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Modeling and Forecasting of Supply of New Energies with Time Series Approach; Sustainable Development Approach

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ABSTRACT

The aim of this paper is modeling and forecasting supply of new energies in Netherlands by time series approach. We have used the methodology of Box-Jenkins for modeling the series of new energies. The variable is Energy production (kt of oil equivalent) for Netherlands. The sample of data is during 1960-2010 period. Based on Schwarz criterion, ARMA(2,1) is the best model for forecasting the series of energy. We have forecasted the supply of new energies of Netherlands during 1960-2013.

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INTRODUCTION

New Energies is one of the most important sources of energy supply in development and developing countries. There are many studies about modeling supply of energy in previous studies as Wang and *et al* (2010), Stoyanova and *et al* (2012), Kumar & Jain (2010), Li and *et al* (2011), Dagdougui and *et al* (2012), Lee& Shih (2011), Dagher& Ruble (2011) and González, Contreras, & Bunn (2012). There are lack studies about supply of new energies as wind, nuclear, solar and hydroenergies as Marquis and *et al* (2011), Jónsson, Pinson, & Madsen, (2010), Chen, Chen, & Lee (2010). Walls (1992) surveyed the literature in empirical oil and gas supply modeling. In the paper of Walls (1992), the models fall into two broad categories: geologic/engineering and econometric. Two types of geologic/engineering models are surveyed — play analysis, or simulation, models and discovery process models. A third category of supply models, 'hybrids', which contained features of both econometric and discovery process models were also discussed Walls (1992). Particular attention is paid to whether or not the models have linkages between a dynamic model of producer optimizing behavior and the factors governing supply of the resource; whether or not expectations of future prices, costs, and other stochastic variables are incorporated; whether the physical characteristics of non-renewable resources are captured; and how well the models perform. He concluded that the best path for future research efforts is a hybrid approach where the econometric component is derived from a stochastic dynamic optimization model of exploration behavior[Walls (1992).

González, Roque, &García-González (2005) haveanalyzedthe electricity price time series that it reflected a switching nature, related to discrete changes in competitors' strategies, which can be represented by a set of dynamic models sequenced together by a Markov chain. An input-output hidden Markov model (IOHMM) is proposed for analyzing and forecasting electricity spot prices. The model provided both good predictions in terms of accuracy as well as dynamic information about the market. In this way, different market states were identified and characterized by their more relevant explanatory variables. Moreover, a conditional probability transition matrix governed the probabilities of remaining in the same state, or changing to another, whenever a new market session is opened. Their model has been successfully applied to real clearing prices in the Spanish electricity market [González, Roque, &García-González (2005).

Amjady & Hemmati (2006) have discussed the value of price forecasting in the electricity market during bidding or hedging against volatility. When bidding in a pool system, the market participants were requested to express their bids in terms of prices and quantities Amjady & Hemmati (2006). Since the bids were accepted in order of increasing price until the total demand was met, a company that was able to forecast the pool price could adjust its own price/production schedule depending on hourly pool prices and its own production costs. They also discussed the challenges of price forecasting and described some of the proposed methods for meeting these challenges Amjady & Hemmati(2006).

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Bunn (2000) has provided a review of some of the main methodological issues and techniques which have become innovative in addressing the problem of forecasting daily loads and prices in the new competitive power markets. Particular emphasis was placed upon computationally intensive methods, including variable segmentation, multiple modeling, combinations, and neural networks for forecasting the demand side, and strategic simulation using artificial agents for the supply side Bunn (2000).

Adams and Shachmurove (2008) have built an econometric model of the Chinese energy economy based on the energy balance. They used that model to forecast Chinese energy consumption and imports to 2020. Their study suggested that China will, indeed, require rapidly growing imports of oil, coal, and gas. This growth is not so sensitive to the rate of economic growth as to increases in motorization. It can be offset, but probably only in small part, by increasing domestic energy production or by improvements in the efficiency of use, particularly in the production of electric power Adams and Shachmurove (2008).

Mohamed andBodger (2005) used gross domestic product, average price of electricity and population of New Zealand during the period 1965–1999. Models are developed using multiple linear regression analysis. It was found that the electricity consumption correlated effectively with all variables. Forecasts made using these models were compared with some available national forecasts. The forecasts were also compared with the forecasts of the previously developed Logistic model Mohamed andBodger (2005).

