Demand for Electricity In Kuwait

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ملخص

الطلب على الكهرباء في الكويت باستخدام طريقة بوكس ـــــــ جنكنز للتنبؤ

تستخدم الدراسة طريقة (بوكس ـ جنكنز) في التنبؤ باستهلاك الكـــهرباء فـــي الكويت. ولقد تم إعداد التنبؤات على ثلاثة مستويات كما تم تطبيق المستوى الأول علـــى البيانات السنوية، وعنه يتضح أن جملة استهلاك الكهرباء في الكويت يتوقـــع أن يصـــل إلى ٢٢,٥٩٣,٣ مليون كيلووات/ساعة مع عام ٢٠٠٥ ويمثل هذا زيادة قدرهـــا ١٢٪ إلى ٤٠٪ فوق المستوى الراهن لاستهلاك الكهرباء. وهذه الزيادة الضخمة سوف يكون لها انعكاسات خطيرة بالنسبة للاحتياجات المستقبلية من أجل بناء أجيال جديدة لتســـهيل توليد الكهرباء. وكذلك فإن على وزارة الكهرباء والمياه أن تأخذ في اعتبارها التخطيـــط من أجل التوسع في توليد الطاقة الكهربية الراهن بنسبة ٤٠٪.

بالإضافة لذلك يوضح التنبؤ ربع السنوى أن الطلب على الكهرباء في الكويـــت يمكن أن يصل إلى ٢٧,١٣٧ مليون كيلووات/ساعة مع عام ٢٠٠٥، بينما يوضح التنبؤ الشهرى لعام ٢٠٠٢، إن الاستهلاك الكلى قد بلغ ٢٣,٤١٢ مليون كيلووات/ساعة وهـــو رقم قريب من الرقم الفعلي المسجل، وهذه النتيجة تدعم الاستخلاصات السابقة فـــي أن هناك حاجة ماسة لتوسعات جوهرية في توليد الطاقة الراهنة.

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The 33 Figures & the Appendices A1 – A2 – A3 mentioned in the study are to be requested from the authors.

I. Introduction

Kuwait's domestic energy consumption has a significant impact on the performance of the economy and on the standard of living of its citizens. Intensity in the consumption of energy is one of the most striking features of modem life in Kuwait. As a resource-based economy, Kuwait has experienced significant structural changes since the beginning of oil exports in 1946, These changes have induced rapid increases in the demand for energy domestically. The consumption of energy in Kuwait has grown consistently since the 1970s at rapid annual growth rates. Electricity, oil products and natural gas mainly meet the domestic demand for energy. The domestic demand for energy represents a small but increasing fraction of the total energy production.

The increase in energy consumption has been due to a number of factors, including economic factors such as rising incomes and low energy prices and demographic and urban factors such as population growth and land use for residential, commercial and industrial urban purposes. In addition, there are technological factors which encompass a host of variables that have a direct impact on Kuwait's energy intensity consumption patterns.

For the most part, consumers in Kuwait are charged a flat rate of 2 fils per kwh, when in fact, the cost of producing each Kilowatt/hour has been estimated to amount to 14 to 26 fils which means that there is a subsidy of 12 to 24 fils per kwh. Furthermore, energy prices have been declining in real terms since 1975. For example, the nominal price for a litre of regular gasoline is 50 fils, however, in real terms, it costs only about 25 fils per litre. In other words, there is no real price incentive for consumers to conserve their consumption. The government is currently considering various measures to reduce the subsidy and induce consumers to conserve their energy use. However, removing the subsidies may drive prices of energy upward, which would have serious consequences on the economic performance of the various sectors in addition to some social impacts.

Econometric energy models are constructed in order to evaluate past experience, assess the impact of possible policy options and forecast energy demand under various price and income assumptions. The building of energy models stems from the need to understand and explain consumer behaviour. Knowing and understanding the underlying determinants of demand allows future behaviour to be predicted. Therefore, the main goal is to develop a framework that can explain consumers' behaviour. However, other methods are also widely used to forecast energy demand. One of these methods is Box-Jenkins approach to forecast energy demand. The aim of this research paper is to forecast the demand for electricity in Kuwait using the Box-Jenkins methodology. The next section of the paper discusses the methodology and data utilized. Section 3 presents the forecasting results for the annual data while sections 4 and 5 give the results of the quarterly and monthly data respectively. Finally, the conclusions are given in section 6.

