A HYBRID NEURO-FUZZY SIMULATION APPROACH FOR IMPROVEMENT OF NATURAL GAS PRICE FORECASTING IN INDUSTRIAL SECTORS WITH VAGUE INDICATORS

Alireza Behrooznia -Ali Azadeh- Habibollah Javanmard -Zahra Saberi - Peiman Pazhoheshfar

Abstract

This study presents a hybrid neural network-fuzzy mathematical programming approach for improvement of natural gas price estimation in industrial sector. It is composed of artificial neural network (ANN), fuzzy linear regression (FLR), and conventional regression (CR). The preferred FLR, ANN and CR models are selected via mean absolute percentage of error (MAPE). The intelligent approach of this study is then applied to estimate natural gas price in industrial sector. Domestic sector is also used to further show the flexibility and applicability of the hybrid approach. The economic indicators used in this paper are consumer price index (CPI), population, gross domestic (GDP), and annual natural gas consumption. The stated indicators could be contaminated with noise and vagueness. Moreover, there is a need to develop a hybrid approach to deal with both noise and vagueness. The input data were divided into train and test data sets. A complete sensitivity analysis has been performed by changing train and test data to show the superiority of the proposed approach. The superiority of ANN for the domestic sector and FLR for the industrial sector was proved by error analysis. The results showed that different models may be selected as preferred model, in different cases and situations.

Key words: Fuzzy Linear Regression (FLR); Artificial Neural Network (ANN); Conventional Regression (CR); Natural Gas Price Estimation

JEL Code: C13,C63, L16.

Introduction

Energy is a vital input for social and economical developments of any nation. Natural gas is known as one of the most important energy sources in the world. Estimation of natural gas price in due time, is a crucial factor for decision makers. Nowadays, there are multiple methods available for forecasting energy prices. An appropriate method may be chosen based on the nature of available data, desired nature, and level of details in the estimation. One customary approach is to employ more than one method and then, to compare the estimations to arrive at a more accurate assessment (Azadeh et al., 2011). Conventional regression analysis refers to a set of methods whereby model parameters are estimated, knowing the values of a given input-output data set. The goals of the regression analysis consist of finding an appropriate mathematical model and determining the best fitting coefficients of the model from the given data. Along with intelligent approaches, regression had been used for energy consumption estimation (Tso & Yau, 2007). The usage of statistical regression is bounded by some strict assumptions of the given data (Chan et al, 2004). FLR models have been successfully applied to various problems such as forecasting (Wang & Tsaur, 2000), and engineering (Chang et al., 1996; Lai & Chang, 1994). FLR models are aimed at finding a regression model that fits all observed fuzzy data within a specified fitting criterion. Depending on which criterion used, different FLR models will be obtained. In general, there are two approaches of FLR due to different fitting criterions (Peters, 1994). The first approach is based on minimizing fuzziness as an optimal criterion (Tanaka, 1982). Different researchers used Tanaka's approach to minimize the total spread of the output (Chang & Lee, 1996). As Wang and Tsaur (2000) point out, the advantage of this approach is its simplicity in programming and computation, but it has been criticized for providing wide ranges in estimation which could not offer much help in application.

The second approach uses least squares of errors as a fitting criterion to minimize the total square error of the output. Hojati et al. (2005) introduced a goal programming-like approach to minimize the total deviation of upper values of *H*-certain estimated, corresponded observed intervals, deviation of lower values of *H*-certain estimated, and related observed intervals. Moreover, there is a need for new approaches for such chaotic and hostile markets. This is why this study presents an integrated flexible approach based on fuzzy mathematical programming and neural network in addition to conventional regression to cover such issues in gas market in general and in gas price forecasting in particular. Also, this study uses the most related indicators to gas price estimation.

1 Methodology : The hybrid neuro-fuzzy simulation

Estimation and assessment of natural gas price could be a complex and nonlinear system which consist of different parts dealing with noisy, limited, and non-integrated data. It therefore, requires methods that can alleviate these problems. In order to do so, we propose a Neuro-Fuzzy Approach.

