Integrated Resource Plan

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PREPARED FOR

KAUA'I ISLAND UTILITY COOPERATIVE

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1 ELECTRIC LOAD FORECASTING

1.1 Overview

This section describes the method, assumptions and data used to develop a 20-year forecast of electricity energy and peak loads out through 2025. In addition to the "most-likely" forecast, alternative sensitivity scenario forecasts are derived, based on high and low forecasts for key explanatory variables such as population, which were used to project loads based on regression equations as described in this section.

The load forecast plays a critical role in Integrated Resource Planning (IRP), determining the level of electricity supply expansion and investment required, to keep pace with the load forecast. Thus, it is essential that the load forecast be as accurate as possible. Future load growth is not only critical, it is also uncertain. There are can be considerable economic and other penalties for both overbuilding and underbuilding. To be prudent and robust in addressing uncertainties and risks, IRP thus typically considers a range of plausible load growth outcomes and their consequences. Hindsight tells us that that the actual future is unlikely to look like today's "most likely" forecast.

The development of three different load forecast scenarios is an important way of addressing uncertainty in the IRP process. Ultimately, an even more powerful and realistic way to address uncertainty is through "volatility analysis." Volatility analyses project probability distributions for key outcomes such as consumer costs and various reliability measures, by assigning probability distributions to key fundamental factors of which long-term load growth and short-term load fluctuations are only two (fuel prices being another).[1]

A "most-likely" or "base case" load forecast is developed as the single scenario best representing the "most likely" future from KIUC's perspective. Then, by changing underlying forecast assumptions, a "Low" and "High" load forecast are developed. By evaluating a resource plan's performance across the three load forecasts, KIUC is able to balance risks and opportunities for any particular plan, imposing its own preferences

[1] In place of "deterministic" simulations of one most likely or a few sensitivity scenarios, IRP tools such as UPLAN can be used to automatically generate probabilistic outcomes based on input probability distributions for loads, fuel, prices, hydrological conditions, outages, and other important but uncertain drivers. Using Monte Carlo techniques to sample from probability distributions for key uncertainties, volatility analyses realistically depict the risk of particular resource plans due to unfavorable outcomes that are not "most likely" but nevertheless may be important. Refer to "How to Incorporate Volatility and Risk in Electricity Price Forecasting – Rajat Deb, LCG.

regarding the likelihood of different forecasts and the significance of the different risks and opportunities.

Due to changing regulatory requirements and higher costs associated with fuel and power plant development, it is important to use a robust methodology to forecast electricity demand.

1.2 Econometric Model of Load Growth

For this study, it is assumed that total energy sales over time (Figure 3.1) are predicted based on the following four explanatory variables

1. Resident Population
2. Visitor Population (Average Daily Visitor Census)
3. Average Electricity Price over a Year (Constant Year 2004 $/MWh)
4. Total Personal Income (Constant Year 2004 M$)

To forecast energy sales, two econometric models were considered: the single equation linear regression model, and the Autoregressive Integrated Moving Average (ARMA) model.

The dependent variable (electricity sales or load) and the independent variables all exhibit compound (exponential) growth with respect to time. However, their behavior can be converted to a linear scale by replacing each variable by its natural log, for the regression equation. This guarantees that there is a linear relationship between parameters, and the linear regression coefficients can then be estimated.

$$\ln(Y_t) = \ln(A_0) + \sum_{i=1}^{4} \beta_i \cdot \ln(X_{it}) + u_t \quad \text{...(3.1)}$$

where:

Y_t- Energy Sales in time period t

A_0- Calculated constant

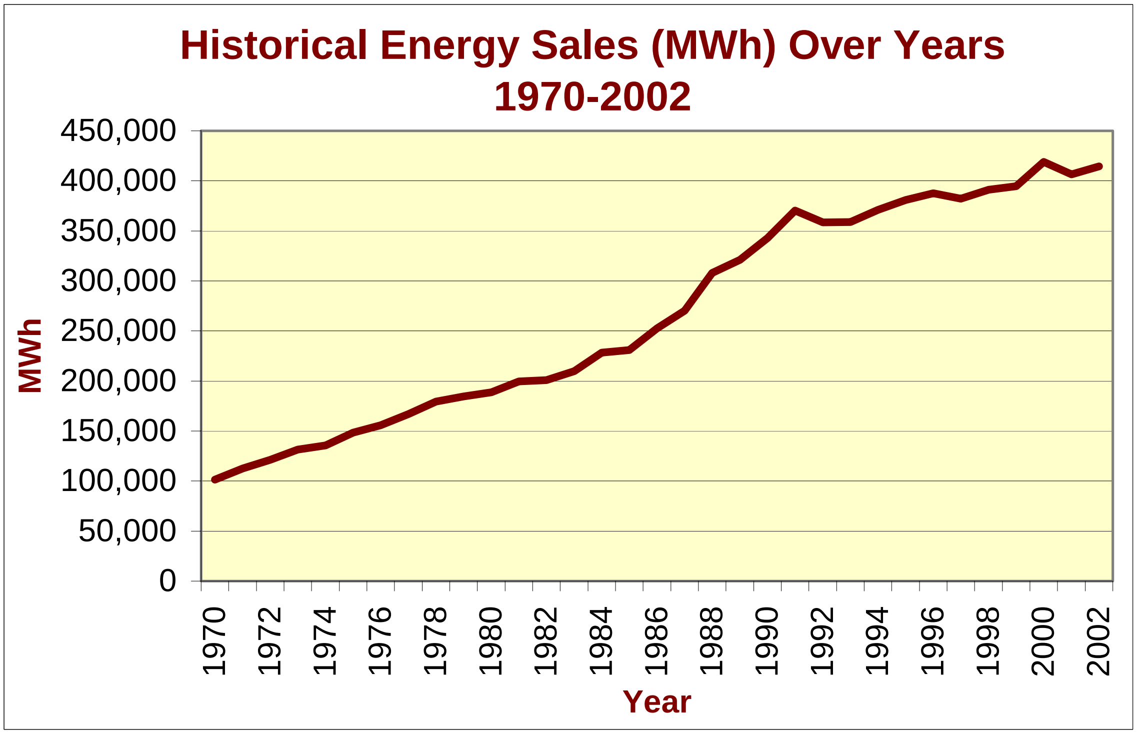
β_i- Regression coefficient

X_{it} - i^{th} Explanatory (Independent) variable at time period t

u_t- Error term with the mean 0 in time period t.

