SELF-GENERATION INCENTIVE PROGRAM

RETENTION STUDY

Submitted To:

PG&E M&E Project Manager Betsy Wilkins
and M&E Committee of the SGIP Working Group

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E EXECUTIVE SUMMARY

The Self-Generation Incentive Program (SGIP) provides financial incentives to eligible utility customers for the installation of new self-generation equipment. "Self-generation" includes the following generation technologies – fuel cells, microturbines, wind turbines, photovoltaic (PV) cells, gas turbines and internal combustion engines (ICE). The purpose of this report is to examine the retention and lifetime of the self-generation devices installed through the SGIP. Any generalized conclusions beyond this specific sample should be made with caution. The sample sizes for fuel cells, wind turbines and gas turbines are too small to make any general conclusions. The sample for PV is relatively large and is expected to be representative. The sample sizes for ICE and microturbines is large enough for some generalization but the technology for this application is evolving so expansion of results beyond the time frame and specific sample may produce misleading results.

The results presented in this retention report are based on analyses prepared by the Team (Summit Blue Consulting, RLW Analytics and Energy Insights) and rely in significant measure on data provided by the SGIP's impact evaluation contractor, Itron. Though Summit Blue Consulting is the prime contractor for this effort, RLW Analytics led the retention study. It is important to note that the results in this study are based on a sample of all SGIP installations, i.e., those that are monitored by Itron for purposes of conducting impact evaluations.

E.1 Retention Analysis Objectives

The objectives of the study were to:

- Examine and summarize interval meter data from 419 self-generation sites, identify irregularities and inconsistencies as seen in the data, and characterize sites into specific categories and groups based on system performance;
- Explore other sources of information regarding system performance such as informal participant telephone surveys and Program Administrators' (PAs) knowledge in an effort to identify failure status and mode;
- Conduct a failure analysis of the technologies used in the SGIP;
- Examine if there exists any correlation between manufacturers and failures;
- Compute the survival proportions of all technologies; and
- Apply SAS-based tools and determine the Effective Useful Life (EUL) of three system types: microturbines, internal combustion engines, and PV cells at the 90 percent confidence level.

E.2 Methodology

The retention study included the following steps:

- Step 1: Obtain Electricity Production Data from the SGIP impact evaluation contractor, Itron:

  Itron provided the Team with meter data for 419 sites obtained from multiple third party sources for the retention analysis. This data served as the primary source for the retention analysis calculations. The meter data contained 15-minute kWh interval load data for six different types of technologies: fuel cells, microturbines, wind turbines, PV cells, gas turbines and internal combustion engines. The datasets altogether contained approximately 30 million records for years 2002-2007.

- Step 2: Examine the Available Data:

  The Team investigated the meter data in SAS[1] and Visualize-IT[2] for initial characterization of failed and problem sites. System sizes (rebated kW) of the sites were examined. The load data were compared to the sites' system sizes. Six different types of problems were identified in the data. The details of these problems are summarized in Appendix B. The Team classified all sites into sites that are "functional" and those that are "not functional." In this study, "functional" is defined as those installations with metered and reported production of electricity, independently confirmed when possible.

- Step 3: Verify Meter Data Conclusion by Site-Specific Notes:

  Whenever site-specific notes were available, the Team used them to verify the conclusions that were drawn from the meter data. This was particularly important for problem sites. Site-specific information was also collected from PAs for each "not functional" site to confirm its classification into this category.

- Step 4: Explore Other Sources of Information to Clarify Failure Status:

  Several additional sources of information regarding system performance were also explored in an effort to further inform the actual status of systems and the reasons behind that status. The PAs helped identify site contacts who might have historical knowledge of system performance. In addition, focus group discussions and site surveys conducted as part of the broader SGIP process evaluation were also examined for information regarding system performance.

- Step 5: Examine Any Correlations between Manufacturers and Failures:

  The Team obtained information on the manufacturers of the systems in the data. This was examined to see if any correlation exists between manufacturers and the types of problems. The

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[1] Statistical Analysis Software

[2] Visualize-IT is Windows Application software designed by RLW that summarizes and graphs time-series interval load data.

goal in this step was to investigate if any particular problem is frequently associated with any specific manufacturer(s).

- Step 6: Analyze Statistics:

  Based on the classification of all sites into "functional" and "not functional," the Team computed the survival proportion (the ratio of the number of systems that are currently functional to the total number of systems in the data) of sites for each technology. Classical SAS-based tools were applied to produce the EULs (Effective Useful Life) of the systems.

- Step 7: Examine Results:

  In this final step, the Team examined results obtained in Step 4. Recommendations for future retention studies were also discussed. The key results obtained in the study were analyzed and discussed in this step.

E.3 Key Findings

Average Output to Capacity Ratio

The average output to capacity ratio is the ratio of actual energy produced in a given period to the rated capacity (hypothetical maximum possible, i.e., running full time at rated power). Example: Suppose a site has a generator with a power rating of 1500 kW. Hypothetically, if it ran at full power for 24 hours a day for 365 days, then this generator would produce: (1500 kW) x (365 x 24 hours) = 13,140,000 kWh in one year. Suppose that in fact it produced 3,942,000 kWh in one year; the generator would have operated at an average output to capacity ratio for that year of 3,942,000 / 13,140,000 or 30.0 percent.

The average output to capacity ratio of the six system types from the data are listed below. Wind turbines and PV cells have relatively low average output to capacity ratios because they rely on naturally variable phenomenon, i.e., neither maximum wind energy nor full sunshine is available 24 hours a day every day of the year. Because there are relatively small numbers of sites with fuel cells, wind turbines and/or gas turbines, the average output to capacity ratios for these systems may not be representative of a larger population.

Table E-1. Average Output to Capacity Ratios

System Type / Technology	Average Output to Capacity Ratio	Sample[3] Size
Fuel Cells	.74	6
Microturbines	.48	38
Wind Turbines	.15	2
Photovoltaic Cells	.17	268
Gas Turbines	.72	2
Internal Combustion Engines	.42	91

Analysis of Manufacturers

No specific relationship was found between manufacturers and reliability of fuel cells. The same was also true for wind and gas turbines. The photovoltaic systems were considered highly reliable and no manufacturing relationship was observed. The Team did identify some specific manufacturers of microturbines and internal combustion engines that had low reliability.

Survival Proportion

The survival proportion for a technology is simply the ratio of the number of systems that are currently functional to the total number of systems in the data. The survival proportions of the different technologies are summarized below. There were no observed system failures for fuel cells, wind turbines, photovoltaic cells or gas turbines, so the survival proportions of these three systems were 100 percent. Table E-2 also shows that 70 percent of the microturbines and 81 percent of ICEs were still functional. Overall, 93 percent of all systems were still functional. The error bounds[4] associated with each of the percentages, at 90 percent confidence interval, are presented in the last column of Table E-2.

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[3] A few outliers were excluded from this computation for microturbines, ICE and PV cells. For microturbines and ICE, the same data that was used to compute EUL was used to compute the average output to capacity ratio.

[4] The error bound (=1.645*standard error, at 90% confidence) or the margin of error is the radius of the confidence interval.

Table E-2. Survival Proportions by System Type

System Type / Technology	Total	System Still Functional	System Not Functional	Percent Functional	Error Bound
Fuel Cells	6	6	0	100%	NA
Microturbines	40	28	12	70%	11.9%
Wind Turbines	2	2	0	100%	NA
Photovoltaic Cells	276	276	0	100%	NA
Gas Turbines	2	2	0	100%	NA
Internal Combustion Engines	93	75	18	81%	6.7%
All	419	389	30	93%	2.1%

Effective Useful Life

The Team applied the standard classical SAS-based routine, the Lifereg[5] procedure, to produce the EULs (Effective Useful Life) of photovoltaic cells, microturbines and internal combustion engines. The results from the SAS analyses are summarized below.

- PV: At the current time, all of the photovoltaic cells in this population are still installed and in operation. Because the current level of retention is so high for photovoltaic cells, (i.e., there are no recorded failures in the sample population) there is insufficient information to determine reliably how long the units will last, i.e., to reliably estimate the EUL.
- Microturbines: 70 percent of microturbines were in operation at the time of this study. The estimated EULs range from a low of 4.0 years (1,466 days) under the Logistic model to a high of 6.6 years (2,414 days) under the Log Normal model. For the best models that fit the data, the EUL was estimated to be 4.7 years.
- ICE: Over 81 percent of ICE systems have been retained to the present time. The EUL for ICEs, on the other hand, ranged between 3.7 years (1,361 days) and 7.2 years (2,637 days). For the best models that fit the data, the EUL was estimated to be 4.4 years.

Practical Functionality

The internal combustion engines and microturbines in this population have both had long-term reliability problems. A subset of the internal combustion engine systems appear to have had basic design problems that resulted in premature failure and abandonment of the market by a manufacturer. The electricity production data and other details obtained from the files and interviews indicate a significant fraction of both kinds of systems had reliability problems, sometimes from the time of initial operation. Over the long term, functional status remains somewhat unclear. In the most basic analysis, these are mechanical systems with many moving parts subject to wear and tear with limited lifetimes. As they age, the need for maintenance tends to increase as more pieces and parts wear out, needing repair or replacement. In attempting to determine functional status, interviews with site personnel were sometimes inconclusive. Of all microturbines and internal combustion engines with zero current metered electricity production, 56 percent were confirmed as non-functional due primarily to mechanical issues, 14 percent were non-

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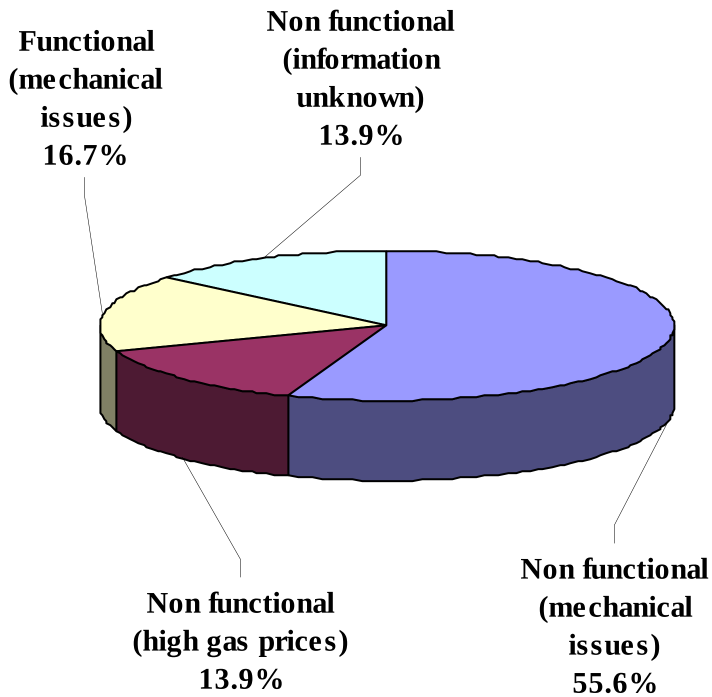
[5] The Lifereg procedure is a SAS based routine that fits parametric models to failure data. The functional forms of the models are described in Appendix B. The best fit model is finally chosen out of the multiple models considered.

functional as they were shut down due to high gas prices, and 17 percent had functional status (currently operating but with mechanical problems). Confirming functional information could not be identified for the remaining 14 percent. The pie chart in Figure E-1 reflects the current status of identified problem sites.

Figure E-1. Identified Problem Sites



A significant number of systems are still installed, but have essentially been abandoned because they are so difficult and time consuming to maintain. For those internal combustion engine and microturbine sites with no electricity production and about which dialogues with knowledgeable site personnel took place, 65 percent were considered by knowledgeable site personnel to be non-functional or considered to be "not worth the trouble" to be made functional. Another 16 percent were not operating because of high natural gas prices. The remaining 19 percent were found be to be functional in spite of periodic breakdowns and major shutdowns. Two of these functional systems, for example, were shut down for almost a year and a half due to major mechanical problems which they still experience. Section 3.1 provides a detailed discussion of functional status.

1 BACKGROUND

1.1 Program Summary

The Self-Generation Incentvie Program (SGIP) was first launched in March 2001 by the California Public Utilities Commission (CPUC). The SGIP operates in the service areas of Pacific Gas and Electric (PG&E), Southern California Edison (SCE), Southern California Gas (SCG), and the San Diego Gas and Electric Company (SDG&E). The program provides financial incentives to eligible utility customers for the installation of new self-generation equipments. "Self-generation" refers to generation technologies (fuel cells, microturbines, wind turbines, photovoltaic (PV) cells, gas turbines and internal combustion engines (ICE)),[6] which are installed on the customer's side of the utility meter and provide electricity for either the entire or a portion of the customer's electric load. The program is targeted towards businesses and large institutional customers. The SGIP is administered by PG&E, SCE, and SCG, in their respective territories. The California Center for Sustainable Energy administers the SGIP in SDG&E's territory. This organization recently changed its name from the San Diego Regional Energy Office (SDREO) to the California Center for Sustainable Energy (CCSE), but is referred to throughout this report as SDREO.

Over time, the SGIP has been modified in a number of ways. A brief overview of key events in the history of the SGIP is presented in Figure 1-1.

Decision D.01-03-073, along with the CPUC's Energy Division, directed the SGIP Program Administrators (PAs) to file plans for evaluation activities. On March 6, 2006, in a responsive Joint Motion, a measurement and evaluation (M&E) Plan for the SGIP was proposed that described a PA Comparative Assessment update, a Market Focused Process Evaluation, a Market Characterization Study and a Retention Study. In a ruling dated May 18, 2006, the Administrative Law Judge approved the M&E plan with minor modifications: Marketing and outreach was added as an element to the PA Comparative Assessment and an analysis of the impact of the transition of applications for PV systems from this program to the California Solar Initiative (CSI) was added to the Process Study. The PA Comparative Assessment was completed and filed with the CPUC on April 25, 2007, the Market Focused Process Study was completed and filed with the CPUC on August 9, 2007, and the Market Study was completed and filed with the CPUC on August 30, 2007.

The results presented in this retention report are based on analyses prepared by RLW Analytics. The study relied in significant measure on data provided by the SGIP's impact evaluation contractor, Itron. Though the retention study was led by RLW Analytics, the study team is referred to as the "Team" because Summit Blue was the prime contractor for this and the three previous studies outlined above.

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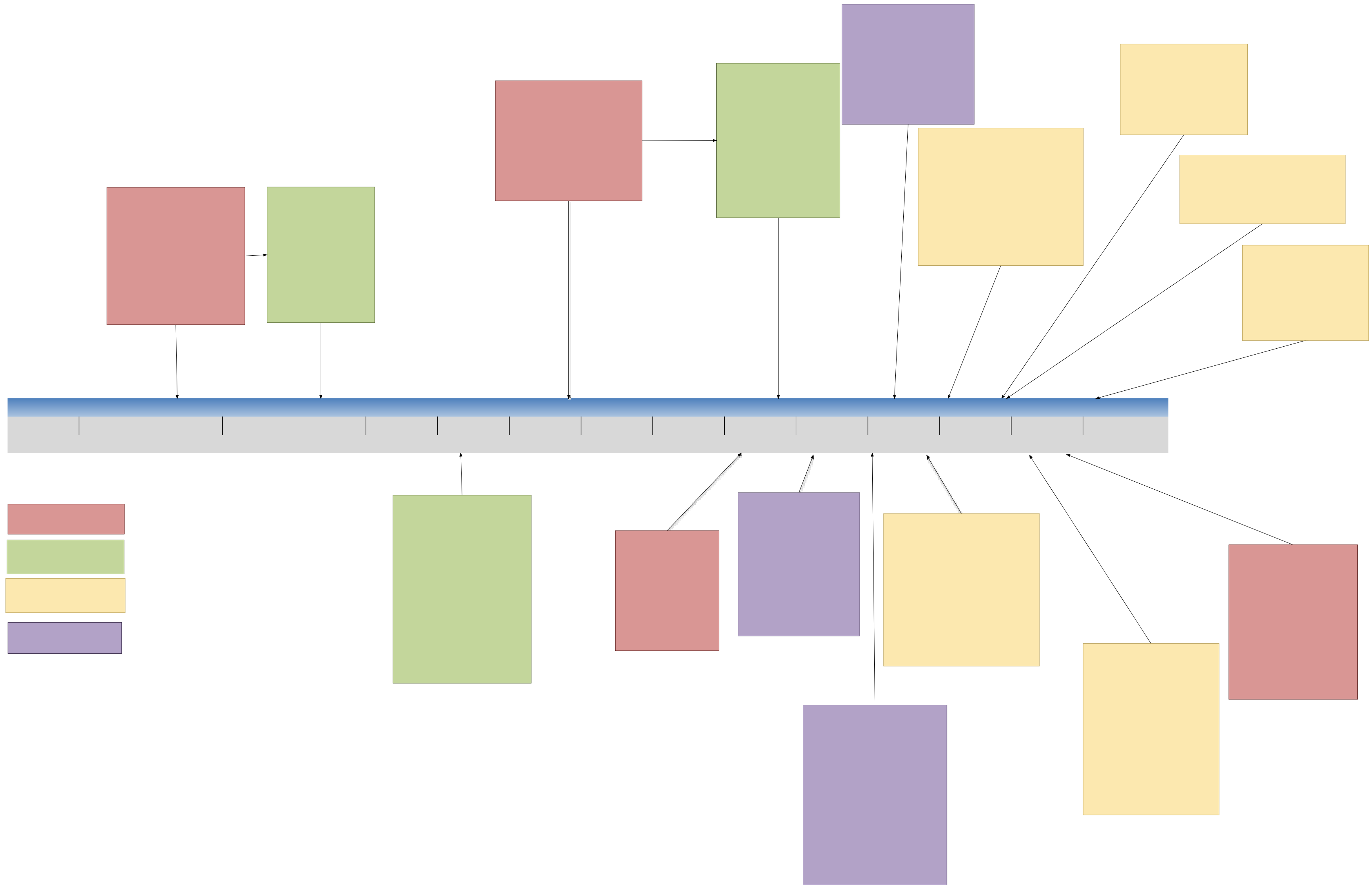
[6] An overview of SGIP technologies is provided in Appendix E.