According to the proposed approach, ANN, FLR, and CR models are applied to estimate natural gas price. After determining the input and output variables, related data are collected. Then, the data are preprocessed in order to decrease multiple correlations and eliminate the noise. The latest FLR models are compared and the best one is selected with respect to mean absolute percentage of error (MAPE). The proper CR model is identified, too. In addition, the best ANN structure with minimum MAPE is selected by six different training methods. Afterwards, the preferred model among the best ANN, FLR and CR models is selected according to the minimum value of MAPE. To verify and validate the results, a sensitivity analysis is also carried out. Hence, the values of MAPE are calculated for ANN, FLR, and CR models, by changing the number of train and test data sets. As noted earlier, the economic indicators used in this paper are consumer price index (CPI), population, gross domestic production (GDP), and annual natural gas consumption. The required data for these indicators are obtained from central bank of Iran. The price of natural gas in Iran depends on the stated four indicators. In the following sections, FLR, CR, ANN models, and error estimation method are described.

1.1 Conventional regression model

Conventional regression is used to determine the best fitting coefficients of the model from the given data. Different data sets have been used to strengthen the power of output which is the best fitted coefficient of regression models, and its general equation is shown below:

$$\hat{Y} = B_0 + A_1 * CPI + A_2 * POP + A_3 * GDP + A_4 * CONSUMPTION \qquad (1)$$

1.2 ANN models

ANNs consist of an inter-connection of a number of neurons. There are varieties of connections under study, such as Multi Layer Perceptron (MLP). In this network, the data continuously flows forward to the output without any feedback. Figure 2 shows a typical three-layer feed forward model used for forecasting purposesp.

The input nodes are the previous lagged observations, while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as:

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{4} \beta_{ij} y_{t-i} + \beta_{0j} \right) + \varepsilon_t \qquad (2)$$

1.3 Error estimation methods

The error estimation method considered in this study is mean absolute percentage of error (MAPE) with the following equation:

$$\mathit{Mean\ Absolute\ Percentage\ Error} = \frac{\sum_{t=1}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right|}{n} \qquad (3)$$

2 Experiment

In this section the steps to provide a proper model for natural gas price estimation are expressed. Forty years of Iran's natural gas data, from 1968 to 2008 is considered. The economic indicators used in this paper are: consumer price index (CPI), population, gross domestic production (GDP), and annual natural gas consumption. For each model, the input data is divided into train and test data. First, the FLR models are applied to different test periods and the best model in each run is selected via MAPE.

3 Experiment

The proposed Hybrid Neuro-Fuzzy Approach is applied to estimate natural gas price in both domestic and industrial sectors of Iran. In the following sections the results and related analysis are discussed.

3.1 Domestic sector

The FLR models are applied for different test periods and the best model in each run is selected via MAPE. The results for the domestic sector are shown in Table 1.

Tab. 1: Results of FLR models for natural gas price estimation in domestic sector

Number of test periods	FLR model	Obtained fuzzy coefficients					Adopted parameter(s) of models	MAPE
		A0	A1	A2	A3	A4		
5	Peters	1.81	0.21	0	0	0.05	P=901	0.0367
6	Peters	1.817	0.214	0	0	0.054	P=901	0.048
7	Ozelkan	1.798	0.204	0	$2.6*10^{-5}$	$1.9*10^{-3}$	H=0.179, u=100	0.094
8	Ozelkan	1.79	0.207	0	$2.6*10^{-5}$	$6.8*10^{-4}$	H=0.259, u=100	0.0711
9	Sakawa	0	0.109	$5.8*10^{-5}$	$5.6*10^{-5}$	0	H=0.2	0.1223
10	Peters	79.39	0	0	0	0	P=2400	0.0075
11	Hojati	1.705	0.021	$8.8*10^{-6}$	$2.3*10^{-5}$	0.11	H=0	0.4652
12	Tanaka	2.52	0.19	0	0	0.011	H=0	0.6391
13	Tanaka	2.52	0.19	0	0	0.011	H=0	0.6907
14	Tanaka	2.56	0.207	0	0	0.0015	H=0	0.7259
15	Peters	0	0	0	0	0.208	P=1160	0.7782

CR model is also used in order to estimate the natural gas price for different test periods. The results for the domestic sector are shown in Table 2.

Tab. 2: Results of CR models for natural gas price estimation in domestic sector

Number of test periods	Obtained CR Coefficients					MAPE
	B0	A1	A2	A3	A4	
5	2.55	0.514	-0.000022	-0.000017	-0.152	0.3347
6	1.84	0.491	0.000001	-0.000007	-0.168	0.33167
7	1.5	0.433	0.000013	0.000008	-0.16	0.350469
8	0.95	0.433	0.000031	0.000021	-0.172	0.380139
9	-0.18	0.303	0.000068	0.000057	-0.19	0.51209
10	2.7	0.488	-0.000027	-0.000027	-0.111	0.15968
11	0.35	-0.011	0.000078	0.000097	-0.045	0.40116
12	1.23	0.053	0.000025	0.000023	0.0661	0.26663
13	2.58	0.136	-0.00002	-0.000032	0.127	0.56636
14	2.56	0.134	-0.00002	-0.000032	0.128	0.531041
15	1.27	0.114	0.000023	-0.000053	0.129	0.8174

Similarly, the ANN models with different training algorithms are used for natural gas price estimation for different test periods. The results for the domestic sector are shown in table3.