This type of model assumes that the effect on electric load of changes in any of the four explanatory variables does not change over the entire historical and forecast period. For example, we assume that the customers' price elasticity exhibited will remain constant into the future; so that customers are expected to have the same response to future increases in electricity prices as they have shown in the past.

Figure 1.1 Electricity Sales for Kaua'i for 1970 - 2002



1.2.1 Limitations of Single Equation Linear Regression Models

When forecasting energy sales growth, it is common to use linear regression analysis. However, this approach fails to incorporate the time series behavior within the temporal pattern of load growth itself. In the linear regression analysis described above, variation of the dependent variable (total annual power sales) is explained by variations in four explanatory variables, assuming constant correlations between the dependent and explanatory variables. In reality this may not be true, as other drivers such as policy or environmental changes may also influence the dependent variable, electricity sales. To minimize the errors caused by this possibility, we utilize the time series analysis forecasting methodology, technically known as the ARMA Methodology. Here, the emphasis is not on constructing single equation predictive models, but on analyzing the probabilistic or stochastic property of the time series of the dependent variable itself, *letting the data speak for themselves.*

1.2.2 An Autoregressive Moving Average (ARMA) Model

In the regression model, the independent variable Y_t (electricity sales) is explained by the k independent variables or "regressors" $X_1, X_2, \ldots, X_k$; (in this study there are k = 4 regressors). In contrast, in the ARMA time series models, Y_t may be explained by past or lagged values of Y (electricity sales) itself, plus stochastic error terms. For this reason, such models are sometimes considered a-theoretic models since they cannot be derived from any economic theory. However, we can have the *best of both worlds* by predicting future variation of the independent variable, electricity sales, based on both its historical relationship to the explanatory variables (the linear regression approach) plus its historical serial autocorrelation (the ARMA approach).. Typically the information that is not explicitly captured in the econometric regression equation lies in the error term u_t. We shall apply time series logic to explain part of the variation represented by the error term, achieving better historical explanation for going-forward prediction than achieved with the simple linear regression model.

It should be noted that the ARMA model can be implemented using any number of past values for Y and for the linear regression error terms. For this reason, such approaches are typically specified as ARMA(p,q). For example, an ARMA (3,1) model would use the past 3 values of the dependent variable, and the past 1 error term. An important step in applying the ARMA model is to find, by trial-and-error, the number of lagged parameters (p and q) that best explain the dependent variable.

To avoid confusion, it should also be noted that there exists a related time-series model, known as ARIMA. This model adds a step before beginning the ARMA model, "differencing" the historical values of the dependent variable. This step is only necessary when the dependent variable is not stationary over the historical period. However, the dependent variable in our ARMA model – the error term from the linear regression equation – is stationary. Therefore the simple ARMA model is used, not the ARIMA model.

Improving on the model represented by equation 3.1, the ARMA model used in this study explain the linear regression error term u_t for any time period (year) *t*, based on both an autoregressive term (ρu_{t-1}) and moving average term for the error term ($\theta\varepsilon_{t-1}$), plus, of course the remaining unexplained error ε_t. The original error term is thus modeled as shown in Equation 3.2.

$$u_t = \rho u_{t-1} + \theta\varepsilon_{t-1} + \varepsilon_t \quad \text{………………………………………………………..(3.2)}$$

1.3 Data Collection

For deriving the predictive model, data for the explanatory and dependent variables (except for Total Income) for the period of 1970 until 1991 was obtained from the previous IRP study done by LCG Consulting[2] prepared for Citizens Utilities. For the remaining data, a variety of sources were used as summarized below.

1.3.1 Resident Population

Historical resident population data for 1970-1991 were obtained from LCG's 1993 IRP report. Corresponding data for years 1992-2002 were obtained from Hawaii County population estimates[3].

1.3.2 Visitor Population

Historical visitor population data for 1970-1991 were obtained from LCG's 1993 IRP report. For 1992-1996, visitors population data were obtained from the Department of Business, Economic Development and Tourism (DBEDT)[4]. For 1997-2001, visitor population data were obtained from the Hawaii State Department of Business[5]. It should

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[2] Integrated Resource Plan, October 1993- LCG Consulting, Los Altos, CA

[3] Source: Population Division, U.S. Census Bureau. Release Date: April 17, 2003, Table CO-EST2002-01-15-Hawaii County Population Estimates: April 1, 2000 to July 1, 2002.

[4] Department of Business, Economic Development and Tourism (DBEDT): Summary of County Tourism, 1999

[5] Hawaii State Department of Business, Economic Development and Tourism, Research and Economic Analysis Division, 2001 Annual Visitor Research Report; "Historical Visitor Data," spreadsheet (http://www.state.hi.us/dbedt/monthly/historical-r.xls)

be noted that in 2001, the anticipated visitor population growth was adversely affected by the events of 9/11 and was below normal. Therefor, the 2002 visitor population was estimated as the average of the year 2000 and year 2001 visitor populations.

1.3.3 Total Income

Total Income (1970–2001) data were obtained from "The State of Hawaii Data Book, 2002"[6]. The total income is assumed to be highly dependent on the levels of tourist activity. In 2001 and 2002, tourism was adversely affected by the events of 9/11 and was below normal. Assuming that the year of 2000 was a 'normal' year, year 2002 total income was calculated as the average of year 2000 and year 2001 total income.

1.3.4 Electricity Sales (Dependent Variable) and Average Electricity Price

Data for electricity sales and average electricity price for 1970-1991 were obtained from LCG's 1993 IRP report.

For 1995-2002, Energy Sales ("Power Sold") and Sales Revenues data were obtained from "The State of Hawaii Data Book"[7]. These data were used to calculate the Average Electricity Price, as shown in Table 3.1.

Table 1.1 Calculation of Average Electricity Price for Kaua'i for years 1995-2002

Year	ENERGY SALES (MWh)	ENERGY REV (nom 1000$)	Average Price ($/MWh)
1995	380,955	62,928	165.2
1996	387,737	73,034	188.4
1997	382,112	77,753	203.5
1998	391,029	72,177	184.6
1999	394,781	77,798	197.1
2000	418,922	94,096	224.6
2001	406,521	91,750	225.7
2002	414,487	90,754	219.0

For the intervening years 1992-1994, total generation data provided by KIUC were used with the appropriate adjustments for losses to estimate the energy sales for these years.