In the paper of Chen and Wang (2012), An improved grey G(1,1) prediction model is proposed to the energy management engineering. It is one approach that can be used to construct a model with limited samples to provide better forecasting advantage for long-term problems. The forecasting performance of the improved GM(1,1) model has been confirmed using the China's energy database. And the results, compared with those from artificial neural network (ANN) and times series. According to the experimental results, our proposed new method obviously can improve the prediction accuracy of the original grey model Chen and Wang (2012).

In the paper ofEkonomou (2010), artificial neural networks (ANN) are addressed in order the Greek long-term energy consumption to be predicted. The multilayer perceptron model (MLP) has been used for this purpose by testing several possible architectures in order to be selected the one with the best generalizing ability. Actual recorded input and output data that influence long-term energy consumption were used in the training, validation and testing process. The developed ANN model is used for the prediction of 2005–2008, 2010, 2012 and 2015 Greek energy consumption. The produced ANN results for years 2005–2008 were compared with the results produced by a linear regression method, a support vector machine method and with real energy consumption records showing a great accuracy. The proposed approach can be useful in the effective implementation of energy policies, since accurate predictions of energy consumption affect the capital investment, the environmental quality, the revenue analysis, the market research management, while conserve at the same time the supply security. Furthermore it constituted an accurate tool for the Greek long-term energy consumption prediction problem, which up today has not been faced effectively Ekonomou (2010).

The aim of this paper is modeling and forecasting supply of new energies by time series approach. This paper is organized by 4 sections, the next section is devoted to research method, section 3 shows empirical results and final section is devoted to conclusion.

2. Research Method:

We have used the methodology of Box-Jenkins for modeling the series of new energies. The case study is Netherlands.

2.1. Box-Jenkins Methodology:

Box-Jenkins forecasting models are based on statistical concepts and principles and are able to model a wide spectrum of time series behavior. It has a large class of models to choose from and a systematic approach for identifying the correct model form. There are both statistical tests for verifying model validity and statistical measures of forecast uncertainty. In contrast, traditional forecasting models offer a limited number of models relative to the complex behavior of many time series with little in the way of guidelines and statistical tests for verifying the validity of the selected model (web.ntpu.edu.tw/).

Data: The misuse, misunderstanding, and inaccuracy of forecasts is often the result of not appreciating the nature of the data in hand. The consistency of the data must be insured and it must be clear what the data represents and how it was gathered or calculated. As a rule of thumb, Box-Jenkins requires at least 40 or 50 equally-spaced periods of data. The data must also be edited to deal with extreme or missing values or other distortions through the use of functions as log or inverse to achieve stabilization (web.ntpu.edu.tw/)].

Preliminary Model Identification Procedure: A preliminary Box-Jenkins analysis with a plot of the initial data should be run as the starting point in determining an appropriate model. The input data must be adjusted to form a stationary series, one whose values vary more or less uniformly about a fixed level over time. Apparent trends can be adjusted by having the model apply a technique of "regular differencing," a process of computing the difference between every two successive values, computing a differenced series which has overall trend behavior removed. If a single differencing does not achieve stationarity, it may be repeated, although rarely if ever, are more than two regular differencings required. Where irregularities in the differenced series continue to be displayed, log or inverse functions can be specified to stabilize the series such that the remaining residual plot displays values approaching zero and without any pattern. This is the error term, equivalent to pure, white noise (web.ntpu.edu.tw/).

Pure Random Series: On the other hand, if the initial data series displays neither trend nor seasonality and the residual plot shows essentially zero values within a 95% confidence level and these residual values display no pattern, then there is no real-world statistical problem to solve and we go on to other things (web.ntpu.edu.tw/).

2.2. Data:

We have used the database of World Development Indicator (WDI) 2012. The variable is Energy production (kt of oil equivalent) for Netherlands. The sample of data is during 1960-2010 period.

Table 1: Data Description

Mean	53006.81
Median	61797.00
Maximum	76316.00
Minimum	9977.000
Std. Dev.	21791.62
Skewness	-1.153039
Kurtosis	2.732956
Jarque-Bera	11.45228
Probability	0.003260
Sum	2703348.
Sum Sq. Dev.	2.37E+10
Observations	51

Table 1 indicates some descriptive statistic of supply of new Energy series.

