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Forecasting Iran Crude Oil Export; an Application of Time Series Models

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ABSTRACT

The aim of this paper is forecasting Iran crude oil with time series model. We estimated AR, MA, ARMA, ARCH, GARCH, TARCH, CGARCH, PARCH and EGARCH models for modeling Iran crude oil export. Based on Akaike information criterion, we choice ARMA (1,1) model. Based on Schwarz criterion, we choice AR (1) model because Schwarz criterion is lowest statistic rather than other models. Based on Hannan-Quinn criterion, we choice ARMA (1,1) model. We have forecasted Iran crude oil export with ARMA(1,1) model. Results indicate that Iran crude oil export will decrease to 2097.317114 thousands oil barrels in Iran.

KEY WORDS: Forecasting, Crude Oil Export, Time Series Models, Iran.

1. INTRODUCTION

Iran's economy has been highly dependent on the production and export of crude oil to finance government spending, and consequently is vulnerable to fluctuations in international oil prices. Although Iran has vast petroleum reserves, the country lacks adequate refining capacity and imports gasoline to meet domestic energy needs.

Energy resources in Iran consist of the third largest oil reserves and the second largest natural gas reserves in the world. Iran is in a constant battle to use its energy resources more effectively in the face of subsidization and the need for technological advances in energy exploration and production. Energy wastage in Iran amounts to six or seven billion dollars (2008). The energy consumption in the country is extraordinarily higher than international standards. Iran recycles 28 percent of its used oil and gas whereas the figure for certain countries stands at 60 percent. Iran paid $84 billion in subsidies for oil, gas and electricity in 2008. Iran is one of the most energy intensive countries of the world with per capita energy consumption 15 time that of Japan and 10 times that of European Union. Also due to huge energy subsidies, Iran is one of the most energy inefficient countries of the world, with the energy intensity three times higher than global average and 2.5 times the Middle Eastern average.

Iran is one of the leading members of OPEC (Organization of Petroleum Exporting Countries) and the Organization of Gas Exporting Countries (GECF). Iran received $47 billion dollars in oil export revenues, which accounts for about 50% of state revenues. Natural gas and oil consumption both account for about half of Iran's domestic energy consumption. With its heavy dependence on oil and gas revenues Iran continues to explore for new sources of natural gas and oil. Recently Iran has focused its energy sector on the exploration of the South Pars offshore natural gas fields in the Persian Gulf.

Iran has become self-sufficient in designing, building and operating dams and power plants and it has won a good number of international bids in competition with foreign firms.

Ye, Zyren and Shore (2002) presented a short-term monthly forecasting model of West Texas Intermediate crude oil spot price using OECD petroleum inventory levels. Theoretically, petroleum inventory levels are a measure of the balance, or imbalance, between petroleum production and demand, and thus provide a good market barometer of crude oil price change. Based on an understanding of petroleum market fundamentals and observed market behavior during the post- Persian Gulf War period, the model was developed with the objectives of being both simple and practical, with required data readily available. As a result, the model is useful to industry and government decision-makers in forecasting price and investigating the impacts of changes on price, should inventories, production, imports, or demand change.

Yua, Wanga and Laib (2008) proposed empirical mode decomposition (EMD) based neural network ensemble learning paradigm for world crude oil spot price forecasting. For this purpose, the original crude oil spot price series were first decomposed into a finite, and often small, number of intrinsic mode functions (IMFs). Then a three-layer feed-forward neural network (FNN) model was used to model each of the extracted IMFs, so that the tendencies of these IMFs could be accurately predicted. Finally, the prediction results of all IMFs are combined with an adaptive linear neural network (ALNN), to formulate an ensemble output for the original crude oil price series.

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For verification and testing, two main crude oil price series, West Texas Intermediate (WTI) crude oil spot price and Brent crude oil spot price, are used to test the effectiveness of the proposed EMD-based neural network ensemble learning methodology. Their empirical results obtained demonstrate attractiveness of the proposed EMD-based neural network ensemble learning paradigm.
In this paper, we have used different time series model to forecast Iran crude oil exports until 2020 year.