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[6] Hawaii State Department of Commerce and Consumer Affairs, Division of Consumer Advocacy,
records- http://www.hawaii.gov/dbedt/db96/17/179610.pdf

[7] From the tables 'Electric Utilities, By Islands'

To estimate the average electricity price for those years, sales revenue was first estimated as follows. Since year 1995 data were available for both Hawaii and Kaua'i of sales, the ratio of Kaua'I revenue to total Hawaii revenue could be calculated as 6.06%. When applied to the 1992-1994 sales revenue for Hawaii[8] this produced estimated total sales revenues for Kaua'i for years 1992-1994 (Table 3.2). Finally, using total generation adjusted for losses (to give sales) and the estimated sales revenue, the average energy price was derived for years 1992-1994 (Table 3.2).

Table 1.2 Estimation of Average Electricity Price for Kaua'i, 1992-1994.

	Hawaii	**Kauai**		
Year	Actual Total Rev ($000 nom)	Actual Rev ($000 nom)		
1995	1,037,702	62,928		
	weight(%) :	6.06%		
Year	**Actual Revenue**	**Estimated Rev**	**Total Gen (MWh)**	**Aver Energy Price**
1992	818,525	49,637	355,863	139.5
1993	922,797	55,960	354,728	157.8
1994	955,907	57,968	379,733	152.7

The complete set of input data used for regression analysis is presented in Table 3.3.

[8] Energy Resources Coordinator's Annual Report 1998

Table 1.3 Input data for regression analysis

Year	Resident Population	Visitor Population (ADVC)	Average Price (Nom$/MWh)	Total Income (Nom $M)	Sales (MWh)
1970	29,800	2,500	39.0	123.60	101,304
1971	30,900	3,100	44.0	136.50	112,711
1972	31,900	3,900	44.0	146.40	121,226
1973	32,900	4,000	46.0	161.70	131,556
1974	32,600	4,200	59.1	225.70	135,587
1975	33,400	4,700	67.9	212.30	148,533
1976	34,900	5,200	74.5	228.70	155,834
1977	35,500	5,800	80.6	251.60	167,035
1978	36,800	6,800	86.2	277.00	179,299
1979	38,100	7,100	108.6	319.10	184,459
1980	39,400	7,000	141.0	397.10	188,798
1981	40,600	6,900	151.0	404.10	199,451
1982	41,900	6,600	152.6	442.90	200,865
1983	43,000	7,600	153.6	495.00	209,712
1984	44,100	10,500	151.3	513.30	228,351
1985	45,300	10,900	148.9	551.30	231,005
1986	46,200	14,200	124.9	594.40	252,509
1987	47,900	14,900	126.6	637.40	270,163
1988	49,300	15,600	119.3	758.00	308,094
1989	51,000	18,500	125.5	868.30	321,256
1990	51,600	18,400	140.3	965.00	342,857
1991	53,100	19,400	133.4	1038.70	370,451
1992	54,003	13,479	139.5	682.00	355,863
1993	54,864	8,283	157.8	1132.00	354,728
1994	55,627	13,268	152.7	1182.00	379,733
1995	55,983	14,439	165.2	1225.00	380,955
1996	56,435	15,572	188.4	1219.00	387,737
1997	56,539	15,999	203.5	1231.00	382,112
1998	56,603	17,909	184.6	1259.00	391,029
1999	58,264	18,214	197.1	1295.00	394,781
2000	58,463	18,041	224.6	1386.00	418,922
2001	59,223	16,830	225.7	1405.00	406,521
2002	59,946	17,436	219.0	1395.50	414,487

1.4 Regression Analysis

Before conducting the regression analysis, some adjustments have been made to the data. First, all values for explanatory and dependent variables such as average electricity price and total income were transformed using the natural logarithmic (nlog or *Ln*) values. Transforming to the natural log is necessary because all of the dependent and independent variables grow at a compound rate (just like a bank account growing at a fixed percent interest rate.) The log function transforms this compound growth into linear growth, which in turn makes it possible for the variables' relationships to be estimated using linear regression. Total sales (MWh) was the dependent variable, while the four dependent variables were: resident population, visitor population, average retail electricity price, and total personal income. Finally, regression coefficients were estimated using the OLS algorithm , and the error terms (residuals) were calculated for each period *t*.

The resulting single equation linear regression model explaining electricity sales (demand) was as follows:

> Ln (Sales) = -4.300 + 1.425 * Ln (Resident Population) + 0.086 * Ln (Visitor Population) – 0.070* Ln (Average Price) + 0.154 * Ln (Total Income)

The adjusted R-squared value for the model is extremely high (0.99145), indicating that nearly all of the variability in electricity demand can be explained using the independent variables selected. It should be noted that both the dependent variable (sales) and at least one of the independent variables (resident population) contain a growth rate that is inherently very similar. It is a well-known econometric principle that this can result in "spurious correlation", where the R -squared value is estimated to be much higher than its true value. However, for several reasons we have chosen not to eliminate this effect through the standard data-detrending process:

1) Unlike textbook examples of spurious correlation where two variables share the same growth rate by coincidence (spuriously), we believe that the similar growth rates of population and electricity demand do in fact reflect a causal relationship, and therefore have predictive power.

2) Even where spurious correlation is present, the resulting regression coefficients are not "biased" per se. The worst problem is an overestimation of the model's explanatory power (overestimation of precision, not accuracy).

3) A high priority was placed on maintaining ease of use and intuitive understandability in our regression model. Detrending the data would undermine both of these goals.

The signs of the coefficients (Table 3.4) indicate that as both resident and visitor populations increase, Electricity Sales also increase. The absolute value of the "t-statistic" greater than 2.33 indicates that the "Resident Population" and "Visitor Population" are significant predictors of Electricity Sales. To be precise, these two population parameters are statistically different from zero at the 99% confidence interval or certainty level. The negative coefficient and high t-statistic for the third independent variable, price, allow us to conclude at a 95% confidence level that demand is price elastic (As the average price of electricity increases, energy sales decrease.) Likewise, we conclude at the 95% confidence interval that electricity demand is income-elastic (as income increases, so does electricity consumption). Figure 3.2 displays how the regression equation accurately explains variation in the dependent variable, actual historical electricity sales. Table 3.5 provides the underlying actual and predicted sales for each year.