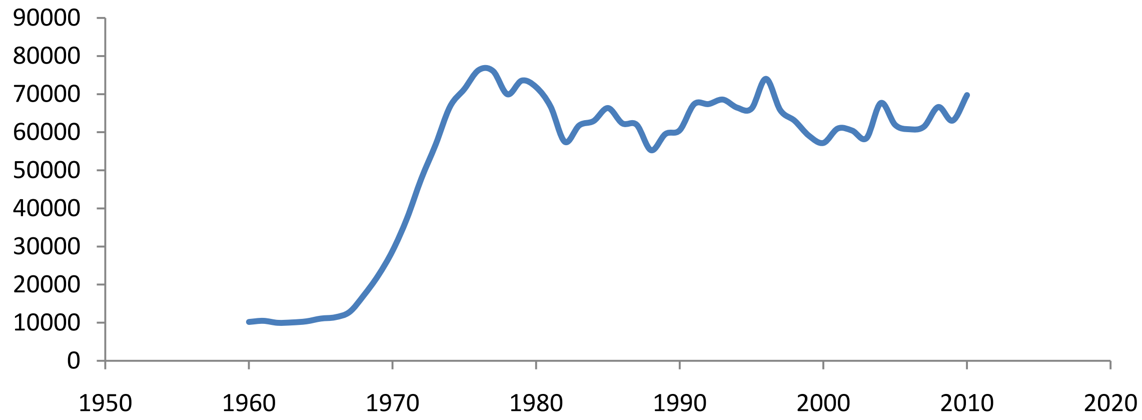

Fig. 1: Supply of New Energies

Figure 1 indicates the series of supply of new energies in Netherlands during 1960-2010 period.

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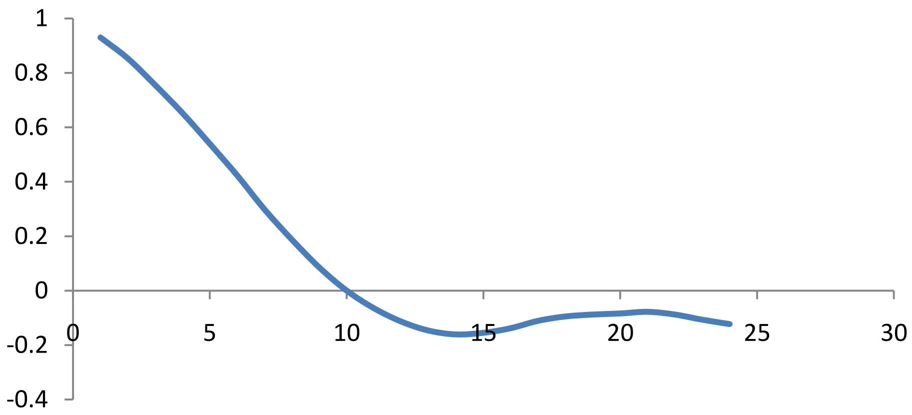

Fig. 2: ACF series

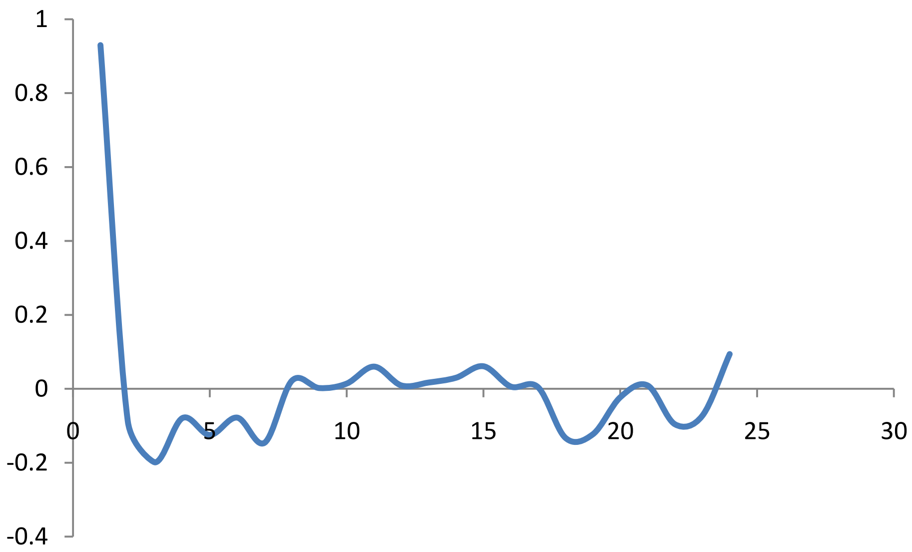

Fig. 3: PACF series

Figure 2 and 3 indicate Auto Correlation Function and Partial Auto Correlation Function respectively. The above figures indicate existence of ARMA process in series of supply energy.

