GE
Energy Consulting

PJM Renewable Integration Study

Task 3A Part F

Capacity Valuation

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imagination at work

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Acronyms and Nomenclatures

2% BAU	2% Renewable Penetration – Business-As-Usual Scenario
14% RPS	14% Renewable Penetration – RPS Scenario
20% LOBO	20% Renewable Penetration – Low Offshore Best Onshore Scenario
20% LODO	20% Renewable Penetration – Low Offshore Dispersed Onshore Scenario
20% HOBO	20% Renewable Penetration – High Offshore Best Onshore Scenario
20% HSBO	20% Renewable Penetration – High Solar Best Onshore Scenario
30% LOBO	30% Renewable Penetration – Low Offshore Best Onshore Scenario
30% LODO	30% Renewable Penetration – Low Offshore Dispersed Onshore Scenario
30% HOBO	30% Renewable Penetration – High Offshore Best Onshore Scenario
30% HSBO	30% Renewable Penetration – High Solar Best Onshore Scenario
AEPS	Alternative Energy Portfolio Standard
AGC	Automatic Generation Control
AWS/AWST	AWS Truepower
Bbl.	Barrel
BAA	Balancing Area Authority
BAU	Business as Usual
BTU	British Thermal Unit
CA	Intertek AIM's Cycling⬍Advisor™ tool
CAISO	California Independent System Operator
CC/CCGT	Combined Cycle Gas Turbine
CEMS	Continuous Emissions Monitoring Systems
CF	Capacity Factor
CO2	Carbon Dioxide
CV	Capacity Value
DA	Day-Ahead
DR	Demand Response
DSM	Demand Side Management
EI	Eastern Interconnection

EIPC	Eastern Interconnection Planning Collaborative
ELCC	Effective Load Carrying Capability
ERCOT	Electricity Reliability Council of Texas
EST	Eastern Standard Time
EUE	Expected Un-served Energy
EWITS	Eastern Wind Integration and Transmission Study
FERC	Federal Energy Regulatory Commission
FLHR	Full Load Heat Rate
FSA	PJM Facilities Study Agreement
GE	General Electric International, Inc. / GE Energy Consulting
GE MAPS	GE's "Multi Area Production Simulation" model
GE MARS	GE's "Multi Area Reliability Simulation" model
GT	Gas Turbine
GW	Gigawatt
GWh	Gigawatt Hour
HA	Hour Ahead
HSBO	High Solar Best Onshore Scenarios
HOBO	High Offshore Best Onshore Scenarios
HR	Heat Rate
HVAC	Heating, Ventilation, and Air Conditioning
IPP	Independent Power Producers
IRP	Integrated Resource Planning
ISA	PJM Interconnection Service Agreement
ISO-NE	Independent System Operator of New England
kV	kilovolt
kW	kilowatt
kWh	kilowatt-hour
lbs	Pounds (British Imperial Mass Unit)
LDC	Load Duration Curve

LM	Intertek AIM's Loads Model ™ tool
LMP	Locational Marginal Prices
LNR	Load Net of Renewable Energy
LOBO	Low Offshore Best Onshore Scenarios
LODO	Low Offshore Dispersed Onshore Scenarios
LOLE	Loss of Load Expectation
MAE	Mean-Absolute Error
MAPP	Mid-Atlantic Power Pathway
MMBtu	Millions of BTU
MVA	Megavolt Ampere
MW	Megawatts
MWh	Megawatt Hour
NERC	North American Electric Reliability Corporation
NOx	Nitrogen Oxides
NREL	National Renewable Energy Laboratory
NWP	"Numerical Weather Prediction" model
O&M	Operational & Maintenance
PATH	Potomac Appalachian Transmission Highline
PJM	PJM Interconnection, LLC.
PPA	Power Purchase Agreement
PRIS	PJM Renewable Integration Study
PRISM	Probabilistic Reliability Index Study Model
PROBE	"Portfolio Ownership & Bid Evaluation Model" of PowerGEM
PSH	Pumped Storage Hydro
PV	Photovoltaic
REC	Renewable Energy Credit
Rest of EI	Rest of Eastern Interconnection
RPS	Renewable Portfolio Standard
RT	Real Time

RTEP	Regional Transmission Expansion Plan
SC/SCGT	Simple Cycle Gas Turbine
SCUC/EC	Security Constrained Unit Commitment / Economic Dispatch
SOx	Sulfur Oxides
ST	Steam Turbine
TARA	"Transmission Adequacy and Reliability Assessment" software of PowerGEM
UCT	Coordinated Universal Time
VOC	Variable Operating Cost
WI	Western Interconnection

1 Capacity Valuation Analysis

1.1 Introduction to the Wind Capacity Valuation

The reliability of a power system is governed by having sufficient generation capacity to meet the load at all times. There are several type of randomly occurring events, such as generator forced outages, unexpected de-ratings, etc., which must be taken into consideration during the planning stage to ensure sufficient generation capacity is available. Since the rated MW of installed generation may not be available at all times, due to the factors described above, the effective capacity value of generation is normally lower than 100% of its rated capacity. This effect becomes more pronounced for variable and intermittent resources, such as wind and solar PV. As an example, a 100 MW gas turbine will typically have a capacity value of approximately 95 MW, while a 100 MW wind plant may only have a capacity value of approximately 15 MW. It is therefore important to characterize the capacity value of such resources so that grid planners can ensure sufficient reserve margin or generation capacity is available at all times under a projected load growth scenario.

This report presents the analysis on the capacity value of wind and solar resources in different scenarios considered in the study. The analysis is conducted using GE Multi-Area Reliability Simulation (GE MARS) Software, and the capacity value is measured in terms of "Effective Load Carrying Capability."

1.2 PJM Rules on Capacity Value of Intermittent Energy Resources

PJM Manual 21 defines the current procedures for estimating the capacity value of intermittent resources, such as wind and solar PV generators. The manual defines capacity value of the intermittent resource (in percentage terms) as the average capacity factor that the resources have exhibited in the last three years during the summer period. The summer period is between the hour beginning at 2 PM and the hour ending at 6 PM, local time, during the months of June, July, and August. The capacity value in MWs can be obtained by multiplying the average capacity factor with the installed MW capacity of the intermittent resource. PJM Manual 21 also indicates the currently effective class average capacity factors as 13% for Wind and 38% for Solar PV.

Table 1-1 presents the average capacity factor of central PV and onshore wind resources during the summer period in 2004-2006 in the 2% BAU scenario. It should be noted that this scenario consists of only central PV (installed capacity of 72 MW) and onshore wind (installed capacity of 5,122 MW). The capacity factor of central PV is between 59% and 60% and that of onshore wind is approximately between 22 and 25%. The table also shows the average of the capacity factor of these resources in these three years, which is 60% for central PV and 23% for onshore wind, based on the modeled data. The modeled data for wind is based on the power curve of a 2.5 MW turbine with a 100-meter tower height. These wind turbines perform much better at higher and lower wind speeds. The modeled data for Solar PV gives 93-95 % rated capacity output at the point of interconnection to the grid, while in reality the Solar PV output maybe limited to 50-80% accounting for cell, module and interconnection losses. These factors may account for the higher capacity value observed in the modeled data as compared to the PJM data.

Table 1-2 repeats the same exercise for the 14% RPS scenario. The average capacity factor in the years 2004 to 2006 shows that the central PV has a higher value than distributed PV. It also shows that offshore wind has a higher average capacity factor than onshore wind. Both of these are well-known facts and supported by the data in these tables. The comparison across the years indicates that the annual weather differences affect the capacity factors, which in turn affects the capacity value.

Table 1-1: Average Summer Capacity Factor of Onshore Wind and Central PV, 2004 to 2006 (2% BAU)

Column1	Residential PV	Commercial PV	Central PV	Onshore Wind	Offshore Wind
2004	-	-	59.0%	24.8%	-
2005	-	-	61.0%	21.8%	-
2006	-	-	59.7%	22.9%	-
Average	-	-	59.9%	23.2%	-

Table 1-2: Average Summer Capacity Factor of Onshore Wind and Central PV, 2004 to 2006 (14% RPS)

Column1	Residential PV	Commercial PV	Central PV	Onshore Wind	Offshore Wind
2004	46.8%	44.7%	61.7%	27.2%	32.4%
2005	49.4%	47.3%	63.8%	19.9%	27.5%
2006	47.5%	45.4%	62.0%	24.5%	36.9%
Average	47.9%	45.8%	62.5%	23.9%	32.3%

As depicted in Figure 1-1, Year 2005 experiences a lower summer capacity factor for onshore wind compared to Year 2006 or Year 2004. The box inside each chart encapsulates the summer-period and clearly shows that Year 2005 has a lower available energy during this period. Appendix A provides a summary of the average capacity factors for each of the resources in each scenario.