2. Forecasting Methods

Let R_t be the oil export in Iran economy from time $t-1$ to t and Ω_{t-1} be the past Information set containing the Realized value of all relevant variables up to time $t-1$. So the conditional mean and variance are $y_t = E(R_t|\Omega_t), h_t = \text{var}(R_t|\Omega_t)$ respectively. Given this definition, the unexpected oil export at time t is $\varepsilon_t = R_t - y_t$. This paper follows Engle and Ng (1993) in treating ε_t as a collective measure of bad news (unexpected decrease in oil export) if $\varepsilon_t < 0$ and good news (unexpected increase in oil export) if $\varepsilon_t \geq 0$. Further, a large value of $|\varepsilon_t|$ implies that the news is "significant" or "big" in the sense that it produce a large unexpected change in oil export.

In order to model the effect of ε_t on oil export we present ARCH models. ARCH models were Introduced by Engle (1982) and generalized as GARCH models by Bollerslev (1986). In developing GARCH (p, q) we will have to provide mean and variance Equation

$$R_t = \delta + \varepsilon_t, \varepsilon_t = \eta_t\sqrt{h_t}, \quad \eta_t \sim N(0,1) \qquad (1)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (2)$$

where $\omega,\ \alpha_i,\ \beta_j,\ \gamma$ are constant parameters and x_t contains exogenous and predetermined regressors. As h_t is variance it must be nonnegative which impose the following conditions: $\omega > 0$, $\alpha_1, \ldots\ldots \alpha_p \geq 0$ and $\beta_1, \ldots\ldots\ldots, \beta_q \geq 0$. The conditional variance under ARCH (p) model reflects only information from time $t-p$ to $t-1$ with more importance being placed on the most recent innovation implying $a_i < a_j$ for $i > j$. To avoid long lag lengths on ε_t in ARCH (p) and difficulty in selecting the optional length p, and ensuring the non-negativity of coefficients of conditional variance equation (2), Bollerslev (1986) present GARCH(P, q). A common parameterization for the GARCH model that has been adopted in most applied studies is the GARCH (1, 1) specification under which the effect of a shock to volatility declines geometrically over time.
One problem with ARCH (p) and GARCH (p, q) is that good news and bad news with some absolute size have the same effect on h_t.This fact is symmetric effect. However, the market may react differently to good and bad news. It is important, to be able to test for and allow asymmetry in the ARCH type specification. Nelson (1991) proposes the exponential GARCH (EGARCH) model as a way to deal whit this problem. Under the EGARCH (1, 1) the h_t is given as:

$$\log(h_1) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta \log h_{t-1} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \qquad (3)$$

The EGARCH news Impact differs from the GARCH new Impact in four ways: (1) it is not symmetric. (2) Big news can have a much greater impact than in the GARCH model. (3) Log construction of Equation 3 ensures that the estimated h_t is strictly positive, thus non-negativity constraints used in the estimation of the ARCH and GARCH are not necessary. (4) Since the parameter of γ typically enters equation 3 with a negative sign, bad news generates more volatility than good news.

Glosten, Jagannathan and Runkle (1993), hereafter GJR, Defined GJR Asymmetric Volatility model as follow:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma s_{t-1}^- \varepsilon_{t-1}^2 \quad (4)$$

Where $s_t^- = 1$ if $\varepsilon_t < 0$, and 0 otherwise.

The GJR model is closely related to the threshold ARCH or TARCH model of Rabemananjara and Zakoian (1993) and Zakoian (1994). Provided that $\gamma > 0$, the GJR model generates higher values for h_t given $\varepsilon_{t-1} < 0$ than for a $\varepsilon_t > 0$ of equal magnitudes.

The Component GARCH (CGARCH) model by Engle and Lee (1993) decomposes returns uncertainty into a short-run and a long-run component by permitting transitory deviations of the conditional volatility around a time-varying trend, q_t, modeled as:

$$\sigma_t^2 - q_t = a(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) \quad (5)$$

$$q_1 = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (6)$$

Here σ_t^2 is still the volatility, while q_t takes the place of ω and is the time varying long run volatility. The first equation describes the transitory component, $\sigma_t^2 - q_t$ which converges to zero with powers of ($\alpha + \beta$). The second equation describes the long run component q_t, which converges to ω with powers of ρ. Typically ρ is between 0.99 and 1 so that q_t approaches ω very slowly. We can combine the transitory and permanent equations and write

$$\sigma_t^2 = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\phi)\varepsilon_{t-1}^2 + \beta - \phi)\sigma_{t-1}^2 - (\beta\rho - (\alpha+\beta)\phi)\sigma_{t-2}^2 \quad (7)$$

which shows that the component model is a (nonlinear) restricted GARCH (2, 2) model. In addition, GARCH(1, 1) is a special case of the CARCH in which $\alpha = \beta = 0$.