II. Methodology and Data

The main source of data on the quantity of energy consumed is "Facts and Figures" published by the Ministry of Oil, Economic Affairs Department. Other sources include the Annual Statistical Abstract of the Ministry of Planning, and the Yearbook of the Ministry of Electricity & Water. The time period chosen depended on how far back consistent statistics exist, however, most of the time series cover the period from 1962 to 1995.

Over that period, a great deal of change took place. Total energy consumption grew substantially from 58.41 million barrels of oil equivalent (mboe) in 1980 to 96.13 mboe in 2000 at an annual growth rate of about 3.4 percent. Total energy demand increased from 58.41 mboe in 1980 to 74.25 in 1985, at annual rate of about 4.9 percent. It also grew from 74.25 mboe in 1985 to about 91.48 mboe in

1989, at annual growth rate of 5.4 percent. However, total energy consumption grew to reach a peak of 96.13 mboe in 2000, at annual growth rate of about 2.6 percent from its level in 1985. In terms of the final demand sector, the consumption also increased from 33.53 in 1980 to 50.85 in 2000 at an annual growth rate of 2.8 percent.

The consumption of electricity that is a major component of the final demand sector has also increased from about 4.30 mboe in 1980 to 9.74 mboe in 2000, reflecting an average growth rate of about 5.6 percent annually. Also, the share of electricity in the total consumption increased from 7.4 percent in 1980 to 10.2 percent in 2000. However, an important point should be mentioned here, in terms of secondary demand, the electricity and water sub-sector alone consumed about 42.94 mboe of oil and natural gas to produce about 10 mboe of electricity along with several million gallons of water. The efficiency rate of electricity production is in the range of 25 to 33 percent that is in line with the rest of the world.

Furthermore, the share of natural gas consumption in total energy demand decreased from 55.21 percent in 1980 to about 42.9 percent in 1995 but increased in terms of volume from 32.25 mboe in 1980 to 43.09 mboe in 2000. This reflects an increase in the volume of consumption of natural gas over the time period of about 2 percent annually. The distribution of energy consumption in Kuwait among the demand of various sectors is characterised by the dominance of the industrial sector followed by the transportation and the residential sectors.

The Box-Jenkins approach to economic forecasting is an alternative to traditional econometric models (Gujarati, 1995; Pindyck and Rubinfeld, 1991). To forecast the values of a time series, the basic Box-Jenkins strategy is as follows.

The series is first examined for stationarity. This can be done by computing the autocorrelation function (ACF) and the partial autocorrelation function (PACF) for the original series (Granger and

Newbold, 1986; Mills, 1990) or by formal unit root analysis (Dickey et. al., 1986). The correlograms associated with ACF and PACF are often good visual diagnostic tools (Hanke and Reitsch, 1995).

If the time series is not stationary, it is differenced one or more times to achieve stationarity (Jenkins and McLeod, 1982).

The ACF and PACF of the stationary time series are then computed to find out if the series is purely autoregressive, purely of the moving- average type or a mixture of the two (Harvey, 1990). There are some broad guidelines that can assist in determining the values of p (order of autoregressivness) and q (number of moving averages) in the autoregressive moving average (ARMA) process to be fitted. The chosen ARMA (p, q) at this stage is tentative.

The tentative model is then estimated. A number of alternative parameter estimation procedures are commonly used. These various procedures typically yield quite similar estimates when the sample size is large. However, for shorter series, there can be larger differences, particularly if the model involves substantial moving-average terms. The full- maximum likelihood approach is usually preferred in those cases for which different estimation procedures yield significantly different results (Newbold and Bos, 1994). This approach is implemented in a few computer program package, including SPSS, SAS and Eview.

The residuals from the tentative model are examined to determine whether or not they are white noise. The adequacy of the model is also indicated by the Box-Ljung statistic (Ljung and Box, 1978). Model inadequacy is indicated by large absolute values for the residual autocorrelations, and consequently large values for the Box-Ljung statistic. If the residuals are white noise, the tentative model is probably a good approximation of the underlying stochastic process. If they are not, the process is started all over again. Therefore, the Box-Jenkins method is iterative.

