2nd AIEE
Energy Symposium

Natural Gas Market Prediction via Statistical and Neural Network Methods

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Agenda

- Overview
- Gas forecasting models
    - o Statistical models
    - o Neural network models
- Application of the proposed forecasting methodology
- Conclusions
- References

Overview

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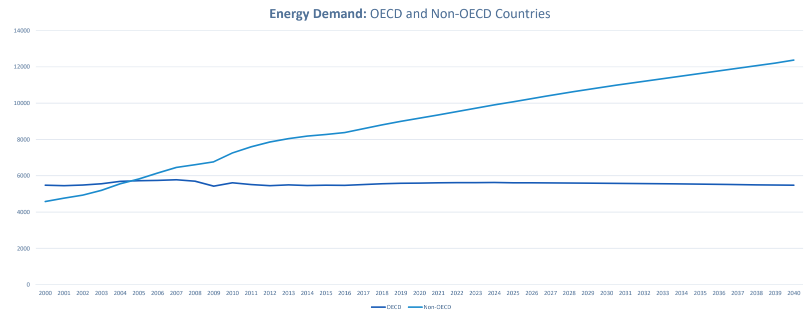
- Natural gas is the only fossil fuel that will maintain its share in energy mix of the coming decades- since it has significant environmental benefits including low-level emissions of greenhouse gases.
- The total world energy demand is projected to increase through 2040 about 47.4% for the non-OECD region. Also, world gas demand boost 69% for non-OECD and 35% for OECD nations that is expected to grow by 1.83 billion cubic meter.



Overview

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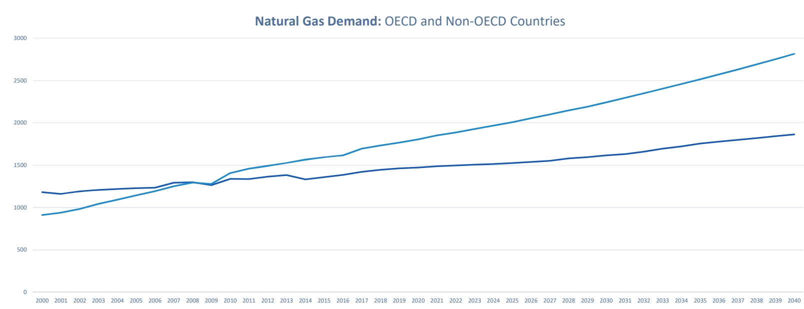

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Overview

- The market price of the energy plays a significant role in determining energy and environmental security.
- We have two kinds of contract pricing methods in the gas market, one of them is spot price which is based on demand and supply and the other which is a term contract and related to oil index.
- Statistical models are capable of providing a prediction of future supply, demand and eventually price of natural gas which are essential for the planning of the energy market.
- The aim of this study is to compare statistical models with neural network models for describing the evolution of supply, demand and price of natural gas.
- Meanwhile, considering that there is a strong interaction between supply, demand and the resulting price, we may be able to take and project the demand as a variable that can be modelled and through which we can to model the other variables.
- Eventually, in order to show the accuracy of the algorithm, a fair comparison is made with Neural network and time series modelling.
- The results show that our forecast are quite close to real values and the time series models can be perform as well as neural network models.

Overview

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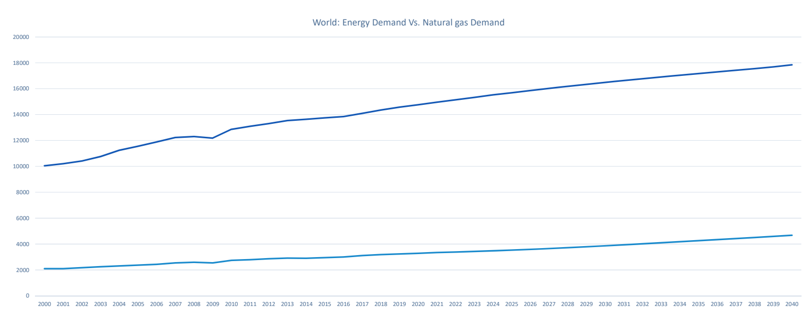