The average capacity factor of wind and solar resources during the peak summer hours is a reasonable proxy to estimate capacity values since most of the capacity adequacy-related reliability risk in PJM is concentrated in the afternoon hours of a summer day. However, including all the afternoon hours in the capacity factor computation, regardless of the actual reliability risk during that hour, may result in over/under estimation of the capacity value. The analyses in this report are based on the ELCC of wind/solar resources, a method that provides an estimation of the capacity value of a resource by focusing primarily on the resource output during the hours that carry more capacity adequacy-related reliability risk.

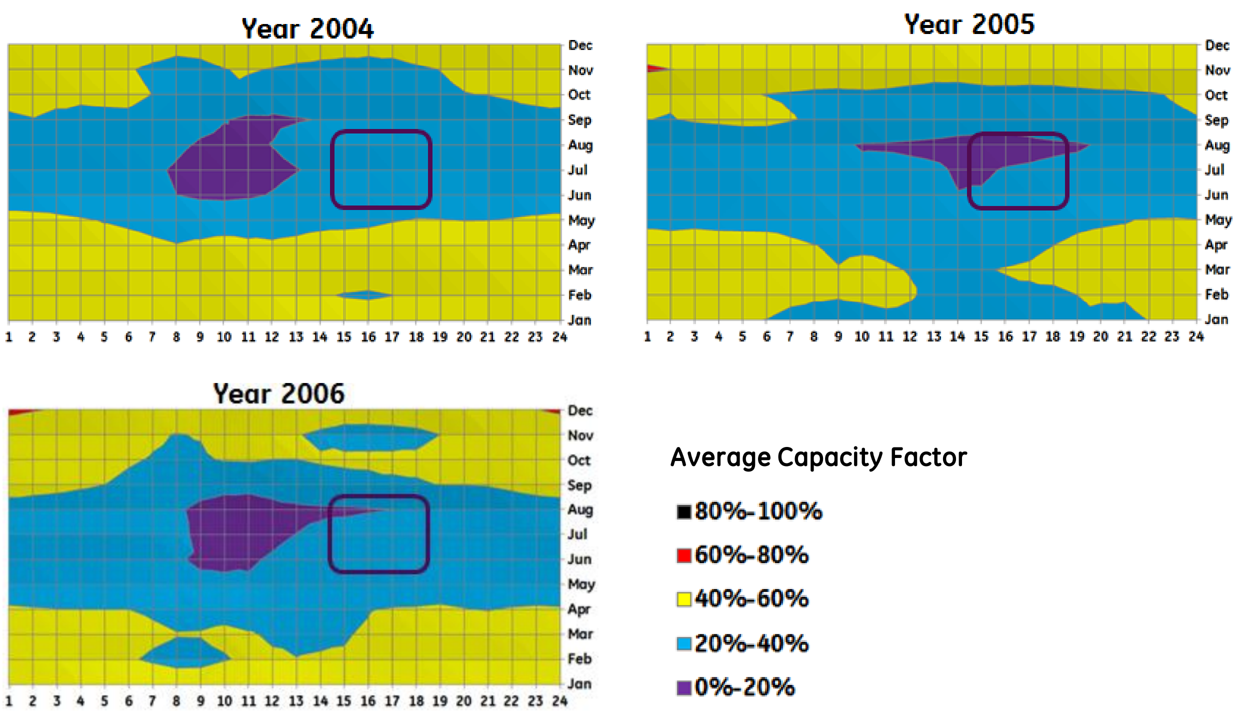


Figure 1-1: Average Capacity Factor of Onshore Wind Resources from 2004 to 2006

1.3 GE Multi-Area Reliability Simulation (GE MARS) Model

A Loss of Load Expectation (LOLE) reliability evaluation was performed for each of the cases. GE Concorda Suite's Multi-Area Reliability Simulation (GE MARS) software was used to calculate the daily LOLE, in days per year, for each scenario. In addition to the daily LOLE, GE MARS also calculated hourly LOLE, in hours per year, and Expected Unserved Energy (EUE), in MWh per year.

The LOLE is determined as the number of days on which loss of load is expected to occur. Since typical generation outages are equally likely at any time of the day, this index is historically calculated at the time of the system daily peak load. However, wind generation varies throughout the day. In recent study work, GE Energy Consulting has expanded the GE MARS program to determine the daily LOLE while looking at every hour of the day. In this way, any off-peak loss of load outages caused by significant drops in the wind generation will be fully accounted for.

The following reliability indices are available on both an isolated (zero ties between areas) and interconnected (using the input tie ratings between areas) basis:

- Daily LOLE (days/year)
- Hourly LOLE (hours/year)
- Loss of Energy Expectation (LOEE) (MWh/year)
- Frequency of loss of load events (events/year)
- Duration of outage (hours/event)
- Need for initiating emergency operating procedures (days/year)

1.3.1 Modeling Assumptions

The approach is based on a sequential Monte Carlo simulation, which provides for a detailed representation of the hourly loads, generating units, and interfaces between the interconnected areas. In the sequential Monte Carlo simulation, chronological system histories are developed by combining randomly generated operating histories of the generating units with the inter-area transfer limits and the hourly chronological loads. Consequently, the system can be modeled in great detail with accurate recognition of random events, such as equipment failures, as well as deterministic rules and policies, which govern system operation, without the simplifying or idealizing assumptions often required in analytical methods. GE MARS is based on a sequential Monte Carlo simulation, and it uses state transition rates rather than state probabilities, to describe the random forced outages of the thermal units. State probabilities give the probability of a unit being in a given capacity state at any particular time, and can be used if one assumes that the unit's capacity state for a given hour is independent of its state at any other hour. Sequential Monte Carlo simulation recognizes the fact that a unit's capacity state in a given hour is dependent on its state in previous hours and influences its state in future hours. It thus requires the additional information that is contained in the transition rate data.

For this analysis, the PJM system was isolated from the rest of the system, and no assistance from the outside was available to PJM. PJM area loads were scaled to obtain a starting risk of 0.1 days/year. With assistance from outside resources, the starting risk would decrease and a different load scaling factor would need to be used to obtain LOLE of 0.1 days/year. Nonetheless, the capacity value obtained under these two system conditions would be the same. It was agreed upon by the study team to model the PJM system with no outside assistance. Unit characteristics and maintenance schedules were copied from the GE MAPS input assumptions. Units were modeled as two state units, either fully available or unavailable, based on their state transition rates. Since state transition rates cannot be calculated from forced outage rates alone, the number of transitions between the two states was taken from the 2007-2011 class averages in the NERC Generating Availability Report, issued in September 2012.

The PJM demand response program was modeled as an operating procedure, since, as mentioned above, GE MARS can provide statistics on the use of operating procedures. The program was modeled with a benefit of approximately 15.7 GW.

The values used for load forecast uncertainty were taken from the data that PJM provides to the Northeast Power Coordinating Council for their reliability analysis.

1.3.2 Load Forecast Uncertainty

Figure 1-2 shows the probability distribution of the load forecast (weighted by area load) that was used by the Northeast Power Coordinating Council (NPCC) for the PJM region in the 2012 NERC reliability analysis. The forecast uncertainty is expressed as multipliers for the mean, as well as one, two, and three standard deviations above and below the mean. In Figure 1-2, the expected value (average value weighted by probability) is shown as approximately 94%, which is less than the intuitive value of 100%. This is consistent with the planning methodology used by PJM internally as part of their capacity analysis.

The data is shown only for the month of July, a peak load month for PJM. This distribution is symmetric around its mean, with an average (expected) value of 0.94 p.u. (per unit). This means, on the average, modeled peak load will be 6% lower than the nominal forecasted peak. Since the system peak load was adjusted to the PJM design criteria of 0.1 days/year LOLE, this will not significantly impact the capacity values determined.

