SEASONAL AND CYCLIC FORECASTING FOR HYDRO- ELECTRIC POWER GENERATING STATION

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Abstract
Effective forecasting is an inevitable tool for managers and administrators who are always occupied with strategic decision making under uncertainty. Electric power load forecasting is a vital process in the planning of electricity industry and the operation of electric power systems. It facilitates electric power-generation strategies, by pre-informing power providers to take appropriate mitigating actions to minimize risks and manage demand. In this paper, monthly electric power load data collected from hydro-electric power generating station, Kainji, for seven years (2008 – 2014), were analyzed and used to forecast future power values. The patterns of distribution of previous power generation data over a period of time (i.e., in form of Time series), which include trend, seasonality, cyclicality, and randomness, were identified using Decomposition approach. The choice of an appropriate forecasting method was then determined, future values were projected and power forecasts were made for the next few periods. For reasons of clarity and uniformity, points of significance and mathematical procedures were discussed and shown in the context of a business case typical of most industries.

***Keywords**: Forecasting, Hydro-electric power generation, Time series, Decomposition approach*

Introduction
Electricity as a product has very different characteristics compared to a material product. For instance, electricity energy cannot be stored as it should be generated as soon as it is demanded. One of the objectives of any commercial electric power company is to provide end users (market demands) with safe and stable electricity. Therefore, Electric Power Load Forecasting is a vital process in the planning of electricity industry and the operation of electric power systems. Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Electricity demand is assessed by accumulating the consumption periodically; it is almost considered for hourly, daily, weekly, monthly, and yearly periods.

The literature on electricity load forecasting extends as far back as the mid-1960s (Heinemann et al. 1966; Hahn et al. 2009). While Kalman filter and state space methods dominated the literature early on, artificial and computational intelligence methods and econometric techniques have largely dominated literature that is more recent. Time series techniques have been extensively used in load forecasting for decades and are among the oldest methods applied in forecasting (Hahn et al., 2009; Bunn & Farmer, 1985a, 1985b; Weron, 2006; Kyriakides & Polycarpou, 2007). Two overarching classes of time series regression models have emerged to address the time-scale issues in different ways. Amaral et al. (2008) contend the two broad classes of conceptual models include: (1) single-equation models and (2) multi-equation (vector) models. This distinction between single-equation models and multi-equation (vector) models is important because we utilize the multi-equation approach in our estimation. Irrespective of which approach is adopted, when constructing a time series model there are four components that must be taken into consideration: trend, cyclicality, seasonality, and a random white noise error. Consequently, the time series literature can be envisioned in terms of how it has addressed each of these components. In general, accounting for both cyclicality and seasonality has been extensively covered in the literature whereas trend, while addressed, is typically not the focus of the analysis.

Within the literature, load data has occasionally been found nonstationary. Some, Darbellay and Slama (2000) for example, first difference the data to account for nonstationarity. Other studies, however, find that fitting a deterministic trend is more appropriate. Soares and Medeiros are highly critical of authors' tendency to first difference without first testing for a unit root or even considering a linear trend (2008). Soares and Medeiros (2008) point out that when the trend is in fact deterministic, taking the first difference will introduce a non-invertible moving average component, which in turn, will cause serious estimation problems. Upon examining hourly load data for Rio de Janeiro, Soares and Medeiros (2008) find that the data display a positive linear trend.

Time series is a collection of data points on a quantitative characteristic of a phenomenon that are typically measured at successive and uniformly- spaced time intervals (Shumway & Stoffer, 2006). It plays an important role in many forecasting approaches, and has been extensively used in subject areas as climate science, finance and econometrics. Thus, time series provides statistical setting for describing seemingly random fluctuating data and projecting the data series into the future.

Forecasting is about predicting future events based on a foreknowledge acquired through a systematic process or intuition (Armstrong, 2001), (Lewis & McGrath, 2011). The birth of forecasting as a science, however, is associated with weather forecasting and, is credited to Francis Beaufort, who developed the popularly known scale for measuring wind force (the Beaufort scale) and Robert Fitzroy, who developed the Fitzroy barometer for measuring atmospheric pressure (Ireneous and Daniel, 2013). Forecasting has advanced over time and has increased in sophistication in many specialized areas, including the fields of health, economics and commerce, sports, environment (including meteorology), technology and politics. The prediction of future events is a critical input into many types of planning and decision making processes. Many decision-making applications depend on a forecast of some quantity. For example, when a company plans its ordering or production schedule for a product it sells to the public, it must forecast the customer demand for this product so that it can stock appropriate quantities-neither too much nor too little.