Table 1.4 Coefficients in Single Equation Regression

Variable	*Coefficients (betas)*	*t Stat*
Intercept Ao	-4.300	-2.72
Resident Population	1.425	7.42
Visitor Population	0.086	2.36
Average Price 2003 $/MW	-0.070	-1.88
Total Income 2003 $M	0.154	1.98

The model suggests that each percentage increase in resident population has historically been associated with a 1.425 % increase in energy sales, while a one percent increase in visitor population is associated with a 0.086% increase in energy sales. On the other hand, a one percent increase in electricity price is associated with a 0.07% decrease in sales. Finally, a one percent increase in total income is associated with a 0.154 % increase in electricity demand.

Figure 1.2 Predicted vs. Actual Sales over the historical period

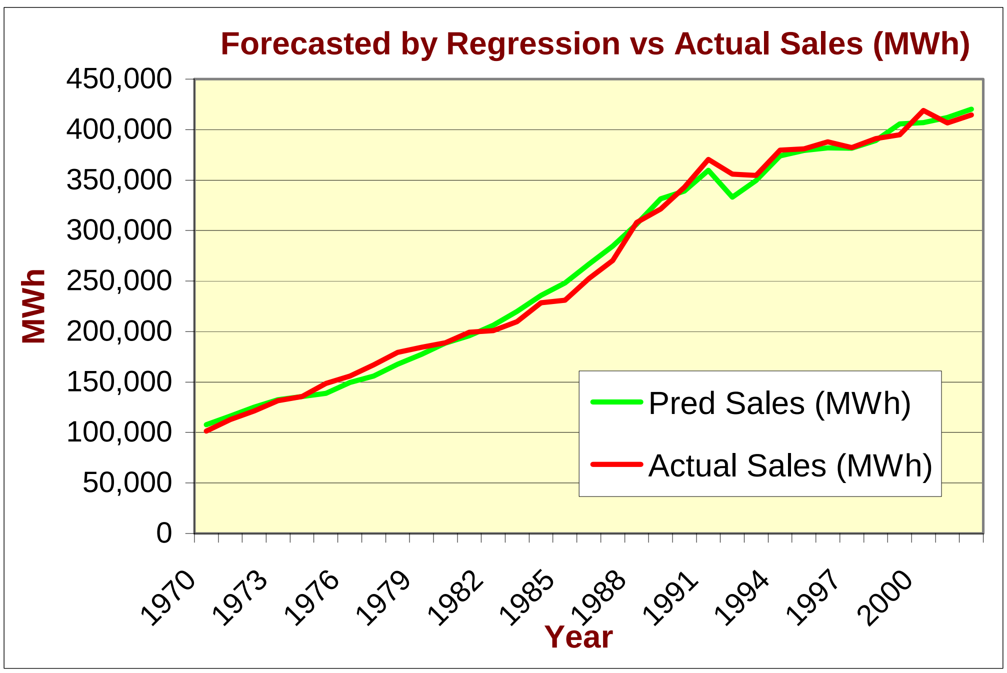


Table 1.5 Actual Historical Sales vs. Sales Predicted by Regression

Year	Actual Sales (MWh)	Pred Sales (MWh)
1970	101,304	105,149
1971	112,711	113,209
1972	121,226	121,391
1973	131,556	127,468
1974	135,587	143,047
1975	148,533	142,916
1976	155,834	150,209
1977	167,035	158,028
1978	179,299	171,160
1979	184,459	182,038
1980	188,798	194,752
1981	199,451	196,617
1982	200,865	202,978
1983	209,712	219,301
1984	228,351	233,645
1985	231,005	245,452
1986	252,509	267,199
1987	270,163	280,831
1988	308,094	300,484
1989	321,256	326,371
1990	342,857	337,093
1991	370,451	352,593
1992	342,112	330,440
1993	350,112	348,986
1994	358,112	357,271
1995	366,112	366,218
1996	374,112	373,899
1997	382,112	378,644
1998	390,000	383,551
1999	396,112	400,392
2000	418,921	402,829
2001	406,521	415,203
2002	414,486	424,485

1.4.1 Results of ARMA Model

To further improve explanatory power, the ARMA[9] model was applied, under the following six (6) combinations of AR (autoregressive) and MA (moving average) processes: ARMA(1,1), ARMA(1,2), ARMA(2,1), ARMA(2,2), ARMA(2,3), ARMA(3,3). For each year 1970 through 2002, Table 3.6 compares actual historical sales with sales predicted by each the six regression/ARMA models. To aid evaluation of the

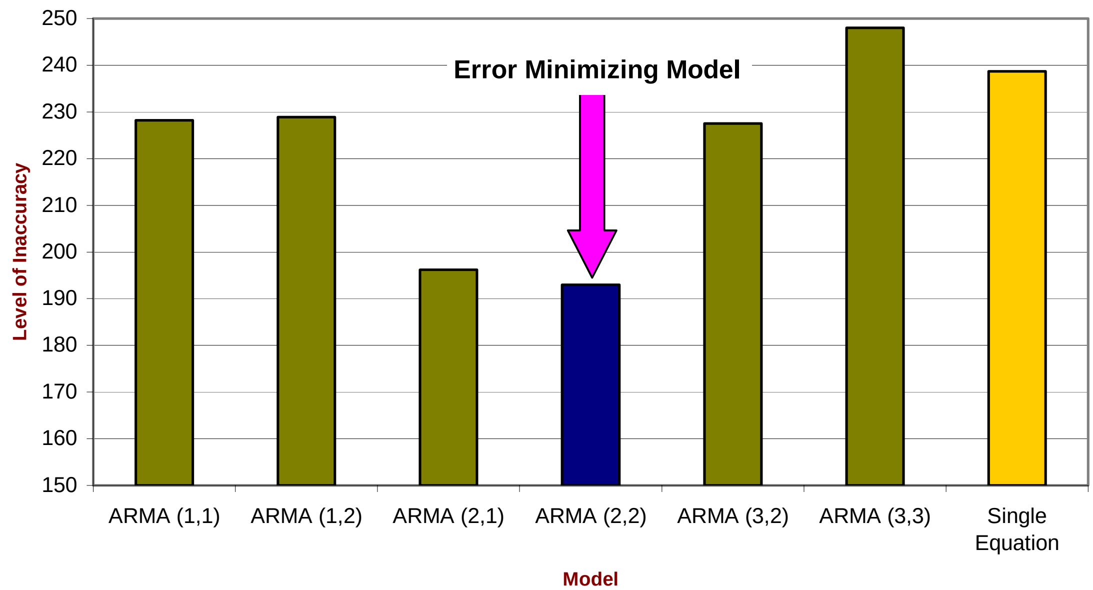
[9] Statistical software called *Intercooled Stata* was used for analysis

different models, for each model "error measure" was calculated as (predicted value – actual value)^2, summed over all 33 years (1970-2002), then divided by the 33-year sum of the actual values. A plot of this error measure for all six regression/ARMA models and for the single regression equation model (Figure 3.3) shows he predictive advantage of the ARMA(2,2) model. The ARMA(2,2) model incorporates the impact on the dependent variable, energy sales, of not only the four explanatory variables on the energy sales, but also captures the time series (autocorrelation) of the energy sales in successive years, giving added explanatory power. The error measures in all but one of the tested ARMA models are lower than in the single equation model.