Figure 1-1. SGIP Event Timeline



March 2001:

Sept 2000:

D. 01-03-073

1.2 Data Summary

A brief overview of the data in the metered population is presented in subsections below. Note that this does not encompass all SGIP sites, but rather those that are monitored by Itron for the SGIP impact evaluations. The table below provides a summary of total SGIP population (all SGIP projects completed as of Dec 31, 2006) by system type and compares it to all SGIP projects that were metered by Itron. Confidence and precision levels are also included. This sample of sites used in the Itron SGIP Impact evaluation was designed to be representative of the total SGIP population.

Table 1-1. Number of SGIP Systems

System Type / Technology	Completed (as of December 31, 2006)[7] [8]	Included in the Retention Study Analysis	Estimated Confidence/Precision[9]
PV	638	276	90/5
Wind	2	2	90/0
Fuel Cell	12	6	90/25
ICE	183	93	90/10
Microturbine	110	40	90/15
Gas Turbine	4	2	90/50
All	949	419	90/5

[7] Data from Itron, "CPUC Self-Generation Incentive Program Sixth Year Impact Evaluation – Final Report," Aug. 2007 and Summit Blue Consulting, LLC, Market Focused Process Evaluation, August 2007.

[8] An additional 605 PV systems, 4 wind systems, 16 fuel cell systems, and 108 engine or turbine systems were considered "active" at this time, meaning that they had not been withdrawn, rejected, completed, or placed on a wait list.

[9] The confidence and precision levels shown in the table are based on formulae for estimating proportions. The largest variance occurs when the proportion is 0.5; i.e., one half of the respondents indicate they are in a group and one half state that they are not in a group. The calculation assumes the variance with this 50/50 split. It should be noted that each question in a survey will have a different confidence interval and precision depending upon the range of possible answers for multi-category questions or continuous variables and the dispersion of responses. While these confidence interval estimates for proportions are potentially misleading for questions that do not ask about a proportion, it has become relatively standard in evaluation research to report these levels since they allow for a comparison across survey efforts. This type of analysis is best used where the sample is randomly drawn. However, based on a review of the CPUC Self-Generation Incentive Program Sixth Year Impact Evaluation Report prepared by Itron, Inc. dated August 30, 2007, Appendix D, the sample while appearing to be fairly representative, is not in fact random. Thus it is possible that these confidence and precision levels are overstated.

A chi-square test was performed to determine if the population (total number of SGIP systems) and the sample (of SGIP sites for which meter data was collected by Itron) distributions[10] [11] were the same. The null hypothesis of equality of distribution of the two groups by system type could not be rejected.

1.2.1 SGIP Participation

There were six different technologies in the data across 419 sites. Table 1-2 provides a distribution of sites by technology and shows that over 65 percent of all systems were photovoltaic cells. Additionally, approximately 9.5 percent of all systems were microturbines and 22.1 percent were internal combustion engines. The remaining system technologies included six fuel cells, two wind turbines and two gas turbines.

Table 1-2. Number of Sites by System Type and Utility

System Type / Technology	Number of Sites				
	Total	PGE	SCE	SCG	SDREO
Fuel Cells	6	3	1	0	2
Microturbines	40	4	9	12	15
Wind Turbines	2	0	2	0	0
Photovoltaic Cells	276	111	50	30	85
Gas Turbines	2	1	0	0	1
Internal Combustion Engines	93	32	15	29	17
All	419	151	77	71	120

[10] Pearson's Chi-Square test for Goodness of fit determines if the sample under analysis was drawn from a population that follows some specified distribution.

[11] The null hypothesis of the Chi-square test states that the distributions of systems in the two groups are the same. Following the standard procedures, the Chi-square test statistic was computed as 1.76 which is less than 7.815 - the 5% value of chi-square for 3 degrees of freedom.

The team analyzed 15-minute electricity usage data (kWh) of sites collected between April 2002 and May 2007. For some sites, data were only available for a period of a few days. For some other sites, data were available for a period of a few years continuously. The electricity production data were compared to the sites' system sizes. The table below provides some summary statistics on the system sizes. The site system size is also its rebated kW.

Table 1-3: Summary Statistics – System Size (Rebated kW)

System Type / Technology	Number of Sites	System Size		
		Average	Minimum	Maximum
Fuel Cells	6	633	200	1,000
Microturbines	40	136	28	600
Wind Turbines	2	824	699	950
Photovoltaic Cells	276	144	30	1,050
Gas Turbines	2	2,955	1,383	4,527
Internal Combustion Engines	93	675	60	1,500
All	419	288	28	4,527

1.2.2 Average Output to Capacity Ratio

The average output to capacity ratio is the ratio of actual energy produced in a given period to the rated capacity (hypothetical maximum possible, i.e., running full time at rated power) and acts as an indicator of system performance. For example, suppose a site has a generator with a power rating of 1500 kW. Hypothetically, if it ran at full power for 24 hours a day for 365 days, then this generator would produce: (1500 kW) x (365 x 24 hours) = 13,140,000 kWh in one year. Suppose that in fact it produced 3,942,000 kWh in one year; the generator would have operated at an average output to capacity ratio for that year of 3,942,000 / 13,140,000 or 30.0 percent.

The table below lists the average output to capacity ratios of the six technologies from the study data.

Table 1-4. Average Output to Capacity Ratios

System Type / Technology	Average Output to Capacity Ratio	Sample Size [12]
Fuel Cells	.74	6
Microturbines	.48	38
Wind Turbines	.15	2
Photovoltaic Cells	.17	268
Gas Turbines	.72	2
Internal Combustion Engines	.42	91

The output to capacity ratio of a self-generation system is defined as the ratio of electrical power delivered to the rated capacity of the system. As the electrical data recorded for every system for this study were in 15-minute kWh, the power delivered by every system for each hour was calculated by multiplying the 15-minute kWh data by four. The average output to capacity ratios of different self-generation technologies vary depending on various factors. The following sub-sections describe output to capacity ratios of the SGIP technologies under different operating conditions. In addition, the general electricity production profiles of the different SGIP technologies are quite different from one another. To illustrate those differences, representative electricity output profiles are included with each technology.

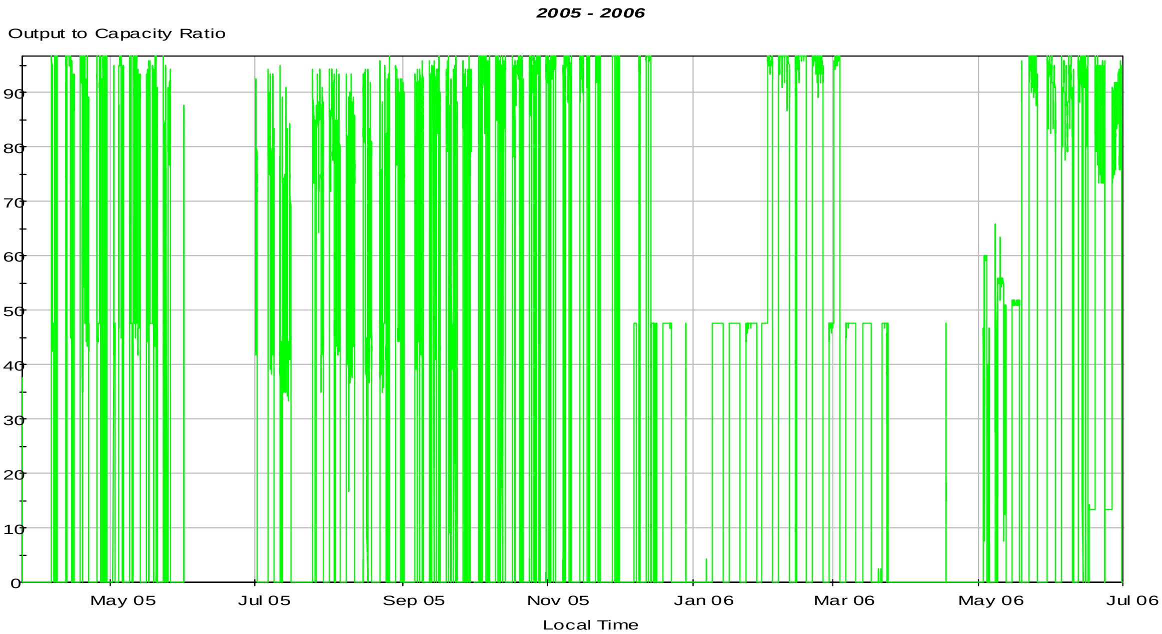
[12] A few outliers were excluded from the computation for microturbines, ICE and PV cells.

For microturbines and ICE, the same data that was used to compute EUL was used to compute the average output to capacity ratio.

Microturbines

Microturbines are well-suited for distributed generation applications due to their flexibility in connection methods and ability to be stacked in parallel to serve larger loads. Output to capacity ratio of a microturbine depends on variation of load on the system, number of systems running and operating condition. Figure 1-2 shows the output to capacity ratio of a microturbine system from May 2005 to July 2006.

Figure 1-2. Output to Capacity Ratio of a Monitored Microturbine

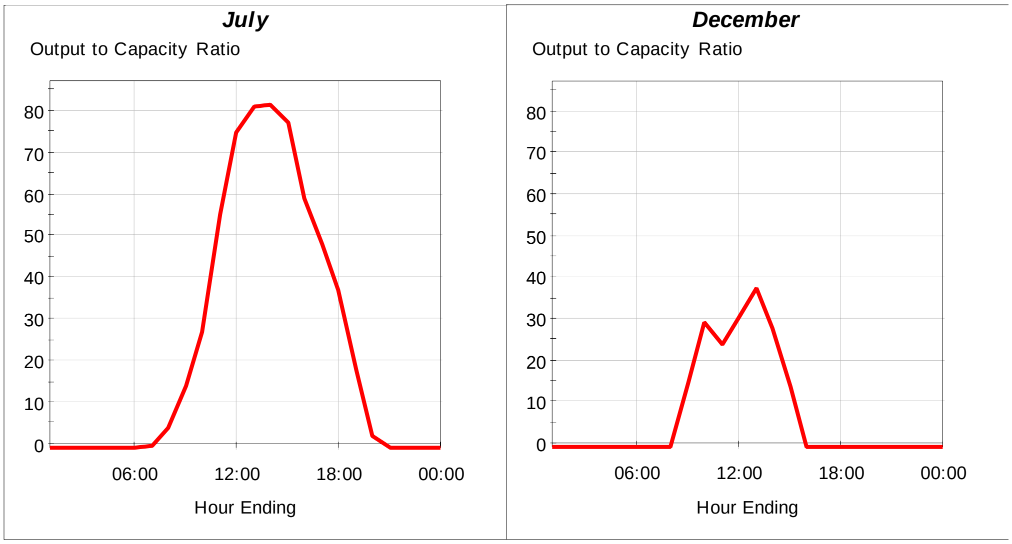


In the figure above, the output to capacity ratio reduces from peaks of 95 percent to peaks of 45 percent in the months of January 2006 and March 2006. This two step output is an indication of multiple systems at a single installation. Generally, SGIP microturbines operate at close to full output capacity during normal business hours with shutdowns on weekends and often overnight.

Photovoltaic Cells

There are various items that affect the output to capacity ratios of a PV system. As the output of a photovoltaic system depends on climatic conditions and time of day, the output to capacity ratio will fluctuate throughout different climatic conditions and time of day. Figure 1-3 shows monthly average output to capacity ratios of a PV system for the months of July and December.

Figure 1-3. Monthly Average Output to Capacity Ratio of a Photovoltaic System

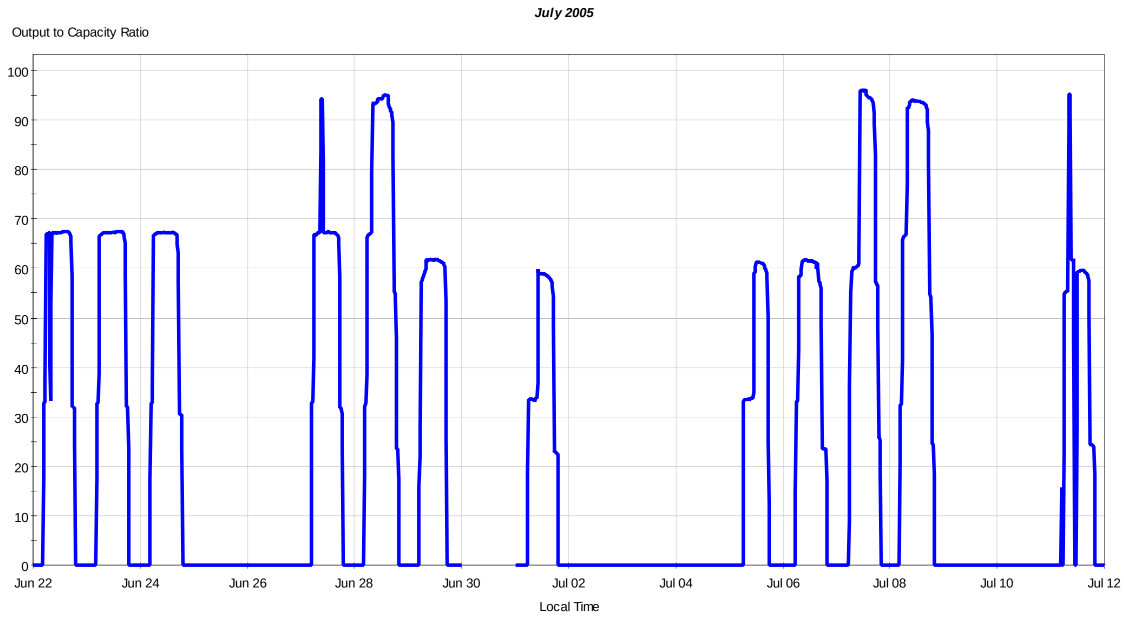


The figure above also depicts that the peak electricity production on a clear, sunny day in summer is 80 percent of the system capacity, whereas on a cloudy day in winter, it is 35 percent of the capacity. PV systems only produce electricity when they receive sunlight so their output varies both over the normal 24 hour diurnal cycle and as well as seasonally.

Internal Combustion Engines

The output to capacity ratio of an internal combustion engine depends on the variation of load on the system and the operating conditions. Figure 1-4 shows the output to capacity ratio of an internal combustion engine for a period of two weeks.

Figure 1-4. Output to Capacity Ratio of an Internal Combustion Engine



As the above figure shows, the output to capacity ratio of the engine varied from 60 percent to 95 percent. The steps in the output data indicate that this installation probably has multiple systems. The systems operate during normal business hours with shutdowns on weekends and holidays.

2 METHODOLOGY

The first step in the analysis was the determination of functional status of different types of technologies. All analysis in later sub-sections is dependent on defining what constituted a failure for different types of systems or technologies (fuel cells, microturbines, wind turbines, photovoltaics, gas turbines and internal combustion engines) in the study. The Team, therefore, first estimated units still "functional" for all systems.

2.1 Functional Status

In the retention analysis, the Team inspected meter data collected by Itron to determine what constituted a failure for each type of system at a self-generation site. For each of the sites included in the analysis, detailed examinations of the data in SAS and Visualize-IT determined if a system had stopped producing electricity. Figure C- 1 (in Appendix C: Data Review) shows an example of a site with microturbines which was characterized as a site with failed generation. To confirm what is seen in the data for this site (and other similar sites that show no production for some period in the end), the team also called the sites for detailed information and looked at the site notes from interviews, whenever available. Finally, the PAs called individual sites to confirm what the Team saw in the data. All of the sites were finally categorized into two groups – sites with systems that are "functional" and those with systems "not functional." Whenever possible the functional status as indicated in the data was confirmed through conversations with site personnel prior to performing the manufacturer reliability and statistical analyses. Appendix D provides detail on failure classifications for each of the PAs.