Almost all managerial decisions are based on forecasts. Every decision becomes operational at some point in the future, so it should be based on forecasts of future conditions. Forecasts are needed continually throughout an organization, and as time moves on, their impact on actual performance is measured; original forecasts are updated; and decisions are modified, and so on. Forecasts of the future values of critical quality characteristics of a production process can help determine when important controllable variables in the process should be changed, or if the process should be shut down and overhauled.

The selection and implementation of the proper forecast methodology has always been an important planning and control issue for most profit maximizing firms and agencies. Often, the financial well-being of the entire business operation may rely on the accuracy of the forecast since such information will likely be used to make interrelated budgetary and operative decisions in areas of personnel management, purchasing, marketing, advertising and capital financing. Any significant over-or-under power forecast error may cause the industry to be overly burdened with excess inventory carrying costs or else create lost sales revenue through unanticipated item shortages.

The classical decomposition of time series is often based on the four components: trend, cyclic, seasonal, and random components, where:

(i) *Trend* is the long-term variation in a time series that is not influenced by irregular effects or seasonally related components in the data. In this case, *Growth or Decay Trends* are tendencies for power to increase or decrease fairly steadily over time. For instance, in power-generation data, an overall record of a progressively increasing generation over a specified period would show an increasing trend, irrespective of any random or systematic fluctuations.

(ii) *Cyclicality* results when the pattern of a time series data (e.g. containing the incidence of power events/situations) is influenced by some periodic (long-term/short-term) fluctuations that are associated with other characteristics (Ireneous & Daniel, 2013). *Cyclic Oscillations* are general up-and-down power changes due to changes in the overall economic environment (not caused by seasonal effects).

(iii) *Seasonality* is also a cyclic phenomenon, but is related to annual events, and is described as the predictable and repetitive positions of data points around the trend line within a year. *Seasonalities* are regular power fluctuations which are repeated from year to year with about the same timing and level of intensity; these effects are usually associated with calendar or climatic changes.

(iv) *Randomness* or *Irregularity* is also a common feature of time series data, and refers to unexpected distortions of existing or anticipated trends. *Irregularities* are any power fluctuations not classified as one of the above.

A reliable power forecast is important for quality and sufficient electric-power service delivery. Thus in this work, monthly electric power load data collected from hydro-electric power generating station, Kainji, for seven years (2008 – 2014), were analyzed and used to forecast future power values.by means of decomposition approach.

Methodology

The data for the analysis are on total monthly generated electric power for seven years (2008 – 2014) collected from Kainji hydro-electric power generating station, Niger state. The data are therefore secondary in nature. There are many forecasting methods available, these methods can generally be divided into three groups:

(i) Judgmental methods
(ii) Extrapolation (or Time Series) methods, and
(iii) Econometric (or causal) methods.

The extrapolation methods are quantitative methods that use past data of a time series variable to forecast future values of the variable. In this work, trend-based regression approach, which is one of the extrapolation methods of forecasting, is adopted. This approach searches for patterns in the historical series and then extrapolates these patterns into the future. The prediction is based on an inferred study of past general electric-power data behavior over time. This forecasting methodology is generally applicable to situations where useful future data estimates are desired. For reasons of clarity and uniformity, points of significance and mathematical procedures are discussed and shown in the context of a business case typical of most industries.

Mathematically, a time series is defined by the values $Y_1, Y_2, \dots$ of a variable Y at times $t_1, t_2, \dots$. Thus,

$$Y = F(t) \tag{2.1}$$

Forecasting as one of the main goals of time series analysis is an uncertain process and because of the uncertainty, the accuracy of a forecast is as important as the outcome predicted by the forecast. The information provided by the forecasting process can be used in many ways. An important concern in forecasting is the problem of evaluating the nature of the forecast error by using the appropriate statistical tests. We define the best forecast as the one which yields the forecast error with the minimum variance. The multiplicative modeling approach is used in this work to examine the four types of components that influence the power data. That is

$$Y_t = S_t \text{ x } T_t \text{ x } C_t \text{ x } I \tag{2.2}$$

Where *S*, *T*, *C*, and I denotes, respectively, seasonal, trend, cyclical and irregular components.