We can include exogenous variables in the conditional variance equation of component models, either in the permanent or transitory equation (or both). The variables in the transitory equation will have an impact on the short run movements in volatility, while the variables in the permanent equation will affect the long run levels of volatility. The asymmetric component combines the component model with the asymmetric TARCH model. This specification introduces asymmetric effects in the transitory equation and estimates models of the form:

$$R_t = x_t'\pi + \varepsilon_t \quad (8)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + \theta_1 z_{1t} \quad (9)$$

$$\sigma_t^2 - q_{t-1} = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})d_{t-1} + \beta(\sigma_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}) + \theta_2 z_{2t} \quad (10)$$

where z the exogenous variables and d are is the dummy variable indicating negative shocks. $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance.

Suppose information is held constant at time $t-2$ and before, Engle and Ng (1993) describe the relationship between ε_{t-1} and h_t as the news impact curve. The news impact curves of GARCH and CGARCH models are symmetric and centered at $\varepsilon_{t-1} = 0$. The news impact curves of EGARCH and TARCH are asymmetric with different slopes.

Autoregressive Moving Average (ARMA) Models

One of the most important models in econometrics is the random walk, which is basically an AR(1) process.

$$y_t = y_{t-1} + u_t$$

The above is the driftless random walk, if a constant is included it becomes the random walk with drift. To determine if an AR(p) process is stationary, involves examining the roots of its characteristic equation. Given the following AR(p) model, it can be said to be stationary if when written in the lag operator notation, the $\phi(L)^{-1}$ converge to zero:

$$\phi(L)y_t = u_t$$
$$y_t = \phi(L)^{-1}u_t$$

If this is the case, the autocorrelations decline to zero as the lag length is increased. For an AR(p) process to be stationary, the roots from the characteristic equation:

$1-\phi_1 z-\phi_2 z^2-...-\phi_p z^p=0$, all need to lie outside the unit circle, i.e. are greater than 1. The random walk is an example of a non-stationary process, as its roots lie on the unit circle not outside:

$$y_t = y_{t-1} + u_t$$
$$y_t = Ly_t + u_t$$
$$y_t(1-L) = u_t$$
$$1-z=0$$
$$z=1$$

Where (1-z) is the characteristic equation and the root (z) lies on the unit circle. The same principle applies to higher orders too:

$$y_t = y_{t-1} - 0.25y_{t-2} + u_t$$
$$y_t = Ly_t - 0.25L^2 y_t + u_t$$
$$(1-L+0.25L^2)y_t = u_t$$
$$1-L+0.25L^2 = 0$$
$$(1-0.5z)(1-0.5z) = 0$$
$$z=2, z=2$$

In the above example both roots lie outside the unit circle, so the AR(2) process is stationary. The same applies for higher orders of lags too, although it becomes increasingly difficult to factorise these. Further characteristics of an AR(p) process are that the mean and variance of an AR(1) process are:

$$E(y_t) = \frac{\mu}{1-\phi_1}, \mathrm{var}(y_t) = \frac{\sigma^2}{(1-\phi_1^2)}$$

3. Empirical Results

First, we estimated AR, MA and ARMA models for modeling Iran crude oil export. Estimation results were shown by following Tables:

Table 1. AR Model Estimation

Dependent Variable: OIL				
Method: Least Squares				
Date: 10/05/11 Time: 22:55				
Sample (adjusted): 1353 1387				
Included observations: 35 after adjustments				
Convergence achieved after 4 iterations				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1992.806	490.0320	4.066685	0.0003
AR(1)	0.820672	0.069074	11.88097	0.0000
R-squared	0.810516	Mean dependent var		2419.586
Adjusted R-squared	0.804774	S.D. dependent var		1073.831
S.E. of regression	474.4652	Akaike info criterion		15.21770
Sum squared resid	7428869.	Schwarz criterion		15.30658
Log likelihood	-264.3097	Hannan-Quinn criter.		15.24838
F-statistic	141.1575	Durbin-Watson stat		1.432253
Prob(F-statistic)	0.000000			
Inverted AR Roots	.82			

