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AN INTELLIGENT DECISION SUPPORT SYSTEM FOR ELECTRICITY PEAK-LOAD FORECASTING FOR THE UNITED ARAB EMIRATES

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This study uses a variety of time series techniques to produce short-term forecasts (one year ahead) of monthly electricity peak-load for eight geographical areas in the UAE by analyzing the behavior of monthly peak-load. The study develop a time series based decision support system that integrates data management, model base management, simulation, graphic display, and statistical analysis to provide near optimal forecasting models. The system can work as an expert to automatically propose the optimal forecasting model. Results show that multiplicative Winters models perform extremely well for most of the data. On the other hand, the Box Jenkins ARIMA models provided optimal fits for other time series cases. For each of the Emirates, a model is suggested to be used in forecasting short-term electricity load.

Introduction

Forecast techniques can be used to supplement the common sense and management ability of decision makers (Hanke & Reitsch, 1989). Actually, the most effective forecaster is able to formulate a skillful mix of quantitative forecasting techniques with good judgement and to avoid the extreme total reliance on either (Makridakis, 1982). At one extreme, there is the decision maker who, through ignorance and fear of quantitative techniques and computers, relies solely on intuition and feeling. At the other extreme is the forecaster skilled in the latest sophisticated data manipulation techniques who is unwilling to relate the forecasting process to the needs of the organization and its decision makers.

One of the important challenges for energy analysts is to forecast future energy consumption levels. Energy is a long lead-time, capital-intensive industry (or process). Hence, the problem of energy demand forecasting and planning is of great importance. The accurate and timely energy demand forecast is critical because it takes many years and millions of dollars to develop and deliver or substitute new energy supply options. A conventional formulation of the purpose of load forecasting is to estimate the most likely future level of demand in order to serve as a basis for electric supply planning.

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Objectives and Justifications

The generation capacity of an electric utility is usually built to meet its peak demand. Therefore, if the forecast is too low, there will be insufficient capacity to meet its customers' loads and the alternative is purchasing expensive emergency capacity. On the other hand, an overly optimistic forecast can lead to financial hardship as a part of the utility's equipment will remain unexploited.

Mainly two Emirates, Dubai and Abu-Dhabi have not encountered any significant electricity shortages in the recent past. This is due mainly to the installed electric power in the two Emirates, which exceed the required demand for electricity. This fact does not mean that the electric authorities in the two Emirates utilize reliable forecasting models for the purpose of planning. On the contrary, the fact remains that no agency has tried to develop and test forecasting, models for electric demand for the two Emirates. Over installing electric power is by no means considered as an efficient policy for planning, but might well reflect the lack of it. We should also add that the lack of a developed and tested forecasting model for electricity demand is also observed with regard to the other five Emirates of Sharjah, Ras Al-Khaimah, Fugairah, Umm-Al-Qwain and Ajman.

Recently, oil revenues have been facing extreme difficulties which have affected public spending to a large degree. Electric power is provided to the public below cost in the form of government subsidies. The planning of large projects combined with the fall of oil prices have necessitated the need to re-think the policy of over installment of electric power in the two Emirates of Dubai and Abu-Dhabi. As a result, the electric authorities can no longer operate efficiently without short term and long term electric demand planning that is based on sound scientific methods of forecasting.

Largely in response to the unavailability of scientific forecasting models and the need to analyze the potential for increased energy efficiency, there has been a growing use of detailed judgmental decision processes by electric utility authorities in UAE. Nevertheless, some elementary quantitative models such as the trend projection approach have been utilized.

This paper focuses on analyzing the behavior of monthly peak demand in the various Emirates of the UAE. The objective is to estimate and test various forecasting models for the various electric authorities in the United Arab Emirates. The approaches include simple univariate tools such as the random walk method (the naive approach), and the moving averages method. In addition, the study includes exponential smoothing models such as the simple exponential smoothing model, the Holt model, the Winter's linear additive and multiplicative models, and the decaying linear trend/additive and multiplicative models. Furthermore, a range of sophisticated multivariate techniques such as Box-Jenkins vector auto-regressive moving arrange (ARIMA) models and dynamic regression econometric techniques are considered. These approaches have not been consistent in performance in various energy demand forecasting tasks. Nevertheless, these approaches have appeared in many other studies that examined the choice of a forecasting model (Makridakis & Hibon, 1979; Fildes & Lusk, 1984; and Makridakis, 1984).

Extensive diagnostic tests are performed to assess the performance of each model. The criteria used for assessment include the forecast error, the mean absolute perçentage (MAPE), the Akaike information criterion (AIC), the Bayes information criterion (BIC), the mean square error (MSE), and the mean absolute deviation (MAD). The models will be a part of a user friendly decision support system that we term the Intelligent Electric Decision support System Forecaster (IEDSSF).

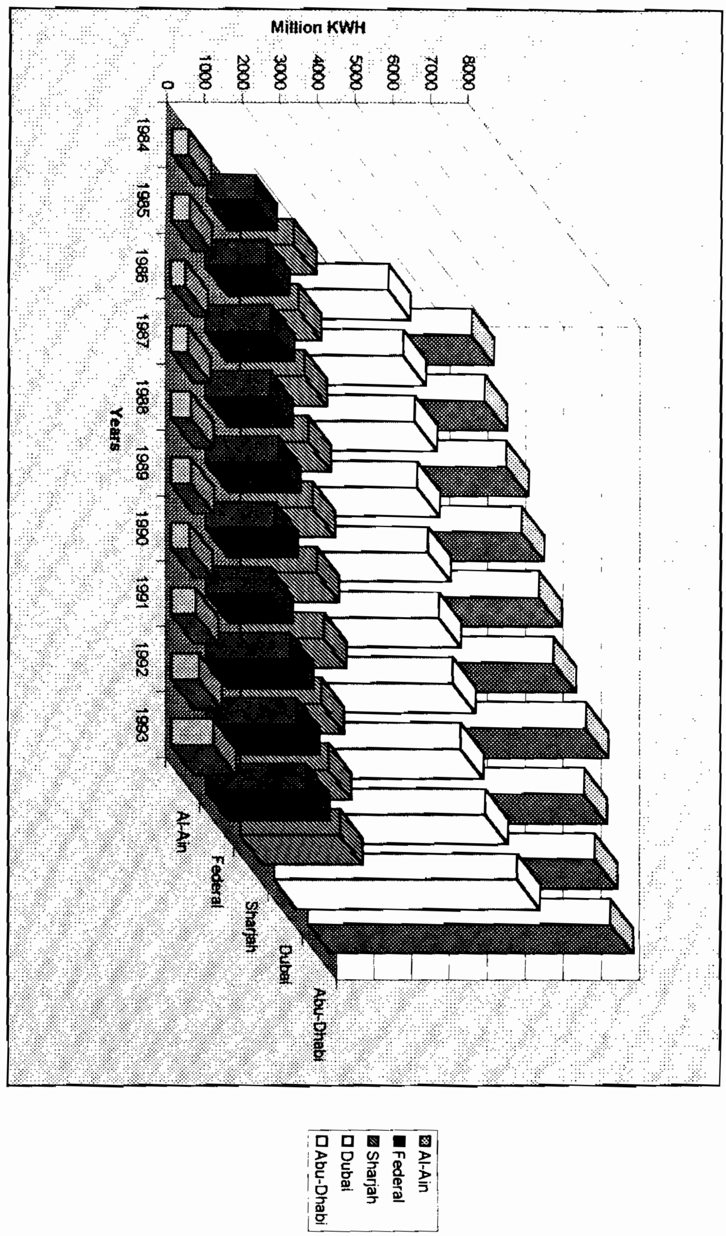
A Historical Perspective of Electricity in the UAE

In the UAE, demand for electric energy rose dramatically in the seventies after the first oil boom. Initially, this was mainly from the residential sector caused by a rapidly growing population and equally rapidly improving standards of living. However, the subsequent boom in the manufacturing industries also placed additional demand on the need for electric energy.

Consequently, there were substantial investments into the development of power plants in the country. Electricity production in the country grew very steadily in the last decade. The figures show that between 1978 and 1985 an average growth of 18.93 percent annually was experienced. Figure (1) provides a better picture of the growth in electricity generation in the UAE from 1984 to 1993 .

1 Most of the data for this study is not published. The data was gathered manually with help from electric authorities in each of the Emirates. The author wishes to thank all those who contributed to the successful completion of this project.

Figure (1) Growth of Electricity Generation In the UAE Over the Years in Million KWH



The development of electric energy took place both with the combined effort of the individual Emirates as well as the Federal Ministry of Electricity and Water. The urgency was such that the individual Emirates, specially the larger ones of Abu-Dhabi, Dubai, and Sharjah, found it prudent to go ahead with their individual plants even before the federal system for this purpose could be evolved. The Dubai Electric Company for instance was formed before the foundation of the UAE as a federal state.

Currently, the UAE is capable of producing around 5471 Megawatts of electricity. The greater part of this capacity belongs to the individual Emirates of Abu-Dhabi, Dubai, and Sharjah which account for up to 84 percent of this total. The remainder 16 percent is produced by stations belonging to Federal Ministry of Electricity and Water. The Ministry owns a large number of smaller capacity power plants with emphasis on the smaller Emirates such as Ajman, Umm Al-Qwain, Fujairah and Ras Al-Khaimah. Clearly, the Emirates/Federal division also highlights the urban/rural distribution strategy in the UAE. Figures (2) and (3) show the share of each of the individual Emirates in term of installed electric power.

Currently, the various Emirates including the large ones of Abu-Dhabi, Dubai and Sharjah have been experiencing constant rise in electric demand edging dangerously close to the overall supply. For the smaller Emirates, especially Ras Al-Khaimah, peak-load electric demand exceeded total generated electric power several times during the past years causing several interruptions and mischiefs for the residents. In fact, the absence of efficient electric planning in terms of peak-load cannot be ignored any longer. It is astonishing that most Emirates rely on very simple methods of electric peak-load forecasting (such as trend projections, moving averages, and random walk methods). This means that comprehensive models that will capture all attributes of time series data are almost entirely neglected.

The only alternative available to electric authorities is to establish better electricity planning through the utilization of scientifically sound methods in coming up with forecasting models that will capture all attributes of electric time series data for each of the Emirates. The development and implementation of these forecasting models, for electricity peak-load, will provide means by which better planning is possible.

Figure (2) Installed Capacity in the UAE as of 1994 (in M.W.)