It is always a good idea to have a feel for the nature of the data before building a model, time series plots can reveal 'patterns' such as random, trends, level shifts, periods or cycles, unusual observations, or a combination of patterns. Excel 2013 and MINITAB 17 were used as aids for analysis.

Results and Discussion

A time series plot of the generated electric power data for the period under review is given in figure 3.1 below.

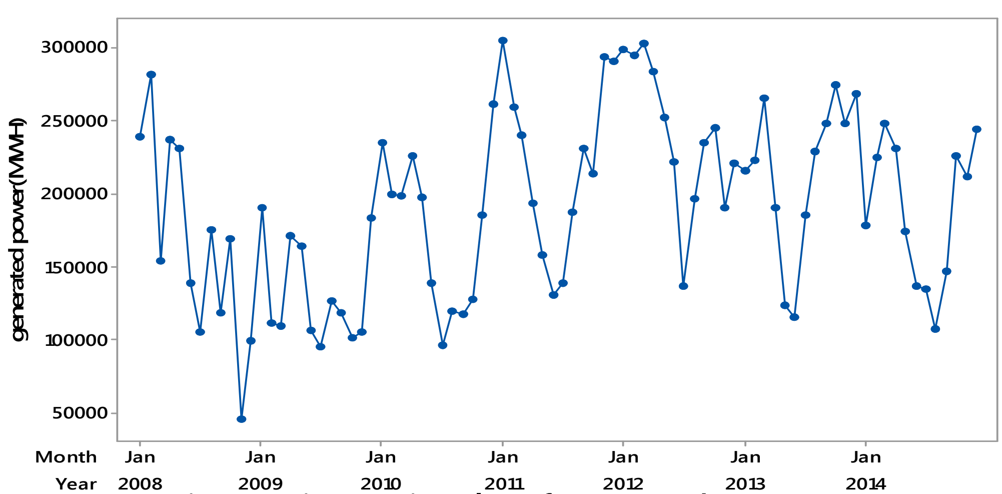

Fig. 3.1: Time Series Plot of generated power

From figure 3.1 above, we observe the following characteristics of the data:

(i) Within each year, there seems to be an initial period of electric power decline followed in turn by an interval of growth with some minor up-and –down power movement.

(ii) The series exhibits a number of peaks, but they do not appear to be equally spaced. This output suggests that if the series has a periodic component, it also has fluctuations that are not periodic--the typical case for real-time series.

(iii) Aside from the small-scale fluctuations, the significant peaks appear to be separated by more than a few months. The series exhibits typical highs during the first and last quarter of every year which is an indication that the time series probably has an annual periodicity.

(iv) The seasonal variations appear to grow with the upward series trend, suggesting that the seasonal variations may be proportional to the level of the series, which implies a multiplicative model rather than an additive model.

Decomposing the Power Data

From the above analysis of the figure 3.1time series plot, it is easily seen that the series consists of all the four components – ***S****easonal*, ***T****rend*, ***C****yclical* and *Irregular* components - so it is very important that these components be separated out of the 'raw' power levels. To be able to make a proper power forecast, we must know to what extent each of these components is present in the power data. Hence to understand and measure these components, the forecast procedure involves initially removing the component effects from the power data (decomposition). After the effects are measured, making a power forecast involves putting back the components on new power estimates (recomposition).

Deseasonalizing the Power Data

We now take the first step in time series decomposition by removing the recurrent and periodic variations (seasonal effects) from the power data over a short time frames (months in this case). To measure seasonal effects, seasonal index for every period, which represent the extent of seasonal influence for that period, is estimated. Seasonal indexes are estimated by

$$S_i = D_i / D \tag{3.1}$$

where:
S_i = the seasonal index for i^{th} period,
D_i = the average values of i^{th} period,
D = grand average,
i = the i^{th} seasonal period of the cycle.

The estimated seasonal indexes for the generated power data are given in Table 3.1 below, with the monthly seasonal indexes in the last row of the table.