Table 2. MA Model Estimation

Dependent Variable: OIL				
Method: Least Squares				
Date: 10/05/11 Time: 22:56				
Sample: 1352 1387				
Included observations: 36				
Convergence achieved after 8 iterations				
MA Backcast: 1351				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	2432.595	216.2018	11.25150	0.0000
MA(1)	0.966907	0.015877	60.89868	0.0000
R-squared	0.687771	Mean dependent var		2500.153
Adjusted R-squared	0.678588	S.D. dependent var		1163.549
S.E. of regression	659.6534	Akaike info criterion		15.87526
Sum squared resid	14794848	Schwarz criterion		15.96323
Log likelihood	-283.7547	Hannan-Quinn criter.		15.90596
F-statistic	74.89438	Durbin-Watson stat		1.013085
Prob(F-statistic)	0.000000			
Inverted MA Roots	-.97			

Table 3. ARMA(1,1) Model Estimation

Dependent Variable: OIL				
Method: Least Squares				
Date: 10/05/11 Time: 22:58				
Sample (adjusted): 1353 1387				
Included observations: 35 after adjustments				
Convergence achieved after 10 iterations				
MA Backcast: 1352				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	2097.301	506.8855	4.137624	0.0002
AR(1)	0.774291	0.097834	7.914301	0.0000
MA(1)	0.391443	0.175449	2.231096	0.0328
R-squared	0.828019	Mean dependent var		2419.586
Adjusted R-squared	0.817270	S.D. dependent var		1073.831
S.E. of regression	459.0293	Akaike info criterion		15.17792
Sum squared resid	6742653.	Schwarz criterion		15.31124
Log likelihood	-262.6136	Hannan-Quinn criter.		15.22394
F-statistic	77.03366	Durbin-Watson stat		2.071101
Prob(F-statistic)	0.000000			
Inverted AR Roots	.77			
Inverted MA Roots	-.39			

Then, we estimated conditional heteroskedasticity models such as ARCH, GARCH, TARCH, CGARCH, PARCH and EGARCH models. Estimation results were shown as following Tables:

Table 4. ARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:07				
Sample: 1352 1387				
Included observations: 36				
Convergence achieved after 6 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	2161.494	320.5815	6.742416	0.0000
	Variance Equation			
C	864947.7	415828.6	2.080059	0.0375
RESID(-1)^2	0.527589	0.642704	0.820890	0.4117
R-squared	-0.087135	Mean dependent var		2500.153
Adjusted R-squared	-0.153022	S.D. dependent var		1163.549
S.E. of regression	1249.405	Akaike info criterion		16.51263
Sum squared resid	51513416	Schwarz criterion		16.64459
Log likelihood	-294.2273	Hannan-Quinn criter.		16.55868
Durbin-Watson stat	0.179576			

Table 5. GARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:08				
Sample: 1352 1387				
Included observations: 36				
Convergence achieved after 10 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	2198.578	91.00054	24.16005	0.0000
	Variance Equation			
C	855552.8	428986.5	1.994358	0.0461
RESID(-1)^2	1.231406	0.068970	17.85422	0.0000
GARCH(-1)	-0.989187	0.014329	-69.03492	0.0000
R-squared	-0.069096	Mean dependent var		2500.153
Adjusted R-squared	-0.169324	S.D. dependent var		1163.549
S.E. of regression	1258.207	Akaike info criterion		15.84007
Sum squared resid	50658689	Schwarz criterion		16.01601
Log likelihood	-281.1212	Hannan-Quinn criter.		15.90148
Durbin-Watson stat	0.182605			

