GE
Energy Consulting

PJM Renewable Integration Study

Task 3A Part B

Statistical Analysis and Reserves

Prepared for: PJM Interconnection, LLC.

Prepared by: General Electric International, Inc.

March 31, 2014

imagination at work

Legal Notices

Contact Information

This report was prepared by General Electric International, Inc. (GEII); acting through its Energy Consulting group (GE) based in Schenectady, NY, and submitted to PJM Interconnection, LLC. (PJM). Technical and commercial questions and any correspondence concerning this document should be referred to:

Gene Hinkle
Manager, Investment Analysis
GE Energy Management
Energy Consulting
1 River Road
Building 53
Schenectady, NY 12345 USA
Phone: (518) 385 5447
Fax: (518) 385 5703
gene.hinkle@ge.com

Table of Contents

LEGAL NOTICES II

CONTACT INFORMATION III

1 STATISTICAL ANALYSIS OF LOAD AND RENEWABLE DATA 14

1.1 OBJECTIVES OF STATISTICAL ANALYSIS 14

1.2 LOAD ANALYSIS 19

1.3 RENEWABLE GENERATION VARIABILITY 26

1.3.1 Variability – Energy Production Summary 28

1.3.2 Capacity Factor 29

1.3.3 Hourly Variability – Diurnal Characteristics 31

1.3.4 Daily Variability –Load net of Renewable Generation 38

1.3.5 Faster variations in renewable generation 48

1.4 RENEWABLE GENERATION FORECASTING AND UNCERTAINTY 69

1.4.1 Day-ahead 70

1.4.2 Hour-Ahead 74

1.4.3 Very Short Term 75

1.5 STATISTICAL CHARACTERIZATION OBSERVATIONS AND CONCLUSIONS 76

2 REGULATION AND OPERATING RESERVES 81

2.1 RESERVE ANALYSIS OVERVIEW 81

2.2 METHODOLOGY 84

2.3 HIGH-RESOLUTION ANALYSIS 85

2.4 RESULTS WITH HOURLY DATA: REGULATION – HOURLY APPROXIMATIONS 93

2.5 IMPACTS ON OPERATING RESERVES 98

2.6 OBSERVATIONS AND CONCLUSIONS 101

3 APPENDIX: LOAD NET RENEWABLES 104

List of Figures

Figure 1-1: Weekday Alignment of 2004 Load Escalated to 2026 (MW) 20
Figure 1-2: Weekday Alignment of 2005 Load Escalated to 2026 (MW) 20
Figure 1-3: Weekday Alignment of 2006 Load Escalated to 2026 (MW) 21
Figure 1-4: Seasonal Load Energy by Profile Year 22
Figure 1-5: Monthly Load Energy by Profile Year 22
Figure 1-6: Weekly Load Energy by Profile Year 23
Figure 1-7: Load Duration Curves of Study Year for Each Annual Profile 24
Figure 1-8: Hour To Hour Load Ramp Duration Curve for Study Year with 2004 Profile 25
Figure 1-9: Hour To Hour Load Ramp Duration Curve for Study Year with 2005 Profile 25
Figure 1-10: Hour To Hour Load Ramp Duration Curve for Study Year with 2006 Profile 26
Figure 1-11: Monthly Energy Production by All Renewable Resources (Average of 3 Years) 28
Figure 1-12: Renewable Energy Production by Season and Scenario for 2006 Profile Year (3 Year Average) 29
Figure 1-13: Average Annual Capacity Factor for Each Scenario and By Year 30
Figure 1-14: Off-Peak and On-Peak Capacity Factor by Season for All Scenarios (Average Over 3 Years) 31
Figure 1-15: Average Daily Wind and PV Generation – Winter Profile (3 Years of Data) 32
Figure 1-16: Average Daily Wind and PV Profile – Spring Profile (3 Years of Data) 33
Figure 1-17: Average Daily Wind and PV Generation – Summer Profile (3 Years of Data) 33
Figure 1-18: Average Daily Wind and PV Profile – Fall Profile (3 Years of Data) 34
Figure 1-19: Average Daily Patterns by Month For 2% BAU Scenario; Maximum and Minimum Values Indicated By Dashed Lines 35
Figure 1-20: Average Daily Patterns by Month for 14% RPS Scenario; Maximum and Minimum Values Indicated By Dashed Lines 35
Figure 1-21: Average Daily Patterns by Month For 20% HSBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 35
Figure 1-22: Average Daily Patterns by Month For 20% LOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 36
Figure 1-23: Average Daily Patterns by Month For 20% LODO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 36
Figure 1-24: Average Daily Patterns by Month For 20% HOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 36
Figure 1-25: Average Daily Patterns by Month For 30% HSBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 37
Figure 1-26: Average Daily Patterns by Month For 30% LOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 37
Figure 1-27: Average Daily Patterns by Month For 30% LODO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 37
Figure 1-28: Average Daily Patterns by Month For 30% HOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines 38
Figure 1-29: Average Daily PJM Load and Net Load for Each Scenario - Winter Season 39
Figure 1-30: Average Daily PJM Load and Net Load for Each Scenario, Spring Season 39
Figure 1-31: Average Daily PJM Load and Net Load for Each Scenario, Summer Season 40
Figure 1-32: Average Daily PJM Load and Net Load for Each Scenario - Fall Season 40
Figure 1-33: Duration Curves for Load and Load Net Renewables, All Scenarios, All Years, All Hours 41
Figure 1-34: Distribution of Hourly PJM Load Changes (3 Years of Data) 42
Figure 1-35: Hourly Changes in Renewables For 30% Penetration Scenarios 42