Tab. 3: Results of ANN models for natural gas price estimation in domestic sector

Number of test periods	Trainb	Trainnfg	Trainbr	Traingdx	Trainlm	Trainrp	Best MAPE
5	0.0327	0.0227	0.0182	0.0190	0.0196	0.0170	0.0170
6	0.0373	0.0206	0.0205	0.0770	0.0556	0.0357	0.0205
7	0.0571	0.0796	0.0618	0.1412	0.0544	0.0527	0.0527
8	0.0906	0.1068	0.0629	0.2099	0.1910	0.0710	0.0629
9	0.3475	0.1467	0.0972	0.2331	0.1291	0.1461	0.0972
10	0.1865	0.2344	0.2237	0.0848	0.2542	0.1826	0.0848
11	0.2099	0.1697	0.2996	0.4762	0.3573	0.3543	0.1697
12	0.2708	0.3237	0.5499	0.6007	0.3249	0.5763	0.1697
13	0.4237	0.4978	0.6294	0.6875	0.4083	0.5212	0.4083
14	0.3450	0.5178	0.4201	0.6533	0.6364	0.5167	0.3450
15	0.5934	0.5267	0.7317	0.7603	0.6943	0.6088	0.5267

Finally, the best model between ANN, FLR, and CR models for each test period is selected via MAPE. Table 4 shows the preferred model for the domestic sector for each test period.

Tab. 4: Comparing the best MAPE of each model for natural gas price estimation in domestic sector

Number of test periods	CR	ANN	FLR	Best MAPE	Preferred model
5	0.3348	0.0172	0.0367	0.0172	ANN
6	0.3316	0.0205	0.0480	0.0205	ANN
7	0.3504	0.0527	0.0940	0.0527	ANN
8	0.3801	0.0629	0.0711	0.0629	ANN
9	0.0520	0.0972	0.1223	0.0520	CR
10	0.1596	0.0848	0.0075	0.0075	FLR
11	0.4011	0.1697	0.4652	0.1697	ANN
12	0.2663	0.2708	0.6391	0.2663	CR
13	0.5663	0.4083	0.6907	0.4083	ANN
14	0.5310	0.3450	0.7259	0.3450	ANN
15	0.8174	0.5267	0.7782	0.5267	ANN
Average	**0.3809**	**0.1868**	**0.3344**	**0.1753**	

According to the results, the preferred model for estimation natural gas price in the domestic sector of is ANN which has the minimum average MAPE in comparison to (the) FLR and CR models.

3.2 Industrial sector

Similar to the domestic sector, for the industrial sector, the FLR models are applied for different test periods, and the best model in each run is selected via MAPE. The results for the industrial sector are shown in Table 5 as follows:

Tab. 5: Results of FLR models for natural gas price estimation in industrial sector

Number of test periods	FLR models	Obtained fuzzy coefficients					Adopted parameter(s) of models	MAPE
		A0	A1	A2	A3	A4		
5	Ozelkan	0.47	0.091	0	7.8*10-6	0	H=0.99, u=20	0.0649
6	Ozelkan	0.24	0.19	0	0	0.0013	H=0.55, u=5090	0.1911
7	Ozelkan	0	0	1.5*10-5	5.5*10-5	0.011	H=0.89, u=1050	0.0950
8	Ozelkan	0.316	0.121	0	3.2*10-5	0	H=0, u=131	0.1242
9	Ozelkan	0	0	1.3*10-5	5.7*10-5	0	H=0, u=70	0.2127
10	Ozelkan	0.47	0	0	6.1*10-5	0.024	H=0.5, u=152	0.2722
11	Ozelkan	0	0	1.4*10-5	5.5*10-5	0.003	H=0,u=50	0.1580
12	Ozelkan	0.49	0	0	5.9*10-5	0.025	H=0.5, u=105	0.3257
13	Ozelkan	0.25	0.207	0	0	0	H=0, u=42	0.2124
14	Ozelkan	0.2385	0.208	0	0	0	H=0.5,u=101	0.5278
15	Peters	0	0.16	1.1*10-5	0	0	P=62	0.6232

Also, CR model is used in order to estimate the natural gas price for different test periods. The results for the industrial sector are shown in Table 6.