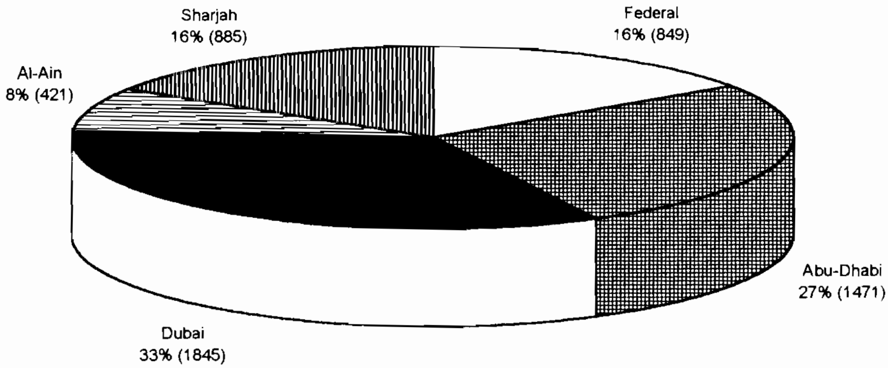
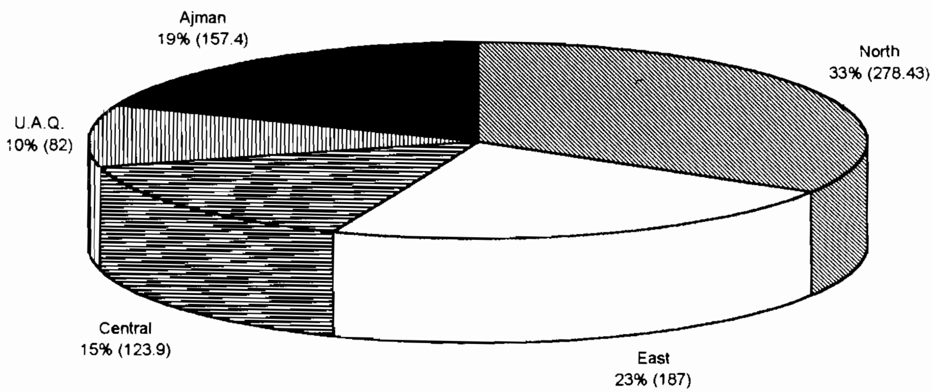


Figure (3) Installed Capacity in Federally Operated Regions as of 1994 (in M.W.)



Energy Demand Forecasting : Review of Literature

Traditional approaches to forecasting energy demand define relationships among observable variables and the desired parameters to be forecasted (Wilson, 1971; Halvorsem, 1975; Farukui et al, 1990; and Badri, 1992). These studies employed a variety of inputs to model electricity demand. These inputs included number of customers, number of heating degree days, total housing units, cost of fuel, average temperature, number of population, per capita personal income, value added in manufacturing, average price of electricity, index of various indicators such as cost of labor in manufacturing or commercial activities, and percent rural population.

Residential energy demand forecasting is usually performed with models which relate energy demand to energy prices, disposable income and other attributes of the consumer (Amemiya, 1981; Assimakopoulos, 1992; Tserkezos, 1992; and Wilder, 1992). Engle et al (1992) developed time series models that use daily average load to forecast hourly loads. The models use diagnostic tests to specify the relations between peaks, loads, holidays and weather in a sequential analysis from simple to general models. Other researchers focused on examining different individual models to predict electrical peak demand (Stanton & Gupta, 1970; Schwartz,1978; Price & Sharp, 1986; Robinson, 1988; and Nagurney, et al, 1991), examined five individual models to predict electrical peak demand. Harris and Liu (1990 - 1991) used the GNP as a predictor of electricity consumption.

While some of the developed models are easy to implement if data is available, other developed models are complex and difficult to comprehend and apply by novice users (Hartman, 1979: Huss, 1985; Assimakopoulos, 1992). Some researchers suggested and developed macro models that require a large number of variables (sometimes 50 variables) and depend on the availability of the associated data (Wilson, 1971; Halvorsen, 1975; Watson et al, 1987; Badri, 1992); most of those models are used for long term planning.

Huss (1985) defines the main characteristics of forecasting peak electricity demands for power capacity planning. This shows that within that particular context univariate methods can give more accurate forecasts six years or more ahead than a variety of other more complex forecasting models. This issue has been addressed by many researchers (Meese & Geweke, 1984; Henderson et al, 1988). The particular forecasting techniques chosen for this study comprise a large subset of those examined by Makridakis & Hibon (1979) and Makridakis (1984).

Methodological Issues

This part of the study will focus on some important methodological issues in this research. These issues include stating methods of data collection used in this study, summarizing the foundation of the forecasting models used, identifying the analysis procedures utilized, describing the diagnostic tests used as assessment criteria, and portraying the operations and the various components of the IEDSSF.

Methods of Data Collection

In this study, we used the series data in terms of monthly electricity peak-loads for the various Emirates. The main difficulty with this research is the fact that the required time series data is not published. As a result, we visited all electricity authorities in the individual Emirates where their assistance was requested. Moreover, some of those authorities did not keep track of historical data in an efficient manner. Actually, some performed these calculations manually when requested.

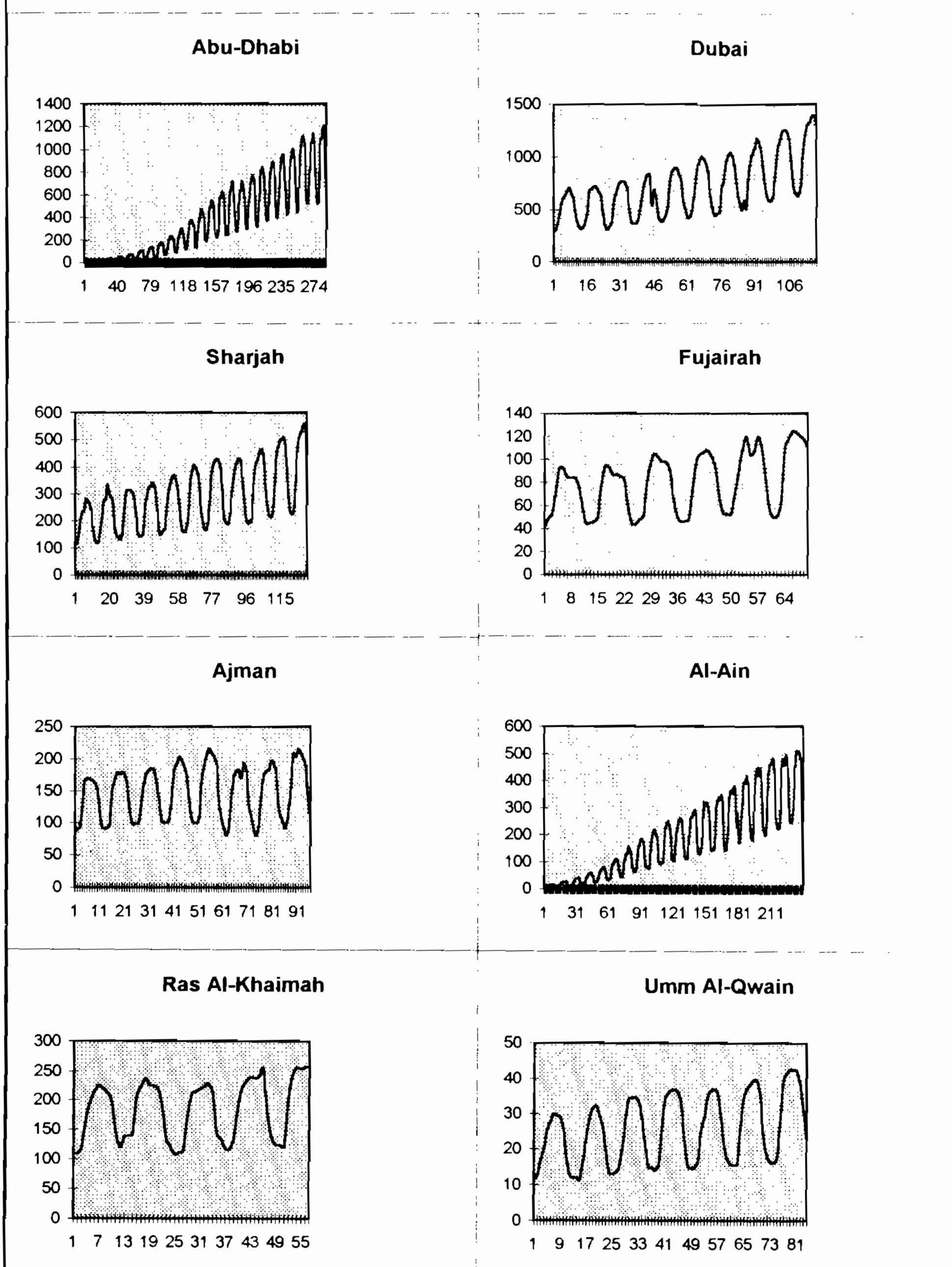
Even though the Emirate of Abu-Dhabi also includes the region of Al-Ain, Al-Ain time series data will be treated independently of that of the Abu-Dhabi. Al-Ain's electricity demand time series has its unique seasonal and trend components that make it more realistic to be studied independently of that of Abu-Dhabi.

Figure (4) provides a graphical presentation of electricity peak-load for each of the Emirates. The horizontal lines present the monthly periods where data are available, while the vertical lines present the peak-load in mega watt. The amount of data available and the magnitudes are different for each series. As a result, each presentation is provided in a separate figure (1969 to 1994 for Abu-Dhabi; 1974 to 1994 for Al-Ain; 1985 to 1994 for Dubai; 1983 to 1994 for Sharjah; 1986 to 1994 for Ajman; 1988 to 1994 for Fujairah and Umm Al-Qwain; and 1989 to 1994 for Ras Al-Khaimah).

Foundation of Forecasting Models Used

Selection of the particular model to be included in the model base of the Decision Support System is based on satisfying several objectives. Notwith standing some models that are included are complex and theoretical, the developed DSS which is fast, accurate and user-friendly makes it extremely attractive to implement. The main objectives considered in model development

Figure (4) Graphical Presentation of Peak-Load [Horizontal is Time, Vertical is M.W.]



and selection are validity (the model being conceptually and theoretically sound), transferability, data availability, output capabilities, and ease of understanding. Basically, there are three models or family of models available in the model base, exponential smoothing, Box-Jenkins, and dynamic regression.

Exponential Smoothing

Exponential smoothing techniques are among the most widely used (Gardner, 1983). They are easy to use, surprisingly accurate, and conceptually easy to understand. Little effort is required to fit a model and less historical data is required than with correlational methods (Goodrich & Mehra, 1984). Furthermore, exponential smoothing models are both robust and adaptive to changes in the structure of the data. There is a large amount of evidence on how well Exponential smoothing performs (Makridakis & Hibon, 1979; Garnder, 1985).

The exponential smoothing models included in the model base are simple exponential smoothing, Holt-Winters linear trend models (non-seasonal, additive seasonal, and multiplicative seasonal), damped or decaying trend models, exponential trend models, and Brown's linear trend models. To determine optimal smoothing constants the method employed by Gardner (1985) is used. This method attempts to minimize the sum of square errors by a coarse grid search.