3. Empirical Results:

First of all we have tested unit root in the data. We have tested Elliott-Rothenberg-Stock test and Ng-Perron test. The results of the test indicated in Table 2 and 3 respectively.

Table 2: Elliott-Rothenberg-Stock test

Null Hypothesis: ENERGY has a unit root				
Exogenous: Constant, Linear Trend				
Lag length: 0 (Spectral OLS AR based on SIC, MAXLAG=10)				
Sample: 1960 2010				
Included observations: 51				
				P-Statistic
Elliott-Rothenberg-Stock test statistic				47.71197
Test critical values:	1% level			4.220800
	5% level			5.718400
	10% level			6.770400

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*Elliott-Rothenberg-Stock (1996, Table 1)				
HAC corrected variance (Spectral OLS autoregression)				21100933

Table 3: Ng-Perron test

Null Hypothesis: ENERGY has a unit root					
Exogenous: Constant, Linear Trend					
Lag length: 0 (Spectral GLS-detrended AR based on SIC, MAXLAG=10)					
Sample: 1960 2010					
Included observations: 51					
		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-1.94304	-0.93544	0.48143	43.6530
Asymptotic critical values*:	1%	-23.8000	-3.42000	0.14300	4.03000
	5%	-17.3000	-2.91000	0.16800	5.48000
	10%	-14.2000	-2.62000	0.18500	6.67000
*Ng-Perron (2001, Table 1)					
HAC corrected variance (Spectral GLS-detrended AR)					22184683

Results of unit root tests indicate that the series of energy is stationary. After sure that the series is stationary, we can modeling the energy with ARMA models.

We have estimated 7 models consist of AR(1), MA(1), ARMA(1,1), ARMA(2,1), ARMA(1,2), ARMA(2,2) and ARMA(3,1). The estimation results reported in Appendix.

Table 4: ARMA Models with Schwarz criterion

AR(1)	19.85943
MA(1)	21.85889
ARMA(1,1)	19.91604
ARMA(2,1)	19.68785
ARMA(1,2)	19.92144
ARMA(2,2)	19.76562
ARMA(3,1)	19.73603

Based on Schwarz criterion, ARMA(2,1) is the best model for forecasting the series of energy.

The estimation of ARMA(2,1) is shown by Table 5.

Table 5: Estimation of ARMA(2,1)

Method: Least Squares				
Date: 01/05/13 Time: 10:55				
Sample (adjusted): 1962 2010				
Included observations: 49 after adjustments				
Convergence achieved after 27 iterations				
MA Backcast: 1961				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	64231.44	2299.109	27.93754	0.0000
AR(1)	1.729766	0.070315	24.60029	0.0000
AR(2)	-0.768818	0.061901	-12.42007	0.0000

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MA(1)	-0.951932	0.079790	-11.93048	0.0000
R-squared	0.962846	Mean dependent var		54747.97
Adjusted R-squared	0.960369	S.D. dependent var		20389.79
S.E. of regression	4059.105	Akaike info criterion		19.53342
Sum squared resid	7.41E+08	Schwarz criterion		19.68785
Log likelihood	-474.5688	Hannan-Quinn criter.		19.59201
F-statistic	388.7243	Durbin-Watson stat		1.940953
Prob(F-statistic)	0.000000			
Inverted AR Roots	.86-.14i	.86+.14i		
Inverted MA Roots	.95			

Estimation Results indicate that:
* All of the parameters are significance.
* R-Square is 0.96 that means the model has goodness of fit.
* F-Statistic indicates that the regression is significance.

Table 6 indicates the normality test (Jarque-Bera). The results of the test shows normality in residual series.