2.2 Manufacturer Reliability Analysis

For all systems that were "non functional" or those that show periodic problems (e.g., multiple major shutdowns throughout the monitoring period), the team analyzed the relationship between manufacturers and performance difficulties. Data on all systems were matched against the manufacturer names and models. Performance of each manufacturer was examined individually. Any correlation(s) between manufacturer and system reliability were noted. Specifically, the number of unreliable systems for each manufacturer was computed and then compared to the number of reliable system for the same manufacturer.

2.3 Statistical Effective Useful Life Analysis

The first step of the statistical analysis first involved was to define what constituted a failure for the different types of SGIP systems or technologies. The analysis estimated survival proportions by system type. The survival proportion for a technology is simply the ratio of the number of systems that survived and the total number systems in the data.

The survival analysis involved estimating the proportion of units still in place for all systems, examining multiple survival models for some selected systems (photovoltaics, internal combustion engines and microturbines),[13] estimating the EUL from the models that best fit the data, and finally examining the estimates and related results from the models.

The methodology for the survival analysis can be explained in the following four steps, which are more fully described in Appendix B:

1. Estimate the current survival proportion $\hat{S}$[14] for all systems. Calculate the standard error of $\hat{S}$.

2. Use this data to estimate survival functions under four different statistical survival models: Exponential, Log Normal, Weibull, and Logistic.

3. Use the survival functions to calculate and graph the predicted survival rates for the first ten years.

4. Use the survival functions to calculate the EUL implied by the assumed survival model.The EUL is defined to be the number of years after which the survival proportion for units would equal 50 percent, that is, the median of the survival distribution.

Each of these steps is discussed briefly.

Step 1: First sites were classified into "functional" and "not functional" after examining data in Visualize-IT. Functional sites were defined as those producing measured electrical output at the end of the metering period. This step also included computing the percentage each technology that survived.

Step 2: Four different survival models (Exponential, Weibull, Logistic, and Log Normal) were applied using classical survival analysis techniques and the Lifereg procedure in the SAS System. The functional form of each of these survival functions can be found in Appendix B. The meter data and Visualize-IT files of the failed sites were able to indicate when a failure occurred. This information was used in the analysis.

Steps 3 and 4: Each of the estimated survival models was used to calculate the expected survival proportions for years one through ten, and to calculate the estimated EUL and associated standard error. The EUL is defined to be the number of years after which the survival proportion for units would equal 50 percent, that is, the median of the survival distribution. To illustrate: If after four years, the survival proportion is equal to 85 percent, i.e., the units have declined by 15 percent in four years, then the EUL for that population would be about 17 years under the exponential survival model, under which the probability of failure is assumed to be constant over time.

In addition, the log-likelihood statistic was examined for each of the four estimated models as a measure of the how well each model fit the data. The likelihood function can be thought of as the probability of observing the study data under the estimated survival model. Thus, a larger value of the likelihood function suggested a model that would fit the data better than a model with a smaller value. The log-likelihood

[13] EULs could not be computed for fuel cells, gas turbines and wind turbines due to a small sample size. EUL for photovoltaic cells could not be computed as the survival rate for photovoltaics was 100%.

[14] $\hat{S}$ is defined as the estimated value of the survival proportion.

function is simply the natural logarithm (ln) of the likelihood function.[15] Therefore, the larger the value of the log-likelihood statistic, the better the model fits the data. The model with the best fit to the data as indicated by the highest log-likelihood statistic was selected.

[15] Maximum likelihood estimation is often based on the log-likelihood function as that function is often easier to maximize. The monotonicity of the natural logarithm ensures that the same value maximizes both functions.

3 RESULTS

Functional status, manufacturer reliability and statistical EUL analyses are presented below.

3.1 Functional Status

Whenever site-specific interview information or notes were available, the Team used them to verify the conclusions that were drawn from the meter data. The final results of this verification process are summarized in the tables below. As can be seen in Table 3-1, 13 microturbines, one photovoltaic cell and 23 internal combustion engines were identified as problem sites.[16] Ultimately, a significant fraction of these sites were able to be classified based on available information. In some cases, knowledgeable parties could not be reached to discuss the status of the installation. The information obtained from the site interviews and notes from previous interviews conducted for the Market Focused Process Study confirmed that 12 microturbines and 13 internal combustion engines are currently non-functional. Interviews also confirmed that the "problem" photovoltaic cell is functional – the meters for this system did not record electricity production data correctly at the end of the monitoring period. Information was not available for five internal combustion engines.

Table 3-1. Functional Status

System Type / Technology	Number of Sites in Sample	Problem Systems Identified	Information		Sites with Information	
			Information Received	Information Not Available	Sites Functional	Sites Non-functional
Microturbines	40	13	13	0	1	12
Photovoltaic Cells	276	1	1	0	1	0
Internal Combustion Engines	93	23	18	5	5	13

The detailed problems of the 25 non-functional sites are listed in the table below. Many of these systems had reliability issues and two systems had catastrophic failures. Replacement parts were not available for some systems while other systems were shut down to avoid high natural gas costs which impacted the cost effectiveness of the system. Of those sites classified as functional, the information indicated that while operational, the microturbine and the internal combustion engines often had to shut down to deal with mechanical problems. All of these technically functional systems identified as "problem sites" experienced multiple major shutdowns in prior years.

[16] Problem sites were defined as systems for which the meter data showed no electricity production at the end of the monitoring period.

Table 3-2. Sites with Information

System Type / Technology	Non-Functional Sites-Types of Problems							Functional Sites	
	Reliability Issues	Policy Changes -Switched to PV system	Change of Owner/System Removed	Replacement Parts not Available	Catastrophic Failure	Problem Not known but Status known	High Natural Gas Prices	Major Breakdowns and Mechanical Problems	Meter Problem
Microturbine	6	1	0	0	0	2	3	1	0
Internal Combustion Engine	3	0	3	3	2	0	2	5	0
Photovoltaic Cells	0	0	0	0	0	0	0	0	1

As shown in Table 3-2, sites that were shut down due to high natural gas prices were considered non-functional for the computation of survival proportions and EUL. There were seven sites that were given “functional” status in the computation, even though they operated with major breakdowns and mechanical problems. Two of these functional systems, for example, were shut down for almost a year and a half. These two systems were still experiencing major mechanical problems at the time of this report. The remaining sites with zero electricity production data, for which no contact was available to verify data conclusions, were considered non-functional – as conclusions on “functional status” of the sites drawn from the data were correct for the majority of confirmed sites. Internet research showed that some of these sites, for which no contact was available, no longer exist. For example, internet research confirmed that at least one of the facilities had ceased operations.

Practical functionality by use for internal combustion engines and microturbines is discussed in Appendix D.

3.2 Manufacturer Reliability Analysis

This section presents the manufacturer-specific reliability analysis of SGIP technologies. For each technology the potential for correlations between manufacturers and their reliability was reviewed. For more information on how the technologies work, please see the brief review in Appendix E.

First those systems which were not fully functional or had any operational problems were identified as described in Appendix C. The section below discusses the reliability rate of the different subject manufacturers by technology. The results of this analysis are applicable only to this sample and should not be generalized. Technologies continue to evolve and manufacturers continue to refine their products based on changing technologies and operational experience.

Specific guidelines were implemented to determine if a system is reliable. Catastrophic failure, frequent shutdown due to mechanical, thermal or electrical problems and permanent shutdowns were issues that were considered in the identification of non-reliable systems.

Fuel Cells

There were only six fuel cells in the population for which data existed. No specific relationship was found between fuel cell manufacturers and system reliability – all fuel cells were found to be operating fine.

Microturbines

Microturbines are well suited for generating electricity between 30 and 350 kW. They also have the ability to be "stacked" together to serve larger load and utilize waste heat more effectively. Due to the ability to use microturbines in this fashion, specific guidelines were implemented to determine if the microturbines were reliable. A few of the problems associated with the microturbines were sporadic operation throughout the metering period, system shutdown for a relatively longer period of time, and non-functional systems. Table 3-3 shows total numbers of microturbines by manufacturer and the reliability of different manufacturers.

Table 3-3. Microturbines – Manufacturer Reliability Analysis

Manufacturer	System Reliable	System Not Reliable	Reliability Percentage	Error Bound
G	1	3	25%	36%
D	1	1	50%	58%
F	1	1	50%	58%
E	23	5	82%	12%
H	2	0	100%	NA

As can be seen from the table above, microturbines by manufacturer G had 25 percent reliability, whereas manufacturers D and F had 50 percent reliability. However, G and H had high reliability percentages of 82 percent and 100 percent respectively. However it should be noted that these are relatively small installation numbers, as a result, they may not be representative of the population as a whole.

Failure modes have significant variability that is not captured in summary statistics. To illustrate that variability, two examples of some unreliable systems are presented below. Figure 3-1 shows the output to capacity ratio of a system from manufacturer E, which became non-functional shortly after installation. Figure 3-2 shows system from G that failed after a couple years of successful operation followed by an apparent repair that failed after a couple months.

Review of the site electricity production data shows that most of the non-functional microturbines had reliability issues. According to facility representatives, the failures were mainly associated with the microturbine fuel compressors, which fail frequently.

Figure 3-1. Load Profile of a System by Manufacturer E

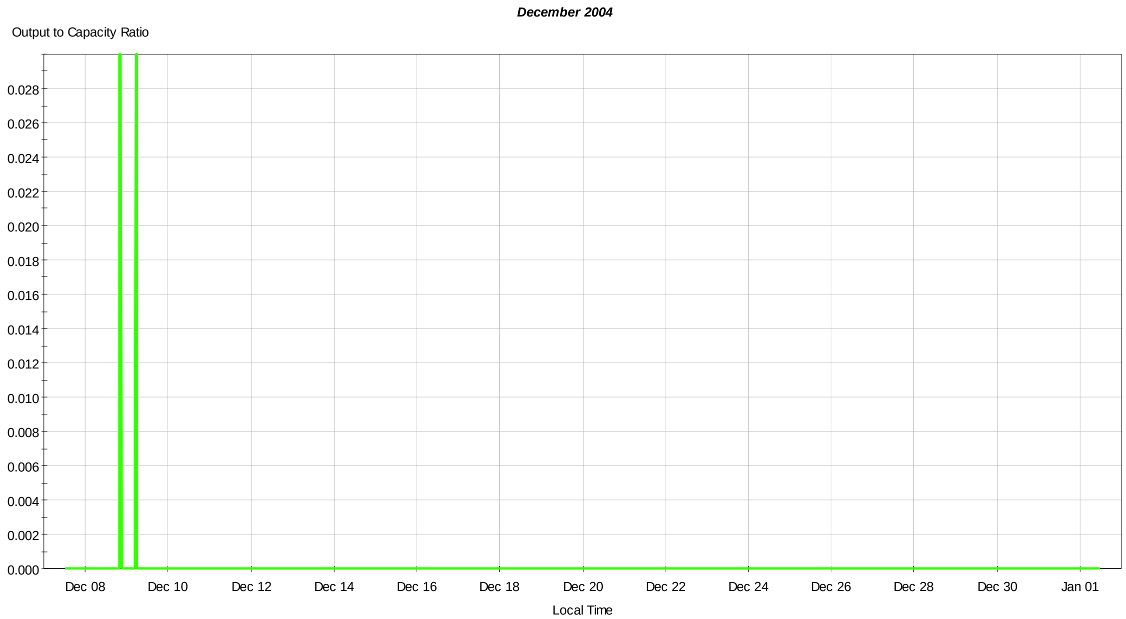
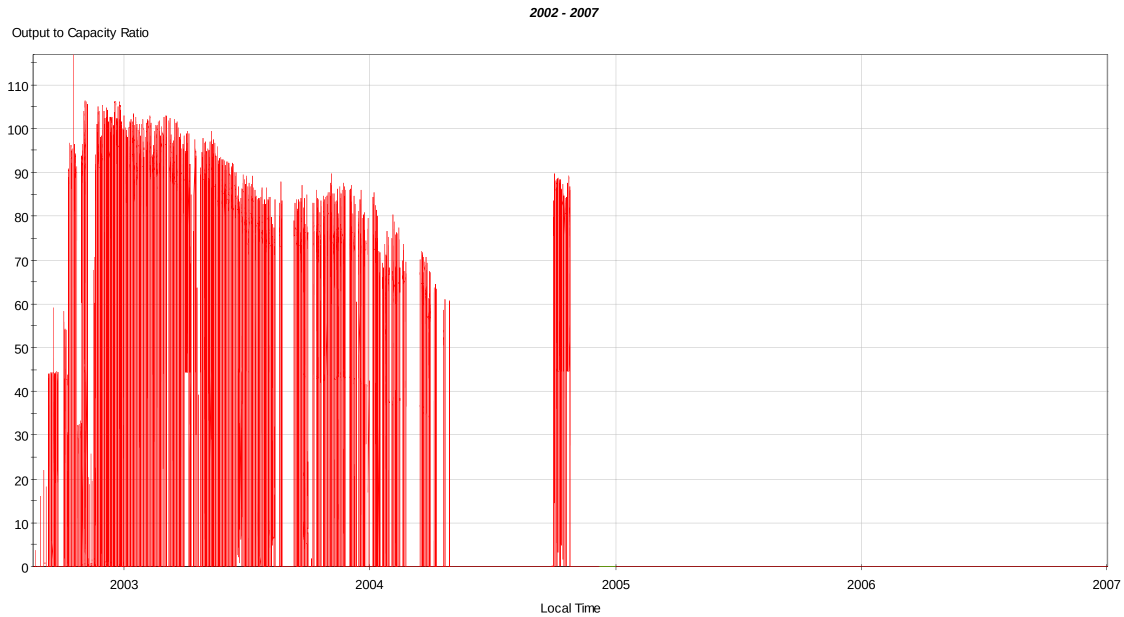


Figure 3-2. Load Profile a System by Manufacturer G



Wind Turbines

There were only two wind turbines in the population data. No specific relationship was found between wind turbine manufacturers and system reliability. All wind turbines were found to be operating reliably but this is not a general conclusion due to the small sample size.

Gas Turbines

There were only two gas turbines in the population data. No specific relationship was found between gas turbine manufacturers and system reliability – as all gas turbines were operating reliably but this is not a general conclusion due to the small sample size.

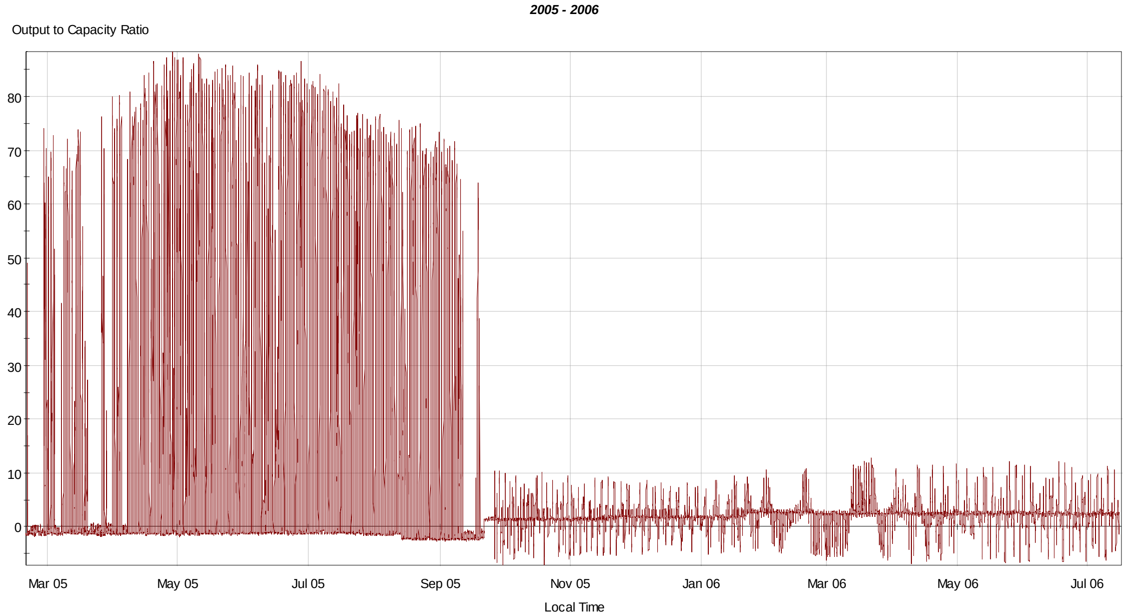
Photovoltaic Cells

All photovoltaic systems were found reliable. All photovoltaic cell manufacturers were found to be reliable – however we had data for a maximum of 5 years. Since they all had the same reliability, no specific relationship differences could be found between photovoltaic cell manufacturers and system reliability.