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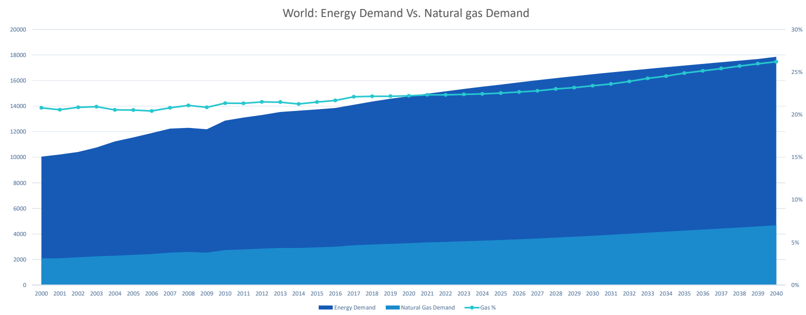

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Gas forecasting Models

OLS regression

Linear regression is a simple model where the output is linear combination of inputs. Unlike the AR, ARMA, or ARIMA models, the input vector of a linear regression can include both historical values of target variables and exogenous variables (e.g. Temperature, Type of day, etc.). This model is given by model (1).

$$y = \sum_{i=1}^{d} w_i x_i = W^T X$$

Where y represents the output of target data, $W = (w_0, w_1, \ldots, w_d)$ is the weight vector.

ARIMA model

Autoregressive integrated moving average (ARIMA) model. ARIMA outperforms the models that can use for non stationary time series by differencing the Equation for ARIMA (p, d, q) model :

$$\underbrace{(1-\varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_p L^p)}_{\text{AR(p)}} \underbrace{(1-L^d)}_{\text{I(d)}} y_t = c + \underbrace{(1+\theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q)}_{\text{MA(q)}} \epsilon_t$$

Statistical Approach

SARIMA model

A seasonal autoregressive integrated moving average model (SARIMA), with degree p, q, P, Q, is an extension of an ARIMA model, which also takes into account seasonality s, and can be written as a

SARIMA (p, d, q) × (P, D, Q)s.

$$\underbrace{\varphi_p(L)\Phi_P(L^s)}_{\text{AR(p, P)}} \overbrace{\nabla^d \nabla_s^D}^{\text{I(d, D)}} y_t = \underbrace{\theta_q(L)\Theta_Q(L^s)\epsilon_t}_{\text{MA(q,Q)}}$$

SARIMAX model

SARIMAX are SARIMA models with exogenous input. The exogenous input X, integrates an ordinary regression model that uses external variables into the SARIMA model. Thus, we get the generic form of a SARIMAX (p, d, q, b) × (P, D, Q)s

$$\underbrace{\varphi_p(L)\Phi_P(L^s)}_{\text{AR(p, P)}} \overbrace{\nabla^d \nabla_s^D}^{\text{I(d, D)}} y_t = \overbrace{\eta_b(L)\xi_t}^{\text{exogenous input (b)}} + \underbrace{\theta_q(L)\Theta_Q(L^s)\epsilon_t}_{\text{MA(q,Q)}}$$

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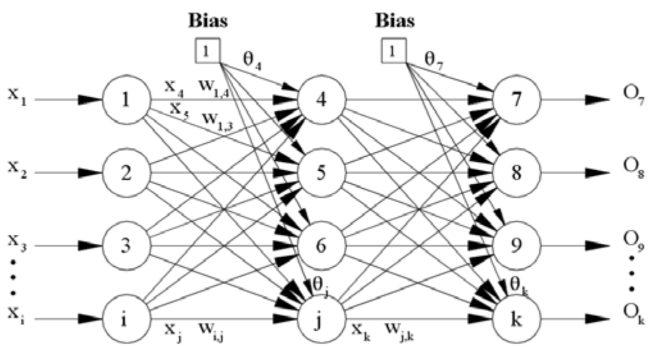
Neural Network Approach



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Neural Network Approach

ANNs are analytic techniques:

- modeled on the learning processes of the human cognitive system and the neurological functions of the brain.
- Considerable interest in the development of NNs for solving a wide range of problems.
- Information processing systems composed of many simple computational elements interacting across weighted connections.
- Simply parameterized nonlinear functions that can be fitted to data for prediction purposes.
- Multilayered feedforward networks use a supervised learning method and feedforward architecture.
- The success of ANN models depends on properly selected parameters such as the number of nodes (neurons) and layers, the nonlinear function used in the nodes, the learning algorithm, the initial weights of the inputs and layers, and the number of epochs for which the model is iterated.
- This model consists of a number of perceptrons organized by layers. Each perceptron has several inputs and one output, which is a non-linear function of the inputs.
- It has been shown that networks with just two layers (i.e. inputs, hidden units, and output layer) are capable of approximating any continuous functional.