Table 3.1: Seasonal indexes

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
2008	238559	281151	154037	237202	230473	138702	105380	175326	118839	169765	46433	99481
2009	190058	112081	109623	171026	164583	106477	95726	127170	119200	102065	106065	183215
2010	235095	200034	198736	225929	197781	138869	96317	119969	117511	127565	185220	261296
2011	304358	258973	240065	193389	158631	131406	139042	187617	231329	213893	293193	290899
2012	298679	294858	302202	283719	251910	221446	137205	197076	235181	244778	190844	220876
2013	215582	222935	264874	190416	124203	115838	185517	229133	247886	274342	248103	268097
2014	178086	224865	248107	231246	174846	137481	135438	108225	146876	226036	211417	244090
IIN DEX	**1.24**	**1.192**	**1.134**	**1.145**	**0.973**	**0.739**	**0.668**	**0.855**	**0.909**	**1.015**	**0.957**	**1.171**

From these indexes, we may quantitatively measure how far above or below a given month stands in comparison to the expected power period (the expected power is represented by a seasonal index of 100%, or 1).

The original power data are then deseasonalized by dividing every observation in the data by the seasonal index of the corresponding month. These are given in table 3.2 below.

The strength of the seasonal effect on the original power data can be seen in column (3) of table 3.2 below, which depicts a plus(+) or minus(-) sign for each period's seasonal index which is above or below expected power level (seasonal index of 100%), respectively. This column clearly shows an annual seasonal pattern of above average power in the beginning periods followed by an interim time interval of below average power, and ending each year alternating 'above' average power with 'below' average power. These uninterrupted 'highs' and 'lows' in the seasonal index set represent a very strong seasonal effect in the data. We then remove this influence so as to further study the power data for other component effects. The remaining columns of table 3.2 give the original and the corresponding deseasonalized power.

Table 3.2: The deseasonalized power

Month	Seasonal index (%)	Seasonal strength	Original 2008 gen. power	2008 deseason-alized power	Original 2009 gen. power	2009 deseason-alized power	Original 2010 gen. power	2010 deseason-alized power
J	124	+	238559	192386.29	190058	153272.581	235095	189592.742
F	119.2	+	281151	235864.933	112081	94027.6846	200034	167813.758
M	113.4	+	154037	135835.1	109623	96669.31	198736	175252.2
A	114.5	+	237202	207163.3	171026	149367.7	225929	197317.9
M	97.3	-	230473	236868.4	164583	169150.1	197781	203269.3
J	73.9	-	138702	187688.8	106477	144082.5	138869	187914.7
J	66.8	-	105380	157754.5	95726	143302.4	96317	144187.1
A	85.5	-	175326	205059.6	127170	148736.8	119969	140314.6
S	90.9	-	118839	130736	119200	131133.1	117511	129275
O	101.5	+	169765	167256.2	102065	100556.7	127565	125679.8
N	95.7	-	46433	48519.33	106065	110830.7	185220	193542.3
D	117.1	+	99481	84953.89	183215	156460.3	261296	223139.2

Table 3.2: cont'd

month	Seasonal index(%)	Original 2011 gen. power	2011 deseason-alized power	Original 2012 gen. power	2012 deseason-alized power	Original 2013 gen. power	2013 deseason-alized power	Original 2014 gen. power	2014 deseason-alized power
J	124	304358	245450	298679	240870.2	215582	173856.452	178086	143617.742
F	119.2	258973	217259.228	294858	247364.1	222935	187026.007	224865	188645.134
M	113.4	240065	211697.5	302202	266492.1	264874	233575	248107	218789.2
A	114.5	193389	168898.7	283719	247789.5	190416	166302.2	231246	201961.6
M	97.3	158631	163032.9	251910	258900.3	124203	127649.5	174846	179697.8
J	73.9	131406	177816	221446	299656.3	115838	156749.7	137481	186036.5
J	66.8	139042	208146.7	137205	205396.7	185517	277720.1	135438	202751.5
A	85.5	187617	219435.1	197076	230498.2	229133	267991.8	108225	126578.9
S	90.9	231329	254487.3	235181	258725	247886	272701.9	146876	161579.8

O	101.5	213893	210732	244778	241160.6	274342	270287.7	226036	222695.6
N	95.7	293193	306366.8	190844	199419	248103	259250.8	211417	220916.4
D	117.1	290899	248419.3	220876	188621.7	268097	228947.1	244090	208445.8

The time series plot of the deseasonalized power data from this table are given in figure 3.2 below.

