hat{x}_0(k)$ is predicted value and n is the number of test data.

In the PSO-GM(1,1) model, PSO is used to determine the optimum value of the generating coefficient. PSO is a population based metaheuristic algorithm and was first introduced by Eberhart and Kennedy (1995). The PSO algorithm is inspired by behavior of bird flocking or fish schooling. The calculation steps of the original PSO algorithm can be described as follows (Shi and Eberhart, 1998):

Step 1: Random initial solution is generated using position and velocity vectors.

Step 2: Fitness function values are calculated for particles.
Step 3:The local best values for each particle are updated.
The obtained fitness value of each particle is compared with the best value of each particle. If the obtained value is better, the best value of each particle is updated to this value.
Step 4: The global best value of the iteration is updated.
The obtained fitness value of the population is compared with the fitness value of previous population. If the obtained value is better, the global best value is updated to this value.
Step 5: Position and velocity values of each particle are updated by using Equation (15)-(17).
Step 6: Step 2-5 is repetad until a maximum number of iterations is reached.

In PSO, following notations and equations are used for movement in the solution space of particles in Step 5.

v_i^k the velocity of particle i in iteration k
x_i^k the position of particle i in iteration k
p_i^k the local best of particle i in iteration k
g^k the global best in iteration k
c_1,c_2 the acceleration coefficients
r_1,r_2 random numbers U[0,1]
w_k the inertia weight of iteration k
w_{max} the maximum inertia force
w_{min} the minimum inertia force
$iter_{max}$ the maximum iteration number

$$v_i^{k+1} = w_k . v_i^k + c_1 . r_1 . (p_i^k - x_i^k) + c_2 . r_2 . (g^k - x_i^k) \quad (15)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (16)$$

$$w_k = w_{\max} - (\frac{w_{\max} - w_{\min}}{iter_{\max}}).k \quad (17)$$

4. Forecasting of Natural Gas Consumption with Proposed Models

This study aims to predict the long-term natural gas consumption in Turkey by using particle swarm optimization based GM (1,1) model. To this end, the annual data of natural gas consumption (billion cubic feet) of Turkey for the period 1985–2014 are provided by U.S. Energy Information Administration database, as shown in Table 1 (see https://www.eia.gov).

Table 1 Natural gas consumption (Million m^3) in Turkey from 1985 to 2014

Years	Natural gas consumption (bcf)	Years	Natural gas consumption (bcf)
1985	2	2000	523.898
1986	16	2001	563.062
1987	26	2002	621.120
1988	43	2003	748.007

1989	114	2004	792.575
1990	122.472	2005	966.748
1991	149.630	2006	1101.228
1992	163.650	2007	1292.494
1993	181.872	2008	1294.118
1994	192.326	2009	1240.086
1995	248.229	2010	1346.455
1996	290.077	2011	1578.086
1997	346.087	2012	1598.145
1998	365.546	2013	1611.777
1999	442.426	2014	1711.224

In this study, the data from 1985 to 2008 (24 data points) are used as training data set (model fitting), while the data from 2009 to 2014 (6 data points) are used in the testing stage (model testing). Rolling procedure is applied to construct the prediction models in this study. In the rolling mechanism; the predicted value for the 2009 year is calculated using training data set (1985-2008). After the predicted value is obtained, the oldest data (1985) is removed from training data set, and the newly predicted data (predicted 2009) is added at the end of the training data set. This procedure is repeated until the size of the prediction data.

In this study, real value encoding is used. Due to decision variable is only α, an particle consists of one element. In other words, a particle is represented by the $X_i=(\alpha_i)$. In the PSO steps, parameter value of generating coefficient (α_i) is restricted by a feasible range ($\alpha_i \in (0,1)$). The fitness of each particle is evaluated as MAPE. Local and global best particles are obtained using MAPE value. The PSO algorithm is terminated if a maximum number of iterations is reached.

Proposed grey forecasting models are programmed on MATLAB 2014a. The parameter optimization problem is solved using MATLAB Optimization Toolbox. In this study, the parameters of PSO are given in Table 2 as follows. The prediction results and MAPE values obtained by the proposed models are given in Table 3.

Table 2 PSO parameter values

Parameter	**Value**
Particle number	20
Maximum iteration number	1000
c_1,c_2	2
v_i	U[0,1]
w_{min}	0.4
w_{max}	0.9

Table 3 MAPE and predicted values of the proposed models

Year	Actual Value	GM(1,1)		PSO-GM(1,1)	
		Predicted Value	Error (%)	Predicted Value	Error (%)
2009	1240.086	1893.812	52.72%	1319.110	6.37%
2010	1346.455	2027.231	50.56%	1403.495	4.24%
2011	1578.086	2200.371	39.43%	1478.815	6.29%
2012	1598.145	2479.614	55.16%	1549.229	3.06%
2013	1611.777	2905.266	80.25%	1632.405	1.28%
2014	1711.224	3333.823	94.82%	1710.271	0.06%
MAPE(%) 2009-2014			**62.16%**		**3.55%**

5. Conclusion

The MAPE of the original GM (1,1) model with rolling mechanism is 62.16%. In the PSO-GM (1,1) model , the minimum MAPE (3.55%) and optimal parameter value α=0.5652 are obtained by using PSO. The application results indicate that the optimization of parameter value with rolling mechanism significantly increases the original GM (1,1) model's performance. The proposed PSO-GM(1,1) model presents an efficient methodology for predicting the natural gas consumption of Turkey.

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