If more than one model fit the data adequately, the general criteria for model selection can be applied. Two of these criteria are commonly used, namely, the Akaike information criterion (AIC) and the Schwartz Bayesian criterion (SBC). The latter is often called the Bayesian information criterion (BIC). The base model is the one that has the lowest AIC and SBC values.

The model finally selected can then be used for forecasting. Forecasts can be made for a single period or several periods in the future. Confidence intervals can also be constructed about these estimates. In general, the further into the future the forecast is, the larger the confidence interval will be.

As more data become available, the same model can be used to revise the forecasts by choosing different time origins. If the series appears to be changing over time, the model's parameters may need to be recalculated, or an entirely new model may have to be developed.

III. Annual Forecast of The Demand

A series of 39 observations, representing total annual consumption of electricity in Kuwait during the period from 1962 to 2000 was collected. The data are given in Table Al (in the Appendix). The figures for the two years 1990 and 1991 (the period of the Iraqi invasion and occupation) were estimated using the average consumption over the previous five years.

Fig. 1 gives a plot of the original series. A close inspection of this figure suggests that electricity consumption in Kuwait experienced exponential growth over the sample period. The series suggests a constant proportional growth rate of approximately 12% per annum. This was estimated using the regression;

$$\text{In } C_t = b + rt + u_t \qquad (1)$$

Where C is the total annual consumption of electricity, t is the time, b is the constant, r is the constant proportional rate of growth, (i.e., (dc/dt)/I/c)), and u is an error term.

As can be seen from Fig. 1 (and indeed, as is suggested by the regression analysis), the original series is not stationary. The sample autocorrelations (SAC) and sample partial autocorrelations (SPAC) of the original series are shown in Figs. 2 and 3 respectively. These autocorrelations were obtained using the SPSS program. For high lags (up to lag 10), the sample autocorrelations remain large and follow a smooth pattern. The probabilities attached to the Box-Ljung statistics are the lowest significance levels at which the null hypothesis for white noise can be rejected. This indicates a need for differencing to achieve a stationary time series.

A first-differenced series was obtained through the transformation:

$$W_t = X_t - X_{t-1} = (1 - B) X_t \qquad (2)$$

Where X is the original series.

Fig. 4 gives a plot of the differenced series. The transformation has contributed towards achieving stationarity. The SPSS program was used to obtain the SACs and SPACs of the first-differenced series. These autocorrelations are shown in Fig 5. An inspection of these figures suggests that the patterns of autocorrelations at high lags are not at all smooth. None of the coefficients is statistically significant. This suggests that further differencing is not necessary. The same conclusion is obtained using the formal unit root test. Both the Dickey-Fuller (DF) and the Augmented Dickey-Fuller (ADF) statistics reject the hypothesis that the differenced series follows a random walk with no drift.

This suggests that an ARIMA (p, 1, q) is suitable for the annual data on total electricity consumption in Kuwait. The SAC and SPAC of the differenced series are examined to suggest autoregressive and moving average orders. Both autocorrelations and partial autocorrelations are relatively high compared with their standard errors for lags 3 and 4, although none of the coefficients is statistically significant. This suggests the suitability of any of the following ARIMA models:

- ARIMA (2,1/1)
- ARIMA (1,1,2)
- ARIMA (0,1,2)
- ARIMA (2,1,0)
- ARIMA (1,1,1)
- ARIMA (1,1,0)
- ARIMA (0,1,1)

All of these ARIMA models were estimated using the SPSS program. The SBC values (Table 1) of the estimated models were then compared.

Table 1. SBC Values for Specific ARIMA Models

ARIMA Model	SBC
(2,1,1)	651.6
(1,1,2)	651.1
(0,1,2)	651.3
(2,1,0)	650.5
(1,1,1)*	647.4*
(0,1,1)	647.7
(1,1,0)	647.6

*** is the selected model**

The smallest SBC value was for the ARIMA (1,1,1) model:

$$Z_t = \delta + \varphi_1 Z_{t-1} + a_1 - \Psi_1 {}^{a}_{t-1} \qquad (3)$$

Where

$$Z_t = X_t - X_{t-1}$$

The model was estimated using the SPSS program. The results are given in Table 2. The fitted model can be written as:

$$(1\text{-}B)Z_t = a_t + 0.979\, Z_{t-1} - 0.906\, a_{t-1} \qquad (4)$$

$$(9.883) \qquad (-4.710)$$

Where the figures in parentheses below the parameter estimates are the corresponding t values.