Exponential smoothing is usually used when the data will not support a correlational approach like Box-Jenkins or dynamic regression. This can happen for one of two reasons (Goodrich, 1989): either (1) the historical data is too short to support accurate calculation of correlation coefficients; or (2) the correlations are not stable. In the M-competition, many of the time series were not stable over time (Makridakis, 1982,1984).

If the autocorrelations of the variable are in fact unchanging, Box-Jenkins usually outperforms exponential smoothing, since the statistical premises of the models are satisfied. Therefore, if one must make the choice of model solely on the basis of exploratory analysis of the data, then that analysis should concentrate on the likelihood that a constant coefficient probability model describes the data adequately. If not, then one should take advantage of the inherent robustness and adaptiveness of an exponential smoothing approach.

An important and comprehensive review of exponential smoothing methods was written by Gardner (1985), who classified 17 basic methods and several extensions of these methods. Since statistical forecasting consists of recognizing and extracting "features" from the past, then extrapolating them to the future, the forecast profiles of the various smoothing methods provides a good way to visualize their characteristics.

The simple exponential smoothing model is used for data that is untrended, nonseasonal and not driven by promotional events. This model uses only one parameter which is mainly concerned with smoothing the data (alpha). The larger the parameter alpha, the more adaptive the model to particular time series component.

Holt's exponential smoothing model uses a smoothed estimate of the trend as well as the level to produce forecasts. The current smoothed level is added to the linearly extended current smoothed trend as the forecast into the indefinite future. The undated value of the smoothed level is computed as the weighted average of new data (first term) and the best estimate of the new level based on old data (second term). As a result, the old and new estimates are combined, thus defining the current linear (local) trend.

In multiplicative Winters, it is assumed that each observation is a product of a de-seasonalized value and a seasonal index for that particular period (i.e., month or quarter). The de-seasonalized values are assumed to be described by the Holt model. The Winters model involves three smoothing parameters to be used in the level, trend and seasonal index smoothing equations. The forecast is computed similarly to the Holt model, then multiplied by the seasonal index of the current period. The seasonal index is estimated as the ratio of the current observation to the current smoothed level, averaged with the previous value for that particular period.

In additive Winters, it is assumed that each observation is the sum of a de-seasonalized value and a seasonal index. The de-seasonalized values are assumed to be described by the Holt model. The equations for additive Winters are nearly identical to those of multiplicative, except that de-seasonalized requires substraction instead of division.

Box-Jenkins Models

The Box-Jenkins forecasting methodology was first described by Box and Jenkins (1976). The main principle of the technique is to build the most parsimonious model possible, in terms of the number of parameters, that reproduces the autocorrelation function of the data adequately. In other words, Box-Jenkins is built squarely on the features of the ACF, just as exponential smoothing is built upon the qualitative features of the data. The methodology offers optimal forecasts of series that could be rendered stationary through differencing and power transforms.

Univariate Box-Jenkins models are built directly on the autocorrelation function (ACF) of a time series variable. Therefore, the prerequisite condition to use Box-Jenkins is that the data should posses a reasonably stable autocorrelation function. Furthermore, univariate Box-Jenkins cannot exploit leading indicators or other explanatory variables.

In terms of performance in competitions, Box-Jenikins has been somewhat disappointing, even compared to exponential smoothing (Makridakis, 1982 and 1984). We now understand that the optimality of the method depends on the properties of the data, specifically on the necessary stationarity assumptions. This is not a fault with Box-Jenkins but with our using it as model data that is too changeable and irregular to satisfy the statistical premises. Another disappointment is that Box-jenkins methodology has not been adopted by a very substantial number of corporations, despite the apparent need for more accurate forecasts (Goodrich, 1989). The principal reason for this has been the complexity of the method and the expense in terms of expertise and time required to model each series.

In the current study, we will try to meet this objection through the use of automatic modeling techniques, in which, we choose the Box-Jenkins model that minimizes the BIC and affords adequate diagnostics. This approach is also recommended by other researchers (Gardner & McCollister, 1978; and Goodrich, 1984, 1986 and 1989).

The Box-Jenkins model uses a combination of autoregressive (AR), integration (I) and moving average (MA) terms in the general Auto-Regressive Integrated Moving Average (ARIMA) model. This family of models can represent the correlation structure of a univariate time series with the minimum number of parameters to be fitted. Thus, these models are very efficient statistically and can produce high performance forecasts.

The Auto Regressive AR (p) model is specified where the dependent variable appears to be regressed on its own lagged values. The Auto-Regressive Moving Average Process ARMA (p,q) combines the features of the two processes of AR and MA. Any time series that can be made stationary by the differencing (d) times can be modelled as an ARIMA (p,d,q) process.

The most general seasonal model includes both seasonal and simple ARIMA models at once. The following equation describes the *multiplicative seasonal* ARIMA model. It is usually symbolized as ARIMA (p,d,q)*(P,D,Q). The model is given by the following formula (Bowerman, 1987 :120):

$$\phi (B)\, \Phi (B^s)\, (1-B)^d (1-B^s)^D\, Y_t = \theta (B)\, \Theta (B^s)\, \varepsilon_t$$

Where ϕ (B) and Φ (B) are autoregressive and moving average operators respectively; B is the back shift operator; and ε_t is called white noise; and Y_t is the time series data, transformed if necessary.

The family of models that the current DSS can identify include simple autoregressive models AR(p), basic autoregressive moving average models ARMA (p,q), more comprehensive autoregressive integrated moving average models ARIMA (p,d,q), and multiplicative seasonal ARIMA models ARIMA (p,d,q)* (P,D,Q).

Model identification is performed automatically via the AIC and BIC criteria. The procedure merely finds the ARIMA model that minimizes one of these criteria. Koehler and Murphee (1986) strongly suggest that the BIC, which points to simpler models than the AIC, is the superior criterion in terms of forecasting accuracy. Standard diagnostic contained in the DSS include the standard error of forecast, R-square (corrected for mean), the F test of overall statistical significance, the Ljung-Box test, the Durbin-Watson test, the standardized AIC statistic, and the standardized BIC statistic.

Dynamic Regression

Model specification for the dynamic regression portion of the DSS include features of dynamics (lagged dependent variables, and autoregressive error models), casual variables (inclusion and exclusion of variables, linear versus non-linear response and distributed lags). Features of the basic structure include single or multiple equations, errors in variables, heteroscedasticity, time varying parameters, and nonlinear distributional response.

The dynamic regression model differs from Box-Jenkins in two important ways. First, it includes one or more independent variables, which drive the process. Second, it does not include moving average terms, which are very useful in Box-Jenkins. Regression models will therefore be less parsimonious than Box-Jenkins for some processes. It will often be found that the errors obtained via dynamic regression are correlated. This may indicate that additional lags of the dependent variable should be introduced, or additional independent variables or new lags of existing independent variables should be introduced, or both.

The generalized Cochrane-Orcutt model is an alternative way to improve model dynamics that often requires estimation of fewer new parameters. In this study, an orderly and systematic strategy is followed for the dynamic regression diagnostics. They are modularized into three batteries of tests aimed at two phases of the model development process, which are development of the dynamic model and the development of the explanatory model. Most of the diagnostics are Chi-square statistics based on Lagrange multiplier tests (Engle, 1993). These tests are asymptotically equivalent to the more commonly used Wald tests and likelihood ratio tests.

System Performance and Diagnostics

After a model has actually been tried, more information becomes available about its appropriateness compared to other models, in the form of summary statistics and diagnostics. Diagnostics allow the user to compare the expected forecasting accuracy of fitted models in order to make a final decision. Most practitioners do not scrutinize diagnostic statistics very closely for exponential smoothing, since they have made no real distributional assumptions about the data (Goodrich, 1989). There is, in other words, no pretence that the correct model has been found, so there is little need to test. However, for this study, we will use the Ljung-Box statistic and the magnitudes of the smoothing coefficients. If any of them are very near unity, it indicates that particular equation has zero memory (Box & Jenkins, 1976; Goodrich, 1989). At best, this indicates a naive forecasting model.

Another diagnostic test is the Durbin-Watson test which involves only the first lag error autocorrelation. Under the null hypothesis that the fitted model is "true" these autocorrelaions should fluctuate around zero. If some of the autocorrelations are significantly different from zero, it may indicate that the fitted model can be improved.

The main principle of forecasting is to find the model that will produce the test forecasts, not the best fit. The current study will attempt to balance model complexity and goodness of fit to the historical data. The Akaike Information Criterion (AIC) and the Schwartz Criterion (BIC) are alternative measures that differ principally in the extent to which they penalize model complexity. By minimizing that AIC or BIC, we hope to minimize out of sample forecast error. These procedures are suggested by many researchers (Akaike, 1974a, 1974b; Osborne & Smith, 1989; and Engle, 1993). There are a number of measures for forecast accuracy in common use. Mean square error (MSE) and mean absolute percentage error (MAPE) are, however, probably, the most common.

The Intelligent Electric Decision Support System Forecaster (IEDSSF)

Figure (5) provides an overview of the main elements of the IEDSSF. The main components are the DATA BASE, the MODEL BASE, the DIAGNOSTER, the FORECASTER, and the OPTIMAL MODEL SELECTOR. The system provides extensive reporting capabilities that includes forecasting reports, diagnostic reports, and other reports. The system can operate in an interactive mode via user queries. Moreover, the system allows for batch forecasting by automatically preparing univariate forecasts for multiple time series. The system integrates data management, diagnostic tests, graphic display, and statistical analysis.