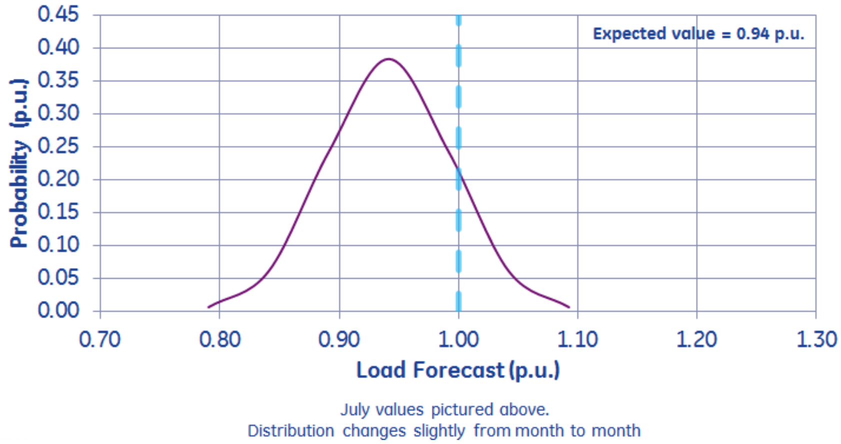


Figure 1-2: Probability Distribution of Load Forecast

1.3.3 Load Shape

In this draft report, the analysis is based on the load shapes from years 2004, 2005, and 2006. In order to get stable estimates on capacity value of a resource many years of load and synchronized resource data is required. A single year load shape and same year resource shape may give highly inflated or deflated values for capacity value (depending on the weather profile and other factors that influence the load profile).

The load shape for each of the years was scaled to meet the projected annual energy in the study year 2026. As an example, Figure 1-3 shows the peak load by month and hour of day for the year 2006. The adjusted 2006 shape has a peak load of 200,288 MW. This occurs on the 26th of July. For comparison, 2004 and 2005 load shapes are also shown in Figure 1-4. The peak days are noted for each of the shapes. The emphasis on peak load days, as will become evident in the later sections, is because the reserve margin or loss of load probability is determined to a large extent by the peak load days. The year 2006 load shape shows the highest peak load (200 GW), while the energy is the same in all three years.

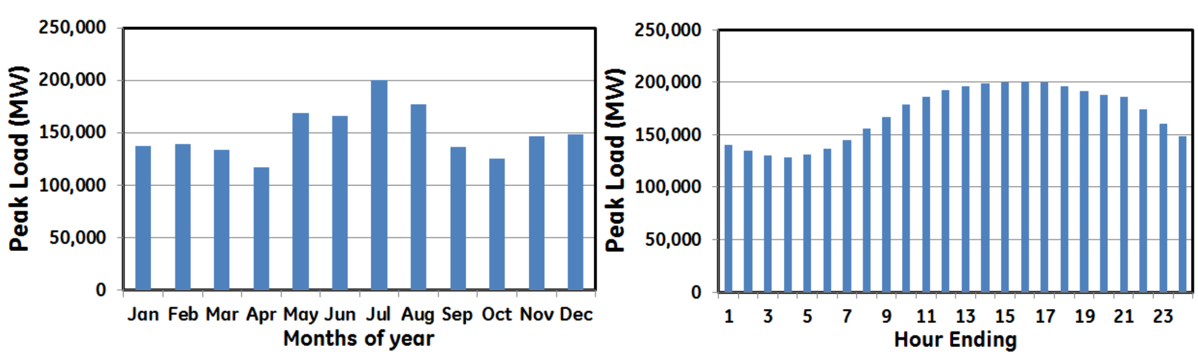


Figure 1-3: 2006 (Scaled to 2026 Energy) Peak Load Variation by Month and Hour of Day

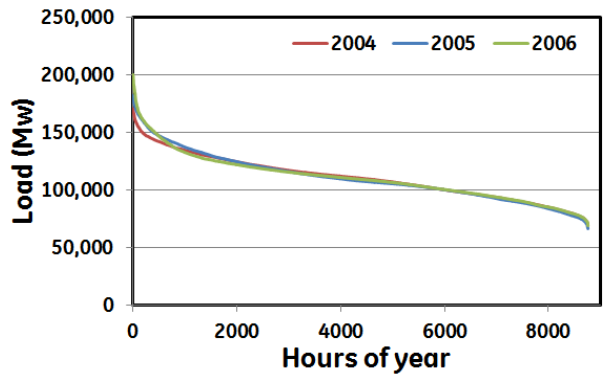


Figure 1-4: Load Duration Curves for 2004, 2005, and 2006

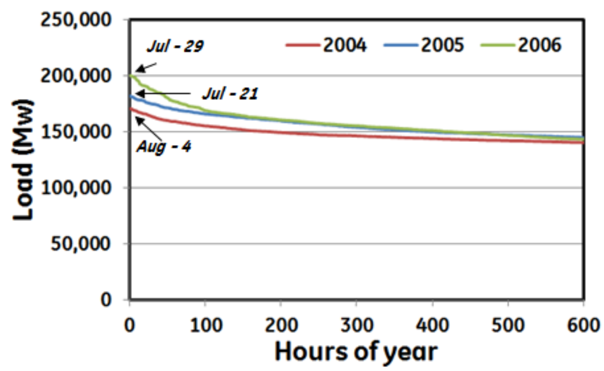


Figure 1-5: Zoomed-in View of the Load Duration Curves for 2004, 2005, and 2006

1.4 LOLE of Base System

As mentioned in Section 1.3, GE MARS can report information on Loss of Load Expectation (LOLE) in days/year, hours/year or MWh/year. LOLE (days/year) is the most frequently used metric by utilities, and PJM also uses this metric in their reliability analysis. Figure 1-6 shows LOLE of the base system (no wind/solar), using the 2006 load shape, on a logarithm axis. The base system has a high reliability of 0.012 days/year at the forecasted 2026 peak load (200,200 MW) and the projected thermal generation mix. The plot shows reliability levels at different system load peaks. The LOLE increases as the peak load is scaled up. LOLE increases to 0.15 days/year at 212,000 MW of peak load (6% higher than the current forecasted peak).

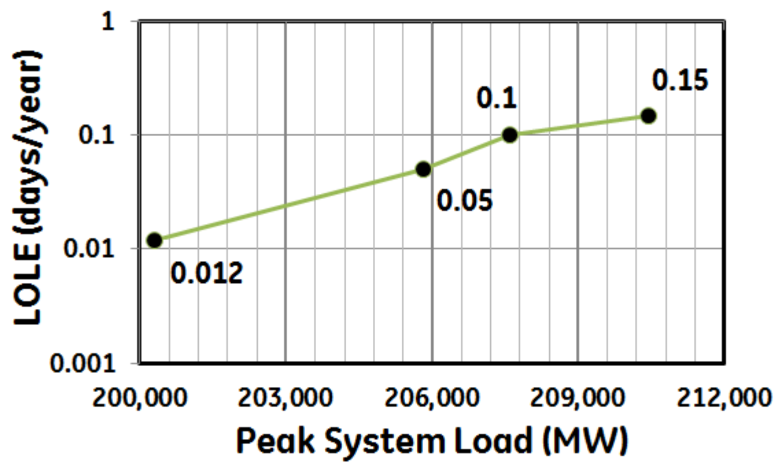
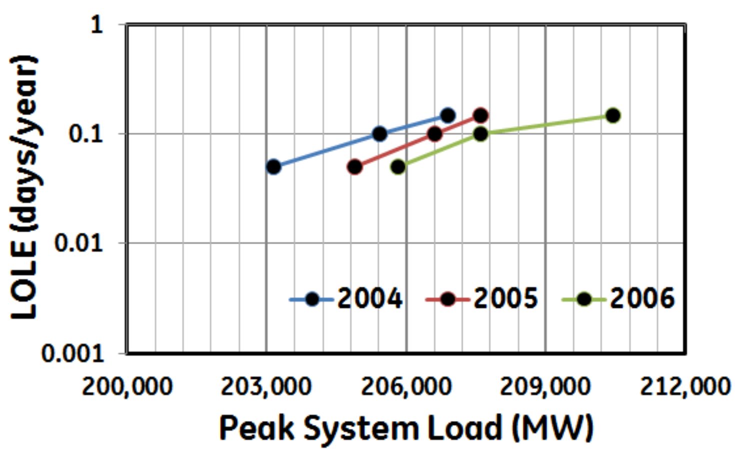


Figure 1-6: LOLE (days/year) for the Base System (2006 Load Shape)

Figure 1-7 shows the relation between LOLE (days/year) and the system peak load for the three years. This figure highlights the peak load in each of the three years that is required to meet PJM's design criteria of 0.1 LOLE days/year. For example, the 2005 load shape needs to be scaled-up such that the peak load increases from 182,086 MW to 206,879 MW in order to have a LOLE of 0.1 days/year. The load shapes in each of the three years is scaled-up to the corresponding values shown in the chart below in GE MARS analysis.