Specific guidelines were established to determine if the photovoltaic cells had problems. Missing data for more than a period of six months and very low output to capacity ratio were taken into consideration for defining a problematic PV system. There were 276 photovoltaic cells in the data. The reliability percentage of photovoltaic cells was found to be much higher than microturbines and internal combustion engines. For this technology, only one system appeared to be non-functional but it was, in fact, a problem with the meter not with the photovoltaic system.

Figure 3-3 shows the load profile of the photovoltaic system. This photovoltaic cell was categorized as "not functional," as its output to capacity ratio was reduced from 75 percent to 1 percent in September 2005.

Figure 3-3. Load Profile of Questionable Photovoltaic System



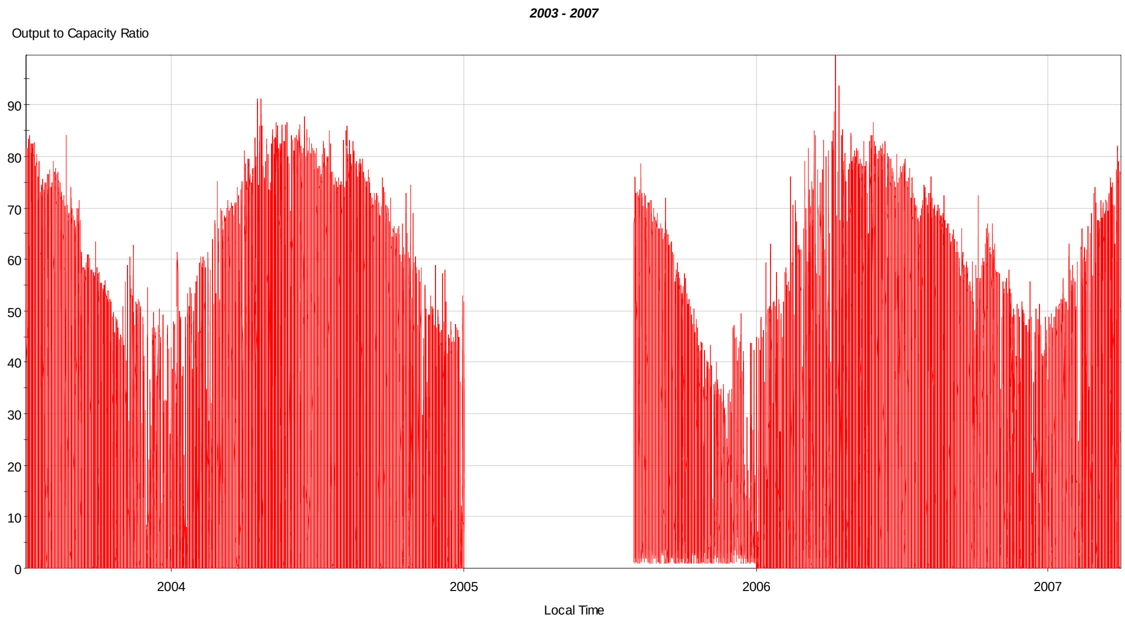
As revealed through discussions with the respective PA and site contacts, this apparent drastic reduction in electricity output was actually a metering problem.

There were many photovoltaics[17] that showed long and short data gaps between two operating periods. The figure below presents an example of missing data for a significant period. It was not clear if the

[17] Approximately 36% of all photovoltaic systems showed long and short gaps between two operating periods.

system was functioning properly in the missing period. This is possibly a period showing a failed inverter. Unfortunately, such failures are difficult to document retrospectively.

Figure 3-4. Load Profile of a Photovoltaic Cell with Missing Data



Internal Combustion Engines

Internal combustion engines are well suited for a variety of self-generation applications. Internal combustion engines were characterized as problem systems if they had not been functional or had sporadic output to capacity ratios throughout the monitoring period. Table 3-4 shows the relationship between the manufacturers of internal combustion engines and their reliability.

Table 3-4. Internal Combustion Engines - Reliability Analysis

Manufacturer	System Reliable	System Not Reliable	Reliability Percentage	Error Bound
O	0	1	0%	NA
Q	16	11	59%	16%
N	2	1	67%	45%
T	10	4	71%	20%
L	3	1	75%	36%
M	4	1	80%	29%
K	12	2	86%	15%
I	1	0	100%	NA
J	7	0	100%	NA
P	2	0	100%	NA
R	1	0	100%	NA
S	8	0	100%	NA
U	1	0	100%	NA
V	1	0	100%	NA
W	2	0	100%	NA

As the above table shows, ICE manufacturer reliability rates range from 0 to 100 percent. The single system from Manufacturer O always had problems and ultimately suffered a catastrophic failure after only a few months of being operational. This led to a 0 percent reliability rate for Manufacturer O, which should not, however, be assumed for the whole of its production. Manufacturers Q and T also showed low reliability percentages, which can be considered more accurate as they each had many more systems in the data. Figure 3-5 shows the output to capacity ratio of the Manufacturer Q's engine throughout the monitoring period. Figure 3-6 shows a system by manufacturer T. Both of these systems are currently not functional.

Failed systems by manufacturer Q were almost always non-functional due to reliability issues. Additionally, replacement parts for these systems were not readily available, slowing repair time. These problems finally led the systems to be considered non-functional. Maintenance problems were frequently cited for non-functional systems from other manufacturers. For example, one site's system was completely disassembled and the engine rebuilt, but the maintenance issues were still unable to be resolved.

Figure 3-5. Load Profile of a System by Manufacturer Q

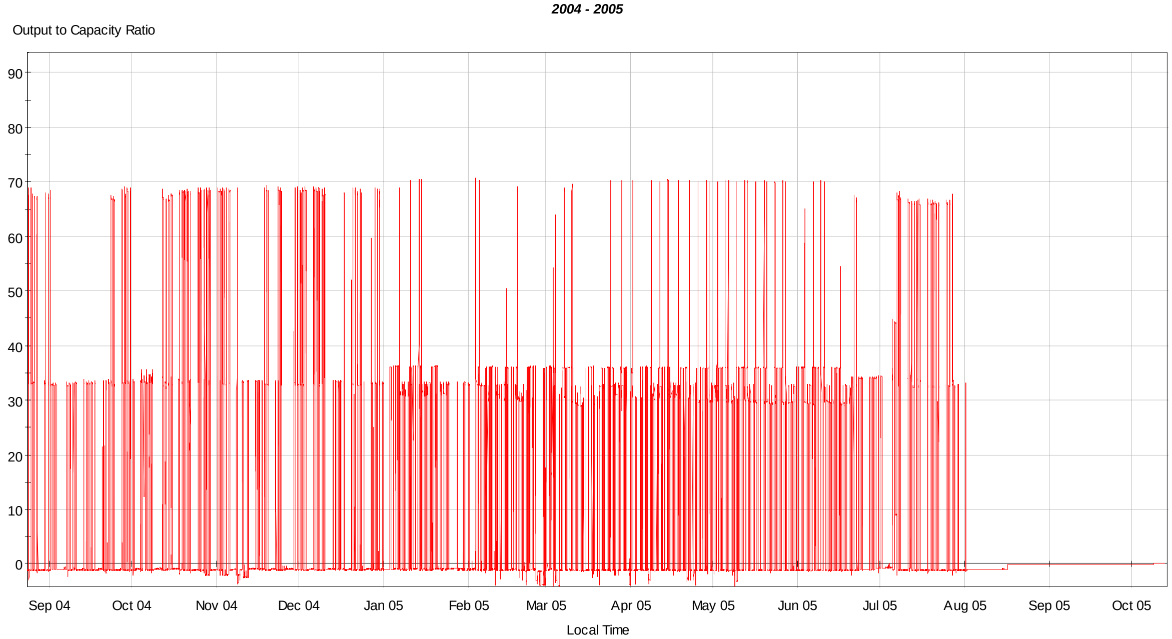
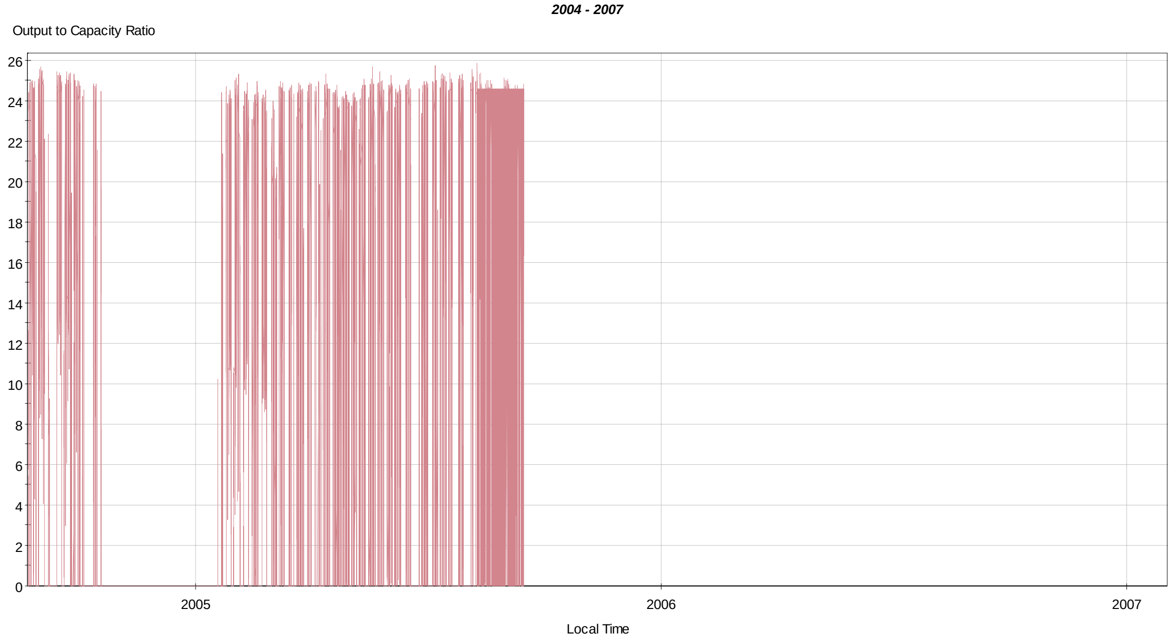


Figure 3-6. Load Profile of a System by Manufacturer T



3.3 Statistical Effective Useful Life Analysis

In the statistical analysis, survival proportion was computed by system type. Multiple survival models for some selected systems (internal combustion engines and microturbines[18]) were examined for computing EUL. EUL was then estimated from the models that best fit the data, and finally the estimates and related results from the models were examined.

3.3.1 Survival Proportion

Table 3-5 summarizes the estimated survival proportions by system type. The survival proportion for a technology is simply the ratio of the number of systems that survived to the total number of systems in the data.

There were no observed system failures for fuel cells, wind turbines, photovoltaic cells or gas turbines, so the survival proportion of each of these four system types was 100 percent. Table 3-5 also shows that 70 percent of microturbines and 81 percent of ICEs are still functional. Overall, 93 percent of all systems are still functional. The error bounds associated with each of the percentages are presented in the last column of Table 3-5.

Table 3-5. Survival Proportions by System Type

System Type / Technology	Population Total	System Still Functional	System Not Functional	Percent Functional	Error Bound
Fuel Cells	6	6	0	100%	NA
Microturbines	40	28	12	70%	12%
Wind Turbines	2	2	0	100%	NA
Photovoltaic Cells	276	276	0	100%	NA
Gas Turbines	2	2	0	100%	NA
Internal Combustion Engines	93	75	18	81%	7%
All	419	389	30	93%	2%

3.3.2 Effective Useful Life

Microturbines

As discussed above, the examination of the SGIP data provided by Itron classified all sites into two categories – "functional" and "not functional." This information was used to estimate the survival function

[18] EULs could not be computed for fuel cells, gas turbines and wind turbines due to a small sample size. EUL for photovoltaic cells could not be computed as the survival rate for photovoltaics was 100%.

assuming four standard survival models, using the SAS procedure "LifeReg." Table 3-6 shows the estimated alpha and beta parameters[19] of each of the four estimated survival functions: Exponential, Weibull, Logistic, and Log Normal. A single parameter, denoted alpha, characterizes the exponential survival function, whereas two parameters characterize the remaining three survival functions. Appendix B provides descriptions of the functional forms of these four models.

The computation of EUL used data on 38 microturbines, after excluding all outliers.

There were two microturbines that were excluded from the analysis as they were outliers. One site had data for only day and the other showed breakdown almost immediately after first operation. If these two sites are included in the computation of EUL, then the results from Weibull, Logistics, and Exponential models do not substantially change– but the EUL computed by the Log Normal model goes up by 10 years. Note that Log Normal was not chosen as the best model for microturbines.

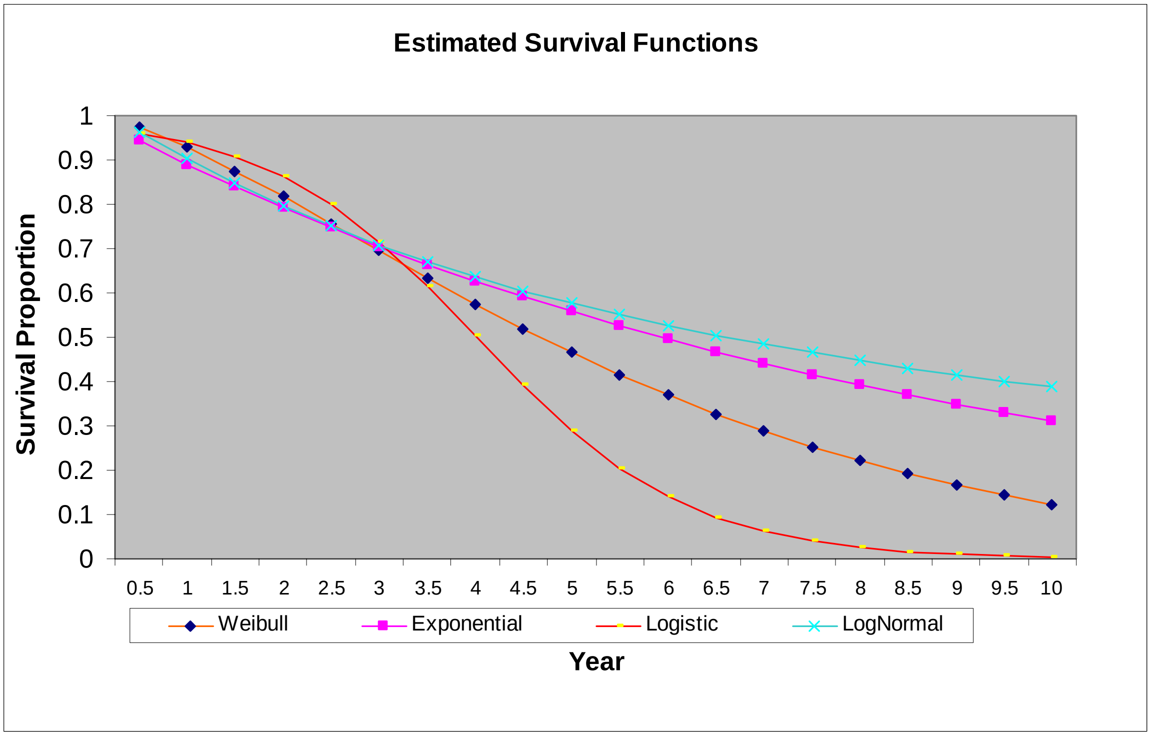
Table 3-6. Estimated Parameters of the Survival Equations – Microturbines

Model	Alpha	Beta
Exponential	3,124.5	NA
Weibull	2,196.7	1.5
Logistic	1,466.1	400.2
Log Normal	7.8	1.4

[19] The functional forms in Appendix A show how parameters alpha and beta shape the survival functions. Some relevant discussion of parameters is also in the "Discussion of the Results" sub-section.

The estimated survival functions were used to calculate the survival proportions for ten years, as shown in Figure 3-7. As expected, the functions declined over time. Note that the survival proportion is equal to .5 when the number of years is between four and seven.

Figure 3-7. Estimated Survival Functions – Microturbines[20]



Each of the four estimated survival functions was used to calculate the EUL of microturbines through the program. The EUL was determined by calculating the number of years at which the survival proportion would equal 50 percent, or the median of the survival distribution.

Table 3-7 summarizes the EUL calculation results. The estimated EULs range from a low of 4.0 years (1,466 days) under the Logistic model to a high of years 6.6 years (2,414 days) under the Log Normal model.

Approximately 30.0 percent of the microturbines in the data were classified as "not functional". The values of the log-likelihood statistics of each survival model were examined to determine which model best fits the current data.