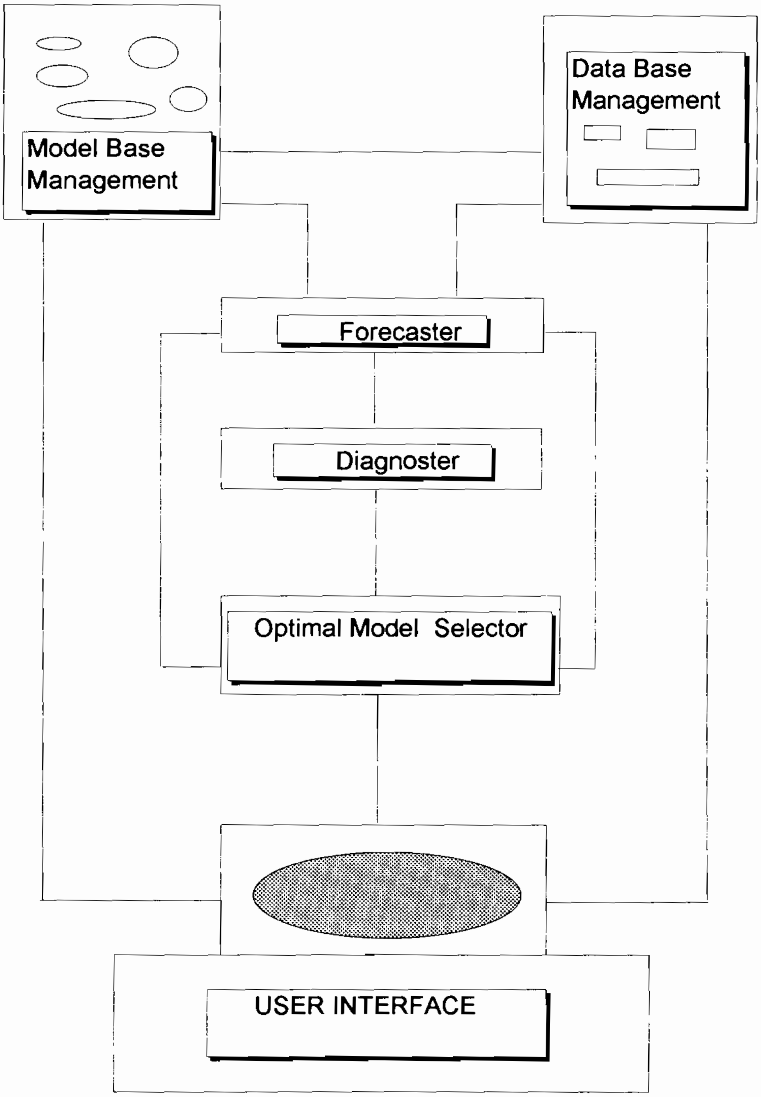
Analysis Procedures

The statistical package of SPSS - Windows (the TREND option) is used for most of the analysis. The IEDSSF allows the user to select and experiment with the various models included in the model base. Yet better, it could be used as an expert and requested to automatically advise on the optimal model based on the criteria considered by its Diagnoster component. To better present the comprehensiveness of the IEDSSF, we will attempt to require it to provide us with the optimal model as a whole, and the best model for each of the family of models in its base. We will also request it to provide all outcome statistics (diagnostics) of the various forecasting models.

Forecasting models will be developed and tested for monthly peak-load for all the Emirates. To better understand the nature of data for each of the Emirates, seasonal indexes for the monthly peak-load will be calculated. In addition, the multiplicative decomposition technique will be used to break down the time series data and identify the various percentages attributed to trend, cycles, seasonal, and irregular variations.

When developing forecasting models, a total of 12-time series data cases (constituting one year) will be considered as holdout samples to test the performance of each of the models. A graphical portrayal of the historical and forecast data for the holdout sample is useful for the purpose of assessment. After the optimal model is identified, the IEDSSF will identify the various parameters of the selected model taking into account all available data cases.

Figure (5) Elements of The Intelligent Electric DSS Forcaster (IEDSSF)



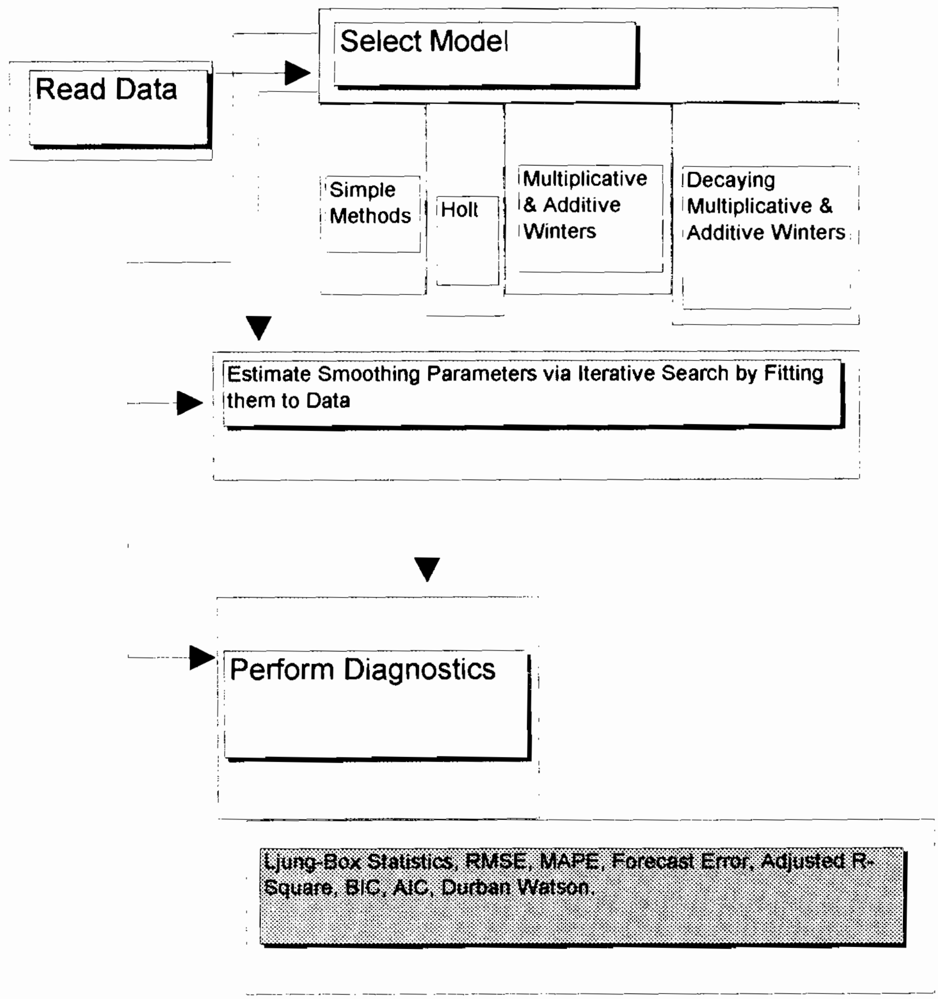
With regard to exponential smoothing computation procedures, the IEDSSF allows the user either to set the smoothing parameters or to have the program estimate them via iterative least squares. The procedure used in the IEDSSF is one that is recommended by Gardner (1983,1985). He recommends that the smoothing constants be fitted to the data. The iterative search requires repeated evaluation of the sum of squares forecast errors over the historical data set. To start up the recursive equations, the methods recommended by Goodrich (1984,1989); Gardner (1983,1985) are employed. Startup values are "forecasted" by running the exponential smoothing filter backwards form the last point to the first. The values of the smoothing parameters that minimize forecasting errors over the historical data set represent a compromise among different features of the data. Figure (6) provides a flow summary of the computation procedures for exponential smoothing used by the IEDSSF.

The Box-Jenkins computation procedure begins by determining the degree of differencing that is required to make the original data stationary. This is done via the autocorrelation function (ACF). Once the degree of differencing is determined, the remainder of the analysis deals with the stationary series. The autoregressive order AR(p) is determined by inspection of the sample partial autocorrelation function (PACE). A pure moving average process MA(q) is identified by examining a graph of the autocorrelation function in the same way that the AR(p) process is identified from the PACF. Model identification is done automatically via the AIC or BIC. The objectives is to find the ARIMA model that minimizes one of these criteria. For estimating the weights, the maximum likelihood approach is used (Goodrich, 1989).

For dynamic regression, other variables that are considered include monthly peak temperature, and several lagged variables of the own time series data. The same diagnostic statistics as in inexponential smoothing and Box-Jenkins will be utilized with special emphasis on the adjusted R-square.

The IEDSSF acts as a consultant that enables novice users to select the right forecasting model. Other objectives of the system are to simplify and increase the effectiveness of the forecasting procedure, to improve forecasting accuracy, to find optimal parameters for a specific model, and to provide forecasts for the future.

Figure (6) A Flow Summary of the Computation Procedures for Exponential Smoothing Used by the EDSSF



Analysis and Results

In this section, first the overall attributes of each of the time series data for the individual Emirates will be investigated, and then, the optimal forecasting model of peak-load for each of the Emirates will be analyzed and identified.

The Seasonal Indexes and Components of the Time Series Data

Multiplicative seasonal decomposition is performed to break down each time series data into trend-cycle, seasonal and irregular components. Table (1) provides the results of the multiplicative decomposition of the various time series data for electricity peak-load for all of the Emirates.

These numbers reveal strong variations from one Emirate to another reflecting the unequal demand for electricity due to variant development programs. Moreover, they reveal that different models for electric peak-load are required for each Emirates.

Table (1)

Time Series Components After Seasonal Decomposition (by Percentage) for Electricity Peak-Load

Emirate (or City)	**Trend-Cycle**	**Seasonal**	**Irregular**
Abu-Dhabi	92.79%	06.84%	0.37%
Dubai	36.18%	61.92%	1.89%
Sharjah	27.75%	71.18%	1.06%
Ajman	3.97%	93.78%	2.250%
Fujairah	10.60%	86.76%	2.64%
R.A.K.	3.58%	93.20%	3.16%
U.A.Q.	8.27%	89.94%	1.79%
Al-Ain	89.13%	10.25%	0.62%

Table (2) provides the monthly seasonal indexes for electricity peak-load in each of the Emirates. Numbers in the table show that for all the Emirates maximum indexes are reached during July or August. On the other hand, minimum indexes are obtained during January and February. Those indexes are important for planning purposes and for maintenance scheduling. Only pure time series methods are employed in this study to concentrate on the importance of the seasonal specification and to avoid the problems raised by comparison with explanatory variables. An inspection of the data pattern provided in tables (1) and (2), and figure (4) reveals the existence of three distinguished features: the existence of basic trend, the existence of seasonality, and the presence of variation positively related to level.

Table (2)

Seasonal Indexes for Electricity Peak-Load for Each of the Emirates (or Cities)

Emirate (or City)	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Abu-Dhabi	0.61573	0.62370	0.73086	1.00996	1.22031	1.29016	1.35601	1.38515	1.37184	1.25658	0.96604	0.71652
Al-Ain	0.62230	0.62763	0.77632	1.14284	1.32081	1.32550	1.32600	1.37162	1.32803	1.19477	0.84159	0.67870
Dubai	0.64974	0.66387	0.70717	0.99076	1.20801	1.30740	1.36671	1.39814	1.33160	1.20408	0.93000	0.73530
Sharjah	0.62121	0.61348	0.68490	1.02159	1.27463	1.35419	1.40736	1.43227	1.41408	1.24626	0.90426	0.67490
Ajman	0.66451	0.60981	0.71374	1.01002	1.30897	1.31503	1.36365	1.34832	1.33581	1.24785	0.90958	0.71339
Fujairah	0.61289	0.62493	0.73120	1.14462	1.32803	1.40385	1.33413	1.31418	1.32151	1.22056	0.89693	0.65933
R.A.K.	0.66100	0.66474	0.69116	1.06358	1.26927	1.32351	1.32096	1.32323	1.32099	1.27462	0.86546	0.72353
U.A.Q.	0.59406	0.59276	0.62820	1.01788	1.31788	1.40624	1.44471	1.45167	1.43709	1.26958	0.93009	0.67335

The underlying pattern of the data follows a relatively stable upward trend. This behavior might reflect the continuous improvement of the living standard in the UAE as far as the consumption of electrical energy is concerned. This growth in energy consumption is combined with the absence of competition of other energy forms. Moreover, the data exhibit a seasonal behavior subject to the level of socioeconomic activities and weather conditions throughout the year. The maximum monthly peak is observed during months with intense wheather phenomena which provoke the simultaneous operation of a large part of the reserves. In addition, as the level of the energy peak demand increases, time between the highest monthly peak and the lowest monthly peak within a year increases, in most cases, as well.