Fig. 7 gives the SAC of the residuals. This figure shows that none of the autocorrelations is individually significant. The Box-Ljung statistics is given by:

$$Q=n(n+2)\ \sum_{k=1}^{m}(n-k)^{-1}r^{n}k^{2} \qquad (5)$$

seems to suggest model adequacy. For example, based on the first 10 and 20 residual observations, the hypothesis that the ARIMA (1,1,1) specification is correct can only be rejected at the 69.9% and the 98.6% levels respectively. Moreover, more elaborated models did not produce superior results. Accordingly, forecasts can be based on the fitted model with confidence.

Table 2. Estimation of the Parameters for the Selected ARIMA Model

Model: **MOD_1**
Model Description:

Variable: DEMAND
Regressors: NONE
Non-seasonal differencing: 1
No seasonal component in model.
Parameters:
AR1 ______ < value originating from estimation >
MA1 ______ < value originating from estimation >
95.00 percent confidence intervals will be generated.
Split group number: 1 Series length: 39
No missing data.
Melard's algorithm will be used for estimation.
Termination criteria:
Parameter epsilon: .001
Maximum Marquardt constant: I.00E+09

SSQ Percentage: .001
Maximum number of iterations: 10
Initial values:

AR1	.75599
MA1	.55969

Marquardt constant = .001
Adjusted sum of squares = 46164988.2

Iteration History:

Iteration	Adj. Sum of Squares	Marquardt Constant
1	47157871.6	.1000000
2	47019666.0	1.0000000
3	46225634.9	.1000000
4	46165281.7	1.0000000
5	46013888.0	.1000000
6	45999675.7	.0100000

Table 2. (Cont.) Estimation of the Parameters for the Selected ARIMA Model

Conclusion of estimation phase.
Estimation terminated at iteration number 7 because:

All parameter estimates changed by less than .001

FINAL PARAMETERS:

Number of residuals	38
Standard error	1122.298
Log likelihood	-320.05707
AIC	644.11415
SBC	647.38932

Analysis of Variance:

	DF	Adj. Sum of Squares	Residual Variance
Residual	36	45994666.0	1259552.7

Variables in the model:

	B	SEB	T-RATIO	APPROX. PROB
ARI	.97912303	.09907023	9.8881205	.00000000

MAI .90626701 .19243140 4.7095590 .00003651

Covariance Matrix:

	AR1	MAI
ARI	.00981491	.01785853
MAI	.01785853	.03702984

Correlation Matrix:

	AR1	MA1
ARI	1.0000000	.9367565
MAI	.9367565	1.0000000

The following new variables are being created:

Name	Label
FIT_1	Fit for DEMAND from ARIMA, MOD_1 NOCON
ERR_1	Error for DEMAND from ARIMA, MOD_1 NOCON
LCL_1	95% LCL for DEMAND from ARIMA, MOD_1 NOCON
UCL_1	95% UCL for DEMAND from ARIMA, MOD_1 NOCON
SEP_1	SE of fit for DEMAND from ARIMA, MOD_1 NOCON

Table 3 gives point forecasts (up to the year 2005) together with the lower and the upper limits of the 95% confidence level intervals.

Table 3. Annual Forecast of Demand for Electricity in Kuwait (Millions KW/h)

Year	Mid. Point	Lower	Upper
2001	20750.3	18474.6	23028
2002	21226.5	17887.3	24565.6
2003	21691.7	17456.6	25926.9
2004	22147.3	17089.9	27204.7
2005	22593.3	16753.5	29433.1

IV. Quarterly Forecast of the Demand

The ARIMA model that was used and fitted to the total annual demand for electricity in Kuwait led to forecasts of future observations that were linear functions of the available data, with the most weight given almost inevitably to the most recent observations (Hanke and Reitsch, 1995). However, if the time series of interest is seasonal, as in the case of quarterly demand for electricity, a rather different pattern of weighing on past observations would be desirable for forecasting the future. For example, while sales in any quarter in a single year are expected to be closely related to sales in the previous quarters exclusive concentration on just the most recent quarters would fail to capture important seasonality in the series. In predicting the demand for summer 2003, for example, it would be sensible, in the presence of seasonality, to give extra weight to observations from past summers, i.e., summer 1999, summer 1998, summer 1997 and so on.