Table 6: Normality Test

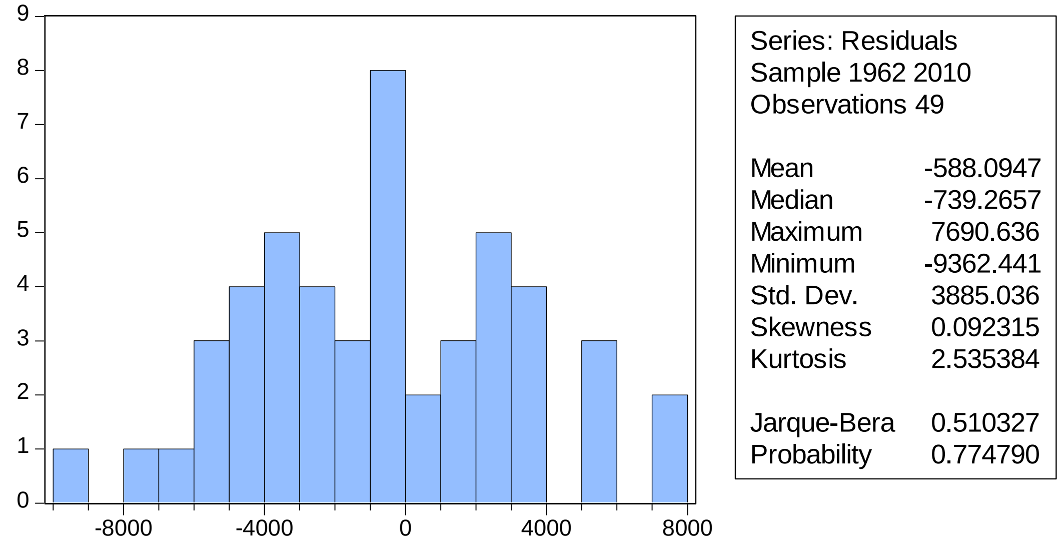

Table 7 shows results of the Breusch-Godfrey Serial Correlation LM Test. Results indicate that there is no serial correlation between residul series.

Table 7: Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.075628	Prob. F(2,43)	0.3501
Obs*R-squared	1.243056	Prob. Chi-Square(2)	0.5371

Table 8: Heteroskedasticity Test: ARCH

F-statistic	0.008442	Prob. F(1,46)	0.9272
Obs*R-squared	0.008807	Prob. Chi-Square(1)	0.9252

Table 8 indicates Heteroskedasticitytest (ARCH LM test). Results indicate that there is no ARCH effect and the residual series has not Heteroskedasticity.

Figure 4 indicates Actual, Residual and Fitted series of ARMA(2,1) model. Figure 4 indicates the model is suitable for estimation the supply of energy.

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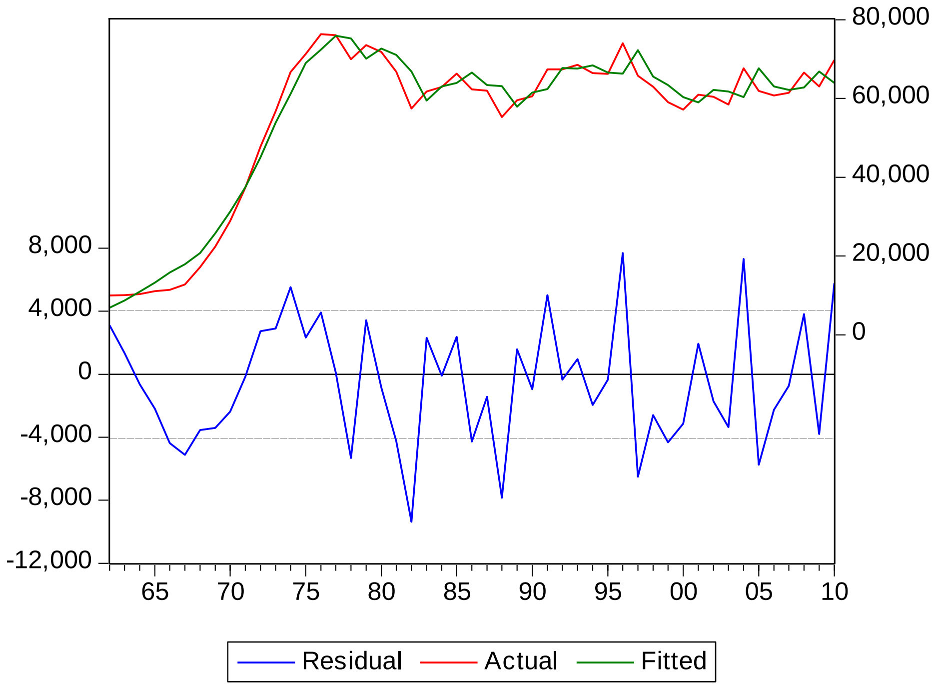