These results provide strong evidence that simple models such as the naive and the moving average approaches might not be suitable as forecasting models for peak electric load. Nevertheless, and for comparison reason, the results of these models will also be presented since some electricity authorities use these models.

It is considered as essential to develop models that will capture those features of the data and produce more accurate forecasts for the energy peak demand. Therefore, the development of the forecast models for electricity peak-load for the UAE must draw heavily upon two main objectives: (i) to take into account the special features and casual forces of peak load and (ii) to be easy to implement without requiring extensive databases.

Forecasting Models for Abu-Dhabi

To derive forecasting models for Abu-Dhabi power peak-load 300 cases (from 1969 to 1994) are available representing the months of the year (or 25 years of monthly times and series data). The data ranged from 3.0 to 1274 MW with mean of 406.564 and standard deviation of 349.543. Table (3) presents the diagnostic statistics for experiment data for electricity peak-load. Several models in the table provide good forecasts including the naive approach. Most exponential smoothing models provide low MAD's and BIC's, with special attention to the linear multiplicative Winter's model and the decaying trend multiplicative seasonality model. Both models provide lowest values for the MAPE, MAD, BIC, and the forecast error also.

Table (3)

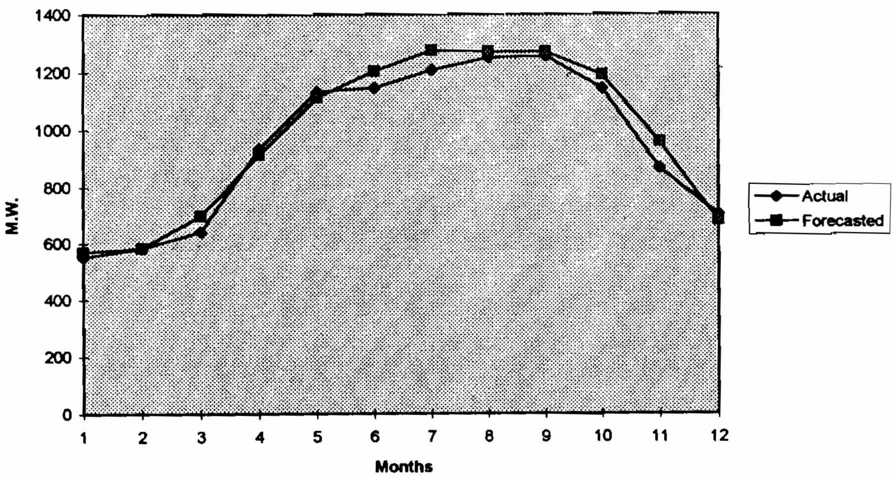
Diagnostics for experiment data for Abu-Dhabi Peak-Load

Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods (Best Models)								
Naive Approach	0.9382	0.6770	82.60	0.1681	52.24	1363	32.60	82.60
Moving Average (2 Periods)	0.8827	0.4478	113.8	0.2466	75.73	1698	113.8	113 8
Moving Average (3 Periods)	0.8216	0.3694	140.4	0.3211	97 44	1911	140 4	140.4
Moving Average (12 Periods)	0.8081	0.3271	145.6	0.3553	110.3	1991	145 6	145.6
Exponential Smoothing								
Simple Exponential Smoothing	0.9383	0.6770	82.60	0.1675	52.06	1463	83.27	82.46
Linear Trend- Additive Seasonality	0.9904	1.3500	32.66	0.1381	23.42	123.8	33.46	32 49
Holt	0.9380	0.6772	82.78	0.1688	52.01	1512	84 13	82.50
Winters	0.9928	1.5600	28.20	0.0601	17.70	48 16	28.89	28 05
Decaying Trend-Additive Seasonality	0.9900	1.1310	33.24	0.1161	23.85	169.8	34.34	33 01
Decaying Trend-Multiplicative Seasonality	0.9924	1.4350	28.95	0.0833	17.79	56.81	29.91	28.75
Dynamic Regression								
Best Model	0.9679	2.073	59.51	0.2816	39.96	177.9	61.48	59 09
Box-Jenkins								
ARIMA (0,1,2)*(0,1,3)	0.9919	1.918	29.71	0.0822	20.83	72.21	31.00	29.44
ARIMA (1,1,1)*(0,1,2)	0.9966	1.999	28.01	0.0516	17.80	22.36	17.61	29.15

Dynamic regression models which consider variables such as own lags and monthly temperatures provide also good presentations of the time series data. Nevertheless, the decision support system recommends the ARIMA (1,1,1)* (0,1,2) model which gives the lowest BIC which is also significant at the 0.005 level. This model provides one autoregressive order, one degree of differencing, and one order of moving average. The model specification also indicates a (0,1,2) seasonal model. A log transform is suggested for this Box-Jenkins model. The purpose of these transformations is to remove any trend in the data, and to make the data covariance stationary.

Validity tests of the holdouts sample provide lowest MAD, BIC, forecast error and MAPE for the recommended model. The model captures all components of the time series, level, trend and seasonality. Figure (7) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as holdout sample. It is clear how well the selected (or recommended) model fits the historic data. The figure shows that in the validation period (last 12 time series cases) the forecasts are tracking the actual series reasonably well. For deriving values for model parameters for electricity peak-load all data points are used without any validation data.

Figure (7) Abu-Dhabi Electric Peak-Load (Forecasted vs. Historic) for Holdout Sample Using the Box-Jenkins ARIMA (1,1,1)*(0,1,2) Model



Forecasting Models for Al-Ain

To derive forecasting models for Al-Ain electricity peak-load, 240 cases are available (from 1974 to 1994). The data ranged from 5.7 to 510 MW with mean of 186.908 and standard deviation of 142.699. Table (4) presents the diagnostic statistics for experiment data. As shown earlier, very low irregularity is experienced in the time series data for Al-Ain peak-load, while the trend-cycle component constitutes more than 89%. As a result, several models in the table provide good forecasts for Al-Ain peak-load including the naive approach.

Table (4)

Diagnostics for experiment data for Al-Ain peak-load

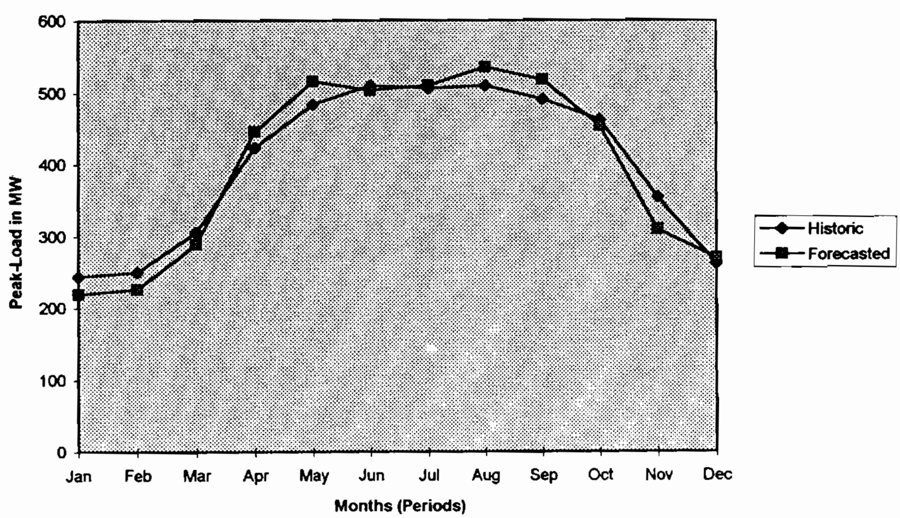
Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods (Best models)								
Naive Approach	0.9093	0.9938	40.81	0.1678	25.15	717.8	40.81	40.81
Moving Average (2 Periods)	0.8414	0.6139	53.97	0.2376	34.93	1057	53.97	53.97
Moving Average (4 Periods)	0.7042	0.3916	73.70	0.3681	53.39	1490	73.70	73.70
Exponential Smoothing								
Simple Exponential Smoothing	0.9095	0.9938	40.81	0.1671	25.04	771.5	41.21	40.72
Linear Trend- Additive Seasonality	0.9831	1.3110	17.74	0.1226	12.71	115.5	18.27	17.62
Holt	0.9050	1.0020	41.83	0.1708	25.67	779.6	42.65	41.64
Winters (Multiplicative Winters)	0.9880	1.5980	14.95	0.0685	9.274	29.99	15.39	14.85
Decaying Trend-Additive Seasonality	0.9829	1.3210	17.74	0.1189	12.47	96.38	18.44	17.59
Decaying Trend-Multiplicative Seasonality	0.9878	1.6530	15.06	0.0659	9.271	29.94	15.65	14.93
Dynamic Regression								
Best Model	0.9810	1.5610	19.50	0.1096	13.72	116	20.07	19.37
Box-Jenkins (Best models)								
ARIMA (0,1,1)*(0,1,1)	0.9810	1.8510	18.40	0.0913	12.39	66.79	18.77	18.31

Four exponential smoothing models provide low MAD's (less than 13), and BIC's (less than 19). The linear multiplicative Winter's model and the decaying trend multiplicative seasonality model provide the best fits. Both models provide lowest values for the MAPE, MAD, BIC, and the forecast error.

The dynamic regression model also provides good presentations of the time series data with low values for MAD, BIC, RMSE, and forecast error. In addition, the decision support system indicates that the ARIMA(0,1,1,)*(0,1,1) model results in low values for these statistics with the BIC of 18.77 significant at the 0.005 level. This model provides no autoregressive order, one degree of differencing, and one order of moving average. The model specification also indicates a (0,1,1) seasonal model. The DSS also recommends a log transform if the Box-Jenkins model is used. Nevertheless, the DSS shows that the multiplicative Winter model outperforms the Box-Jenkins model by 20.582 to 23.172 out of sample MAD. As a result, the linear-multiplicative Winter is recommended for Al-Ain peak-load.

Figure (8) provides graphical portrayals of historic and forecasted values for the last 12-times series cases considered as a holdout sample. The figure shows that in the validation period (last time series cases) the forecasts are tracking the actual series reasonably well.

Figure (8) Al-Ain Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Multiplicative Winter's Model



Forecasting Models for Dubai

To derive forecasting models for Dubai electricity peak-load, 118 cases are available (from 1985 to 1994). The data ranged from 296 to 1393 MW with mean of 718.559 and standard deviation of 275.395. Table (5) presents the diagnostic statistic for experiment data. As discussed earlier, seasonality constitutes the largest decomposition component for Dubai peak-load. The low irregularity in the data results in several models providing good forecasts. The table shows that three models provide unacceptable fits, they include all the simple methods, the simple exponential method and the Holt method.