To capture the effects of seasonality, further seasonal differencing, or seasonal autoregressive or seasonal moving average terms, would also be required. In general, it may be possible to consider introducing seasonal differences (D), seasonal autoregressive terms (P) and seasonal moving average terms (Q), so that the no seasonal series (Z_t) is derived from:

$$(1-\Phi_1 B^S-\ldots\ldots-\Phi_P B^{PS})(1-B^S)^D X_t \qquad (6)$$

$$=(1\ \Psi_1 B^S-\ldots\ldots\Psi_Q B^{QS})Z_t$$

Where, Φ_i and Ψ_j are fixed seasonal autoregressive and moving average parameters (I =1, ... p; j = 1, ...,q).

If the series Z_t in the above equation is no seasonal, it could be represented by the regular ARIMA (p, q, d) model:

$$(1-\varphi_1 B-\ldots\ldots-\varphi_P B^P)(1-B)^d Z_t \qquad (7)$$

$$=(1\ \Psi_1 B-\ldots\ldots\Psi q B^q)a_t$$

Where a_t is white noise. Amalgamating Equations (6) and (7) then yields the model:

$$(1-\varphi_1 B-\ldots\ldots-\varphi_P B^P)(1-\Phi_1 B^S-\ldots\ldots-\varphi_P B^{PS})X(1-B)^d(1-B^S)^D X_t$$

$$=(1-\Psi_1 B-\ldots\ldots\Psi q B^q)\ (1-\Psi_1 B^S-\ldots\ldots\Psi_Q B^{QS})a_t \qquad (8)$$

The class models from Equation (8) have been widely used to represent seasonal business and economic time series. They are called multiplicative seasonal ARIMA (p, d, q) (P, D, Q) models.

It was possible to obtain data on quarterly (total) demand for electricity for the period from 1987 to 2000. These data cover 56 quarters. However, the figures for the last quarter in 1990 and for the four quarters in 1991 were estimated using average figures for corresponding quarters in the previous five years. These data are given in Table A2 in the Appendix. The original series is plotted in Fig. 8. The SACs and SPACs of the original series are shown in Figs. 9 and 10.

Fig. 8 suggests that the original series is trended. The SAC of the undifferenced series are persistently large and seem to exhibit strong seasonal behavior. It certainly appears that differencing of some kind is desirable.

A first-differenced series is plotted in Fig. 11, and its SACs are shown in Figs. 12 and 13. The correlations at a multiple of 4 lags are very large suggesting the necessity for seasonal differencing. The seasonally differenced series and its SACs are plotted in Fig. 14 and SPACs are plotted in Figs. 15, 16.

The SACs, for the seasonally differenced series seem to be large, relative to their standard errors, at lags 1,2, 11 and 12. This pattern suggests that both regular and seasonal differencing may be desirable. The SACs of $(1-B^4)\ X_t$ provide no suggestions that yet more differencing is needed, as can be seen from Figs. 17, 18 and 19. The autocorrelations in these figures suggest a number of plausible models. This is not surprising with such a short series-after differencing only 50 observations remain. The SAC at lag 4 is quite large. However, those at lags 8, 12 and 16 are small. This suggests that a single seasonal parameter-either autoregressive or moving-average-should be sufficient.

Since the first SAC is large, at least one regular parameter will also be required. Ten models were fitted. Six of these models included two regular parameters and one seasonal parameter, while the other four included one regular parameter and one seasonal parameter. The best results, in terms of the significance of the coefficients, i.e., the AIC and SBC values and the size of the residual autocorrelations, are from ARIMA (0,1,1) or:

$$(1 - B)(1 - B^4)X_t = (1 - \psi_1 B)(1 - \psi_1 B^B)a_1 \qquad (9)$$

fitted to the data on quarterly consumption of electricity in Kuwait. The estimates are given in Table 4. These estimates were obtained using the SPSS Program. It can be seen that all the parameter estimates are highly significant (i.e., the parameter MA1 is more than 4.3 times its standard error while the parameter SMA1 is more than 4.7 its standard error). Figure 20 gives the residual autocorrelations of the fitted model. These residuals are generally quite small compared with their standard errors.

The Box-Ljung statistic seems to suggest model adequacy. For example, for a test based on the first M=10 residual autocorrelations, the null hypothesis that the model is correctly specified can only be rejected at significance levels of 73.5% or higher. Similarly, 86% is the lowest significance level for rejecting the models specification when the test is based on the first 16 residual autocorrelations.