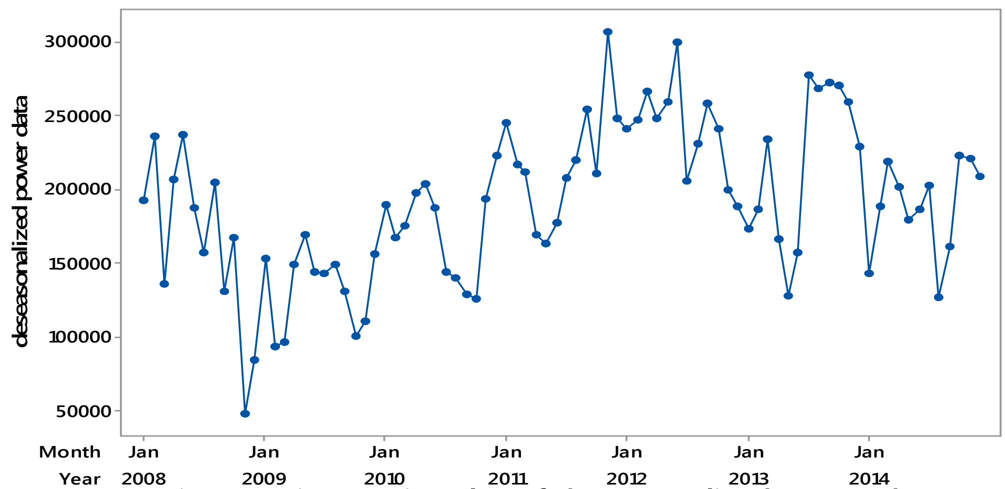

Fig. 3.2: Time Series Plot of deseasonalized power data

We can see from this figure that the deseasonalized power data do not oscillate as widely as the original power levels. Any remaining up-and –down movement must therefore be due to trend, cyclic, or irregular effects. Next we fit a trend equation to the original power data using the least squares method. This is given as

$$\hat{Y} = \hat{a} + \hat{b}t \qquad (3.2)$$

Where $\hat{Y}$ = predicted power level (due to the trend effect) occurring in period *t*,
$\hat{a}$ = intercept of the trend line equation,
$\hat{b}$ = power growth rate per period (i.e., slope of the trend line equation).

By the least squares method, the fitted trend line equation for the original power data was

$$Y_t = 157222 + 800t \qquad (3.3)$$

This line represents the overall linear trend of the power growth over time. Next we estimate the trend components and then remove the trend effect from the deseasonalized data. Figure 3.3 below shows a plot of the original, deseasonalized and estimated trend data.

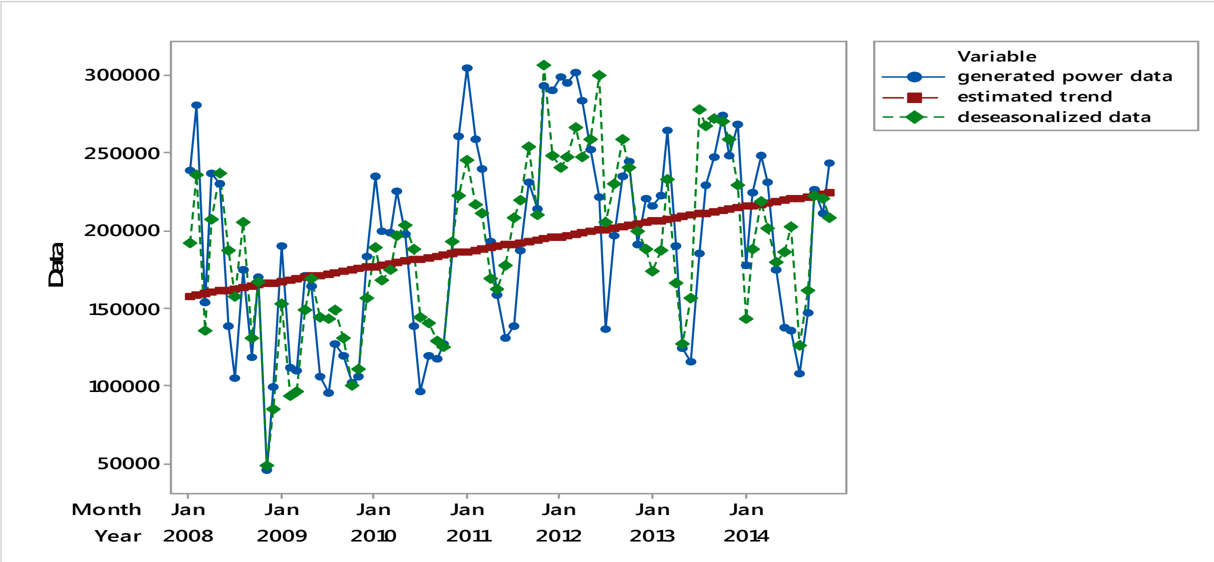

Figure 3.3: Time series plot of the original, deseasonalized and estimated (trend) power