Table 1.6 Sales Over the Historical Period: Actual vs. Predicted Under Different Regression/ARMA Models

Year	Actual Sales (MWh)	Predicted Sales (MWh)					
		ARMA (1,1)	ARMA (1,2)	ARMA (2,1)	ARMA (2,2)	ARMA (3,2)	ARMA (3,3)
1970	101,304	120,264	105,097	107,219	105,995	106,323	106,473
1971	112,711	122,592	111,069	111,326	115,039	114,611	115,436
1972	121,226	126,595	121,432	121,854	120,822	121,911	124,865
1973	131,556	136,693	129,190	129,475	129,686	128,074	129,266
1974	135,587	137,300	130,503	132,710	131,204	130,038	130,856
1975	148,533	141,717	138,272	141,015	138,706	137,713	135,845
1976	155,835	154,959	156,217	159,905	152,952	153,481	150,934
1977	167,035	160,072	163,179	163,448	165,145	165,312	158,584
1978	179,299	171,775	175,399	175,199	172,319	174,078	176,361
1979	184,459	178,919	189,503	188,247	184,595	180,211	181,096
1980	188,797	186,122	194,465	195,569	197,612	196,809	193,399
1981	199,450	194,145	197,744	196,024	200,146	205,187	197,209
1982	200,865	206,414	207,264	205,876	203,329	207,243	208,530
1983	209,712	209,169	217,762	217,969	221,301	217,473	215,820
1984	228,351	232,480	226,066	231,225	233,926	236,767	238,788
1985	231,004	236,161	242,033	240,333	239,685	241,335	243,504
1986	252,508	256,439	250,810	254,514	260,714	256,673	263,590
1987	270,163	284,956	270,322	271,029	272,423	273,350	277,920
1988	308,094	308,415	292,722	292,152	292,889	292,214	295,632
1989	321,255	330,189	324,073	331,280	320,267	318,810	321,303
1990	342,857	334,616	335,474	337,824	344,852	340,909	331,350
1991	370,452	357,485	354,804	354,846	351,973	350,928	367,548
1992	355,863	354,421	343,865	347,820	341,182	342,981	343,159
1993	354,729	361,939	352,558	353,670	354,006	351,783	351,403
1994	379,732	379,595	383,096	379,918	380,595	381,780	370,178
1995	380,956	381,398	382,958	381,876	379,994	379,314	385,062
1996	387,736	379,030	386,540	384,135	384,400	383,306	382,763
1997	382,112	376,393	388,648	385,563	384,312	386,760	388,862
1998	391,030	385,957	390,886	389,111	392,178	393,529	385,787
1999	394,782	402,041	405,704	405,639	405,080	405,863	411,424
2000	418,922	398,882	402,194	401,270	408,505	406,517	403,733
2001	406,521	407,269	414,157	414,248	403,741	406,549	419,035
2002	414,486	418,064	432,684	423,297	421,033	429,093	412,710

Figure 1.3 Error Measures for Different Models



The regression coefficient for the four explanatory variables in the ARMA(2,2) model are similar to those in the single equation regression modeling; and take the following form.

> Ln (Sales) = -4.615 + 1.440 * Ln (Resident Population) + 0.117 * Ln (Visitor Population) – 0.031* Ln (Average Price) + 0.102 * Ln (Total Income)

However, additional predictive power is provided by the serial correlation and moving average terms in the ARMA model. Furthermore, when the ARMA(2,2) model is used, the average electricity price as an explanatory variable is not significant, even at a 90% confidence interval. Resident Population is the most significant explanatory variable, followed by Visitor Population and Total Income. Table 3.7 shows the ARMA model coefficients.

Table 1.7 ARMA Model Coefficients

Variable	*Coefficients (betas)*	*t Stat*
Intercept Ao	-4.615	-3.72
Resident Population	1.440	9.62
Visitor Population	0.117	2.05
Average Price 2003 $/MW	-0.031	-0.54
Total Income 2003 $M	0.102	1.67

1.5 Electricity Sales Forecast for Years 2003-2025

The final step is to develop a forecast of electricity demand for the years 2003-2025 using the ARMA regression model with a second order autoregressive process and first order moving average process. This required development of a forecast for each of the independent (explanatory) variables for 2003-2025. Forecast values for resident population, visitor population and total income are based on population and economic projections[10] for the State of Hawaii for years 2005, 2010, 2015, 2020 and 2025, with linear interpolation for the intervening years. Average electricity price is forecast based on an escalation rate of 2.5%.[11] Forecast values for all four explanatory variables are shown in the Table 3.8. Using the regression/ARMA(2,2) model, this produces the projected electricity sales trend shown in Figure 3.4.