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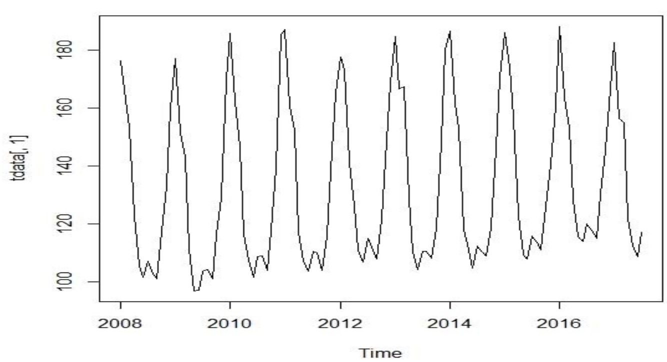
Application of the methodology

- We consider Gas consumption monthly data for OECD countries, the tsPlot of the data between 2008 till July, 2017 is as follows (Bcm):



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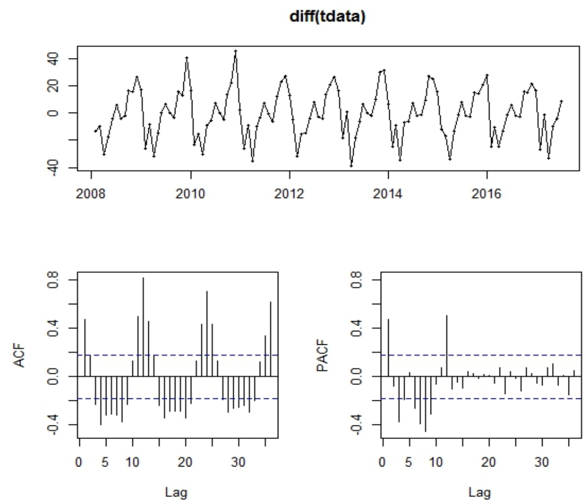
Application of the methodology



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Application of the methodology

We apply the best model which is SARIMA (2,0,1)*(0,1,2) with min AICC and BIC.

```
fit2<-Arima(tdata, order=c(2,0,1), seasonal=c(0,1,2))
```

```
> fit2<-Arima(tdata, order=c(2,0,1), seasonal=c(0,1,2))
> fit2
Series: tdata
ARIMA(2,0,1)(0,1,2)[12]

Coefficients:
         ar1      ar2      ma1     sma1     sma2
      1.2931  -0.2932  -0.9436  -0.9384  -0.0194
s.e.  0.1121   0.1118   0.0731   0.7202   0.1715

sigma^2 estimated as 23.36:  log likelihood=-317.04
AIC=646.07   AICc=646.95   BIC=661.88
> Res2<-residuals(fit2)
> Box.test(Res2, lag=16,fitdf=12)

        Box-Pierce test

data:  Res2
X-squared = 1.675 , df = 4, p-value = 0.5425
```

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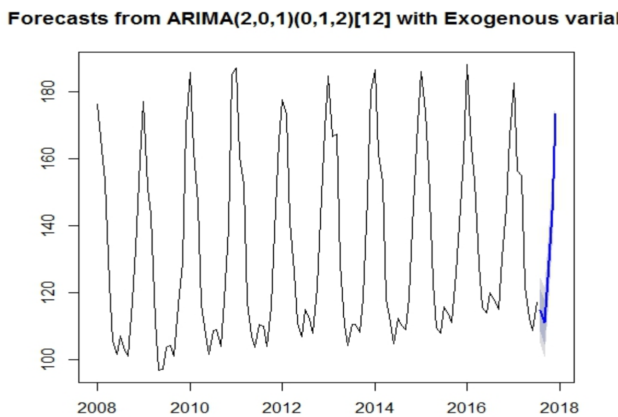
Application of the methodology

We apply the best model which is SARIMAX (2,0,1)*(0,1,2) which X represent the temperature which calculated with weighted average.