As shown in the table, the Weibull survival model best fits the microturbine data at this time.[21] The survival function of this model in Figure 3-7 suggests that the failure rate did not vary much over time. The Weibull

[20] Appendix C: Data Review contains scatter-plots of the raw data used in EUL computation.

[21] All standard errors were computed using the Lifereg procedure in SAS. Using the values of the log-likelihoods of each model and Bayesian statistics, the Team also calculated the probability that each survival model is the correct model given the sample

model was selected as the final survival model for microturbines. The EUL is estimated to 4.7 years (1,706 days) under Weibull.

Table 3-7. Effective Useful Life for Microturbines

Model	EUL (in days)	Standard Error	90% Conf. Interval		Log Likelihood	P(M|S)
			Lower Bound	Upper Bound		
Exponential	2,166	684.9	1,039	3,292	-27.8	0.27
Weibull	**1,706**	434.0	**992**	**2,420**	**-26.9**	**0.61**
Logistic	1,466	188.5	1,156	1,776	-90.5	0.00
Log Normal	2,414	1,035.7	711	4,118	-28.6	0.12

Photovoltaics

All photovoltaic systems have survived until the current time.

As the survival rate for photovoltaics was 100 percent, the Team could not conduct any survival analysis nor compute EULs for the photovoltaic systems.

The total lifetime of a photovoltaic system varies by application and manufacturer. EUL is a statistical expression of lifetime that is not normally used by manufacturers. Most manufacturers today guarantee that their systems will achieve no less than 80 percent output after 20 years. Note that the Team had meter data for a maximum period of five years.

data (P(M|S)), as shown in the last column of each table presenting EUL. Given the sample data, the Weibull model is the most likely to be the correct model for microturbines.

Internal Combustion Engines

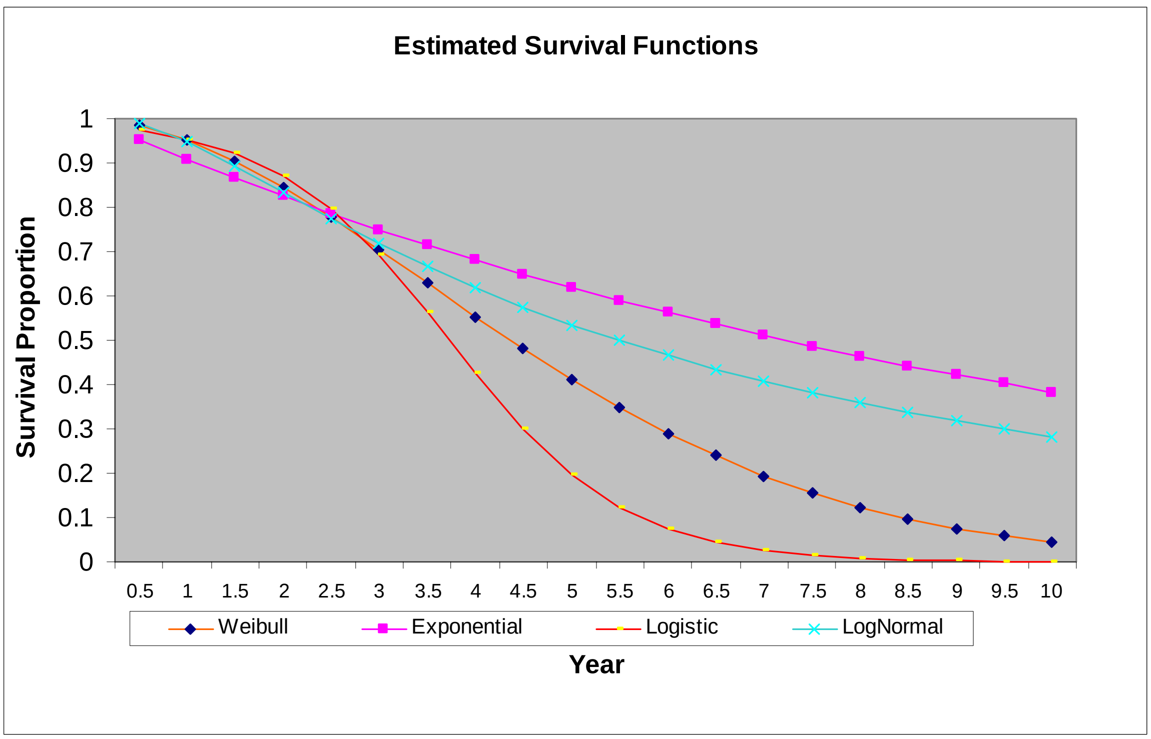
Table 3-8 shows the estimated parameters of each of the four estimated survival functions for ICEs. The estimated survival functions were used to calculate the survival proportions for ICEs for ten years, as shown in Figure 3-8.

Data on 91 internal combustion engines was used for the computation of EUL, after excluding all outliers.

Table 3-8. Estimated Parameters of the Survival Equations – Internal Combustion Engines

Model	Alpha	Beta
Exponential	3,803.9	NA
Weibull	1,947.3	1.8
Logistic	1,361.3	330.5
Log Normal	7.6	1.1

Figure 3-8. Estimated Survival Functions – Internal Combustion Engines[22]



Each of the four estimated survival functions was used to calculate the EUL of internal combustion engines. The EUL was determined by calculating the number of years at which the survival proportion would equal 50 percent, or the median of the survival distribution. Table 3-9 summarizes the results. The estimated

[22] Appendix C: Data Review contains scatter-plots of the raw data used in EUL computation.

EULs range from a low of 3.7 years (1,361 days) under the Logistic model to a high of 7.2 years (2,637 days) under the Exponential model.

The values of the log-likelihood statistics of each survival model were examined to determine which model best fits the current data. As shown in the table, the Weibull survival model best fits the ICE failure data. The ICE EUL is estimated to be 4.4 years (1,591 days).

Table 3-9. Effective Useful Life for Internal Combustion Engines

Model	EUL (in days)	Standard Error	90% Conf. Interval		Log Likelihood	P(M|S)
			Lower Bound	Upper Bound		
Exponential	2,637	639.4	1,585	3,689	-77.5	0.00
Weibull	**1,591**	**279.7**	**1,131**	**2,052**	**-47.3**	**0.63**
Logistic	1,361	128.9	1,149	1,573	-156.2	0.00
Log Normal	2,000	512.1	1,158	2,843	-47.9	0.37

3.3.3 Results Discussion

In the SGIP retention study, the Team saw that overall about 92.8 percent of systems have survived to the current time. For different survival functions, microturbines, for example, would survive anywhere from 4.0 years to 6.6 years with 0.5 probability. The Exponential survival model assumes that the failure rate is constant from year to year over the life of the systems. Under the Exponential survival function, microturbines would survive 5.9 years with 0.5 probability. Under the Weibull model, the value of the beta parameter determined if the survival function has increasing or decreasing failure rates. If the value of the beta parameter is less than one, the resultant survival model assumes a failure rate that decreases over time, and if the beta parameter is greater than one, the survival model assumes the failure rate increases over time. The estimated beta parameter for internal combustion engines is 1.8, indicating an increasing failure rate for the initial years under the model. The beta parameter for microturbines was 1.5. Note that a decreasing failure rate is generally counterintuitive due to technological degradation.

The Team did not have data for more than five years for any of the systems. Since none of the PV systems have failed to date, it was impossible to calculate a failure rate for them. Therefore, at the present time, the observed data for photovoltaics are insufficient to correctly identify the EUL.

3.4 Lessons Learned

This study examined only a sample of the installations in the SGIP; the results cannot be generalized beyond that population. The principal substantive and methodological conclusions of this study are:

- At the current time, all of the photovoltaics are still installed and in operation. Since the current level of retention is so high for photovoltaics, there is too little information to determine reliably how long the units will last, i.e., to reliably estimate the EUL.

- Approximately 70 percent of microturbines were in place at the time of this study. The estimated EULs range from a low of 4.0 years (1,466 days) under the Logistic model to a high of years 6.6 years (2,414 days) under the Log Normal model.
- Over 80 percent of internal combustion engine systems have been retained to the present time. The EUL for ICEs, on the other hand, ranged between 3.7 and 7.2 years.
- Many internal combustion engine and microturbine SGIP installations experienced significant problems with reliability.
- For the models that best fit the data, the EUL was estimated to be 4.7 years for microturbines and 4.4 years for internal combustion engines.
- Interval load data is a reliable way to measure retention – provided the site is metered accurately. However, acquiring data from many of the sites proved problematic.

4 ISSUES FOR FUTURE STUDIES

The following issues should be taken into consideration for future studies of this nature:

- The study assumed availability of reliable meter data over a continuous period of time. However, in many instances the meters did not accurately record the load data. Data were often missing for significant periods. The metering contractors recognize the importance of accurate output measurements and are taking steps to correct these concerns. Recorded electrical output data offer a robust method for identifying system failure, but data stream integrity must be confirmed prior to relying on them for use in future retention studies.

- Practical functionality or functional status is often difficult to determine. Details about specific problem sites from telephone interviews took time and patience. Calls to host customers were often not returned or host customers were difficult to locate, due to changes in business status or contact person. The most common problem was staff and/or ownership changes that resulted in the inability to identify a knowledgeable person to interview. The help of PAs was critical in reaching conclusions regarding site functionality.

- This analysis found significant variation in reliability between various manufacturers. The SGIP technologies continue to evolve and it is probable that differences in reliability by manufacturer will continue to be present but it is also likely to change over time as manufacturers resolve problems they encounter. Future SGIP retention studies should continue to explore reliability differences between manufacturers to track any such change.

- Information on photovoltaic cells is needed for a much longer time period to determine the EUL. At the present time, all of the photovoltaics systems survived. The observed meter data were insufficient to correctly identify the EUL with any degree of reliability.

APPENDIX A: TYPICAL LOAD PROFILES

The annual or daily load profiles of systems vary by technology. The typical load profile of a photovoltaic system, for example, is very different from the load profile of a wind turbine. This Appendix graphs some typical load profiles from the meter data.

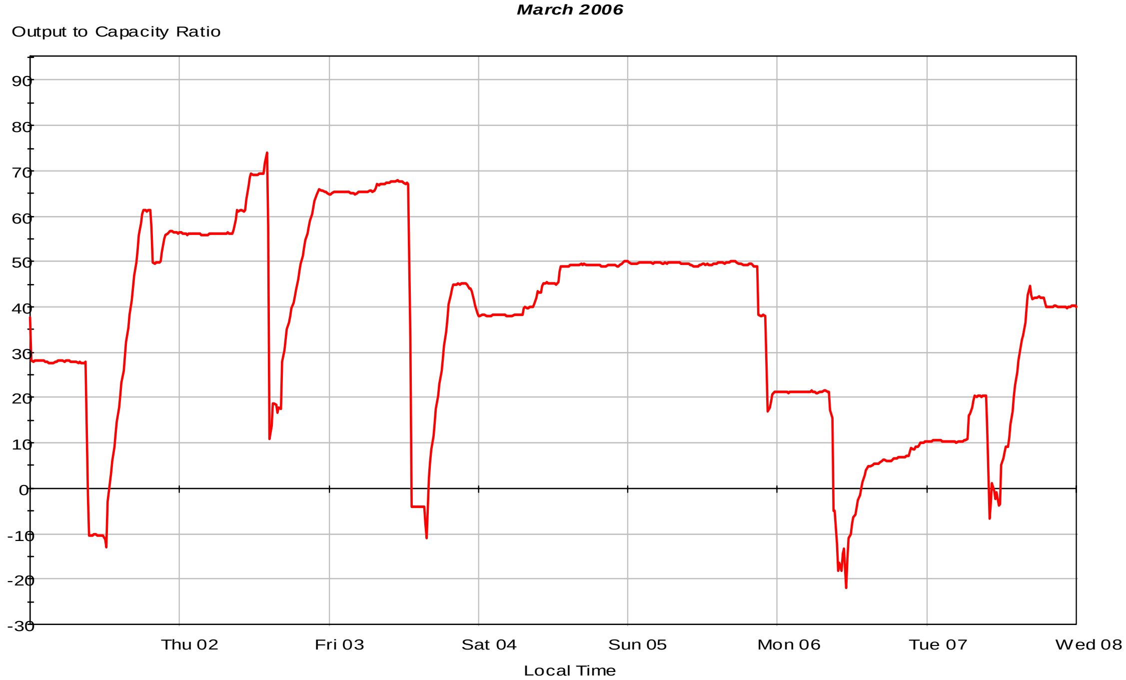
Fuel Cells

Data were available on only six fuel cells. Below is the load profile of a fuel cell from the data.

Figure A- 1. Load Profile of a Fuel Cell from Metered Data (Renewable Fuel)

The figure below plots the output to capacity ratio of the same fuel cell over a period of four days: March 2 - March 07, 2006.

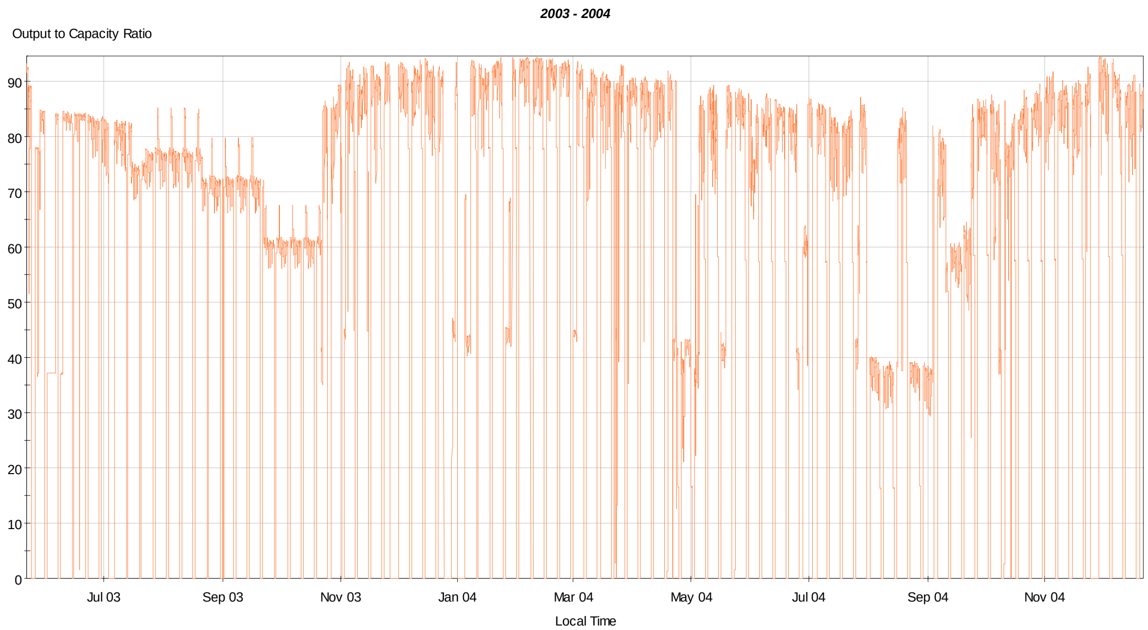
Figure A- 2. A Fuel Cell – March 02 - March 07, 2006 (Renewable Fuel)



Microturbines

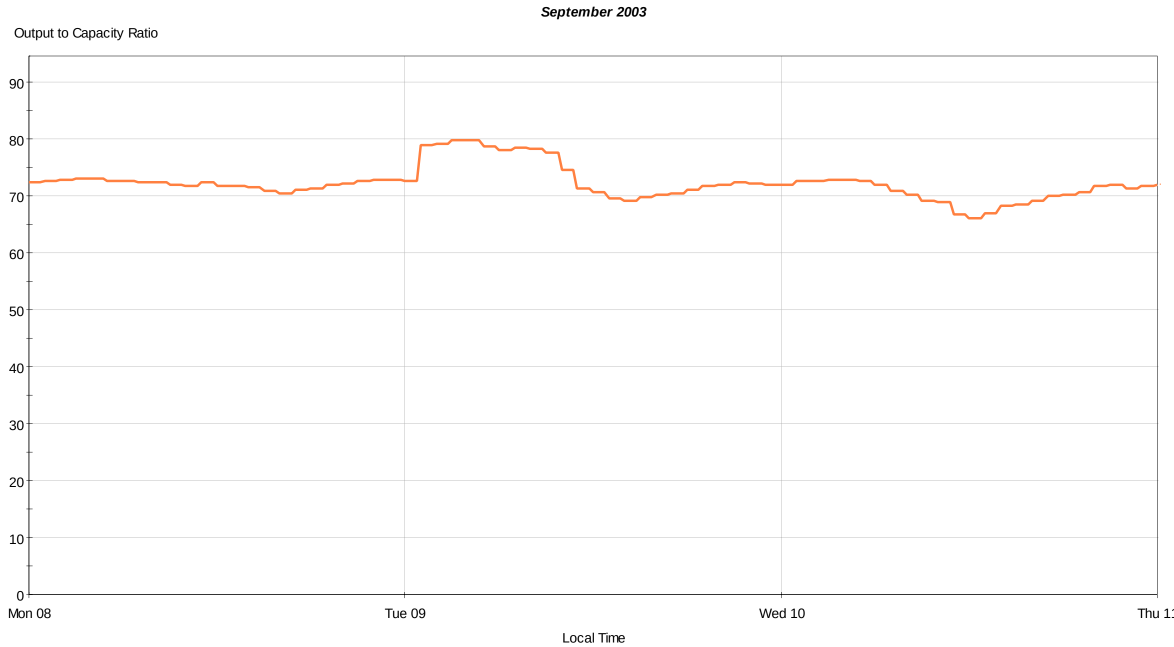
The Team had data on 40 microturbines. The load profile of a microturbine from the data is below.