Fig. 4: Actual, Residual and Fitted series of ARMA(2,1)

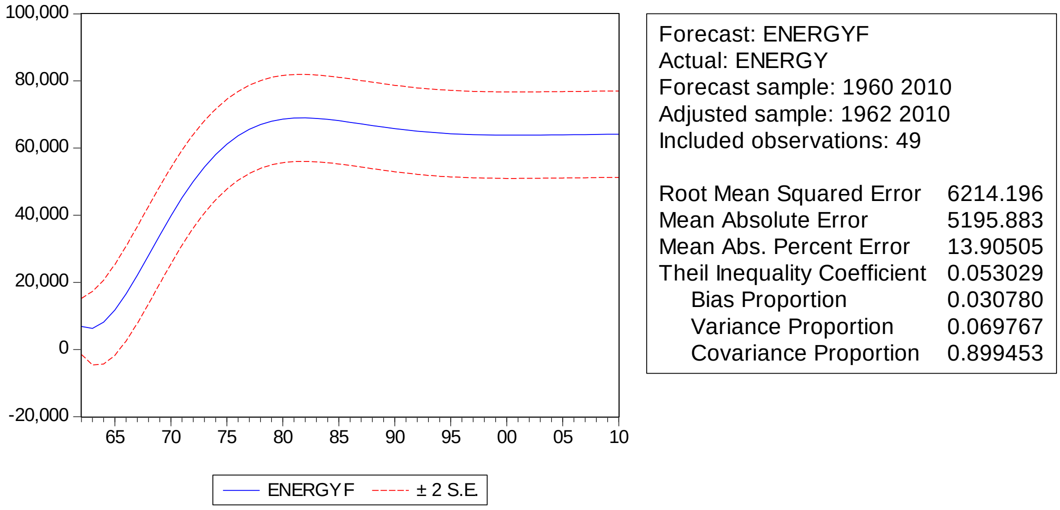

Fig. 5: Forecasted Supply of New Energy

Figure 5 indicates the forecasted series of supply of new energy in Netherlands.

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Table 9: Forecasted supply of new energies 1960-2013

1962	6865.351045630348
1963	6313.546419017534
1964	8151.131796090624
1965	11753.96222804028
1966	16573.2468802631
1967	22139.5600475515
1968	28062.82551106508
1969	34029.20573750917
1970	39795.73294793727
1971	45183.41376322707
1972	50069.42958626005
1973	54378.94636234233
1974	58076.94386955031
1975	61160.37910845122
1976	63650.91259063587
1977	65588.35144881524
1978	67024.8997136363
1979	68020.25369457195
1980	68637.53862862217
1981	68940.05079405612
1982	68988.7461081642
1983	68840.40071145933
1984	68546.36002066817
1985	68151.78905958771
1986	67695.33745780796
1987	67209.13633624121
1988	66719.05047494206
1989	66245.11689891949
1990	65802.10965776721
1991	65400.17956951386
1992	65045.52661491741
1993	64741.07117552574
1994	64487.0981694617
1995	64281.85519554497
1996	64122.09195931927
1997	64003.53348974391
1998	63921.28397276798
1999	63870.1614712909
2000	63844.96643774915
2001	63840.68883924547
2002	63852.65999817697
2003	63876.6559994103
2004	63908.95982264941
2005	63946.389315567
2006	63986.29781227559
2007	64026.55369688116
2008	64065.50457771913
2009	64101.93102907636
2010	64134.99411869392
2011	64164.18020683193
2012	64189.24580338106
2013	64210.16462305346

Table 9 indicates forecasted supply of new energies in Netherlands during 1960-2013. Results indicate the supply of new energies of Netherlands in 2013 is 64210.1646(kt of oil equivalent).

Conclusion:

New Energies is one of the most important sources of energy supply in development and developing countries. There are many studies about modeling supply of energy in previous studies but there are lack studies about supply of new energies as wind, nuclear, solar and hydro energies. The aim of this paper is modeling and forecasting supply of new energies in Netherlands by time series approach.