From figure 3.3, the effect of the seasonal component is apparent in the sense that the deseasonalized data oscillates less widely than the original data. The fitted trend line shows the direction of movement of the two series.

Measuring the Cyclic Effects

We now calculate a series of cyclic indexes to enable us measure the effect of the general hydro-generating cycle on the power levels. We do this by expressing each value in the deseasonalized power data as a percentage of the calculated trend for the same date using the above trend line equation. The resulting time series has no trend, but oscillates around a central value of 100. These are given in Table 3.3 below.

Table 3.3: Cyclical Index

month	2008 deseasonalized power	Predicted (trend) power	Cyclic index (%)	2009 deseasonalized power	Predicted (trend) power	Cyclic index(%)	2010 deseasonalized power	Predicted (trend) power	Cyclic index(%)
J	192386.3	**153364**	125.4	153272.6	164759	93	189592.7	176153	107.6
F	235864.9	154314	152.8	94027.68	165708	56.7	167813.8	177103	94.8
M	135835.1	155263	87.5	96669.31	166658	58	175252.2	178052	98.4
A	207163.3	156213	132.6	149367.7	167607	89.1	197317.9	179002	110.2
M	236868.4	157162	150.7	169150.1	168557	100.4	203269.3	179951	112.9
J	187688.8	158112	118.7	144082.5	169506	85	187914.7	180901	103.9
J	157754.5	159061	99.2	143302.4	170456	84.1	144187.1	181850	79.3
A	205059.6	160011	128.2	148736.8	171405	86.8	140314.6	182800	76.8
S	130736	160960	81.2	131133.1	172355	76.1	129275	183749	70.4
O	167256.2	161910	103.3	100556.7	173304	58	125679.8	184699	68
N	48519.33	162859	29.8	110830.7	174254	63.6	193542.3	185648	104.3
D	84953.89	163809	51.9	156460.3	175204	89.3	223139.2	186598	119.6

Table 3.3: Cont'd

month	2011 deseasonalized power	Predicted (trend) power	Cyclic index (%)	2012 deseasonalized power	Predicted (trend) power	Cyclic index (%)	2013 deseasonalized power	Predicted (trend) power	Cyclic index (%)
J	245450	**187548**	130.9	240870.2	198942	121.1	173856.5	210337	82.7
F	217259.2	188497	115.3	247364.1	199892	123.7	187026	211286	88.5
M	211697.5	189447	111.7	266492.1	200841	132.7	233575	212236	110.1
A	168898.7	190396	88.7	247789.5	201791	122.8	166302.2	213185	78
M	163032.9	191346	85.2	258900.3	202740	127.7	127649.5	214135	59.6
J	177816	192295	92.5	299656.3	203690	147.1	156749.7	215084	72.9
J	208146.7	193245	107.7	205396.7	204639	100.4	277720.1	216034	128.6
A	219435.1	194194	112.9	230498.2	205589	112.1	267991.8	216983	123.5
S	254487.3	195144	130.4	258725	206538	125.3	272701.9	217933	125.1
O	210732	196093	107.5	241160.6	207488	116.2	270287.7	218882	123.5
N	306366.8	197043	155.5	199419	208438	95.7	259250.8	219832	117.9
D	248419.3	197993	125.5	188621.7	209387	90.1	228947.1	220782	103.7

Table 3.3: Cont'd

Month	2014 deseasonalized power	Predicted (trend) power	Cyclic index (%)
J	143617.7	221731	64.8
F	188645.1	222681	84.7
M	218789.2	223630	97.8
A	201961.6	224580	89.9
M	179697.8	225529	79.7
J	186036.5	226479	82.1
J	202751.5	227428	89.1
A	126578.9	228378	55.4
S	161579.8	229327	70.5
O	222695.6	230277	96.7
N	220916.4	231227	95.5
D	208445.8	232176	89.8

We now assign each period a plus(+) or minus(-) to signify whether the period is thought to be above or below the cyclic average (cyclic index = 100%) for power. Such assignments for all periods in all given years are shown in table 3.4 below using the above full cyclic index calculations.