Table (5)

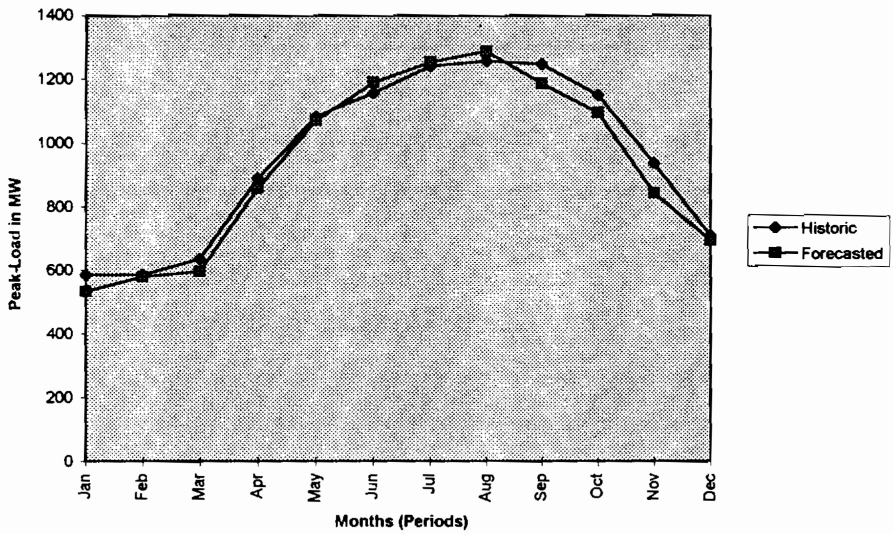
Diagnostics for experiment data for Dubai Peak-Load

Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods (best models)								
Naive Approach	0.7829	0.9690	115.1	0.1409	89.12	436.4	115 1	115 1
Moving Average (2 Periods)	0 6219	0.5212	151.9	0.1945	122.6	645.3	151 9	151.9
Moving Average (4 Periods)	0 2369	0.3545	215.8	0.2963	186.2	773 2	215.8	215.8
Moving Average (12 Periods)	0.3347	0.3313	201.5	0.2882	181 5	680.0	201 5	201 5
Exponential Smoothing								
Simple Exponential Smoothing	0.7859	0.9690	115.1	0.1395	88 29	476 6	117.1	114 6
Linear Trend- Additive Seasonality	0.9565	1.5420	51.87	0.0563	36 58	33 32	54 6	51 14
Holt	0.7837	0.9698	115.7	0.1396	88.23	488 2	119 7	114 6
Winters (Multiplicative Winters)	0.9671	1.7660	45.1	0.0463	30.00	13.92	47 47	44 46
Decaying Trend-Additive Seasonality	0.9561	1.5360	52.13	0.0563	36.67	34.21	55 81	51 15
Decaying Trend-Multiplicative Seasonality	0.9666	1.7420	45.43	0.0465	30.17	19 24	48 65	44 58
Dynamic Regression								
Best Model	0.9436	1.645	59.43	0.0581	37.77	48.45	64 02	58 17
Box-Jenkins (Best models)								
ARIMA (2,0,1)*(0,1,1)	0.9545	1.890	53.38	0 0583	38.35	23.60	57 50	52 54
ARIMA (1,0,1)*(0,1,1)	0.9547	1.882	53 27	0.0589	38.04	24.86	56.33	52.43
ARIMA (1,0,0)*(1,1,2)	0.9674	2 523	43.43	0 0440	30.11	19.29	46 43	43 59

The series is nonstationary and seasonal. With regard to exponential smoothing, mainly two models provide better forecasts, the Winter's model and the decaying trend-multiplicative seasonality model. One can not ignore noticing how well the Box-Jenkins model resemble the peak-load data. Three ARIMA models outperform other models in the Box-Jenkins family of models. The decision support system recommends the ARIMA (1,0,0)*(1,1,2) model for its lowest MAD, BIC, RMSE, and forecast error. Because of severe seasonality, seasonal differences are strongly suggested. It should also be mentioned that the dynamic regression model also provided good forecasts with an adjusted R-square of 0.9436. This model of own lags and monthly temperatures provides results in relatively low values for MAS, BIC, RMSE, and forecast error but not lower than the recommended model. For the recommended Box-Jenkins model the square root transfer is recommended. The recommended model outperforms exponential smoothing by 32.562 to 34.375 out of sample MAD.

Figure (9) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample. The figure shows that the forecasts are tracking the actual series reasonably well.

Figure (9) Dubai Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Box-Jenkins ARIMA (1,0,0)*(1,1,2) Model



Forecasting Models for Sharjah

To derive forecasting models for Sharjah electricity peak-load, 130 cases are available (from 1983 to 1994). The data ranged from 114 to 560 MW with mean of 292.115 and standard deviation of 112.702. Table (6) presents the diagnostic statistics for experiment data for Sharjah electricity peak-load. As discussed earlier, seasonality constitutes the largest decomposition component for Sharjah peak-load. In addition, low irregularity is experienced in the data for Sharjah peak-load. The table shows that two models provide reasonably good fits. They include dynamic regression and ARIMA.

The series is trended and seasonal. With regard to exponential smoothing, mainly two models provide better forecasts than other models in that family, the Winter's model and the decaying trend-multiplicative seasonality model. Nevertheless, these models do not perform as well as the other two models mentioned earlier. However, the decision support system recommends the ARIMA (1.1,0)*(0,1,2) model for its lowest MAD, BIC, RMSE, and forecast error.

The dynamic regression model also provided good forecasts with an adjusted R-square of 0.9039. This model of own lags and monthly temperatures results in relatively low values for MAD, BIC, RMSE, and forecast error but not lower than the recommended model. For the recommended Box-Jenkins model the square root transfer is recommended. With regard to the best exponential model, the recommended model outperforms it by 9.297 to 20.927 out of sample MAD.

Table (6)

Diagnostics for experiment data for Sharjah Peak-Load

Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods (Best Models)								
Naive Approach	0.7500	0.6753	42.10	0.1209	28.88	599.4	42.10	42.10
Moving Average (2 Periods)	0.522	0.4501	58.21	0.1793	42.37	740.6	58.21	58.21
Exponential Smoothing								
Simple Exponential Smoothing	0.7528	0.6760	42.10	0.1199	28.63	651.7	42.78	41.92
Linear Trend- Additive Seasonality	0.8307	0.4873	34.84	0.1159	26.64	332.9	36.55	34.39
Holt	0.7504	0.6761	42.30	0.1199	28.61	666.1	43.68	41.94
Winters	0.8793	0.6929	29.42	0.0914	22.01	231.8	30.87	29.04
Decaying Trend-Additive Seasonality	0.8131	0.4496	36.62	0.1199	27.58	340.9	39.04	35.99
Decaying Trend-Multiplicative Seasonality	0.8752	0.6432	29.91	0.0882	20.97	222.0	31.89	29.40
Dynamic Regression								
Best Model	0.9039	2.2500	25.89	0.0825	19.49	80.77	27.62	85.43
Box-Jenkins								
ARIMA (1,1,0)*(0,1,2)	0.9363	2.056	21.11	0.0607	14.61	52.53	22.26	20.80

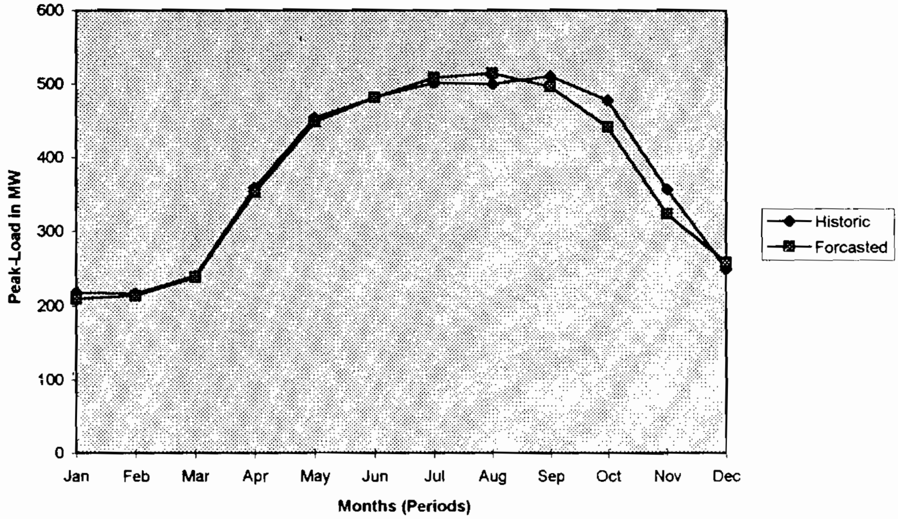
Figure (10) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample. The figure shows that in the validation period (last 12 time series cases) the forecasts are tracking the actual series reasonably well (from January to July the fit is almost perfect).

Forecasting Models for Ajman

To derive forecasting models for Ajman electricity peak-load, 96 cases are available (from 1986 to 1994). The data ranged from 80.5 to 216 MW with mean of 147.792 and standard deviation of 40.975. We should recall here that Ajman electricity production is controlled by the federal government.

Table (7) presents the diagnostic statistics for experiment data for Ajman electricity peak-load. As discussed earlier, seasonality constitutes the largest

Figure (10) Sharjah Electric Peak-Load (Forcasted vs. Historic) for the Holdout Sample using the Box-Jenkins ARIMA (1,1,0)*(0,1,2) Model



decomposition component for Ajman's peak load. In addition, relatively high irregularity is experienced in the data for Ajman peak-load. The table shows that four exponential smoothing models as well as the ARIMA (1,0,0)*(0.1,1) models performing better than the other models.

The series is non-stationary and seasonal. With regard to exponential smoothing, mainly four models provide better forecasts than other models in that family, the linear trend-additive seasonality, the Winters, the decaying trend-additive seasonality and the decaying trend-multiplicative seasonality models. Nevertheless, these models do not perform as well as the other two model mentioned earlier. The decision support system recommends the multiplicative Winters model for its lowest MAD, BIC, RMSE, and forecast error.

Relative to other models discussed, the dynamic regression model does not provide good forecasts with an adjusted R-square of 0.8452, which is much lower than that of other models. This model of own lags and monthly temperatures results in relatively higher values for MAD, BIC, RMSE, and forecast error. For the recommended Winter's model, it outperforms the best Box-Jenkins model by 9.036 to 11.738 out of sample MAD.