Table 6. EGARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:09				
Sample: 1352 1387				
Included observations: 36				
Convergence achieved after 33 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)				
***RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))**				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2261.578	39.04335	57.92479	0.0000
	Variance Equation			
C(2)	0.275641	0.984394	0.280011	0.7795
C(3)	0.790350	0.619830	1.275107	0.2023
C(4)	0.092057	0.288987	0.318550	0.7501
C(5)	0.911647	0.091180	9.998341	0.0000
R-squared	-0.043243	Mean dependent var		2500.153
Adjusted R-squared	-0.177855	S.D. dependent var		1163.549
S.E. of regression	1262.788	Akaike info criterion		15.42238
Sum squared resid	49433627	Schwarz criterion		15.64231
Log likelihood	-272.6029	Hannan-Quinn criter.		15.49914
Durbin-Watson stat	0.187131			

Table 7. PARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:10				
Sample: 1352 1387				
Included observations: 36				
Failure to improve Likelihood after 13 iterations				
Presample variance: backcast (parameter = 0.7)				
@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(				
-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2167.962	85.76698	25.27735	0.0000
	Variance Equation			
C(2)	1316238.	13761807	0.095644	0.9238
C(3)	0.559381	0.608742	0.918913	0.3581
C(4)	-0.400236	0.258465	-1.548509	0.1215
C(5)	-0.578867	0.177186	-3.267006	0.0011
C(6)	2.316911	1.700227	1.362706	0.1730
R-squared	-0.083838	Mean dependent var		2500.153
Adjusted R-squared	-0.264477	S.D. dependent var		1163.549
S.E. of regression	1308.398	Akaike info criterion		15.91409
Sum squared resid	51357196	Schwarz criterion		16.17801
Log likelihood	-280.4537	Hannan-Quinn criter.		16.00621
Durbin-Watson stat	0.180122			

Table 8. TARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:11				
Sample: 1352 1387				
Included observations: 36				
Convergence achieved after 11 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +				
C(5)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	2239.946	142.8934	15.67564	0.0000
	Variance Equation			
C	855548.6	600686.9	1.424284	0.1544
RESID(-1)^2	1.296070	0.450935	2.874183	0.0041
RESID(-1)^2*(RESID(-1)<0)	-0.671939	0.937880	-0.716445	0.4737
GARCH(-1)	-1.011483	0.162179	-6.236832	0.0000
R-squared	-0.051440	Mean dependent var		2500.153
Adjusted R-squared	-0.187110	S.D. dependent var		1163.549
S.E. of regression	1267.739	Akaike info criterion		16.14739
Sum squared resid	49822058	Schwarz criterion		16.36733
Log likelihood	-285.6531	Hannan-Quinn criter.		16.22416
Durbin-Watson stat	0.185672			

Table 9. CGARCH Model

Dependent Variable: OIL				
Method: ML - ARCH (Marquardt) - Normal distribution				
Date: 10/05/11 Time: 23:13				
Sample: 1352 1387				
Included observations: 36				
Failure to improve Likelihood after 24 iterations				
Presample variance: backcast (parameter = 0.7)				
Q = C(2) + C(3)*(Q(-1) - C(2)) + C(4)*(RESID(-1)^2 - GARCH(-1))				
GARCH = Q + (C(5) + C(6)*(RESID(-1)<0))*(RESID(-1)^2 - Q(-1)) + C(7)				
*(GARCH(-1) - Q(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2256.066	61.70737	36.56072	0.0000
	Variance Equation			
C(2)	1316238.	1854797.	0.709640	0.4779
C(3)	0.968135	0.021617	44.78594	0.0000
C(4)	0.753239	0.532684	1.414045	0.1573
C(5)	-0.095826	0.374531	-0.255856	0.7981
C(6)	0.190507	0.563276	0.338212	0.7352
C(7)	0.876838	0.491814	1.782864	0.0746
R-squared	-0.045264	Mean dependent var		2500.153
Adjusted R-squared	-0.261526	S.D. dependent var		1163.549
S.E. of regression	1306.870	Akaike info criterion		15.51697
Sum squared resid	49529400	Schwarz criterion		15.82487
Log likelihood	-272.3054	Hannan-Quinn criter.		15.62444
Durbin-Watson stat	0.186769			

3.1. The Choice of Best Model

In this section, we choice the best time series model based on Akaike information criterion, Schwarz criterion and Hannan-Quinn criterion. Based on Akaike information criterion, we choice ARMA(1,1) model. Based on Schwarz criterion, we choice AR(1) model because Schwarz criterion is lowest statistic rather than other models. Based on Hannan-Quinn criterion, we choice ARMA(1,1) model.