Table 3.4: Plus/Minus Indicators of Cyclic Index Set

M	2008	2009	2010	2011	2012	2013	2014
J	+	-	+	+	+	-	-
F	+	-	-	+	+	-	-
M	-	-	-	+	+	+	-
A	+	-	+	-	+	-	-
M	+	+	+	-	+	-	-
J	+	-	+	-	+	-	-
J	-	-	-	+	+	+	-
A	+	-	-	+	+	+	-
S	-	-	-	+	+	+	-
O	+	-	-	+	+	+	-
N	-	-	+	+	-	+	-
D	-	-	+	+	-	+	-

On examination of the plus/minus assignments from the above table, beginning and ending periods for the first three years are difficult to discern. However, from June to December 2009 is a time interval of economic downturn, and from July 2011 to October 2012, there is clearly an economic upturn shown by the long string of plus signs during this time interval.

The whole 2014 is another economic downturn. To gain further insight, we plot the cyclic indexes for all periods in Figure 2.4.

However, as the business cycle is usually longer than the seasonal cycle, cyclic analysis is not expected to be as accurate as a seasonal analysis. Due to the tremendous complexity of general economic factors on long term behavior, a general approximation of the cyclic factor is the more realistic aim. Thus, in reference to the Figure 3.4 plot of cyclic indexes, the specific sharp upturns and downturns are not so much the primary interest as the general tendency of the cyclic effect to gradually move in either direction.

To study the general cyclic movement rather than precise cyclic changes (which may falsely indicate more accuracy than is present under this situation), we 'smooth' out the cyclic plot by replacing each index calculation with a centered 7-month moving average. This is to dampen out the many up-and-down minor actions of the cycle index plot so that only the major changes remain. These moving averages are given in Table 3.5 below. Plots of the cyclic index set and smoothed index set are shown in Figure 3.4.

Table 3.5: 7-month index smoothing of the cyclic indexes

M	2008	2009	2010	2011	2012	2013	2014
J	*	68.8	88.8	105.5	126.9	94.5	97.5
F	*	68.4	96.7	107.9	129.9	86.4	91.2
M	*	76.3	102.4	106.3	128.7	83.1	86.1
A	123.8	80.9	101	104.6	125.1	88.6	84
M	124.2	80	96.6	102	123.8	94.5	82.7
J	114	82.8	93.1	104.2	124	99.7	80.6
J	116.3	82.8	88.8	103.6	121.7	101.6	80.5
A	101.6	79.1	87.9	113.1	117.8	107.3	81.3
S	87.5	77.6	88.9	118.9	112.4	113.6	82.7
O	83.8	80.8	92.8	122.9	103.2	112.4	*
N	77.7	82.3	97.9	125.2	101.5	106.2	*
D	67.7	83.9	102.9	128.1	101.2	102.5	*