Year	2026 scaled Peak Load (MW)	Peak Load (MW) for LOLE of 0.1 days
2004	170,768	205,421
2005	182,086	206,879
2006	200,288	207,600

Figure 1-7: LOLE (days/year) for Different Load Shape Years

1.4.1 Capacity Value based on Effective Load Carrying Capability

Effective load carrying capability of a resource is defined as the increase in peak load that will give the same system reliability as the original system without the resource. This methodology of measuring capacity value is applicable even when the system is saturated (i.e. conditions when system LOLE with the new resource is extremely low). Figure 1-8 illustrates the process of determining ELCC of a resource. Assume that the base case LOLE is 0.1 days/year and it decreases to 0.001 days/year when a new resource (such as wind or solar PV) is added. The system peak load is then increased such that the system returns to the original LOLE of 0.1 days/year. In this case, the peak load needed to be increased by 30,000 MW. Thus, the ELCC of the resource is equal to serving 30,000 MW of additional load. Assuming the installed capacity of the resource was 50,000 MW, ELCC is simply equal to the ratio of these two quantities, 30,000 / 50,000 = 60%.

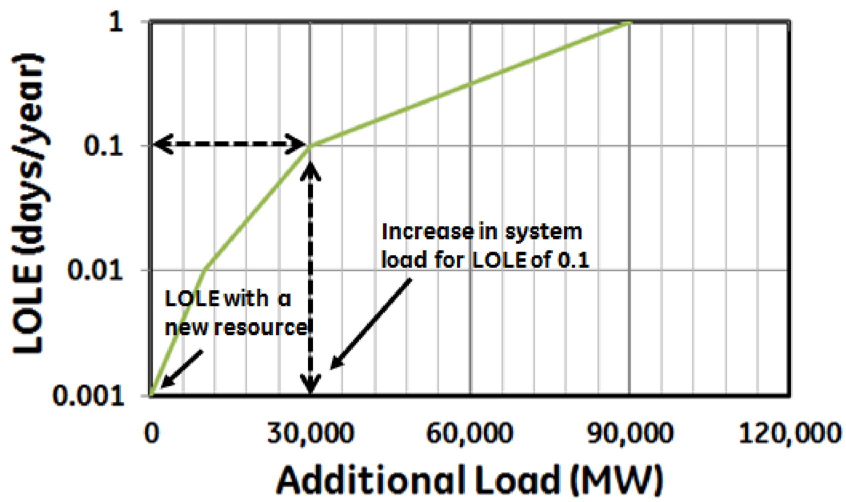


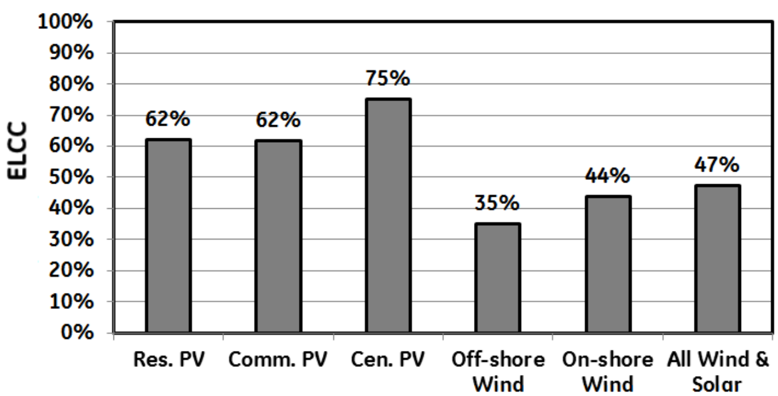
Figure 1-8: Addition of Onshore Wind in 14% RPS Scenario

ELCC methodology can establish the capacity value of a resource even when the installed capacity is extremely high, resulting in almost zero LOLE of the system. Conventional methods for estimating the capacity value of the resource under these conditions would fail. For this reason, all results in this study are based on the ELCC methodology.

1.5 Proposed Methodology to Estimate Capacity Value in Absence of Multiple Years of Load and Resource Data

This section highlights the requirement to have many years of load and resource data in order to obtain a stable capacity value of a resource. IEA Wind Task 25 recommends that at least eight years of synchronized load and wind data may be required to obtain stable capacity values [1]. In this study, we are limited to 3 years of load and resource data. The following sections explain the different methods that were tried in the study to calculate the capacity value of a resource under the constraint of having limited datasets. The final proposed methodology is able to produce stable capacity values by inducing artificial variability in the dataset. The 14% RPS scenario is used as a test system to report the results and findings in this section.

Figure 1-9 shows the installed capacity (in megawatts) and ELCC of the wind/solar resources in the 14% RPS scenario, based on the 2006 load and resource shape. Distributed PV (residential and commercial) shows an ELCC of 62%, lower than the ELCC of central PV (which is 75%). This result is expected because of the tracking system on central PV plants that results in a higher capacity factor and therefore higher capacity value (or ELCC). Offshore Wind shows a lower ELCC (35%) as compared to the onshore wind (44%). This result is counter-intuitive at first glance because offshore wind normally has a higher capacity factor than onshore wind and therefore should have a higher capacity value. This observation is explained in the next section.



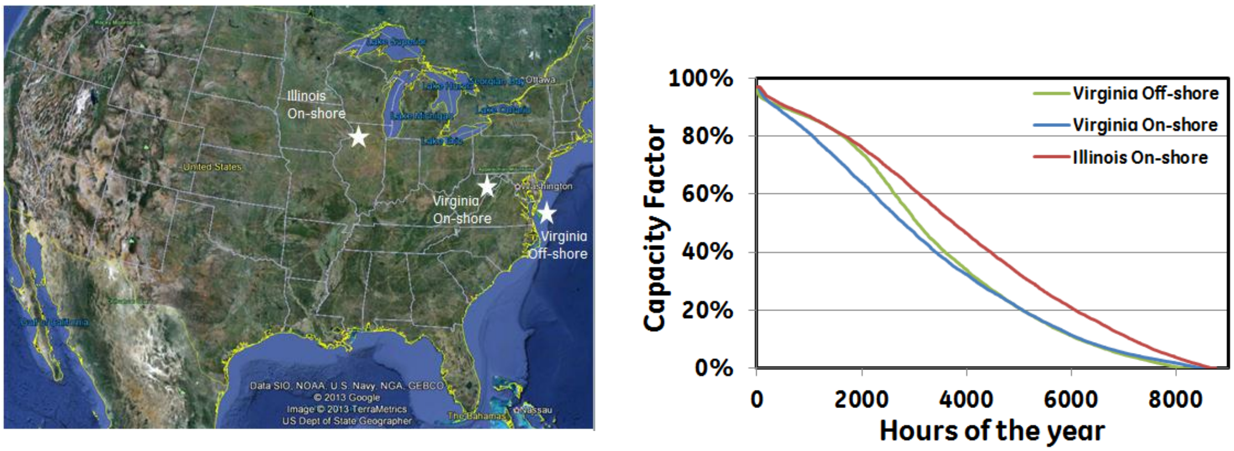
Resource	MW
Residential PV	851
Commercial PV	3,251
Central PV	3,253
Off-shore Wind	4,000
On-shore Wind	28,833

Figure 1-9: Wind and Solar ELCC and Installed Capacity in the 14% RPS Scenario Based On 2006 Load & Resource Shape

1.5.1 Higher ELCC of Onshore Wind than Off-shore Wind

Figure 1-10 shows three wind sites in the RPS-14% case: onshore wind plant in Illinois (150 MW), another onshore wind plant in Virginia (38 MW), and an offshore wind plant in Virginia (20 MW). The instantaneous capacity factor of these plants is plotted on an annual duration curve. The graph shows that the Virginia offshore plant has a higher capacity factor than the Virginia onshore plant for many hours of the year. The average capacity factor for the year (shown in the chart) is also higher for Virginia offshore plant. This is consistent with known facts that an offshore wind plant at a location has a higher capacity factor than the onshore wind facility in the same geographical location.

However, Illinois onshore wind plant has a higher capacity factor than the Virginia onshore as well as offshore for almost all hours of the year. This indicates that weather conditions in Illinois are more favorable for wind power than in Virginia to such an extent that an onshore wind plant in Illinois has a better capacity factor than an off-shore wind plant in Virginia. It is this effect that makes the ELCC of onshore wind higher than that of the offshore wind in this scenario.