Tab. 6: Results of CR models for natural gas price estimation in domestic sector

Number of test periods	Obtained CR Coefficients					MAPE
	B0	A1	A2	A3	A4	
5	-0.154	0.19	0.000021	-0.000015	-0.0468	0.104043
6	0.114	0.128	0.000014	0.000001	-0.0265	0.20807
7	0.09	0.158	0.000014	-0.000007	-0.0343	0.12768
8	0.005	0.148	0.000017	-0.000004	-0.035	0.13372
9	-1	0.0728	0.000051	0.000025	-0.0538	0.54912
10	0.555	0.134	0.000034	0	-0.0414	0.14085
11	-0.694	0.0728	0.00004	0.000013	-0.0281	0.17104
12	-0.701	0.0748	0.00004	0.000014	-0.0277	0.17076
13	-0.743	0.0758	0.000041	0.000012	-0.0273	0.13953
14	-0.623	0.0946	0.000037	0.000009	-0.0312	0.13077
15	-1.47	-0.0223	0.000066	0.000011	0.0098	0.61114

Similarly, the ANN models with different training algorithms are used. The results for the industrial sector are shown in Table7.

Tab. 7: Results of ANN models for natural gas price estimation in industrial sector

Number of test periods	Trainb	Trainnfg	Trainbr	Traingdx	Trainlm	Trainrp	Best MAPE
5	0.1728	0.1630	0.1613	0.1806	0.2031	0.1633	0.1613
6	0.1438	0.1661	0.1523	0.1714	0.1956	0.1669	0.1438
7	0.1689	0.2363	0.1705	0.2949	0.1996	0.1627	0.1689
8	0.1694	0.1764	0.1546	0.2216	0.1813	0.1647	0.1546
9	0.2394	0.1869	0.1757	0.2531	0.2390	0.3194	0.1757
10	0.2737	0.3377	0.2638	0.3864	0.4167	0.3143	0.2638
11	0.3757	0.2921	0.4376	0.3729	0.3936	0.4090	0.2921
12	0.4416	0.4508	0.5559	0.5005	0.4704	0.3770	0.3770
13	0.4537	0.5396	0.5440	0.5458	0.5823	0.5238	0.4537
14	0.5333	0.6017	0.5526	0.6231	0.6313	0.5598	0.5526
15	0.7013	0.5482	0.7699	0.7823	0.7371	07514	0.5482

Finally, the best model between ANN, FLR and CR models for each test period is selected via MAPE. Table 8 shows the preferred model of the industrial sector for each test period.

Tab. 8: Comparing the best MAPE of each model for natural gas price estimation in industrial sector

Number of test periods	CR	ANN	FLR	Best MAPE	Preferred model
5	0.1040	0.1613	0.0649	0.0649	FLR
6	0.2080	0.1438	0.1911	0.1438	ANN
7	0.1276	0.1627	0.0950	0.0950	FLR
8	0.1337	0.1546	0.1242	0.1242	FLR
9	0.5491	0.1757	0.2127	0.1757	ANN
10	0.1408	0.2737	0.2722	0.1408	CR
11	0.1710	0.2921	0.1580	0.1580	FLR
12	0.1707	0.3770	0.3257	0.1707	CR
13	0.1395	0.4537	0.2124	0.1395	CR
14	0.1307	0.5333	0.5278	0.1307	CR
15	0.6111	0.5482	0.5332	0.5332	FLR
Average	0.2260	0.2978	0.2470	0.1705	

According to the results, the preferred model for estimating natural gas price in the industrial sector of Iran is FLR which has the minimum MAPE in comparison to (the) ANN and CR models.

For the domestic and the industrial sectors, ANN and FLR models are selected as the preferred models to estimate natural gas price, respectively. This shows that the domestic sector is associated with severe environmental complexity and nonlinearity. However, the results of the industrial sector reveal environmental uncertainty and ambiguity. Hence, it is shown how the flexible approach of this study is ideal for complex, nonlinear, noisy and uncertain data sets.