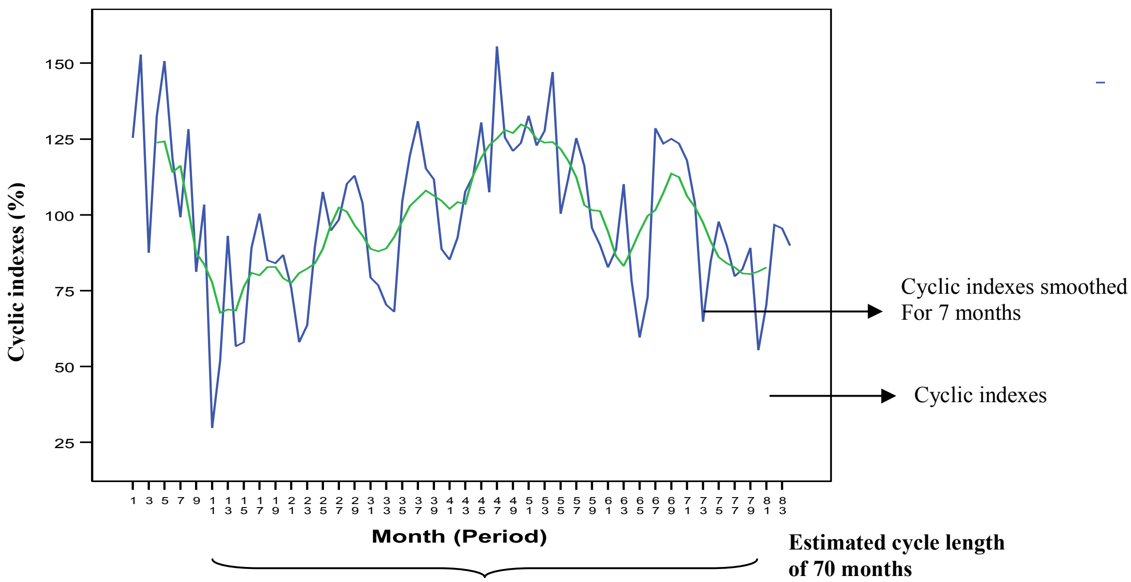

Figure 3.4: Cyclic index and smoothed cyclic index plot

From the above Figure, note the following characteristics:

(i) Cyclic peaks occurring in periods 2 (February 2008) & 47 (November 2011), and 5 (May 2008) & 54 (June 2012) are approximately of the same magnitude and may thus be parts of different power generating cycles.

(ii) Much of the index plot lies between 100-150%.

Based on the above observations, we infer that the cyclic length (i.e., the amount of elapsed time before the cycle repeats itself) is about 70 months. The general behaviour of the cycle is a slightly sharp rise at the beginning followed by a reasonably stable period between 100 and 150%, then a cyclic decline starting in about the 59th period of the cycle. In order to make power forecast, we project the approximate continuation of this cycle curve in to the next few periods of 2015.

Making the Power Forecast

At this point of the power analysis, we have completed the study of the power components. We now project the future values in making forecasts for the next few periods. The procedure is summarized below:

Step 1: We compute the future power trend levels using the trend equation.

Step 2: We multiply the power trend levels from Step 1 by the period seasonal index to include seasonal effects.

Step 3: Then we multiply the result of Step 2 by the projected cyclic index to include cyclic effects and get the final forecast result.

The Table 3.6 below gives sample calculations for a 5-period –ahead forecast (2015).

Table 3.6: Power forecast calculations for 7 periods ahead

Month	(a)X	(b) Predicted (trend) power	(c) Seasonal index (%)	(d) =(b).(c) estimated power with trend & seasonal effects	(e) projected cyclic index (%)	(f) power forecast
Jan	85	233126.07	124	289076.33	123.1	355852.96
Feb	86	234075.61	119.2	279018.13	130.4	363839.64
Mar ch	87	235025.15	113.4	266518.52	89.1	237468
April	88	235974.69	114.5	270191.02	140.1	378537.62
May	89	236924.24	97.3	230527.29	149.3	344177.24
June	90	237873.78	73.9	175788.72	116.1	204090.7

Conclusion

Electricity demand forecasting represents the main task in the planning of electricity production because it determines the required resources to operate the electricity plants such as daily consumption of fuels. Furthermore, it is the corner stone of planning for electric plants and networks. Electric-Power forecasting is a dynamic process and requires frequent updates. This can be done with novel techniques and data, taking into consideration the principles involved. The methodologies currently used involve time series analyses with smoothing or moving average models, and less probabilistic forecasting models like Quantile regression models (QRMs), which are potential probabilistic techniques that could be adopted for predicting extreme power situations/conditions.

The points of significance and mathematical procedures discussed and shown in this paper are in the context of a business case. Therefore, such procedure may be utilized by businesses that have some degree of regularity to sales, to study and decompose the relevant components of sales variation. Once these components are understood, sales forecasts can be made for future periods by recombining these component effects into projected sales estimates, as illustrated in Table 3.6. By illustrating the procedure in a real business case situation, we have shown that combining mathematical calculations with management's firsthand knowledge of the situation can lead to logical and justified new power estimates. Finally, in view of the relative complexity of forecasting techniques, we recommend that management implements a simple forecasting method that is well understood. Power forecasting is a valuable resource for enhancing and promoting power services provision. This work is carried out to stimulate further discussions on standardizing electric-power forecasting approaches and methods, so that it can be used as a tool to facilitate power services delivery.

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