Illinois On-shore (Site: 90052)	Virginia On-shore (Site: 90176)	Virginia Off-shore (Site: 68037)
44%	35%	38%

Figure 1-10: Onshore and Offshore Wind Capacity Factors in Illinois and Virginia

1.5.2 Year-to-year Variation in ELCC

Figure 1-11 shows the ELCC of different resources in 14% RPS scenario in different years. Each of the years was modeled with the provided load shape (scaled to 2026 energy) and a provided wind/solar profile. Year 2006 shows a higher ELCC for almost all resources. One observation that stands out is the large variation in ELCC for onshore wind. Year 2005 shows an abnormally lower ELCC for onshore wind; around five times lower than Year 2006. The reason behind this, as explained below, is the low capacity factor for onshore wind during high load periods in 2005.

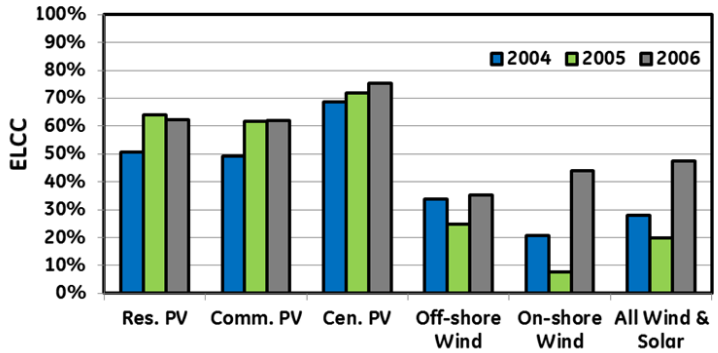


Figure 1-11: ELCC of Wind and Solar Resources across Different Years in 14% RPS Scenario

Figure 1-12 shows the average net load factor for a particular hour in a particular month. A higher net load factor implies that the wind resource was not strong enough to reduce the load and vice versa. In other words, a higher net load factor would imply lower capacity or ELCC for the wind resource. A comparison across the three plots shows that average net load factor is the highest in 2005 during the peak summer period (2-6 pm in the months of Jun-Aug), which explains the low ELCC for onshore wind in this year (Figure 1-11).

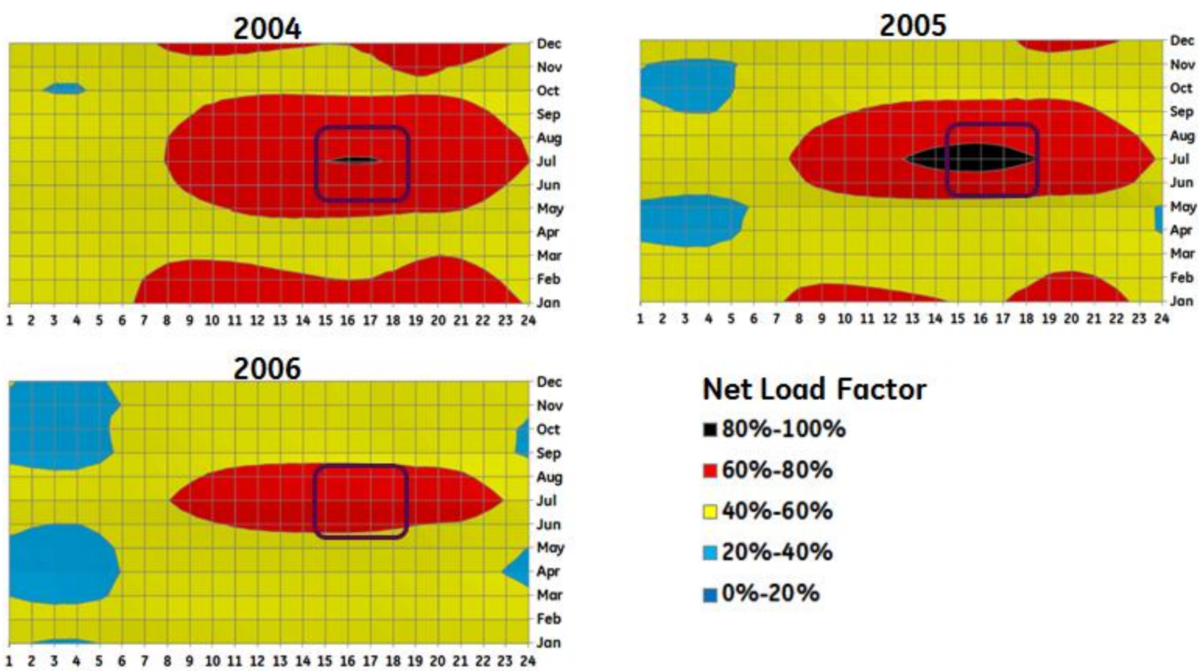


Figure 1-12: Net Load Factor with Onshore Wind in 14% RPS Scenario for Different Years

The results indicate that year-to-year differences in wind/solar shape, as well as differences in the load shapes can significantly alter the capacity value of the wind/solar resources. For this study, only three years of synchronized wind, solar, and load data are available. In order to account for these year-to-year differences and large variability, the following three methods are examined.

Method 1 *<u>Average of the three-year ELCC values</u>*: This methodology proposes to use the average of the ELCC values that a resource exhibits in the three years (2004 to 2006). Figure 1-13 shows the year-to-year variation in the ELCC of onshore wind: from 7.6% to 43.9%. The average of these three years approximates the ELCC at 24%. However, chances are that this can still be an inflated or deflated value due to the small sample size considered. The advantage of this method is that it preserves the synchronization between load and resource shape.

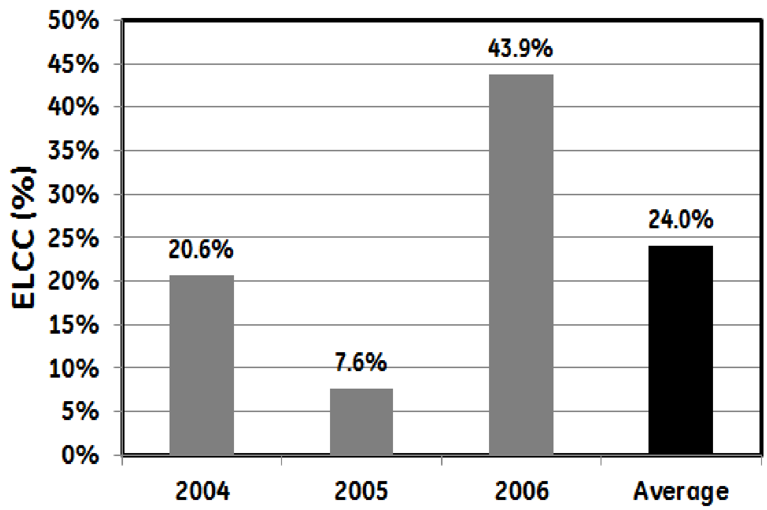


Figure 1-13: Variation of Onshore Wind ELCC in Different Years

Method 2 *<u>Convolving a single year load shape with a resource shape from every year</u>*: This methodology increases the number of combinations of load and resource shapes. Figure 1-14 shows the capacity value for each combination of convolving a single year load shape with onshore wind shape from each of the three years (2004, 2005, and 2006). Again, there is a big variation in the capacity value from one combination to another. The average of these nine combinations gives a capacity value of 16.7% for onshore wind. This methodology however tends to lose the synchronization between load and seasonal (year-to-year) weather characteristics.

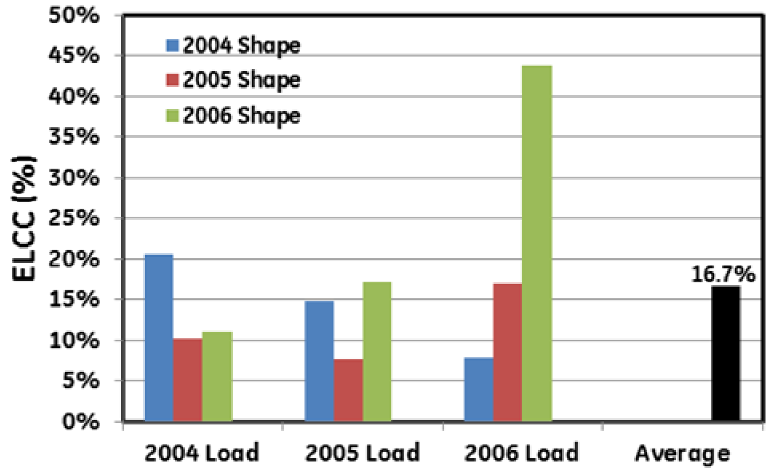


Figure 1-14: Variation of Onshore Wind Capacity Value with Different Combinations of Load & Shape Years

Method 3 *Introducing artificial variability in the resource shape*: This is simulated by using a random draw for the current day resource profile from a given number of days around the present day, such as ± 7 days, for a total of 15 days (7 days before the simulation day, 7 days after the simulation day, and the simulation day). Once the draw determines a particular day, the profile for all the hours of the current day is used from the chosen day. This methodology tends to preserve the synchronization between load and weather better than Method 2 since the weather occurring on days within that window is likely to be similar. The results are shown in Figure 1-15. For comparison purposes, sensitivities with ±14 days and ± 30 days are also shown. The observed year-to-year variation is smaller, and the average ELCC across the years (with any window length) is between 16.8% and 17.4%. In comparison, Method 1 (equivalent to have a 0 day window) gives a higher average ELCC of 24%.