We have used the database of World Development Indicator (WDI) 2012. The variable is Energy production (kt of oil equivalent) for Netherlands. The sample of data is during 1960-2010 period.We have estimated 7 models consist of AR(1), MA(1), ARMA(1,1), ARMA(2,1), ARMA(1,2), ARMA(2,2) and ARMA(3,1). The estimation results reported in Appendix. Based on Schwarz criterion, ARMA(2,1) is the best

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model for forecasting the series of energy.Results indicate the supply of new energies of Netherlands in 2013 is 64210.1646(kt of oil equivalent).

REFERENCES

Adams, F.G., & Y. Shachmurove, 2008. Modeling and forecasting energy consumption in China: Implications for Chinese energy demand and imports in 2020. Energy Economics, 30(3): 1263-1278.

Amjady, N., & M. Hemmati, 2006. Energy price forecasting-problems and proposals for such predictions. Power and Energy Magazine, IEEE, 4(2): 20-29.

Bunn, D.W., 2000. Forecasting loads and prices in competitive power markets. Proceedings of the IEEE, 88(2): 163-169.

Chen, Y.H., C.Y. Chen, & S.C. Lee, 2010. Technology forecasting of new clean energy: The example of hydrogen energy and fuel cell. Afr. J. Bus. Manage, 4(7): 1372-1380.

Chen, Z., & X. Wang, 2012. Applying the Grey Forecasting Model to the Energy Supply Management Engineering. Systems Engineering Procedia, 5: 179-184.

Dagdougui, H., R. Minciardi, A. Ouammi, M. Robba, & R. Sacile, 2012. Modeling and optimization of a hybrid system for the energy supply of a “Green” building. Energy Conversion and Management, 64: 351-363.

Dagher, L., & I. Ruble, 2011. Modeling Lebanon’s electricity sector: Alternative scenarios and their implications. Energy, 36(7): 4315-4326.

Ekonomou, L., 2010. Greek long-term energy consumption prediction using artificial neural networks. Energy, 35(2): 512-517.

González, A.M., A.M.S. Roque, & J. García-González, 2005. Modeling and forecasting electricity prices with input/output hidden Markov models. Power Systems, IEEE Transactions on, 20(1): 13-24.

González, V., J. Contreras, & D.W. Bunn, 2012. Forecasting Power Prices Using a Hybrid Fundamental-Econometric Model. Power Systems, IEEE Transactions on, 27(1): 363-372.

Jónsson, T., P. Pinson, & H. Madsen, 2010. On the market impact of wind energy forecasts. Energy Economics, 32(2): 313-320.

Kumar, U., & V.K. Jain, 2010. Time series models (Grey-Markov, Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. Energy, 35(4): 1709-1716.

Lee, S.C., & L.H. Shih, 2011. Forecasting of electricity costs based on an enhanced gray-based learning model: A case study of renewable energy in Taiwan. Technological Forecasting and Social Change, 78(7): 1242-1253.

Li, J., X. Dong, J. Shangguan, & M. Hook, 2011. Forecasting the growth of China’s natural gas consumption. Energy, 36(3): 1380-1385.

Marquis, M., J. Wilczak, M. Ahlstrom, J. Sharp, A. Stern, J.C. Smith, & S. Calvert, 2011. Forecasting the wind to reach significant penetration levels of wind energy. Bulletin of the American Meteorological Society, 92(9): 1159.

Mohamed, Z., & P. Bodger, 2005. Forecasting electricity consumption in New Zealand using economic and demographic variables. Energy, 30(10): 1833-1843.

Stoyanova, I., P. Matthes, H. Harb, C. Molitor, M. Marin, R. Streblow & D. Muller, 2012. Challenges in modeling a multi-energy system at city quarter level. In Complexity in Engineering (COMPENG), 2012 (pp. 1-5). IEEE.

Walls, M.A., 1992. Modeling and forecasting the supply of oil and gas: A survey of existing approaches. Resources and Energy, 14(3): 287-309.

Wang, J., S. Zhu, W. Zhang, & H. Lu, 2010. Combined modeling for electric load forecasting with adaptive particle swarm optimization. Energy, 35(4): 1671-1678.

web.ntpu.edu.tw/~tsair/1Teaching/.../TimeSeriesUnder/Box.doc