Figure A- 3. Load Profile of a Microturbine from Monitored Data (Natural Gas)



The figure below plots the output to capacity ratio of the same microturbine over a period of four days, September 8 through September 11, 2003.

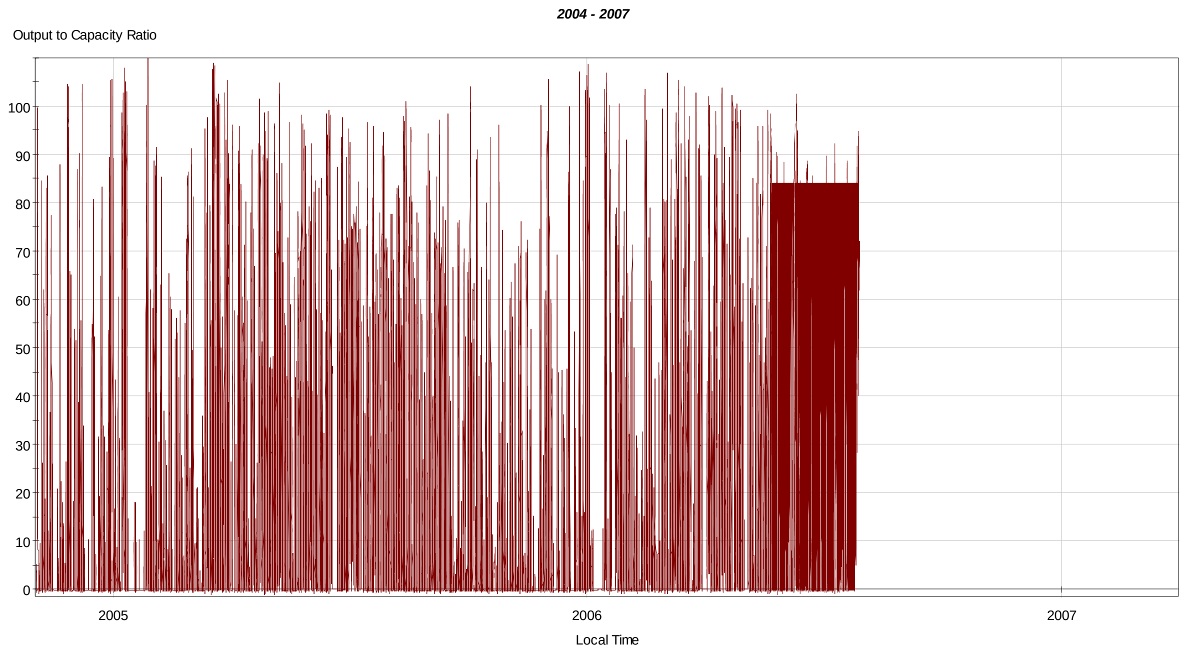
Figure A- 4. A Microturbine – September 8 – September 11, 2003 (Natural Gas)



Wind Turbines

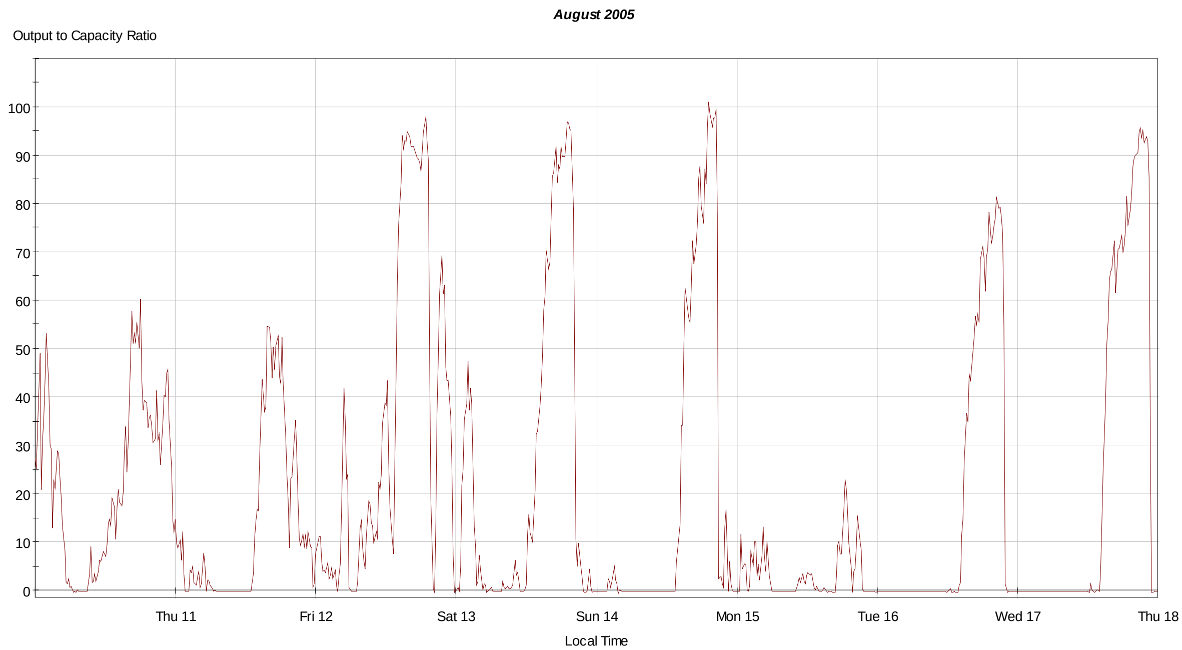
The Team received data on only two wind turbines. Below is the load profile of one wind turbine from the data.

Figure A- 5. Load Profile of a Wind Turbine from Metered Data



The figure below plots the output to capacity ratio of the same wind turbine over a period of four days: August 10 through August 18, 2005. As can be seen from the figure below, electricity production from wind turbines is highly variable but seems to have general daily patterns with low production in the early morning and higher production in the afternoons.

Figure A- 6. A Wind Turbine – August 10 - August 18, 2005



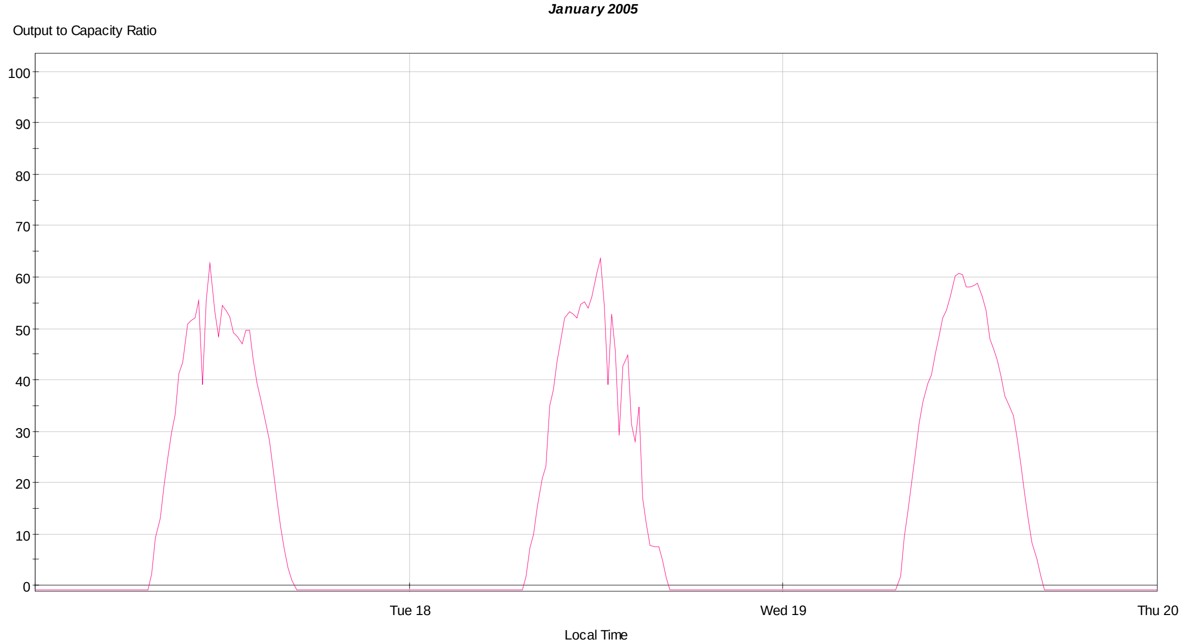
Photovoltaic Cells

The Team had load data on 276 photovoltaic cells in the analysis. The load profile of a typical photovoltaic cell from the data is below. The graph plots output to capacity ratio over time. As expected, the output to capacity ratio in summer is significantly higher compared to winter. In Figure A-7 below, the year stamps (2005, 2006, 2007) below the horizontal axis mark the month of January or the beginning of the year. The electricity production appears to be quite reliable and predictable, tracking closely to available sunlight.

Figure A- 7. Load Profile of a Photovoltaic Cell from Data

The figure below plots the output to capacity ratio of the same site over a period of 3 days: January 17, 2005 through January 20, 2005. Slight day-to-day variation is the result of varying cloud and other weather conditions.

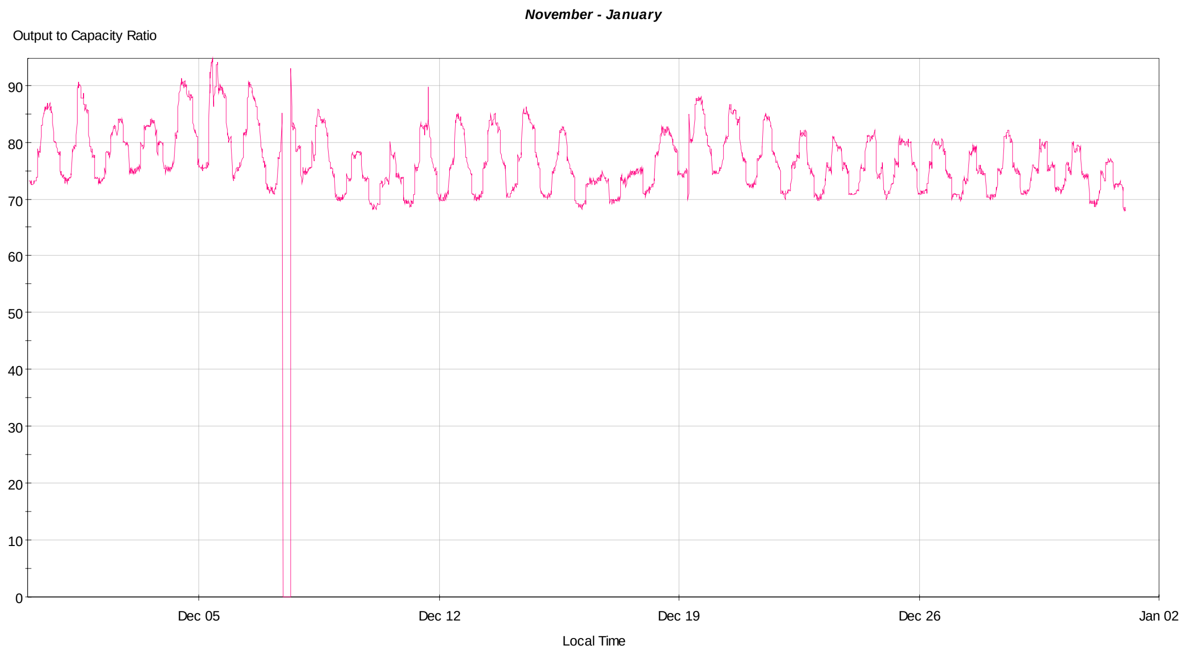
Figure A- 8. A Photovoltaic Cell: January 17 – January 20, 2005



Gas Turbines

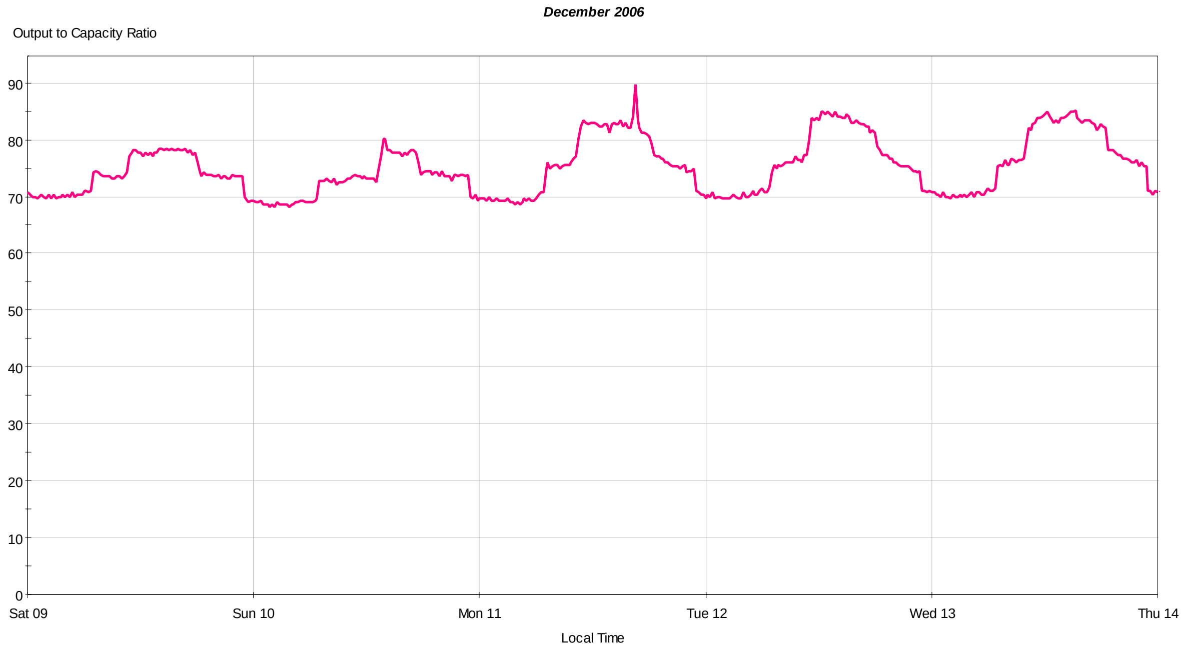
There were two gas turbines in the monitored dataset. Below is the load profile of a gas turbine from the data. As can be seen from the figure below, there was a minor shutdown of this system on December 7 from 10:30am to 3:45pm.

Figure A- 9. Load Profile of a Gas Turbine from Metered Data (Natural Gas)



The output to capacity ratio of the same gas turbine for a period of five days (December 9 – December 14, 2006) is below.