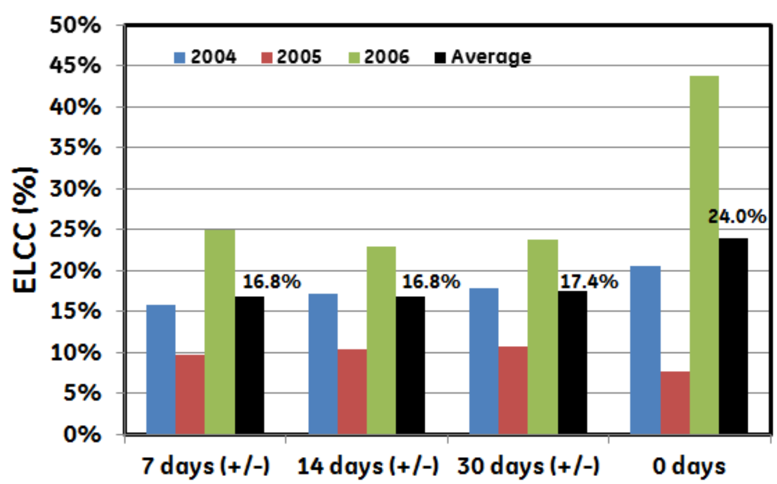


Figure 1-15: Onshore Wind ELCC after Introducing Artificial Variability in Wind Shape

Figure 1-16 compares the average ELCC across the different methods discussed in the above sections. Method 2 and Method 3 give similar average ELCC. Method 1 gives a higher ELCC due to the use of a smaller sample size. Method 2 convolves each year load against each year wind shape and hence tends to lose the year-to-year synchronization between load and wind. Method 3 introduces sufficient variability and smoothens out the year-to-year differences in weather patterns, while also preserving to a certain extent the relation between load and weather patterns. This methodology was only evaluated for the 14% on-shore wind resource. Based on these results, the project team decided to use Method 3 for estimating the average capacity value of every resource type in each scenario. All the analysis beyond this section and the final results for each of the scenarios are based on this methodology.

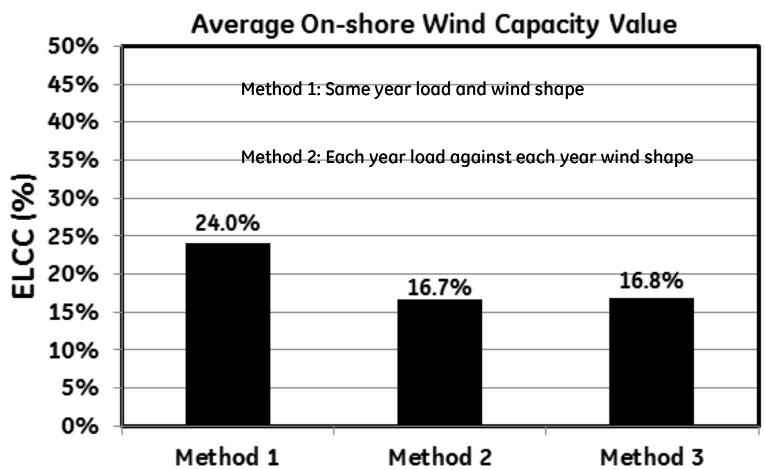
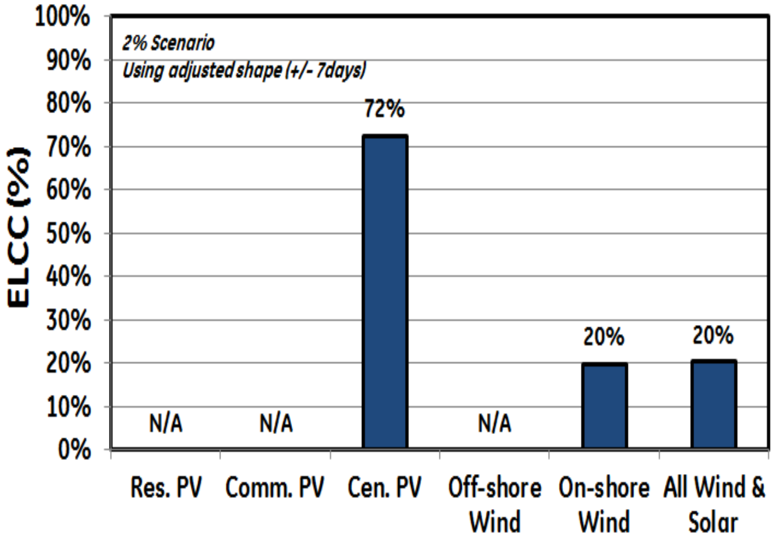


Figure 1-16: Comparison of Onshore Wind ELCC Value with the Three Methods

1.6 ELCC of 2% BAU Scenario

Figure 1-17 shows the ELCC and the installed capacity of the resources (central PV and onshore wind) in the 2% BAU scenario using Method 3. Central PV (72 MW installed capacity) has an ELCC of 72%. Similarly, 5,122 MW of onshore wind has an ELCC of 20%.



Resource	MW
Residential PV	-
Commercial PV	-
Central PV	72
Off-shore Wind	-
On-shore Wind	5,122

Figure 1-17: ELCC of Different Resources in 2% BAU Scenarios Using Method 3

1.7 ELCC of 14% RPS Scenario

Figure 1-18 shows the average ELCC of wind and solar resources in the RPS 14% scenario using Method 3. This method uses load shape of same year against the wind/solar shape of the same year with the adjustment that the current day wind/solar profile can be drawn from ± 7-day period. Compared to Figure 1-9, it can be observed that the average ELCC of all the resources decreases when artificial variability is introduced using Method 3. This is summarized in Table 1-3. The biggest decrease is seen in the value of onshore wind (from 44% to 17%). The reported capacity values are similar to the values observed in the Western Wind Integration Study [2].

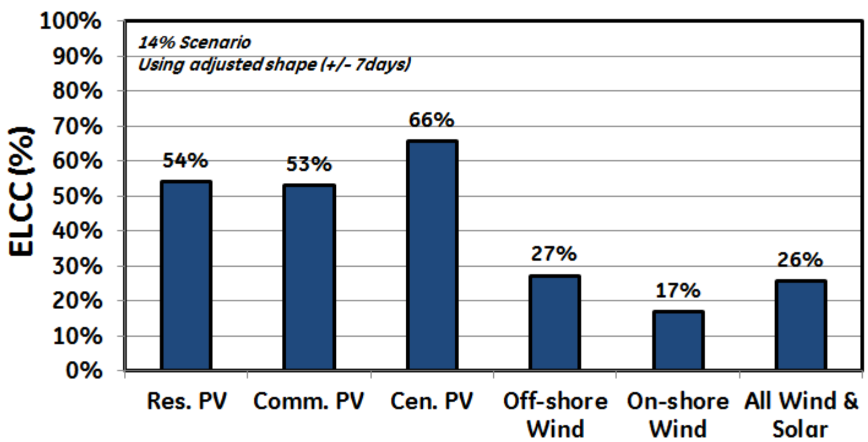


Figure 1-18: ELCC of Different Resources in 14% RPS Scenario Using Method 3

Table 1-3: Comparison of Results Using Method 3 and 2006 Load & 2006 Resource Shape (14% RPS)

	2006 Load/Resource Shape	Method 3
Residential PV	62%	54%
Commercial PV	62%	53%
Central PV	65%	66%
Off-shore Wind	35%	27%
Onshore Wind	44%	17%
All Wind and Solar	47%	26%

1.8 ELCC of 20% Scenarios

Table 1-4 shows the installed capacity of wind/solar resources in the 20% scenarios. The ELCC of the different resources is shown in Figure 1-19.