3.2. Forecasting Iran Crude Oil Export with Selected Model

The following plot indicates forecastingthe Iran crude oil export will decrease to 2097.317114 thousands oil barrels in Iran based on ARMA(1,1) model.

Plot 1. Forecasting Crude Oil Export until 2020 year

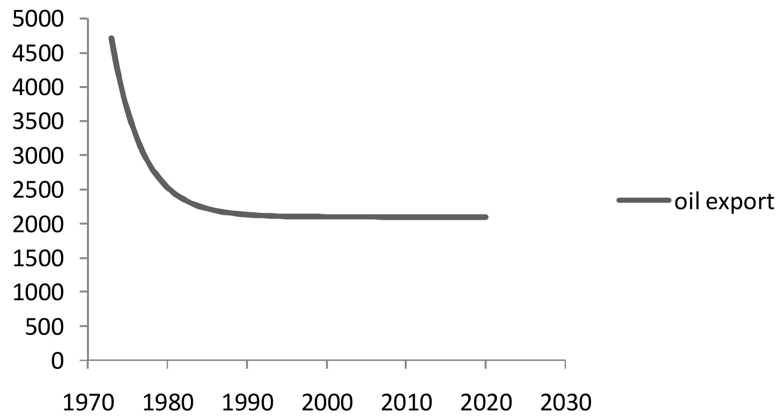

Table 10. crude oil export forecasts

2000	2099.919
2001	2099.328
2002	2098.87
2003	2098.516
2004	2098.242
2005	2098.03
2006	2097.865
2007	2097.738
2008	2097.64
2009	2097.563
2010	2097.504
2011	2097.458
2012	2097.423
2013	2097.396
2014	2097.374
2015	2097.358
2016	2097.345
2017	2097.335
2018	2097.328
2019	2097.322
2020	2097.317

The growth in consumption of domestically produced oil has been modest, owing to refining constraints. By contrast, fuel imports rose to 180,000 barrels per day (29,000 m3/d) in January 2005 from 30,000 barrels per day (4,800 m3/d) in 2000, and petrol consumption is estimated to have been around 1,800,000 barrels per day (286,000 m3/d) in 2007 (before rationing), of which about one-third is imported. These imports are proving expensive, costing the government about US$4bn in the first nine months of 2007/08, according to parliamentary sources. Nearly 40% of refined oil consumed by Iran is imported from India.

Iran contains 27 onshore and 13 offshore oil producing fields which are largely concentrated in the southwestern Khuzestan region near the Iraqi border. The Iranian government is heavily reliant on oil revenues and they have heavily subsidized the energy industries which figures out to be about 12% of Iran's GDP. However, domestic oil consumption has decreased due to the alternative use of natural gas. Economic growth from these resources is uncertain and stunted in Iran due to these subsidies and population growth. Iran has been unable to reach it full production levels due to a combination of sanctions and war which has plagued the region. Iran's oil fields have a natural decline rate at 8 percent for onshore wells and 10% for offshore fields. The Iranian recovery rate is currently approximately 27 percent which is well below the world average. Iran needs structural improvements made to coincide with their enhanced oil recovery efforts.

4. Conclusion

Iran's economy has been highly dependent on the production and export of crude oil to finance government spending, and consequently is vulnerable to fluctuations in international oil prices. Although Iran has vast petroleum reserves, the country lacks adequate refining capacity and imports gasoline to meet domestic energy needs.

The aim of this paper is forecasting Iran crude oil with time series model. We estimated AR, MA, ARMA, ARCH, GARCH, TARCH, CGARCH, PARCH and EGARCH models for modeling Iran crude oil export. Based on Akaike information criterion, we choice ARMA (1,1) model. Based on Schwarz criterion, we choice AR (1) model because Schwarz criterion is lowest statistic rather than other models. Based on Hannan-Quinn criterion, we choice ARMA (1,1) model. We have forecasted Iran crude oil export with ARMA(1,1) model. Results indicate that Iran crude oil export will decrease to 2097.317114 thousands oil barrels in Iran.

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