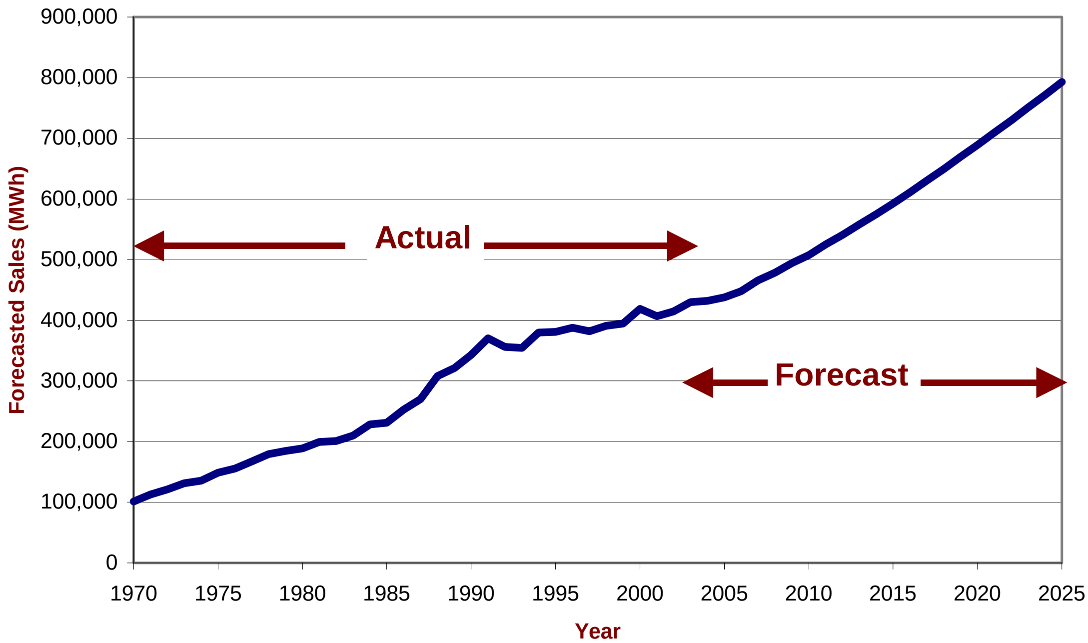
[10] The values for these projections for five distinct years were obtained from the report entitled, "Population and Economic Projections for the State of Hawaii to 2025."

[11] The escalation rate was assumed to be equal to the Consumer Price Index of 2.5% for the first half of 2003, as reported by the Bureau of Labor Statistics, US Department of Labor.

Table 1.8 Projected Values of Explanatory Variables, Forecast of the Annual Peak and Energy Sales, and Electricity Growth Rate for 2003 – 2025

Year	Resident Population	Visitor Population	Average Price (2004 $/MWh)	Total Income (2004 $M)	Annual Energy Sales (MWh)	Annual Peak Sales (MW)	Sales Growth Rate (%)
2002	**59,946**	**17,436**	**219.02**	**1,396**	**414,486**	**68.83**	**1.95**
2003	60,131	20,126	228.9	1,548	429,914	67.97	2.10
2004	60,315	20,963	234.6	1,646	432,248	68.83	0.59
2005	60,500	21,800	240.5	1,744	438,055	70.04	1.52
2006	61,560	22,400	246.5	1,795	447,992	72.15	3.44
2007	62,620	23,000	252.7	1,847	465,846	74.26	3.24
2008	63,680	23,600	259.0	1,898	478,380	76.21	3.11
2009	64,740	24,200	265.5	1,950	494,321	78.59	3.01
2010	65,800	24,800	272.1	2,001	507,656	80.76	2.81
2011	67,040	25,340	278.9	2,060	524,662	83.31	3.15
2012	68,280	25,880	285.9	2,119	540,965	85.64	3.08
2013	69,520	26,420	293.0	2,179	558,048	88.44	3.02
2014	70,760	26,960	300.4	2,238	574,980	91.08	2.97
2015	72,000	27,500	307.9	2,297	592,378	93.72	2.92
2016	73,340	28,100	315.6	2,364	611,139	96.38	3.08
2017	74,680	28,700	323.5	2,432	630,261	99.57	3.03
2018	76,020	29,300	331.5	2,499	649,592	102.51	2.98
2019	77,360	29,900	339.8	2,567	669,241	105.5	2.93
2020	78,700	30,500	348.3	2,634	689,133	108.24	2.88
2021	80,040	31,160	357.0	2,705	709,319	111.62	2.84
2022	81,380	31,820	366.0	2,776	729,759	115.11	2.80
2023	82,720	32,480	375.1	2,847	750,496	118.28	2.76
2024	84,060	33,140	384.5	2,918	771,498	121.57	2.72
2025	85,400	33,800	394.1	2,989	792,676	124.79	2.66

Figure 1.4 Actual (1970-2002) and Most-likely Case Forecast Electricity Sales (2003-2025)



For the 2005-2025 forecast period, annual peak loads are projected by assuming that the peak load/annual load ratio reported for 2002 continues to be experienced in the future, and applying this ratio to projected annual sales. (Sales were adjusted for losses to obtain load met by generation.) For each forecast year, each monthly peak loads was calculated to be the same fraction of the annual peak as it was in 2002 (Table 3.7).

Table 1.9 Monthly Peaks as Fractions of Annual Peak

Month	Fraction (%)
January	97.09
February	93.09
March	93.55
April	97.04
May	92.47
June	94.26
July	99.37
August	97.53
September	100.00
October	99.94
November	99.29
December	99.44

1.5.1 Alternative Load Forecast Scenarios

As noted above, it is desirable for IRP studies to consider alternative load forecast scenarios because of the inherent uncertainty in load growth and because of the substantial impact this can have on the absolute and relative benefits and risks of alternative resource plans. Over the 20-year planning horizon, there is considerable uncertainty regarding trends in the factors used to predict load growth as discussed above. This translates into considerable uncertainty for load growth.

To be able to capture this uncertainty, a standard approach is to identify the situations under which the High (higher than the Most-likely load forecast) or Low (lower than the Most-likely load forecast) forecast would occur. Alternative trends in the predictive factors can be based on information and forecasts from recognized institutions and studies. For the low growth scenario, the resident population growth projection is taken from Table B-1 of the University of Hawaii Economic Research Organization's Kaua'i Economic Outlook[12]; and for the high load growth scenario, it is taken from Table 4.01[13] of the same document. Visitor population projections for the low and high load growth scenarios are taken from Alternative Residential and Average Daily Visitor Projections provided by the County of Kauai[14] Total income projections for the low and high load growth scenarios are from several State of Hawaii sources.[15]

Forecast resident population trend and visitor population trend under the three load growth scenarios are depicted in Figure 3.5, using interpolation for intervening years. The full set of explanatory variables for the three load growth scenarios (resident population, visitor population, income and electricity price) for each year 2003-2025 are presented in Table 3.8.

Using the this forecast of the explanatory factors combined with the regression/ARMA developed as discussed above, energy sales projections were developed for the Low and High load growth scenarios. The High (Low) energy sales reflect high (low) resident and visitor population, high (low) total income and high (low) energy prices over 2003-2025. In developing high and low scenarios we concentrated on the factors that would have the most impact on the loads, that is resident and visitor population and total income. Previous regression analysis showed those factors to have significant coefficients with relatively high values for t-statistics (Table 3.4).

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[12] Kaua'i Economic Outlook: University of Hawaii Economic Research Organization - June 2003: Table B.1

[13] Table 4.01—Alternative Residential and Average Daily Visitor Projections: 2020, Page 60.