Table 1-4: Installed Capacity of Wind and Solar Resources in 20% Scenarios

Resource	High Off	Low Off (Best)	Low off (Disp)	High Solar
Residential PV	2,148	2,148	2,148	4,296
Commercial PV	8,265	8,265	8,265	16,530
Central PV	8,078	8,078	8,078	16,198
Off-shore Wind	22,581	4,851	4,851	4,026
On-shore Wind	22,699	40,255	41,745	32,228

The ELCC value of distributed PV is between 55% and 58%, while that of central PV is between 63 and 65% in each of the sub-scenarios. This is expected because of the higher capacity factor of a single-axis tracking system on central PV plants. The ELCC of central PV decreases in the "High Solar" sub-scenario because of saturation effects.

Offshore wind has an ELCC between 25% and 27%. The low ELCC in the "High Off-shore" sub-scenario is due to saturation effects. The ELCC of Onshore wind is between 16% and 18%.

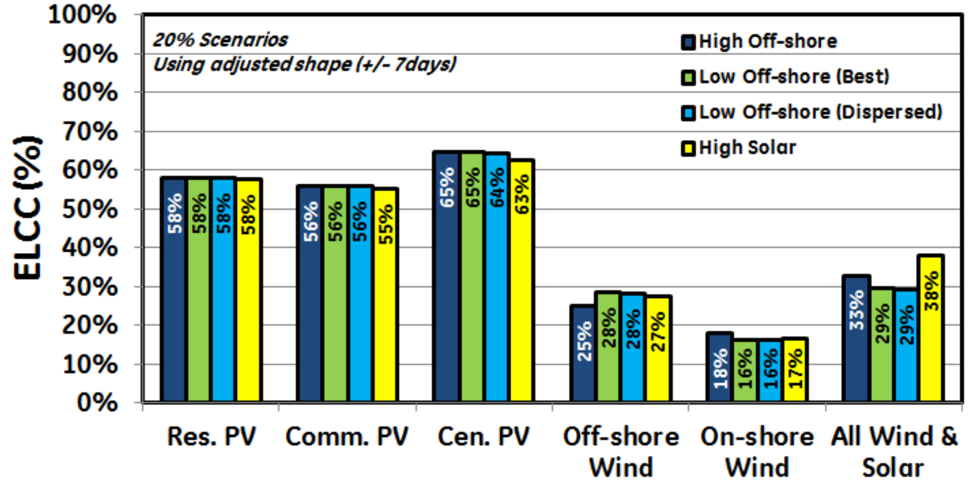


Figure 1-19: ELCC of Different Resources in 20% Scenarios

1.9 ELCC of 30% Scenarios

Table 1-5 shows the installed capacity of wind/solar resources in the 30% scenarios. The ELCC of the different resources is shown in Figure 1-20.

Table 1-5: Installed Capacity of Wind and Solar Resources in 30% Scenarios

Resource	High Off	Low Off (Best)	Low off (Disp)	High Solar
Residential PV	3,580	3,580	3,580	7,160
Commercial PV	13,775	13,775	13,775	27,550
Central PV	13,465	13,465	13,465	27,454
Off-shore Wind	34,489	6,846	6,846	5,430
On-shore Wind	33,806	60,669	64,125	47,126

The ELCC of the resources in the different sub-scenarios is similar to the 20% cases. The ELCC of some resources is lower because of saturation. As an example, the offshore wind ELCC drops from 25% to 21% in the “High Off-shore” sub-scenario, as the installed capacity is increased from 22,581 MW to 33,489 MW. Each additional MW of offshore wind has a lower load carrying capability, implying diminishing returns in the capacity value of the resource.

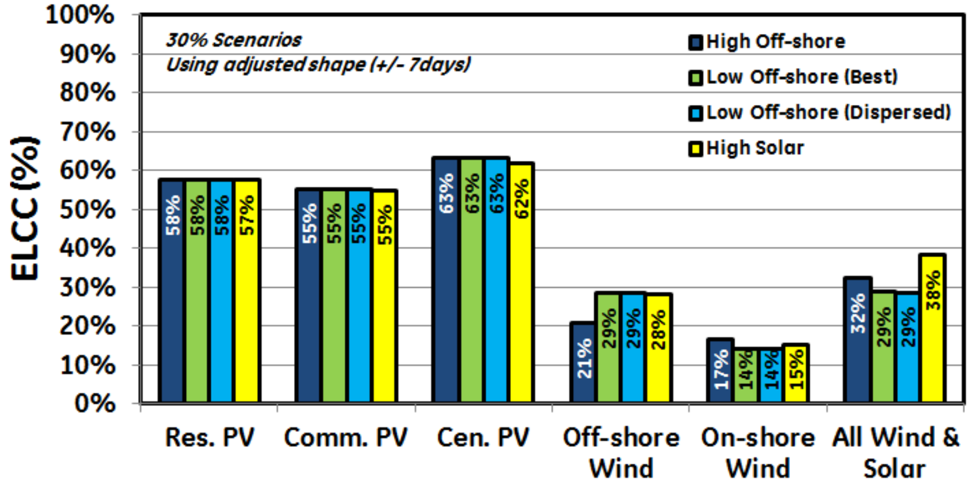
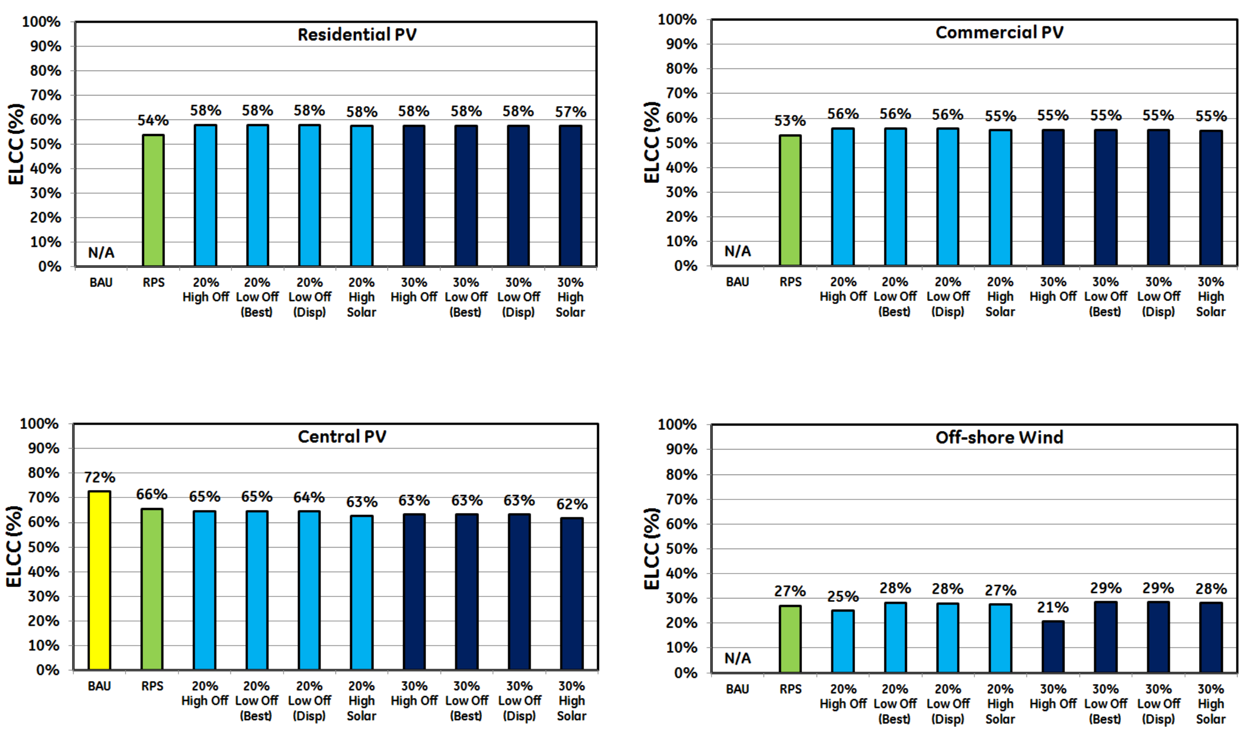


Figure 1-20: ELCC of Wind and Solar Resources in 30% Scenarios

1.10 Capacity Valuation Study Conclusions

This section summarizes the ELCC of the wind and solar resources in each of the scenarios. Figure 1-21 presents ELCC of different wind/solar resources in all scenarios.