Table (7)

Diagnostics for experiment data for Ajman Peak-Load

Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods								
Naive Approach	0.6584	0.8285	23.16	0.1259	17.23	330.9	23.16	23.16
Moving Average (2 Periods)	0.3748	0.5349	31.33	0.1792	24.30	443.4	31.33	31.33
Exponential Smoothing								
Simple Exponential Smoothing	0.6636	0.8289	23.16	0.1244	17.02	365.9	23.64	23.02
Linear Trend- Additive Seasonality	0.9546	1.1500	8.510	0.0471	6.318	82.02	9.045	8.357
Holt	0.6591	0.8289	23.32	0.1245	17.04	374.9	24.28	23.04
Winters	0.9665	1.5710	7.310	0.0372	5.127	30.04	7.769	7.178
Decaying Trend-Additive Seasonality	0.9538	1.1050	8.582	0.0467	6.312	83.41	9.307	8.375
Decaying Trend-Multiplicative Seasonality	0.9661	1.5620	7.355	0.0373	5.135	30.74	7.977	7.178
Dynamic Regression								
Best Model	0.8452	2.322	15.49	0.0877	11.99	79.23	16.83	15.11
Box-Jenkins								
ARIMA (1,0,0)*(0,1,1)	0.9646	2.250	7.503	0.0399	5.620	22.75	7.857	7.395

Figure (11) Ajman Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Multiplicative Winter's Model

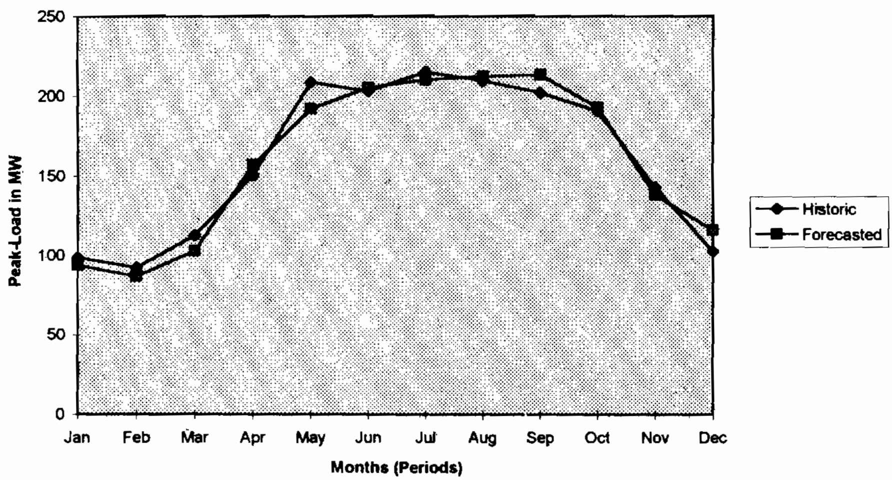


Figure (11) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample for peak-load Ajman. The figure shows that in the validation period (last 12 time series cases) the forecasts are tracking the actual series reasonably well. Despite the fact that the holdout data behaved with some irregularity as shown, the Winters model picked that up very well. This fact gives further support for its suitability.

Forecasting Models for Fujairah

To derive forecasting models for Fujariah electricity peak-load 70 cases are available (from 1988 to 1994). The data ranged from 42 to 125 MW with mean of 80.471 and standard deviation of 25.521. Fujairah's electricity production is controlled by the federal government. Table (8) presents the diagnostic statistic for experiment data for Fujairah electricity peak-load. Seasonality constitutes the largest decomposition component for Fujairah peak-load. In addition, relatively low irregularity is experienced in the data for Fujairah peak-load. The table shows that four exponential smoothing models as well as two ARIMA models perform better than the other models.

Table (8)

Diagnostics fór experiment data for Fujairah Peak-Load

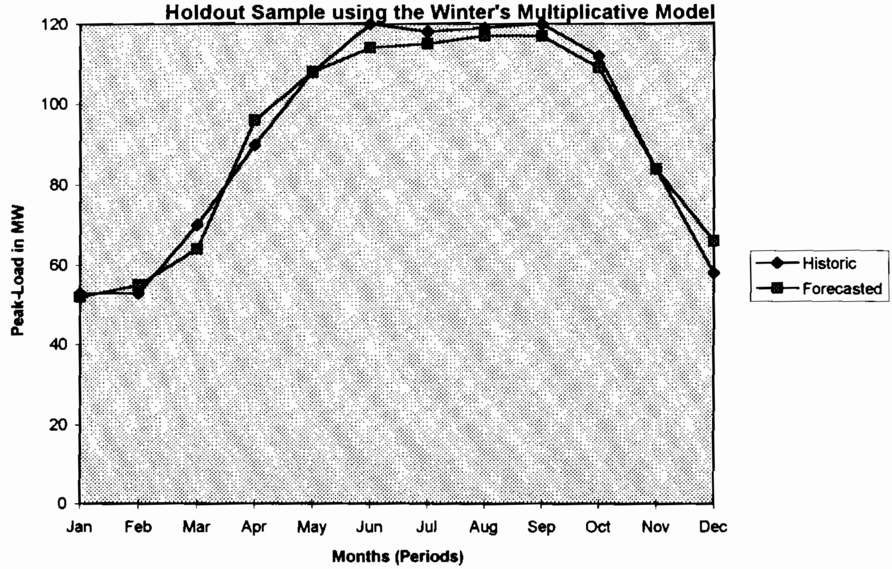
Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods (Best Models)								
Naive Approach	0.6788	0.8596	13.24	0.1308	9.727	170.3	13.24	13.24
Moving Average (2 Periods)	0.4243	0.6037	17.73	0.1879	13.66	231.0	17.73	17.73
Moving Average (3 Periods)	0.1763	0.4407	21.20	0.2349	16.81	294.0	21.20	21.20
Exponential Smoothing								
Simple Exponential Smoothing	0.6802	0.9053	13.24	0.1285	9.554	184.8	13.60	13.12
Linear Trend- Additive Seasonality	0.9478	0.9519	5.348	0.0483	3.709	26.37	5.795	5.203
Holt	0.6743	0.9064	13.36	0.1288	9.573	187.2	14.10	13.12
Winters	0.9682	1.9290	4.286	0.0424	3.259	10.36	4.564	4.188
Decaying Trend-Additive Seasonality	0.9468	0.9498	5.400	0.0487	3.724	25.70	6.008	5.204
Decaying Trend-Multiplicative Seasonality	0.9521	0.9980	5.127	0.0492	3.770	23.69	5.704	4.940
Dynamic Regression								
Best Model	0.8467	2.085	9.167	0.0947	6.838	76.59	10.20	8.833
Box-Jenkins (Best Models)								
ARIMA (0,0,1)*(0,1,0)	0.9557	2.248	5.058	0.0473	3.703	10.19	5.220	5.000
ARIMA (0,0,1)*(0,1,1)	0.9543	1.015	5.098	0.0471	3.669	23.48	5.524	4.960

The series is trended and seasonal. With regard to exponential smoothing, mainly four models provide better forecasts than other models in that family; the linear trend-additive seasonality, the Winters the decaying trend-additive seasonality and the decaying trend-multiplicative seasonality models. The decision support system recommends the multiplicative Winters model for its lowest MAD, BIC, RMSE, and forecast error.

Relative to other models discussed, the dynamic regression model does not provide good forecasts with an adjusted R-square of 0.8467, which is much lower than that of other models. This model of own lags and monthly temperature result in relatively higher values for MAD, BIC, RMSE, and forecast error. For the recommended Winters model, it outperforms the best Box-Jenkins model by 5.123 to 8.344 out of sample MAD.

Figure (12) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample for peak-load Fujairah. The figure shows that in the validation period (last 12 time series cases) the forecasts are tracking the actual series reasonably well. Despite the fact that the holdout data behaved with some irregularity as shown, the Winters model picked that up very well, which gives further support for its suitability.

Figure (12) Fujairah Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Winter's Multiplicative Model



Forecasting Models for Umm Al-Qwain

To derive forecasting models for Umm Al-Qwain electrici , peak-load, 72 cases are available (from 1988 to 1994). The data ranged from 11.2 to 42.7 MW with mean of 26. 322 and standard deviation of 9.647. Table (9) presents the diagnostic statistics for experiment data. The table shows that three models provide reasonably good fits. They include exponential smoothing (four models), dynamic regression and ARIMA.

Table (9)

Diagnostics for experiment data for Umm Al-Qwain (Peak-Load)

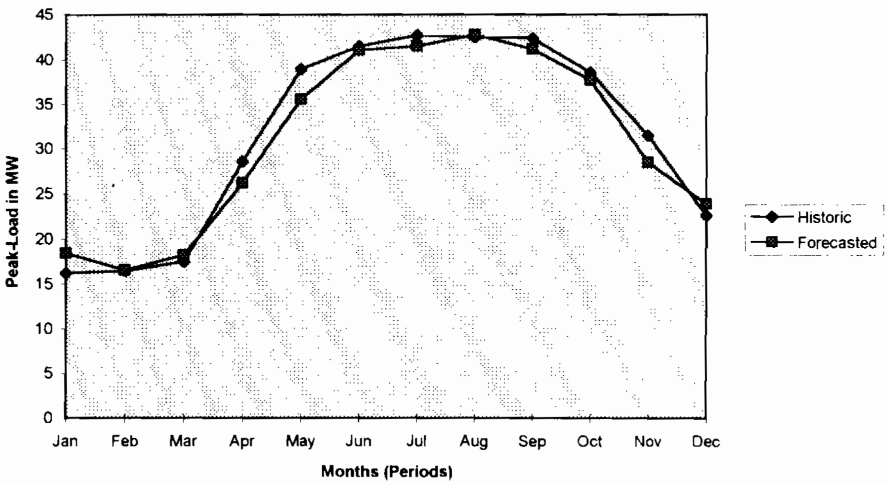
Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods								
Naive Approach	0.7262	0.6157	4.938	0.1559	3.640	432.8	4.938	4.938
Moving Average (2 Periods)	0.4764	0.4406	6.829	0.2312	5.331	521.7	6.829	6.829
Exponential Smoothing								
Simple Exponential Smoothing	0.7304	0.6163	4.938	0.1541	3.596	469.9	5.040	4.909
Linear Trend- Additive Seasonality	0.7268	0.6163	4.971	0.1543	3.597	477.7	5.178	4.911
Holt	0.9647	1.2350	1.787	0.0584	1.345	25.32	1.899	1.755
Winters	0.9679	1.2650	1.704	0.0489	1.206	25.94	1.811	1.677
Decaying Trend-Additive Seasonality	0.9649	1.2580	1.795	0.0567	1.317	26.42	1.947	1.792
Decaying Trend-Multiplicative Seasonality	0.9675	1.2870	1.715	0.0485	1.201	25.64	1.859	1.673
Dynamic Regression								
Best Model	0.9553	1.2660	2.055	0.0622	1.441	33.37	2.199	2.011
Box-Jenkins								
ARIMA (0,1,2)*(0,1,1)	0.9731	1.9330	1.580	0.0479	1.148	10.28	1.692	1.546

The series is trended and seasonal. With regard to exponential smoothing, mainly three models provide better forecasts than other models in that family, the Winter's additive and multiplicative models, and the decaying trend-multiplicative and additives seasonality models. One can not ignore noticing how well the Box-Jenkins model resembles the peak-load data.