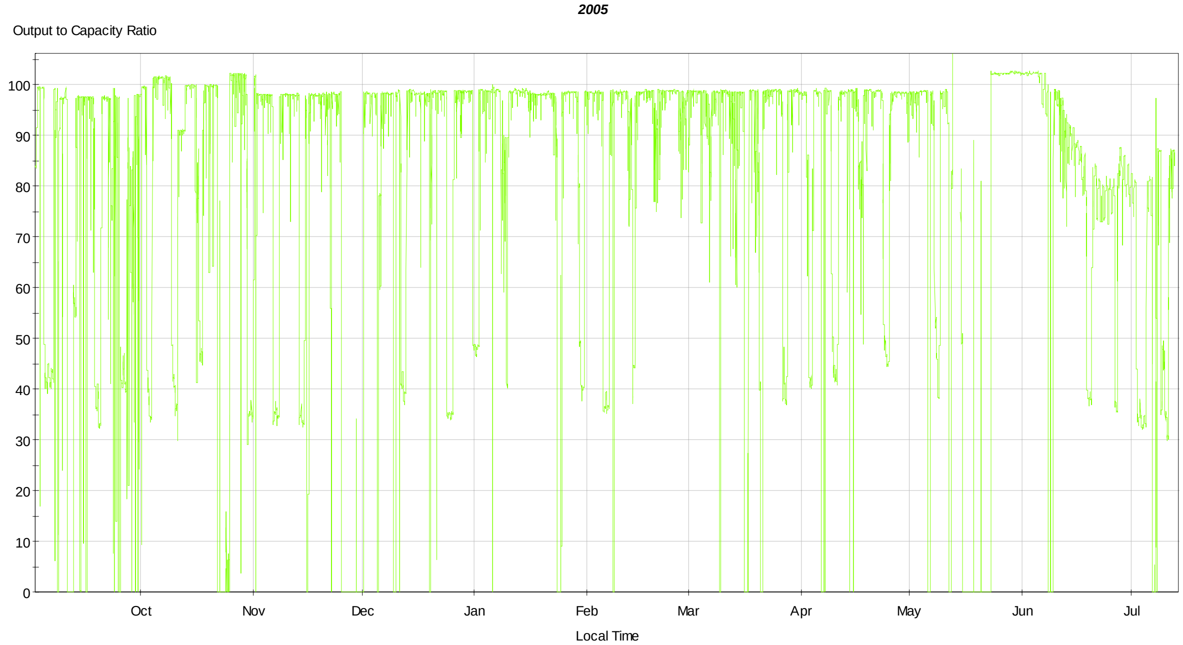
Figure A- 10. A Gas Turbine – December 9 – December 14, 2006 (Natural Gas)



Internal Combustion Engines

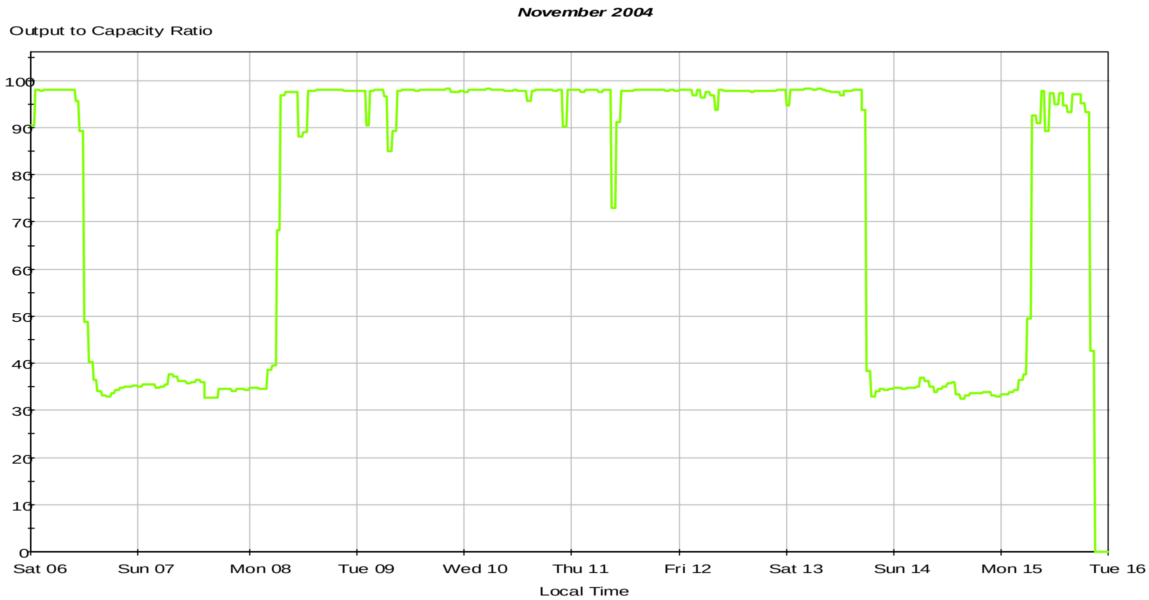
The Team received data on 93 internal combustion engines. The load profile of an internal combustion engine from the data is shown below. The output to capacity ratio of this system is often close to 100 percent.

Figure A- 11. Load Profile of an Internal Combustion Engine from Monitored Data (Natural Gas)



The figure below plots the output to capacity ratio of the same internal combustion engine over a period of one week, November 6 through November 16, 2004. As can be seen from the figure below, the output to capacity ratio of this site dropped significantly during the weekends (November 6, 7, 13 and 14), as might be expected during non-business hours. The load profile of the engine seemed lower on weekends.

Figure A- 12. Output to Capacity Ratio of an Internal Combustion Engine – November 6 – November 16, 2004 (Natural Gas)



APPENDIX B: SURVIVAL FUNCTION

The survival function, conventionally denoted Ŝ, is defined as:

$$\hat{S}(t)=\Pr(T>t)=1-F(t),$$

Where t is some time, T is a random variable denoting the time of death, "Pr" stands for probability, and F is the cumulative distribution function. In other words, the survival function is the probability that the time of death is later than some specified time. The survival function is also called the reliability function in mechanical survival problems. Usually one assumes $\hat{S}(0) = 1$, although it could be less than 1 if there is the possibility of immediate death or failure. Some survival distributions (for example the Gaussian distribution) have the property that $\hat{S}(t) < 1$ for all finite t.

The survival function must be non-increasing: $\hat{S}(u) <= \hat{S}(t)$ if $u > t$. This expresses the notion that survival is only less probable as time increases.

Survival models are constructed by choosing a basic survival distribution. The best-fit parameters of the distributions are then selected using the available data after maximizing the log likelihood functions. Distributions can be substituted for another, in order to study the consequences of different choices. It is natural to choose a statistical distribution which has non-negative support since survival times are non-negative. There are several distributions commonly used in survival analysis – the distributions are listed below:

Exponential: The survival function of the exponential model is below.

$$\hat{S}(t)=\exp(-\alpha*t)$$

Weibull: The Weibull model is a bit more general than the exponential model. Weibull is a two parameter distribution, with parameters alpha and beta. The parameter beta is a shape parameter.

$$\hat{S}(t)=\exp(-\alpha*t)\ \beta$$

Similarly, the survival models for the following Logistics and Log Normal distributions are below.

Logistics:

$$\hat{S}(t)=\frac{1}{1+e^{-(t-\alpha)/\beta}}$$

Log Normal:

$$\hat{S}(t)=\phi(-\beta(\ln(\alpha\, t))$$

where ф is the cumulative distribution of the normal distribution.

APPENDIX C: DATA REVIEW

The meter data was collected by Itron through multiple third party data providers. The meter data contained 15 minute kWh interval load data. Data was stored in 275 SAS datasets. The datasets altogether contained approximately 30 million records for years between 2002 and 2007.

After initial quality checking in SAS and analyzing this interval data in Visualize-IT, some sites were found to have irregularities in their data stream. For example, some sites had data missing for more than six months in the middle of the monitoring period. It appeared the meters did not accurately record the load data and overwrote data from prior periods. Some sites also had sporadic operations throughout their monitoring period. The next sub-section discusses all irregularities that were seen in the data.

Data Assessment

The irregularities seen in the data can be broadly classified into the following six categories.

- Short or Long Gaps in the data:

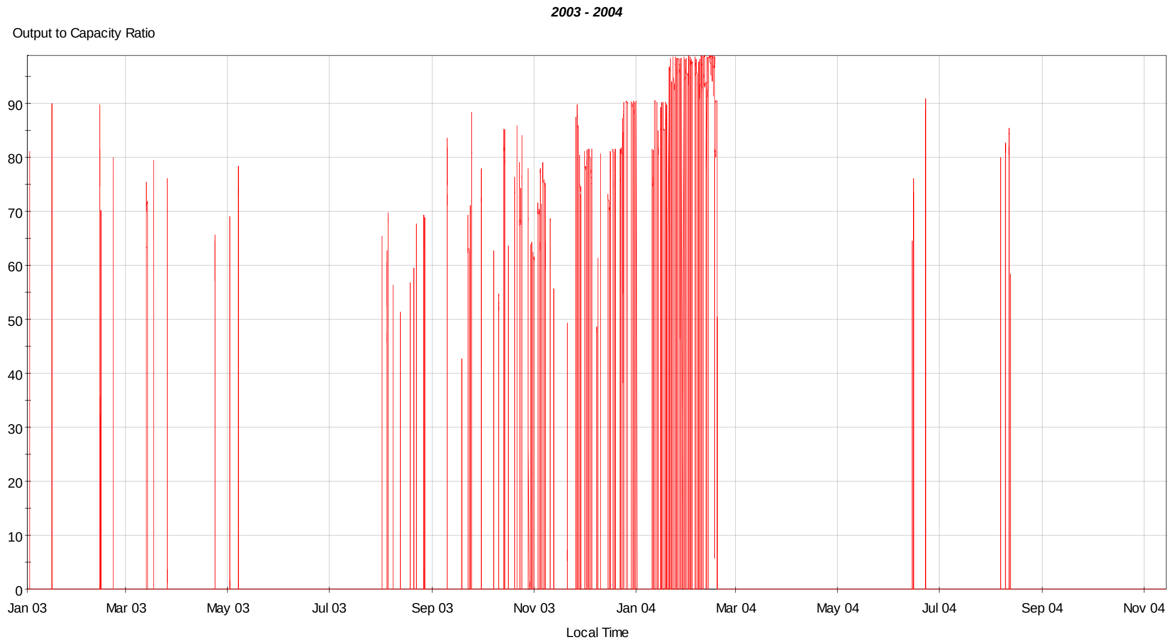
  In some cases, meters overwrote previous data collected by the same meter in prior periods. These meters had memory problems at times, especially when too many parameters were monitored. The oldest data in such cases were deleted before normal monthly data collection could occur. This resulted in long or short gaps in the data for the missing time period. Figure 3-4 shows such gaps in the data.

- System Became Non-functional:

  In some cases the sites seemed to have stopped functioning. Readings recorded at the end of the monitoring periods (and sometimes for a considerable period of time) were all zeros for these sites.

  Below is an example of a site with microturbines that was characterized as a site with failed generation. As can be seen from the graph, the output to capacity ratio was almost always zero after February 2004. This is an example of a "not functional" site.

Figure C- 1. Example of a "Non-functional" Site - Microturbine



- Pattern Change/Sporadic Operation:

  In some cases the data showed significant drops in the output to capacity ratio for some part of the operating period. The actual reason behind a fall in the output to capacity ratio may vary by technology. For example, in case of a microturbine, a fall in the output to capacity ratio may be due to multiple systems operating. It may be the case that some (out of the multiple) systems were not operating at all times. Declines in the output to capacity ratio of an internal combustion engine, on the other hand, may be due to drastic load variations.

  Figure 3-2 shows a microturbine with much lower output to capacity ratio in July and August of 2004.

- Minor or Major Shutdown:

  In some cases there were major or minor shutdowns in between two operational periods. These shutdowns occurred for various reasons. For example, one host customer had a complete shutdown of their system for several months. Their heat exchanger was out in November and December of 2004, preventing the system from operating. The site began its operation again in February 2005. Figure C-1 shows a microturbine with several shutdowns before the system finally became non-functional.

- Spikes in the Data:

  In some cases, the Team saw spikes in the data. The output to capacity ratio in such cases went up significantly higher than normal, but for a very short period of time. The exact reasons behind the spikes are not known. Figure A- 7, a load profile for a photovoltaic system shows such a spike.

- Negative output to capacity ratio:

  In some cases, the Team saw negative output to capacity ratio in the load data. Negative kW values were recorded in such cases for a significant time period. Figure A- 1 above shows such an example.

Telephone Interviews

The above irregularities in the data stream could have been due to malfunctioning of the monitoring equipment, system being non-functional, data acquisition issues or some other reason. To identify what caused the irregularities, the Team used telephone surveys whenever possible to obtain information for the individual sites. In these surveys, the Team asked the site contact several questions about their system's performance, including the following:

- Is the site operating reliably?
- If it not operating, what is the reason behind the breakdown?
- If the system is fully functional, then is it providing desired output?

Unfortunately, the response rate of these interviews was low.

Raw Data in EUL Computation

The following table (Table C- 1) shows the summary statistics of the data that was used in EUL computation. After excluding all periods that had missing data, the meter data showed that the average number of days a microturbine ran was 822 days. The internal combustion engines, on the other hand, ran for 710 days on average.

Data for systems that are currently functional were right-censored.[23] For example, if we had meter data for 2 years for a system that is currently functional, then we concluded that the system operated successfully for a minimum of 2 years. The scatter-plots of the raw data (in figures below) would show only 2 years for this particular system.

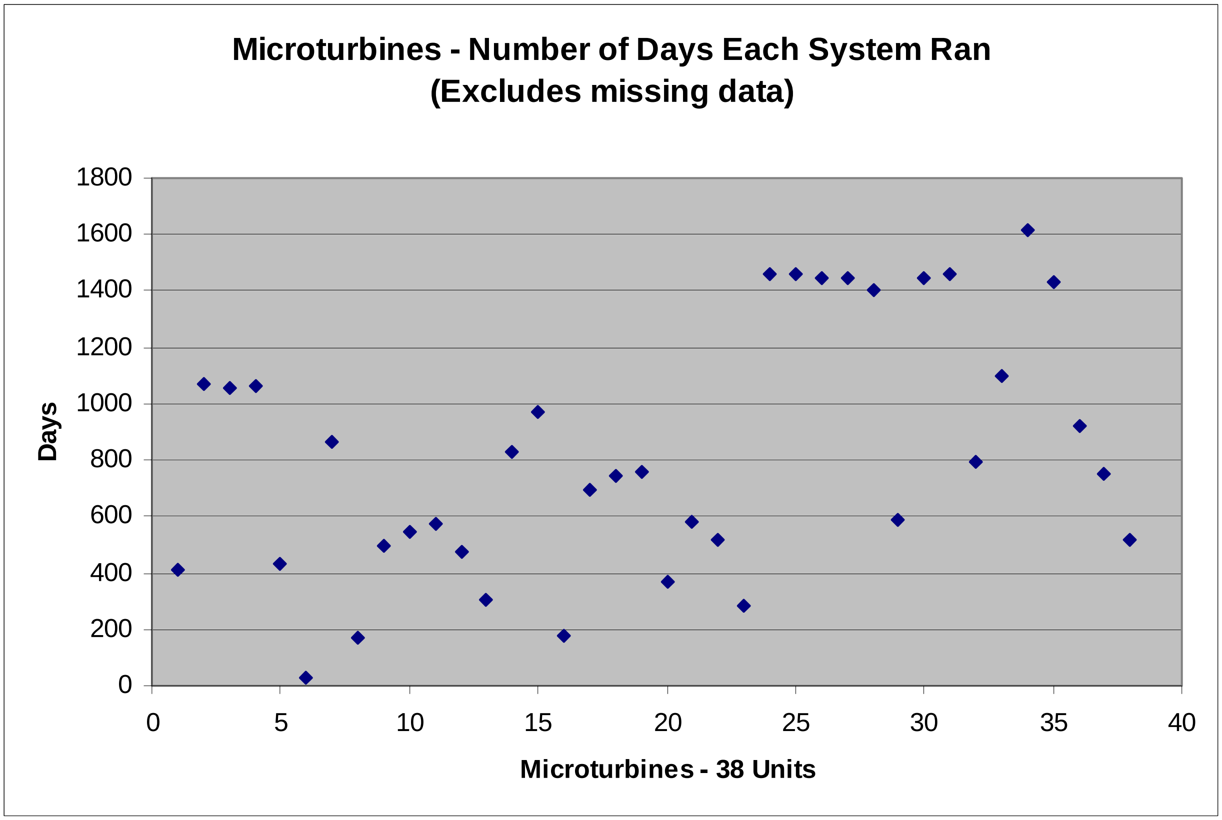
Table C- 1. Summary Statistics of Data (Number of Days Systems ran) used in EUL computation

System Type / Technology	Sample Size	Mean	Min	Max	Std Dev
Microturbines	38	822	30	1,630	443
Internal Combustion Engines	91	710	62	1,460	336

The scatter-plot of the raw data used in the EUL computation for microturbines is presented in Figure C-2.