Table 4. Parameter Estimation for the Selected Model

Model: MOD_1
Model Description:

Variable: DEMAND
Regressors: NONE

Non-seasonal differencing: 1

Seasonal differencing: 1
Length of Seasonal Cycle: 4

Parameters:

MA1 ______ < value originating from estimation >

SMA1 ______ < value originating from estimation >

95.00 percent confidence intervals will be generated.

Split group number: 1 Series length: 56

No missing data.

Melard's algorithm will be used for estimation.

Termination criteria:

Parameter epsilon: .001

Maximum Marquardt constant: I.00E+09

SSQ Percentage: .001

Maximum number of iterations: 10

Initial values:

MA1 .56888
SMA1 .26483

Marquardt constant = .001
Adjusted sum of squares = 11670843.0

Iteration History:

Iteration	Adj. Sum of Squares	Marquardt Constant
1	11221249.7	.00100000
2	11124536.2	.00010000
3	11093880.4	.00001000

4	11082771.1	.00000100
5	11078573.7	.00000010
6	11076954.5	.00000001
7	11076324.0	.00000000
8	11076077.0	.00000000

Table 4. (Cont.) Parameter Estimation for the Selected Model

Conclusion of estimation phase.
Estimation terminated at iteration number 9 because:

Sum of squares decreased by less than .001 percent.

FINAL PARAMETERS:

Number of residuals	51
Standard error	464.55061
Log likelihood	-385.7222
AIC	775.4444
SBC	779.30805

Analysis of Variance:

	DF	Adj. Sum of Squares	Residuals Variance
Residuals	49	11075979.9	215907.27

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB
MA1	.53429203	.12275621	4.3524643	.00006841
SMA1	.61783981	.13108708	4.7132012	.00002060

Covariance Matrix:

	MA1	SMA1
MA1	.01506909	-00262242
SMA1	-.00262242	.01718382

Correlation Matrix:

	MA1	SMA1
MA1	1.0000000	-.1629668
SMA1	-.1629668	1.0000000

The following new variables are being created:

Name	Label
FTT_1	Fit for DEMAND from ARIMA, MOD_1 NOCON
ERR_1	Error for DEMAND from ARIMA, MOD_1 NOCON
LCL_1	95% LCL for DEMAND from ARIMA, MOD_1 NOCON
UCL_1	95% UCL for DEMAND from ARIMA, MOD_1 NOCON
SEP_1	SE of fit for DEMAND from ARIMA, MOD_1 NOCON

Table 5 gives forecasts from the fitted model until the fourth quarter of the year 2005 together with the limits of the associated 95% confidence intervals. These forecasts were obtained from the SPSS program.

Table 5. Quarterly Demand for Electricity In Kuwait (M KW/h)

Year	Quarter	Mid. Point	Lower	Upper
2001	1	4092.41	3158.64	5026.17
	2	6073.5	5043.44	7103.56
	3	7498.95	6380.86	8617.03
	4	4571.59	3371.92	5771.27
2002	1	4398,73	2961.36	5836.10
	2	6379.82	4821.85	7937.80
	3	7805.26	6135.37	9475.16
	4	4877.91	3103.15	6652.67
2003	1	4705.05	2688.28	6721.82
	2	6686.15	4528.37	8843.93
	3	8111.59	5821.47	10401.7
	4	5184.24	2769.01	7599.46
2004	1	5011.37	2347.38	7675.36
	2	6992.47	4169.68	9815.26
	3	8417.91	5444.80	11391.1
	4	5490.56	2374.36	8606.75
2005	1	5317.69	1944.94	8690.45
	2	7298.79	3751.31	10846.3
	3	8724.23	5010.24	12438.3
	4	5796.89	1923.53	9670.24

V. Monthly Forecast of the Demand

It was possible to collect monthly data on the consumption of electricity in Kuwait for the period from 1986 to 2000. However, due to the Iraqi invasion of Kuwait in August 1990, the series was interrupted for 1990 and 1991. The data for the last four months of 1990 and for the 12 months of 1991 were estimated using average consumption figures for the corresponding months in the previous five years. This made it possible to use a continuous, longer series (156 observations). The original series is given in Table A3 in the Appendix and is plotted in Fig. 20. The series exhibits seasonal variations.