[14] Planning for Sustainable Tourism in Hawaii: Part 1 Infrastructure and Environmental Overview Study, Volume IV County of Kaua'i, December 2002: Table 4.01—Alternative Residential and Average Daily Visitor Projections: 2020, Page 60

[15] Kaua'i 2020 Projection of Total Jobs and Resident Population: (Sources: State of Hawaii Department of Labor and Industrial Relations; State of Hawaii Department of Agriculture; State of Hawaii Department of Business, Economic Development, and Tourism; Hawaii Visitors and Convention Bureau; and PlanPacific.): Table 4

Average price seems to have the least significant impact on the loads and for this reason we decided not to model it separately from the base case in high/low scenarios. These projected energy sales forecasts are net of the transmission and distribution losses. They are scaled up to account for losses, producing the electricity load to be served by the KIUC system that is the focus of this supply-side IRP study.

Figure 1.5 Forecast Population (Low, Most-likely and High Growth Scenarios)

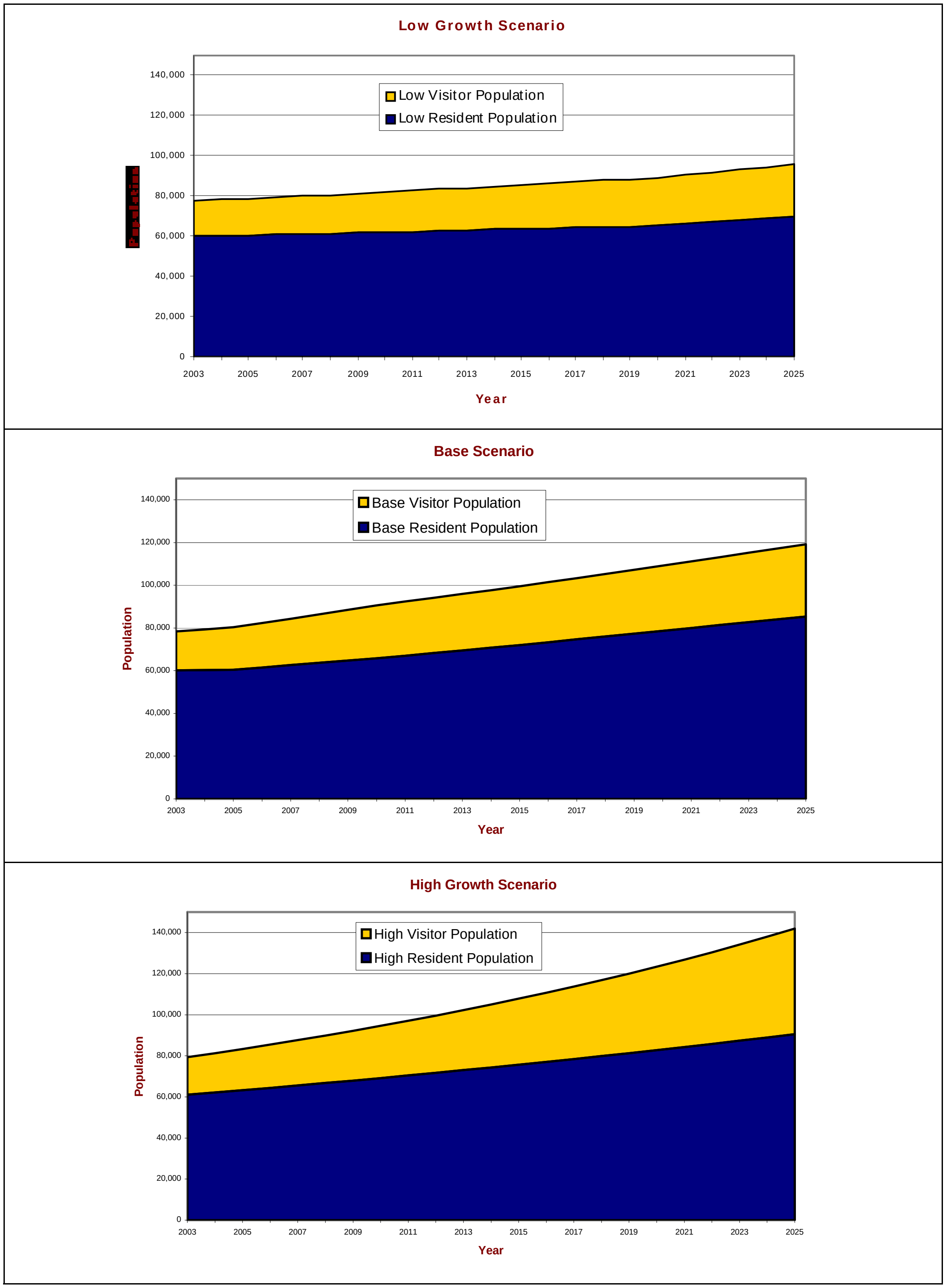

Table 1.10 Forecast of Scenario Drivers

Year	Low Resident Population	Base Resident Population	High Resident Population	Low Visitor Population	Base Visitor Population	High Visitor Population	Average Price (2003 $/MWh)	Low Total Income (2003 $M)	Base Total Income (2003 $M)	High Total Income (2003 $M)
2003	60,066	60,131	61,031	17,748	18,221	18,274	229	1,571	1,576	1,579
2004	60,186	60,315	62,136	18,066	19,041	19,152	235	1,626	1,636	1,642
2005	60,306	60,500	63,261	18,389	19,898	20,073	241	1,675	1,692	1,704
2006	60,625	61,560	64,407	18,719	20,794	21,038	247	1,725	1,750	1,769
2007	60,945	62,620	65,573	19,054	21,731	22,050	253	1,777	1,809	1,836
2008	61,266	63,680	66,760	19,395	22,709	23,110	259	1,830	1,871	1,906
2009	61,589	64,740	67,969	19,743	23,731	24,221	265	1,885	1,935	1,978
2010	61,914	65,800	69,199	20,096	24,800	25,386	272	1,942	2,001	2,054
2011	62,241	67,040	70,452	20,456	25,340	26,606	279	1,984	2,060	2,126
2012	62,569	68,280	71,728	20,822	25,880	27,885	286	2,028	2,119	2,200
2013	62,900	69,520	73,027	21,195	26,420	29,226	293	2,073	2,179	2,277
2014	63,232	70,760	74,349	21,575	26,960	30,631	300	2,118	2,238	2,357
2015	63,565	72,000	75,695	21,962	27,500	32,104	308	2,165	2,297	2,439
2016	63,901	73,340	77,065	22,355	28,100	33,647	316	2,212	2,364	2,524
2017	64,238	74,680	78,461	22,755	28,700	35,265	323	2,261	2,432	2,613
2018	64,577	76,020	79,881	23,163	29,300	36,961	332	2,311	2,499	2,704
2019	64,917	77,360	81,328	23,578	29,900	38,738	340	2,362	2,567	2,799
2020	65,260	78,700	82,800	24,000	30,500	40,600	348	2,414	2,634	2,897
2021	66,043	80,040	84,299	24,430	31,160	42,552	357	2,467	2,705	2,998
2022	66,869	81,380	85,825	24,867	31,820	44,598	366	2,521	2,776	3,103
2023	67,705	82,720	87,379	25,313	32,480	46,742	375	2,577	2,847	3,212
2024	68,551	84,060	88,961	25,766	33,140	48,989	384	2,633	2,918	3,324
2025	69,408	85,400	90,572	26,228	33,800	51,345	394	2,691	2,989	3,441