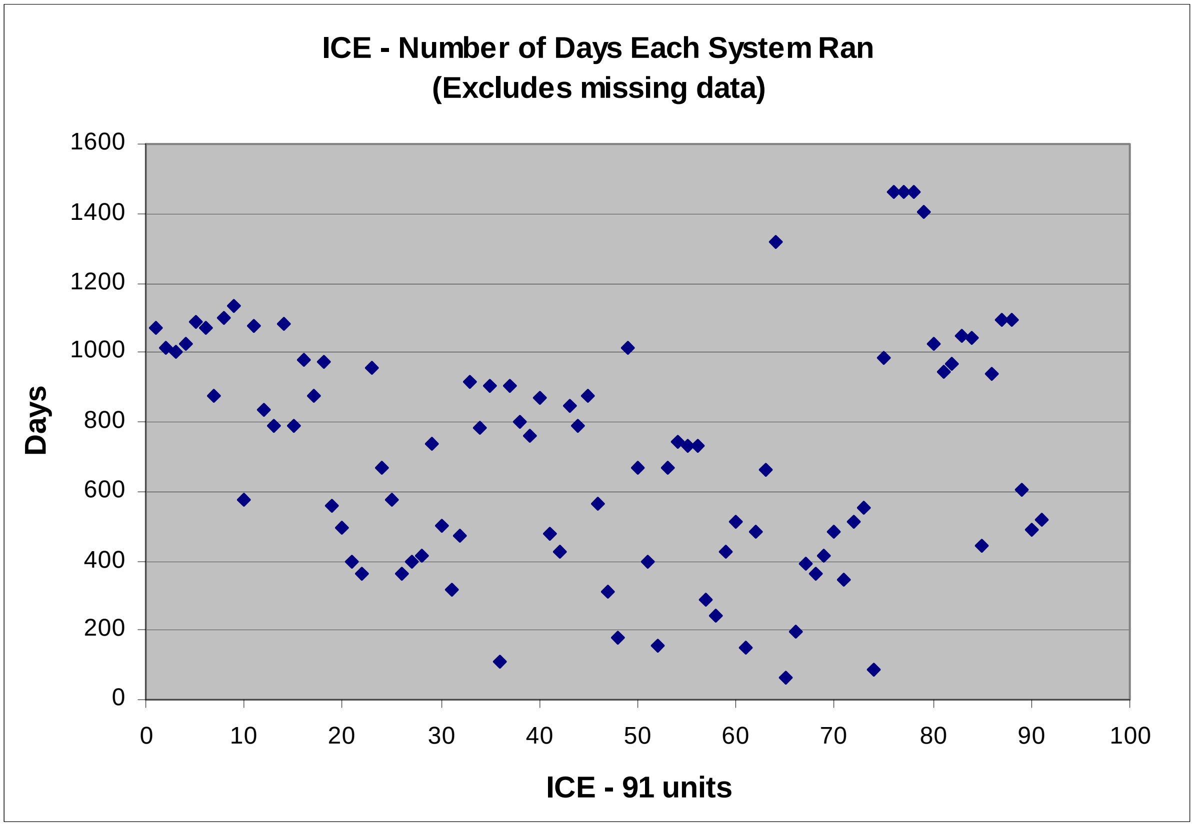
[23] That is, the event of interest (or failure) is to the right of our data point.

Figure C- 2. Microturbines – Raw data for EUL



The scatter-plot of the raw data that was used in the EUL computation for ICE is shown in Figure C- 3.

Figure C- 3. ICE – Raw data for EUL



APPENDIX D: PRACTICAL FUNCTIONALITY

PG&E Failure Classifications

Microturbines

In the PG&E service territory, no microturbines were categorized as non-functional. There were only 4 microturbines in the population data.

Internal Combustion Engines

The six non-functional internal combustion engines in the PG&E service territory mostly had reliability issues and related mechanical problems. Information on some engines could not be verified as the telephone numbers and email addresses of the host customers were no longer valid.

SCG Failure Classifications

Microturbines

In the SCG service territory, six sites with microturbines were categorized as non-functional sites. The majority of these sites had reliability issues. According to the facility representatives, the failures were mainly associated with microturbine compressors, malfunctioning of valves and related mechanical problems. The compressors failed from time to time. They fixed the compressors and the system came back on. It usually takes a week to a month to fix a compressor, depending on the problem. Hence, there was no fixed shutdown period. The load data for these turbines also showed irregular shutdowns in the monitoring period, which generally agrees with the problems identified in the site surveys.

One of these sites had load data available only for a day. The facility personnel stated that the system is functional but the shutdown was due to company policy changes. They are planning to replace the microturbines with a photovoltaic system.

Internal Combustion Engines

There were two internal combustion engines that were considered non-functional.

There was one internal combustion engines that was identified as a problem system. There were maintenance issues associated with this engine. The facility completely disassembled the whole unit and rebuilt the engine and still could not get away with the maintenance issues.

One other site was found to be non-functional due to high gas prices.

SCE Failure Classifications

Microturbines

In the SCE service territory two sites with microturbines were classified as non-functional. For one system, there was a new owner in the facility, who didn't want to "mess with" the already problematic system. For the other non-functional system, no information was available on the technical issues – although the program administrator confirmed that the system is no longer functional.

Internal Combustion Engines

There were four internal combustion engines identified as problem systems in the SCE service territory. Three of these four systems were manufactured by a firm that could not supply the needed replacement parts. This problem finally led the systems to be non-functional. Information is not available on the fourth engine.

SDREO Failure Classifications

Microturbines

In the SDG&E territory, four sites with microturbines were classified as non-functional. One of the microturbines had compressor and other mechanical problems. Information from the interviewees confirmed that a couple of microturbines were non-functional due to high gas prices. These microburbines were non-functional as natural gas prices were no longer economically feasible. Information on one engine could not be verified as the telephone numbers and email address of the host customer were no longer valid.

Internal Combustion Engines

There were six internal combustion engines identified as problem systems in the SDG&E territory. Two of these systems had catastrophic failures. For one other site, the owner of the facility changed and the new owner sold the engine. One non-functional system had compressor, head gasket and related mechanical issues – this facility was also concerned about high gas prices. Information on the remaining engines could not be verified.

APPENDIX E: TECHNOLOGY OVERVIEW

The SGIP provides incentives for a variety of self-generation technologies, each with unique physical, economic, and environmental characteristics. This appendix describes some of the more technical details of these technologies and provides some useful comparisons. For the purposes of this appendix, technologies are grouped by either *non-fuel-fired renewable* (photovoltaics and wind turbines) or *fuel-fired* (fuel cells, microturbines, turbines, and internal combustion engines).

Non-fuel-fired Renewable Technologies

Power from sunlight and wind can be harnessed to generate electricity. The SGIP provides incentives for photovoltaics and wind turbines, which convert solar radiation and the kinetic energy of wind, respectively, into electricity.

Photovoltaics

Photovoltaics are semiconductor materials used to convert solar radiation into direct current (DC) electricity. For self-generation applications, an inverter is then used to convert this to alternating current (A/C). Manufacturers typically guarantee their photovoltaics for 20 years, during which time a degradation of 1 percent per year is allowed for. Inverters can last for 10 years, and therefore need to be replaced at least once over the lifetime of the photovoltaic installation. However, anecdotal evidence from SGIP focus groups suggests that inverter failure may occur somewhat more often.

Self-generation system sizes range from 1 kW or less for residential applications, which are not covered by SGIP, to larger than 1 MW for larger commercial or industrial sites. These capacity ratings are the output of the system a full solar insolation (1000 W/m^2), with actual output depending on the amount of solar insolation available.

Wind Turbines

Wind turbines harness the kinetic energy from wind. They are mounted on towers, large turbines typically 100 feet in the air, taking advantage of stronger and less turbulent winds. Wind blowing over turbine blades creates aerodynamic lift, which rotates the blades. This mechanical energy converted to A/C electricity through an electric generator and power electronics. In general, wind speeds must be greater than 11 miles per hour for small, grid-connected wind power to be cost effective.[24]

Fuel-fired Technologies

Fuel-fired self-generation technologies are those in which the chemical energy contained in a gaseous (e.g., natural gas, biogas) or liquid (e.g., gasoline, diesel) fuel is converted into useful electrical (and often thermal) energy. Conversion processes inevitably produce a thermal byproduct, i.e., *waste heat*, which is often useful at the self-generation site for space, water or process heating. Waste heat can also be used for thermally-activated cooling, via absorption or adsorption chillers.

[24] American Wind Energy Association, Resources Web site: http://www.awea.org/faq/. 2007.

This appendix only discusses *prime-power* self-generation applications. Information in this section is adapted from a similar section in Firestone (2007)[25] and includes information from NREL (2003),[26] which provides a more detailed description of the technologies than that presented here. The following sub-sections describe each of the fuel-fired technologies. The table below provides a comparison of characteristics across technologies.

Internal Combustion Engines

Internal combustion engines (ICEs) are a prevalent technology used for a wide range of applications, including lawn-movers, back-up generators, automobiles, and prime-power generation. These engines are characterized by combustion of fuel - ignited either by electric spark (i.e., *spark ignition*) or compression (i.e., *diesel engines*) - in a series of chambers to move pistons in a sequence. This mechanical power from the engine is converted to electrical power through an electric generator.

ICEs for prime-power applications are typically fueled by natural gas or diesel, although in California, diesel engines have limited application for prime power applications due to current California Air Resources Board (CARB) standards. Natural gas ICEs for prime power range in power capacity from 10s of KW to several MW.

- ICEs have been an important technology for self-generation smaller than several MW.
- Electrical efficiency typically ranges from 25 percent (higher heating value (HHV)) for small engines to greater than 40 percent for larger engines.
- The portion of fuel energy not converted to electricity is roughly evenly split between exhaust gas (400-600°C) and engine cooling loop (~85°C).
- ICEs have relatively fast start-up times (~ 1 minute) and ramp up or down over a wide-range of power outputs (typically from 40 percent to 100 percent or 110 percent of rated capacity) quickly enough for load-following applications.

Gas Turbines

In a gas turbine, air is compressed, combined with gaseous fuel, combusted, and expanded through a turbine in a continuous process. Gas turbines are typically available in the range of 1 MW to 100s MW, and prime-power on-site generation above ~5 MW (i.e., not included in SGIP) is most commonly provided by gas turbines.

- Gas turbines typically have electrical efficiencies in the range of 25-40 percent.
- The portion of fuel energy not converted to electricity exits the turbine in the form of hot exhaust (250-750°C).
- Start-up times range from a few minutes for smaller units to a half hour for utility-scale turbines.

Microturbines

In recent years, smaller versions of gas turbines have become commercially available. These *microturbines* are available in the range of 30 kW to 100s kW. Microturbines have been designed with all moving parts on a single shaft and with air bearings to eliminate the need for lubrication oils. Such a

[25] Firestone, Ryan. “Optimal Real-time Dispatch for Integrated Energy Systems.” Doctorial dissertation, University of California, Berkeley. September 2007. Published as Lawrence Berkeley National Laboratory report LBNL-63485.

[26] National Renewable Energy Laboratory. “Gas-Fired Distributed Energy Resource Technology Characterizations.” (NREL/TP-620-34783) November 2003

design offers the potential for low maintenance/high reliability machines, although this has yet to be conclusively demonstrated in the field.

- Microturbines have electrical efficiencies in the range of 25-30 percent.
- Exhaust gas (200-300°C) accounts for the remainder of fuel energy.
- Microturbines have a start-up time of approximately two minutes.
- Experience has shown that microturbine failure increases when the power output varies (i.e., load-following). Typically, microturbines are operated in the range of 85 percent to 100 percent of nameplate capacity.
- Relative to reciprocating engines, microturbines (and gas turbines) offer significantly lower rates of NO_x emissions.

Fuel Cells

Unlike combustion-driven electricity generation equipment, fuel cells harness chemical oxidation to convert the chemical energy of gaseous fuels (reformed into hydrogen) to electricity, and fuel cells emit virtually no NO_x, SO_x, or particulate matter (PM). Fuel cells are available in sizes ranging from several kW to several MW, although they are still a developing technology and not yet commercially viable. Public subsidies have spurred fuel cell adoption at hundreds of sites across the U.S.

- Electrical efficiencies are in the range of 30-50 percent.
- The remainder of fuel energy is rejected through the stack cooling loop at temperatures 80-600°C, depending on the type and design.
- Fuel cells have the poorest start-up times (minutes to hours) and ramping rates of fuel-fired DG and are not good candidates for responsive self-generation applications, such as load following or price-responsive controls.

Biogas for Fuel-fired Technologies

The most prevalent fuel for fuel-fired self-generation technologies is natural gas. However, biogases may be available at little or no cost, and often it is the availability of this potential fuel that creates a self-generation opportunity. Biogas self-generation projects can have lower economic risk than natural gas self-generation projects because biogas does not have the price volatility that natural gas has.

Biogas is a product of anaerobic (i.e., without oxygen) digestion of organic matter. Biogas is primarily methane, and can be cleaned to form a product similar in composition to natural gas. It can be used in all of the fuel-fired technologies described here. The primary sources of biogas for self-generation are landfills and manure digesters.

Landfills

Biogas is formed in landfills when organic matter beneath the surface of the landfill decomposes. This gas can be directed through vents dug into the landfill and collected for electrical and/or thermal energy generation. Because of the explosive danger of landfill gas, it is often flared as it can be difficult to find another use for it. However, increasing the capture of landfill gas has been identified as an early response action by California Environmental Protection Agency and CARB under AB 32, the Global Warming Solutions Act.

Manure Digesters

Manure can also be used to generate biogas. Agricultural manure is often not cost effective to collect for this purpose. However, dairy farms, where dairy cows are kept in close proximity, do provide a relatively low-cost opportunity for manure-collection. Typically, manure is periodically rinsed from the floor where the cows are to a tank. Here, the manure decomposes over time, producing methane. This process has several added benefits, including odor and pathogen reduction, and several byproducts that can be used as fertilizer.

Waste Heat Recovery

Waste heat from fuel-fired technologies can be transferred to a useful operating fluid through the use of a heat exchanger. Waste heat can be applied to space, water, or process heating, or to thermally-activated cooling, via absorption or adsorption chillers. It is often the displacement of separate fuel consumption for these thermal loads that makes the economic and energy-efficiency case for self-generation, relative to the purchase of grid electricity.

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Comparison of Fuel-fired Technology Characteristics

Table E-1 provides a comparison of fuel-fired self-generation technologies. It is adapted from a similar table in NREL (2003).

Table E-1. Gas-Fired Distributed Energy Resource Technology Characterizations[27]

	ICE	Gas Engine	Microturbine	Fuel Cell
Technology Status	Commercial	Commercial	Early Entry	Early Entry/Development
Size (MW)	0.01-5	0.5-50	0.03-0.25	0.005-2
Electric Efficiency (HHV)	30-37%	22-37%	23-26%	30-46%
Total CHP Efficiency (HHV)	69-78%	65-72%	61-67%	65-72%
Power-Only Installed Cost ($/kW)	700-1,000	600-1,400	1,500-2,300	2,800-4,700
CHP Installed Cost ($/kW)	900-1,400	700-1,900	1,700-2,600	3,200-5,500
O & M Cost ($/kWh)	0.008-0.018	0.004-0.01	0.013-0.02	0.02-0.04
Equipment Life (years)	20	20	10	10
Fuel Pressure (psi)	1-65 (may require fuel compressor)	100-5—(may require fuel compressor)	55-90 (may require fuel compressor	0.5-45
Fuels	Natural gas, biogas, liquid fuels	Natural gas, biogas, distillate oil	Natural gas, biogas	Hydrogen, natural gas
NO□ Emissions (lb/MWh)	0.2-6	0.8-2.4	0.5-1.25	<0.1
Uses for Heat Recovery	Hot water, low pressure steam, district heating	Direct heat, hot water, LP-HP steam, district heating	Direct heat, hot water, low pressure steam	Hot water, low pressure steam
Thermal Output (Btu/kWh)	3,200-5,600	3,200-6,800	4,500-6,500	1,800-4,200
	Recip Engine	Gas Engine	Microturbine	Fuel Cells
Technology Status	Commercial	Commercial	Early Entry	Early Entry/Development
Size (MW)	0.01-5	0.5-50	0.03-0.25	0.005-2
Electric Efficiency (HHV)	30-37%	22-37%	23-26%	30-46%
Total CHP Efficiency (HHV)	69-78%	65-72%	61-67%	65-72%
Power-Only Installed Cost ($/kW)	700-1,000	600-1,400	1,500-2,300	2,800-4,700

[27] Adapted from National Renewable Energy Laboratory, "Gas-Fired Distributed Energy Resource Technology Characterizations," November 2003, NREL/TP-620-34783, Table 2. Comparison of DG Technologies, 1-8.

CHP Installed Cost ($/kW)	900-1,400	700-1,900	1,700-2,600	3,200-5,500
O & M Cost ($/kWh)	0.008-0.018	0.004-0.01	0.013-0.02	0.02-0.04
Equipment Life (years)	20	20	10	10
Fuel Pressure (psi)	1-65 (may require fuel compressor)	100-5—(may require fuel compressor)	55-90 (may require fuel compressor	0.5-45
Fuels	Natural gas, biogas, liquid fuels	Natural gas, biogas, distillate oil	Natural gas, biogas	Hydrogen, natural gas
NOx Emissions (lb/MWh)	0.2-6	0.8-2.4	0.5-1.25	<0.1
Uses for Heat Recovery	Hot water, low pressure steam, district heating	Direct heat, hot water, LP-HP steam, district heating	Direct heat, hot water, low pressure steam	Hot water, low pressure steam
Thermal Output (Btu/kWh)	3,200-5,600	3,200-6,800	4,500-6,500	1,800-4,200

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