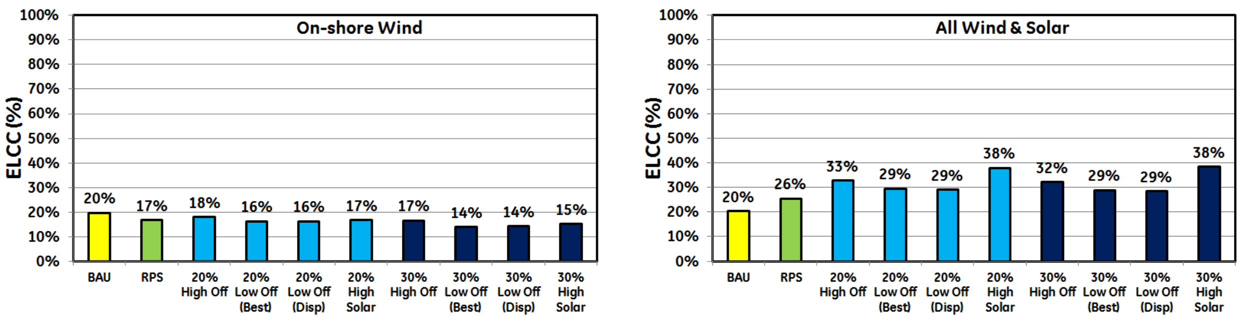


Figure 1-21: ELCC of Different Wind/Solar Resources in All Scenarios

Major findings and lessons learned are summarized below:

- ELCC overcomes the limitations of measuring the capacity value of a resource under saturation, i.e., under conditions when the installed capacity of a resource is high enough to drive the system LOLE close to zero days/year.
- Modified ELCC methodology (referred to as Method 3) is recommended in this study. This methodology helps estimate stable capacity values of a resource (and reduce the variation from one year to another) in absence of many years of load and resource data. The comparison is shown in Figure 1-16. This method should be used for some years until actual wind and solar data is available.
- The capacity factor of a resource under peak load conditions drives the ELCC value of the resource. The initial increase in ELCC from 2% BAU scenario to higher penetration scenarios is because of the inclusion of best sites, which have higher capacity factors.
- ELCC of some resources decreases as the installed capacity increases. As an example, the ELCC value of Central PV decreases from 75% in BAU to 62% in "High Solar" scenario. This occurs because at higher penetration levels the resource may saturate the system and hence the incremental value of serving an additional MW of load will decrease. ELCC of some resources, such as Off-shore Wind, increases in the high penetration scenario. This occurs due to inclusion of sites that have higher capacity value (or higher capacity factor during the peak load periods).

Table 1-6 compares the range of ELCC values to those determined using the PJM Manual 21 methodology. These values can be compared since they were based on the same hourly generation profiles. ELCC values vary as the resource penetration levels change and therefore a range is provided for each resource type. The ELCC values for each resource in other scenarios are shown in Figure 1-21. The comparison to PJM methodology can be made based on the results provided in Section 1.11. The modeling assumptions are listed in Section 1.3.1. As a reference, in the "New England Wind Integration Study," the average capacity value of on-shore wind in the "20% Best Sites Onshore Scenario" was 20%; while the average capacity value of off-shore wind in the "20% Best Sites Offshore Scenario" was 32%. Please note that "20% Best Sites Onshore Scenario" had 8% off-shore wind by installed capacity, and the "20% Best Sites Offshore Scenario" had 58% off-shore wind by installed capacity.

Table 1-6: Range of Effective Load Carrying Capability (ELCC) for Wind and Solar Resources in 20% and 30% Scenarios

Resource	ELCC (%)	PJM Manual 21 (Summer Peak Hour Average Capacity Factor)
Residential PV	57% - 58%	51%
Commercial PV	55% - 56%	49%
Central PV	62% - 66%	62% - 63%
Off-shore Wind	21% - 29%	31% - 34%
Onshore Wind	14% - 18%	24% - 26%

These values are larger than the current class averages of 13% for wind and 38% for solar which were based on actual historical values. This is because the profiles were developed at optimum sites using the most current power conversion technologies. It was felt that these would provide a better estimate of the likely capacity values of the renewable plants in the future. Individual plants will continue to have their capacity values based on their actual performance and it is expected that the plants with newer technology will have higher values than existing ones.

1.11 Average Capacity Factors of Wind and Solar during Summer Peak Period

The following tables show the average capacity factor of wind and solar resources (as described in Section 10.3) in the peak summer period of 2004 to 2006. PJM Manual 21 uses the average capacity factors during the summer peak period of the last three years as the capacity credit value of that intermittent energy resource.

Table 1-7: Average Capacity Factor of Wind & Solar Resources in the Peak Summer Period of 2004 – 2006

2% "BAU"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	-	-	-	-
Comm PV	-	-	-	-
Cen PV	59.0%	60.1%	59.7%	*59.6%*
Off Wind	-	-	-	-
On Wind	24.8%	21.8%	22.9%	*23.1%*

14% "RPS"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	46.8%	49.4%	47.5%	*47.9%*
Comm PV	44.7%	47.3%	45.4%	*45.8%*
Cen PV	61.7%	63.8%	62.0%	*62.5%*
Off Wind	32.4%	27.5%	36.9%	*32.2%*
On Wind	27.2%	19.9%	24.5%	*23.9%*

20% "High Off-shore"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.6%	50.7%	*51.0%*
Comm PV	47.7%	50.7%	48.7%	*49.0%*
Cen PV	61.6%	64.5%	62.6%	*62.9%*
Off Wind	30.7%	28.7%	37.0%	*32.1%*
On Wind	27.9%	23.0%	25.2%	*25.4%*

20% "Low Off-shore (Best sites)"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.6%	50.7%	*51.0%*
Comm PV	47.7%	50.7%	48.7%	*49.0%*
Cen PV	61.6%	64.5%	62.6%	*62.9%*
Off Wind	33.2%	28.7%	38.0%	*33.3%*
On Wind	28.0%	23.1%	25.4%	*25.5%*

20% "Low Off-shore (Dispersed sites)"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.6%	50.7%	*51.0%*
Comm PV	47.7%	50.7%	48.7%	*49.0%*
Cen PV	61.6%	64.5%	62.6%	*62.9%*
Off Wind	33.2%	28.7%	38.0%	*33.3%*
On Wind	26.5%	22.2%	24.6%	*24.4%*

20% "High Solar"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.6%	50.7%	*51.0%*
Comm PV	47.7%	50.7%	48.7%	*49.1%*
Cen PV	61.1%	63.7%	62.1%	*62.3%*
Off Wind	32.5%	27.5%	36.9%	*32.3%*
On Wind	27.5%	20.4%	24.8%	*24.2%*

30% "High Off-shore"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.7%	50.7%	*51.0%*
Comm PV	47.7%	51.3%	48.7%	*49.2%*
Cen PV	61.4%	63.9%	62.2%	*62.5%*
Off Wind	29.8%	27.8%	36.2%	*31.3%*
On Wind	27.7%	20.5%	25.0%	*24.4%*

30% "Low Off-shore (Best sites)"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.7%	50.7%	*51.0%*
Comm PV	47.7%	51.3%	48.7%	*49.2%*
Cen PV	61.4%	63.9%	62.2%	*62.5%*
Off Wind	32.9%	29.4%	38.4%	*33.6%*
On Wind	28.0%	23.7%	25.8%	*25.9%*

30% "Low Off-shore (Dispersed sites)"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.7%	50.7%	*51.0%*
Comm PV	47.7%	51.3%	48.7%	*49.2%*
Cen PV	61.4%	63.9%	62.2%	*62.5%*
Off Wind	32.9%	29.4%	38.4%	*33.6%*
On Wind	26.4%	21.9%	24.2%	*24.2%*

30% "High Solar"

	2004 Cap Factor (%)	2005 Cap Factor (%)	2006 Cap Factor (%)	Average
Res PV	49.7%	52.7%	50.7%	*51.0%*
Comm PV	47.7%	51.3%	48.7%	*49.2%*
Cen PV	61.0%	63.2%	61.7%	*62.0%*
Off Wind	33.1%	29.0%	38.2%	*33.4%*
On Wind	28.1%	21.7%	25.8%	*25.2%*

It should be pointed out that the wind profiles used in this study assumed advanced turbine design expected to be available in the future, and therefore, the values reported here would be slightly higher than what has been historically observed in PJM.

1.12 Capacity Valuation References

[1] Michael Milligan, "IEA Wind Task 25 Recommended Practices for Wind Integration Studies: Recent Work on Capacity Value Estimation," UVIG Spring Workshop, Charleston SC, April 2013

[2] NREL, "Western Wind and Solar Integration Study":

http://www.nrel.gov/wind/systemsintegration/pdfs/2010/wwsis_final_report.pdf

[3] GE Energy Consulting, EnerNEX Corporation, AWS Truepower, "New England Wind Integration Study": http://www.uwig.org/newis_es.pdf