1.5.2 Comparison of Alternative Load Growth Scenarios

The trends in annual energy sales under the Low, Most Likely and High load growth scenarios are shown in both tabular and plotted format in Figure 3.6. Scaled up to account for 6% losses, the corresponding load projections to be met by system generation are shown in Figure 3.7. Finally, the corresponding annual peak load projections (including losses) are shown in Figure 3.8. Under the Most Likely load growth scenario, peak load grows from 71.3 MW in 2003 to 132 MW in 2025. Under the Low and High load growth scenarios, the projected 2025 peak load reaches 94MW and 154 MW respectively. On a percentage basis, the range in projected energy growth across the three scenarios is similar to the range in projected peak load growth. Clearly, over the 20-year planning horizon, load growth uncertainty can have a large impact on the magnitude and composition of a desirable supply plan, as well as on the underlying financial and reliability risks.

Figure 1.6 Forecast Annual Energy Sales (High, Most-likely and Low Growth Scenarios)

	Forecasted Energy Sales (GWh)		
Year	Low	Base	High
2003	425	430	436
2004	428	432	452
2005	431	438	467
2006	436	448	484
2007	441	466	501
2008	447	478	518
2009	452	494	536
2010	458	508	555
2011	463	525	574
2012	468	541	594
2013	473	558	615
2014	478	575	636
2015	484	592	658
2016	489	611	681
2017	494	630	705
2018	500	650	729
2019	506	669	754
2020	511	689	780
2021	522	709	807
2022	533	730	835
2023	545	750	864
2024	557	771	894
2025	569	793	925

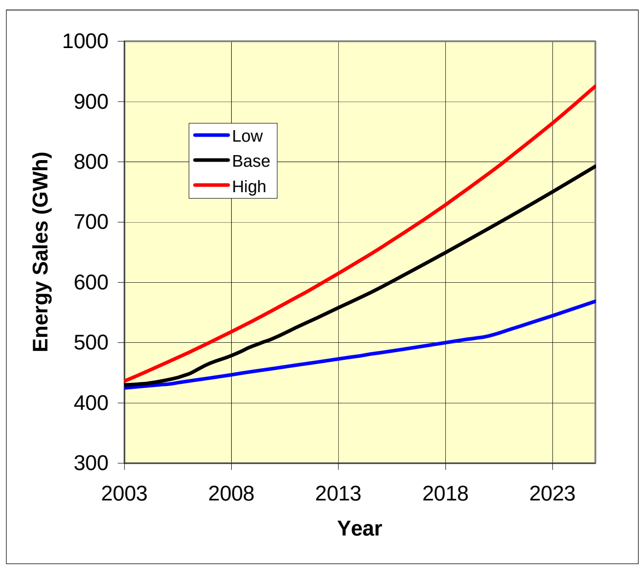

Figure 1.7 Forecasted Total Generation (High, Most-likely and Low Growth Scenarios)

	Total Generation (GWh)		
Year	Low	Base	High
2003	448	454	460
2004	452	456	476
2005	455	462	493
2006	460	473	510
2007	466	491	528
2008	471	505	547
2009	477	522	566
2010	483	536	586
2011	488	554	606
2012	494	571	627
2013	499	589	649
2014	505	607	671
2015	510	625	694
2016	516	645	718
2017	522	665	743
2018	527	685	769
2019	533	706	796
2020	539	727	823
2021	551	748	852
2022	563	770	881
2023	575	792	912
2024	587	814	944
2025	600	836	976

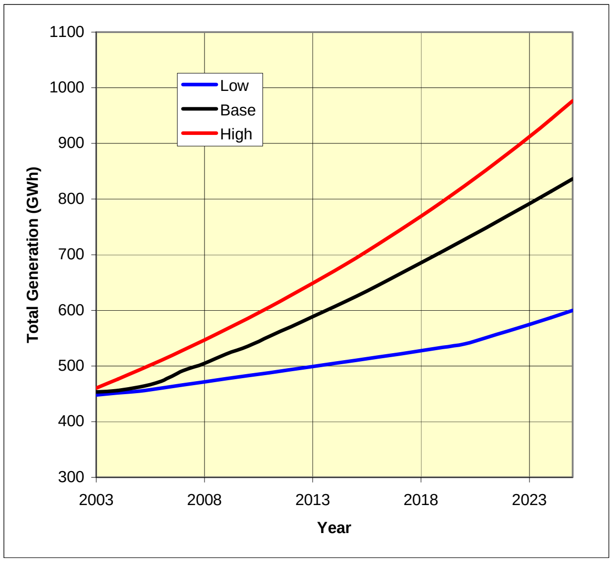

Figure 1.8 Forecasted Peak Generation (High, Most-likely and Low Growth Scenarios)

	Peak Generation (GWh)		
Year	Low	Base	High
2003	70	71	72
2004	71	72	75
2005	72	73	78
2006	72	74	80
2007	73	77	83
2008	74	79	86
2009	75	82	89
2010	76	84	92
2011	77	87	95
2012	77	89	98
2013	78	92	102
2014	79	95	105
2015	80	98	109
2016	81	101	112
2017	82	104	117
2018	83	107	121
2019	84	111	125
2020	84	114	129
2021	86	117	134
2022	89	121	138
2023	90	124	143
2024	92	128	148
2025	94	131	154