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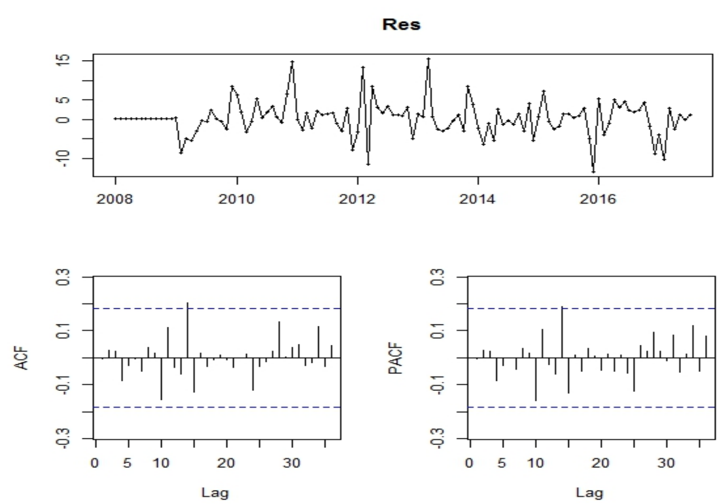
Application of the methodology



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Application of the methodology

The accuracy of the forecasting methods are compared by using 3 different performance measures. These are root mean squared error (RMSE), mean absolute deviation (MAE), and mean absolute percentage error (MAPE).

$$RMSE = \frac{1}{n}\{\sum_{t=1}^{n}(Y_t - \widehat{Y}_t)^2\}^{\frac{1}{2}}$$

$$MAE = \frac{1}{n}\{\sum_{t=1}^{n}|Y_t - \widehat{Y}_t|\}$$

$$MAPE = \frac{1}{n}\left\{\sum_{t=1}^{n}\frac{(Y_t - \widehat{Y}_t)}{Y_t}\right\}$$

Where Y_t and $\widehat{Y}_t$ represent the real and forecast value of natural gas consumption, respectively.

Application of the methodology

- ✓ In this study, the neural network model consisted of an input layer, two hidden layer, and an output layer.
- ✓ i= 115 , input variables.
- ✓ The number of nodes in the hidden layer was decided after testing the different models.
- ✓ The MSE decreased for both the training data and the test data when 27 nodes were used in the hidden layer. In the first neural network model, the hyperbolic tangent transfer function was used in the hidden layers, and a linear transfer function was used in the output layer.
- ✓ The Levenberg-Marquardt backpropagation algorithm was used to train the ANN model as the learning algorithm.
- ✓ The default number of hidden neurons for this network is calculated as 1/2 (number of inputs + number of outputs) + square root of the training patterns.
- ✓ NeuroShell's TurboProp training method was employed for the model.

Table 1 provides the average MSE, MAPE, MAE, and RMSE for the data set of the methods.

Model	RMSE	MAE	MAPE
SARMAX	0.0365	0.0319	0.1981
NeuroShell TurboProp learning algorithm	0.0525	0.8210	0.4580
NeuroShell GeneHunter learning algorithm	0.0512	0.0968	0.2778
Backpropagation/gradient descent algorithm	0.0343	0.0372	0.1831

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Conclusions

- Good opportunity to see global energy picture for better analysis
- Providing better decisions for natural gas prediction in gas market using approaches SARMAX and Neural Networks.
- It has been observed that the time series models help in understanding the way in which energy interactions work.
- This research concluded that the neural network model with backpropagation outperforms multiple regression, neural network NeuroShell, the neural network model with the GA, and the SARMAX model for natural gas forecasting.
- SARMAX and ANNs with backpropagation models indicated that temperature and the first lag of demand were the most important factors for natural gas prediction.
- ANN with backpropagation model, which had the lowest performance scores in terms of MSE, MAPE, and RMSE.
- The SARMAX and ANN with backpropagation models are the best models.
- Determine annual gas demand, including seasonal variation, temperature and population.
- The results show that the use of forecasting data improves the performance of prediction techniques.

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References

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Thank you for your attention

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