Conclusion

This paper presented an appropriate Hybrid Neuro-Fuzzy Approach for the improvement of natural gas price estimation and forecasting in industrial sector. The latest FLR models were utilized in the hybrid approach to cover environmental uncertainty and noise. ANNs with six different training algorithms are used to cover the data nonlinearity and complexity. The conventional regression approaches were applied to support the mechanism and results of this study. The preferred model was then selected by MAPE. The proposed approach was applied to estimate natural gas price in industrial sectors of Iran. Also, it was applied to domestic sector to show the flexibility of the intelligent approach. The annual population, consumer price index (CPI), gross domestic production (GDP) and annual natural gas consumption were considered as economic indicators. The stated indicators could be contaminated with noise and vagueness. Moreover, there is a need to develop a hybrid approach to deal with both noise and vagueness. The input data were divided into train and test data sets. Different scenarios were designed by varying the number of test periods between 5 and 15. The superiority of ANN for the domestic sector and FLR for the industrial sector was proved by error analysis. The results showed that different models may be selected as preferred model, in different cases and situations. The proposed approach of this study would help the policy makers to effectively manage natural gas price in vague, noisy and complex manufacturing sectors.

References

Azadeh, A., Saberi, M. Asadzadeh, S.M. (2011) ‘An adaptive network based fuzzy inference system–auto regression–analysis of variance algorithm for improvement of oil consumption estimation and policy making: The cases of Canada, United Kingdom, and South Korea’, Applied Mathematical Modelling, Vol. 35, Issue 2, 581-593.

Azadeh, A., A., Seraj, O. and Saberi, M. (2011). An integrated fuzzy regression–analysis of variance algorithm for improvement of electricity consumption estimation in uncertain environments, The International Journal of Advanced Manufacturing Technology, 2011, Vol. 53, Numbers 5-8, pp. 645-660.

Chang, P.T. and Lee, E.S. (1996) ‘A generalized fuzzy weighted least-squares regression’, Fuzzy Sets and Systems, Vol. 82, pp. 289-298.

Chan, W. S. Cheung, S. H. Wu K. H. (2004) ‘Multiple forecast with autoregressive time series models: case studies’, Mathematics and Computers and Simulation, Vol. 64, Issues 3-4, pp. 421-430.

Hojati, M., Bector, C.R. and Smimou, K. (2005) ‘A simple method for computation of fuzzy linear regression’, European Journal of Operational Research, Vol. 166, pp. 172–184.

Lai, Y.J. and Chang, S.I. (1994) ‘A fuzzy approach for multi-response optimization: An off-line quality engineering problem’, Fuzzy Sets and Systems, Vol. 63, pp. 117-129.

Ozelkan, E.C. and Duckstein, L. (2000) ‘Multi-objective fuzzy regression: A general framework’, Computers and Operations Research, Vol. 27, pp. 635–652.

Peters, G. (1994) ‘Fuzzy linear regression with fuzzy intervals’, Fuzzy Sets and Systems, Vol. 63, pp. 45-55.

Sakawa, M. and Yano, H. (1992) 'Multi-objective fuzzy linear regression analysis for fuzzy input-output data', Fuzzy Sets and Systems, Vol. 47, pp. 173-181.

Tanaka, H., Uejima, S. and Asia, K. (1982) 'Linear regression analysis with fuzzy model', IEEE Trans. System Man Cybernetics, Vol. 12, pp. 903-907.

Tso, G.K.F. and Yau, K.K.W. (2007) 'Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks', Energy, Vol. 32, No. 9, pp. 1761-1768.

Wang, H.F. and Tsaur, R.C. (2000) 'Insight of a fuzzy regression model', Fuzzy Sets and Systems, Vol. 112, pp. 355-369.

Wang, H.F. and Tsaur, R.C. (2000) 'Resolution of fuzzy regression model', European Journal of Operational Research, Vol. 126, pp. 637-650.

Contact

Alireza Behrooznia
Department of Management, Tafresh Branch, Islamic Azad University, Tafresh, Iran
Moallem Square,Moien Abad st. Islamic Azad University, P.O. Box 39515-164, Tafresh, Iran
Alirezabehrooznia@gmail.com

Ali Azadeh
Department of Industrial Engineering, Center of Excellence for Intelligent-Based Experimental Mechanics, College of Engineering, University of Tehran, P.O. Box 11365-4563, Tehran, Iran
Aazadeh@ut.ac.ir

Habibollah Javanmard
Department of Management, Arak Branch, Islamic Azad University, Arak, Iran
H-javanmard @iau-arak.ac.ir

Zahra Saberi
Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran
Zahra.saberi.aut@gmail.com

Peiman Pazhoheshfar
Young Researchers Club, Tafresh Branch, Islamic Azad University, Tafresh, Iran

Moallem Square,Moien Abad st. Islamic Azad University, P.O. Box 39515-164, Tafresh, Iran
P.Pazhohesh@gmail.com