The dynamic regression model also provided good forecasts with an adjusted R-square of 0.9553. This model of own lags and monthly temperature resulted in relatively low values for MAD, BIC, RMSE, and forecast error but not lower than the recommended model. For the recommended Box-Jenkins model the square root transfer is recommended. With regard to the best exponential model, the recommended model outperforms it by 2.548 to 2.778 out of sample MAD.

The decision support system recommends the ARIMA (0,1,2)*(0,1,1,) model. Figure (13) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample for peak-load Umm Al-Qiwan. Little variation is observed with regard to January, May and November; but a BIC value of 1.692 which is also significant provides great support for the recommended model.

Figure (13) Umm Al-Qwain Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Box-Jenkins ARIMA (0,1,2)*(0,1,1) Model



Forecasting Models for Ras Al-Khaimah

To derive forecasting models for Ras Al-Khaimah electricity peak-load, 57 cases are available (from 1989 to 1994). The data ranged from 107.5 to 257.5 MW with mean of 183.667 and standard deviation of 50.134. Table (10) presents the diagnostic statistics for experiment data for Ras Al-Khaimah electricity peak-load. As discussed earlier, seasonality constitutes the largest decomposition components for Ras Al-Khaimah peak-load. In addition, relatively modest irregularity is experienced in the data for peak-load. The table shows that four exponential smoothing models, the dynamic regression model as well as two ARIMA models provide adjusted R-square of greater than 0.9.

The series is trended and seasonal. With regard to exponential smoothing, mainly four models provide better forecasts than other models in that family; the linear trend-additive seasonality, the Winters the decaying trend-additive seasonality and the decaying trend-multiplicative seasonality models. The decision support system recommends the multiplicative Winters model for its lowest MAD, BIC, RMSE, and forecast error.

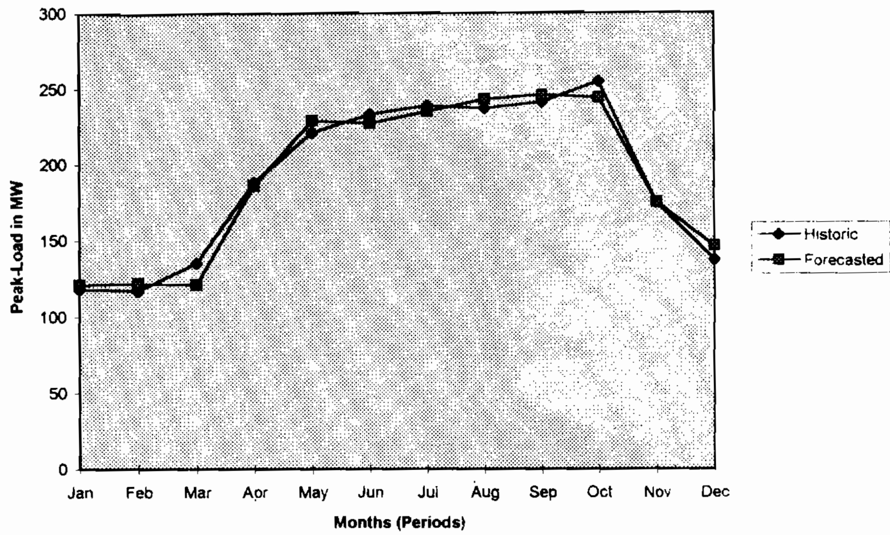
Table (10)
Diagnostics for experiment data for Ras Al-Khaimah Peak-Load

Model	Diagnostic Tests on Experiment Data							
	Adjusted R-square	Durbin Watson	Forecast Error	MAPE	MAD	Ljung-Box	BIC	RMSE
Simple Methods								
Naive Approach	0.6536	1.0920	29.46	0.1166	20.04	144.4	29.46	29.46
Moving Average (2 Periods)	0.4097	0.6625	38.45	0.1656	28.33	225.9	38.45	38.45
Exponential Smoothing								
Simple Exponential Smoothing	0.6609	1.0920	29.46	0.1146	19.69	159.8	30.25	29.20
Linear Trend- Additive Seasonality	0.9390	1.0060	12.50	0.0565	9.354	37.83	13.53	12.16
Holt	0.6548	1.0940	29.72	0.1147	19.68	161.8	31.34	29.19
Winters	0.9476	0.8758	12.63	0.0542	9.152	42.35	13.68	12.13
Decaying Trend-Additive Seasonality	0.9332	1.1660	12.39	0.0565	9.433	35.79	13.77	11.95
Decaying Trend-Multiplicative Seasonality	0.9398	0.8819	12.75	0.0542	9.187	41.81	14.17	12.30
Dynamic Regression								
Best Model	0.9008	0.8142	16.22	0.0772	12.75	80.16	17.26	15.86
Box-Jenkins								
ARIMA (1,0,0)*(0,1,0)	0.9404	2.277	12.58	0.0556	9.390	24.68	12.97	12.44
ARIMA (0,1,1)*(0,1,0)	0.9376	1.967	12.87	0.0569	9.783	17.76	13.29	12.73

Relative to other models discussed, the dynamic regression provides reasonably good forecasts with an adjusted R-square of 0.9008, which is still much lower than that of other models. This model of own lags and monthly temperature results in relatively in higher values for MAD,BIC, RMSE, and forecast error. For the recommended Winter's model, it outperforms the best Box-Jenkins model by 8.645 to 16.432 out of sample MAD.

Figure (14) provides graphical portrayals of historic and forecasted values for the last 12-time series cases considered as a holdout sample for peak-load Ras Al-Khaimah. The figure shows that the data series from April to October is slightly trended upward and almost straight. The Winter's model picked that up very well, which gives further support for its suitability.

Figure (14) Ras Al-Khaimah Electric Peak-Load (Forecasted vs. Historic) for the Holdout Sample using the Multiplicative Winter's Model



Summary and Conclusion

In any type of an organization, successful short term forecasting is the first step in building and developing competitive strategic plans. For electric utility companies, forecasting peak-load has become a necessity. Recently in the United Arab Emirates, rising electrical energy costs coupled with declining oil revenues have caused many utilities to closely examine their strategic planning policies.

Successful load programs that are directed toward efficient production of electrical energy are necessary for the implementation of these policies. The current study understands the urgent need for making available to electricity authorities the most appropriate time series model to forecast electricity peak-load for the various Emirates of the UAE.

The availability of these models provides great incentives to reduce the need for additional generation, transmission and distribution capacity. Moreover, the implementation of these models leads to conserving scarce resources through the encouragement of more efficient use of existing resources, and ensures equitable levels of service to customers.

Table (11)

Final Recommended Models for Selected Emirates
(Winter's Linear-Multiplicative Exponential Smoothing)

Emirate (or City)	Component	Smoothing Weight	Final Value
Sharjah (Peak-Load)	Level Trend Seasonal	0.20445 0.01510 0.36513	390.700 1.69930 1.24630
Ajman (Peak-Load)	Level Trend Seasonal	0.27155 0.01476 0.56385	150.550 0.14388 0.71289
R.A.K. (Peak-Load)	Level Trend Seasonal	0.17139 0.00830 0.55449	193.930 0.50950 1.32100
Fujairah (Peak-Load)	Level Trend Seasonal	0.05974 0.03079 0.40311	90.9610 0.41758 1.22050
Al-Ain (Peak-Load)	Level Trend Seasonal	0.13689 0.00743 0.37128	392.750 1.62300 0.67870

Table (12)

Final Recommended Models for Selected Emirates (or Cities)
(Box-Jenkins ARIMA Models)

Emirate (or City)	Component	Coefficient	Standard Error	t-Statistic	Significance Level
Abu-Dhabi **(Peak-Load)** ARIMA (1,1,1)*(0,1,2)	a[1] b[1] B[12] B[24]	0.3467 0.7208 0.5913 0.1900	0.1093 0.0814 0.0572 0.0563	3.1712 8.8512 10.3363 3.3747	0.0025 0.0000 0.0000 0.0007
Dubai **(Peak-Load)** ARIMA (1,0,0)*(1,1,2)	a[1] A[12] B[12] B[24]	0.96730 -0.3242 0.5282 0.3773	0.0239 0.5765 0.5689 0.5105	40.5154 -0.5622 0.92830 0.73900	0.0000 0.6862 0.4664 0.5726
Umm Al-Qwain **(Peak-Load)** ARIMA (0,1,2)*(0,1,1)	b[1] b[2] B[12]	0.2258 0.3414 0.7595	0.1129 0.1152 0.0596	2.00030 2.96400 12.7364	0.0050 0.0010 0.0000

This study examined the relevancy of various models to forecasting electricity peak-load. In effect, the study "screened" all these models in order to recommend the best for short horizons. The techniques dealt with were Box-Jenkins, exponential smoothing, and dynamic regression. Particular attention was given to the validity of the models recommended as well as their forecasting performance based on monthly data. The study shows that two models particularly provide superior results in term of validity and forecasting performance. The two models are the Winter's linear multiplicative and the Box-Jenkins ARIMA. In addition, it should be pointed out that energy demand, especially in the UAE, is a seasonal phenomena with a strong upward trend (see Figure 4). As a result, it is meaningless for electricity authorities to consider some simple models that do not take these facts into account. As expected, the study reflected this fact since the simple models such as the random walk method, the moving average technique, and the simple exponential smoothing performed rather poorly relative to other models.

Table (11) provides the coefficients for the Winter's models recommended by the IEDSSF for the various Emirates. In addition, Table (12) provides the coefficients for the recommended Box-Jenkins ARIMA models. Because of the characteristics inhibited in the time series data for the Emirates of the UAE in term of seasonality, trend and irregularity, decision makers could choose either the Winter's or the specified ARIMA models without significant loss of accuracy. Both of the models provided good forecasts. The final models recommended by the decision support system passed a sequence of stringent diagnostic tests.

This study serves as the base towards long term strategic electricity planning for the UAE. Future studies, should continuously reexamine the performance of these models and test new models such as neural networks and genetic algorithms. The recommended models have many characteristics that make them extremely appealing to decision makers. These characteristics include validity (the models are conceptually and theoretically sound and the relationships and specifications are accepted by the professional community), transferability (the models are capable of being specified, estimated and implemented in a way that makes them applicable to a variety of areas), data availability (the data is available for model estimation and the quality of the data is sufficient to make key planning decisions), ease of understanding (the models' structure and implementation can be understood by critical decision makers who must have confidence in the models and their results to make decisions), and output capabilities (the models are capable of being formulated in such a way as to satisfy the need).

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