The SACs of the undifferenced series are given in Figs. 21 and 22. These autocorrelations are persistently high and follow quite smooth patterns at high lags. This suggests that some differencing is desired.

The first-differenced series is plotted in Fig. 23 and its autocorrelations are shown in Figs. 24 and 25. The SACs are high at lags that are multiples of 12, indicating the desirability of seasonal differencing.

The autocorrelations of the seasonally differenced series are given in Figs. 26 and 27. The autocorrelations of the first-differenced seasonal series are high at lags 12 and 24, so a second differencing might have been needed. This was obtained and is plotted in Fig. 28. The autocorrelations of the second-differenced seasonal series are shown in Figs. 29 and 30. The SACs of the second-differenced seasonal series are quite smooth at the high lags suggesting that regular as well as seasonal differencing are needed.

The $(1-B)(1-B^{12})^2X_t$ series is plotted in Fig. 32, and its autocorrelations are shown in Fig. 31. The SACs are very large for lag 12, while the SPACs are very large for lags 12 and 14. This suggests the use of any of the following ARIMA models:

ARTMA (1,1,0) (2,2,0), ARIMA (1,1,0) (2,2,1), and ARIMA (1,1,0) (2,2,2). These three (and other more elaborate ARIMA) models were tested. The ARIMA model (1,1,0) (2,2,1) has the lowest SBC value.

So, this model was selected. The SPSS output for the model:

$$(1-\varphi_1 B)(1-\Phi_1 B^{12}-\Phi_2 B^{24})(1-B)(1-B^{12})^2 X_t \qquad (10)$$
$$= (1-\psi_1 B^{12})a_t$$

is given in Table 6. It can be seen that the fitted model is:

$$(1+0.188B)(1+0.798B^{12}+0.397B^{24})(1-B)(1-B^{24})^2 X_t$$
$$(0.077) \qquad (0.093) \qquad (0.091) \qquad (11)$$
$$=(1-0.808B^{12})a_t$$

Table 6. Estimation of the ARIMA Model Selected for the Monthly Data

Model: MOD_1

Model Description:

Variable: DEMAND

Regressors: NONE

Non-seasonal differencing: 1

Seasonal differencing: 2

Length of Seasonal Cycle: 12

Parameters:

AR1 ________ < value originating from estimation >

SAR1 ________ < value originating from estimation >

SAR2 ________ < value originating from estimation >

SMA1 ________ < value originating from estimation >

95.00 percent confidence intervals will be generated.

Split group number: 1 Series length: 156

No missing data.

Melard's algorithm will be used for estimation.

Termination criteria:

Parameter epsilon: .001

Maximum Marquardt constant: I.00E+09

SSQ Percentage: .001

Maximum number of iterations: 10

Initial values:

AR1	-.16274
SAR1	-.88084
SAR2	-.38915
SMA1	.09075

Marquardt constant = .001
Adjusted sum of squares = 2986206.6

Iteration History:

Iteration	Adj. Sum of Squares	Marquardt Constant
1	2494631.6	.00100000
2	2447709.9	.00010000
3	2438733.3	.00001000
4	2435352.2	.00000100
5	2434144.0	.00000010
6	2433745.4	.00000001
7	2433621.1	.00000000
8	2433583.7	.00000000

Table 6. (Cont.) Estimation of the ARIMA Model Selected for the Monthly Data

Conclusion of estimation phase.
Estimation terminated at iteration number 9 because:

Sum of squares decreased by less than .001 percent.

FINAL PARAMETERS:

Number of residuals	131
Standard error	120.24537
Log likelihood	-831.9645
AIC	1671.929
SBC	1683.4298

Analysis of Variance:

	DF	Adj. Sum of Squares	Residual Variance
Residuals	127	2433572.7	14458.950

Variables in the Model:

	B	SEB	T-RATIO	APPROX. PROB
AR1	-.18763398	.07722837	-2.4295993	.01651403
SAR1	-.79774478	.09308721	-8.5698645	.00000000
SAR2	-.39705869	.09133106	-4.3474662	.00002811
SMA1	.80791899	.11087614	7.2866804	.00000000

Covariance Matrix:

	AR1	SAR1	SAR2	SMA1
AR1	.00596422	.00012883	.00005504	.00043309
SAR1	.00012883	.00866523	.00622916	.00524209
SAR2	.00005504	.00622916	.00834136	.00441448
SMA1	.00043309	.00524209	.00441448	.01229352

Correlation Matrix:

	AR1	SAR1	SAR2	SMA1
AR1	1.0000000	.0179203	.0078029	.0505783
SAR1	.0179203	1.0000000	.7326917	.5078976
SAR2	.0078029	.7326917	1.0000000	.4359358
SMA1	.0505783	.5078976	.4359358	1.0000000

The following new variables are being created:

Name	Label
FIT_1	Fit for DEMAND from ARIMA, MOD_1 NOCON
ERR_1	Error for DEMAND from ARIMA, MOD_1 NOCON
LCL_1	95% LCL for DEMAND from ARIMA, MOD_1 NOCON
UCL_1	95% UCL for DEMAND from ARIMA, MOD_1 NOCON
SEP 1	SE of fit for DEMAND from ARIMA, MOD_1 NOCON

All the parameters are very large compared with their standard error (shown under each coefficient).

The residual autocorrelations from the fitted model are given in Fig. 33. Generally, these residuals are quite small. The Box-Ljung statistics based on the first 12, 24 and 36 residual autocorrelations indicate that the hypothesis that the model specification is correct can only be rejected at significance levels of 63.7%; 92.9% and 95.3% respectively. In addition, none of the more elaborate alternative models that were tried produced superior results.

Accordingly, the fitted model was used to yield forecasts of future monthly demand for electricity. Table 7 provides the forecasts through the end of 2002. Also in this table, are the upper and lower limits of the forecasts based on 95% confidence levels.

Table 7. Monthly Demand for Electricity In Kuwait (M KW/h)

Year	Month	mid. Point	Lower	Upper
2001	1	1233.17	994.47	1471.88
	2	1064.15	756.74	1371.56
	3	1147.32	779.42	1515.23
	4	1504.89	1085.89	1923.90
	5	2218.14	1753.48	2682.79
	6	2647.27	2141.09	3153.44
	7	2811.53	2266.99	3356.07
	8	2858.92	2278.54	3439.30
	9	2575.42	1951.29	3189.55
	10	2084.09	1437.97	2730.21
	11	1383.26	706.67	2059.86
	12	1369.69	663.93	2075.45
2002	1	1221.07	455.67	1986.45
	2	1076.56	262.35	1890.76
	3	1183.31	321.97	2044.64
	4	1539.50	633.67	2445.32
	5	2320.38	1372.12	3268.64
	6	2756.21	1767.34	3745.09
	7	2870.14	1842.25	3898.03
	8	2917.27	1851.80	3982.74
	9	2615.67	1513.90	3717.44
	10	2077.61	940.69	3214.52
	11	1414.45	243.45	2585.46
	12	1419.37	215.24	2623.50

VI. Conclusions:

The Box - Jenkins Methodology was used in this study to forecast the demand for electricity in Kuwait. The Forecasts were made at three levels. The first was applied to annual data. The total electricity consumption in Kuwait is predicated to reach an average of about 22593.3 millions KW/h in the year 2005. However, this figure could be as high as 28433 MKW/h. This represents an increase of about 12 % to 40 % over the level of the current consumption. This substantial increase would have very serious implications for the future need to build new electricity generations facilities. The ministry of electricity and water should consider planning to expand the current electricity generation by as much as 40 %.

Furthermore, the forecast using quarterly data are not strictly comparable with those obtained from annual data because of the difference in time periods over which the forecast methodology was made in the two cases.

Based on more recent trend and shorter time period, the quarterly forecasting suggests that the demand for electricity in Kuwait could reach 27137 MKW/h by the year 2005. That is 5317.7, 7298.8, 8724.2 and 5797 MKW/h for the first, second, third and fourth quarter respectively.
This result strengthens the previous conclusion that an immanent expansion of the current electricity generation production capacity is needed.

Finally, the monthly forecast for the year 2002 gives a total consumption of about 23412 MKW/h which is close to the actual consumption recorded by the ministry of electricity for that year. This gives a great confidence in the entire forecast results and validates the appropriateness of utilizing the Box - Jenkins methodology. Also, the monthly and quarterly forecasts should be used as a short term guide to help policy makers with the direction of short run production and financial needs.

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