Figure 1-36: Hourly Changes in Renewables For 20% Penetration Scenarios ... 43
Figure 1-37: Hourly Changes in Renewables For 14% RPS Scenario ... 43
Figure 1-38: Hourly Changes in Renewables For 2% BAU Scenario ... 44
Figure 1-39: Hourly Change in PJM Load and Net Load For 2% BAU Scenario (3 Years of Data) ... 44
Figure 1-40: Hourly Change in PJM Load and Net Load For 14% RPS Scenario (3 Years of Data) ... 45
Figure 1-41: Hourly Change in PJM Load and Net Load For 20% HOBO Scenario (3 Years of Data) ... 46
Figure 1-42: Hourly Change in PJM Load and Net Load For 20% HSBO Scenario (3 Years of Data) ... 46
Figure 1-43: Hourly Change in PJM Load and Net Load For 30% HOBO Scenario (3 Years of Data) ... 47
Figure 1-44: Hourly Change in PJM Load and Net Load For 30% HSBO Scenario (3 Years of Data) ... 47
Figure 1-45: Distribution Tails of Hourly Changes for PJM Load and Net Load for 20% HOBO Scenario ... 48
Figure 1-46: Distribution Tails of Hourly Changes for PJM Load and Net Load for 20% HSBO Scenario ... 48
Figure 1-47: 10-Minute Wind + Solar Variability as a Function of Production Level For 2% BAU Scenario ... 49
Figure 1-48: 10-Minute Wind + Solar Variability as a Function of Production Level For 14% RPS Scenario ... 50
Figure 1-49: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% HOBO Scenario ... 50
Figure 1-50: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% LODO Scenario ... 51
Figure 1-51: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% LOBO Scenario ... 51
Figure 1-52: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% HSBO Scenario ... 52
Figure 1-53: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% HOBO Scenario ... 52
Figure 1-54: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% LODO Scenario ... 53
Figure 1-55: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% LOBO Scenario ... 53
Figure 1-56: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% HSBO Scenario ... 54
Figure 1-57: Statistical Characterization of 10-Minute Wind Variability for The 2% BAU Scenario ... 55
Figure 1-58: Statistical Characterization of 10-Minute Wind Variability for The 14% RPS Scenario ... 56
Figure 1-59: Statistical Characterization of 10-Minute Wind Variability for The 20% HSBO Scenario ... 56
Figure 1-60: Statistical Characterization of 10-Minute Wind Variability for The 20% LOBO Scenario ... 57
Figure 1-61: Statistical Characterization of 10-Minute Wind Variability for The 20% LODO Scenario ... 57
Figure 1-62: Statistical Characterization of 10-Minute Wind Variability for The 20% HOBO Scenario ... 58
Figure 1-63: Statistical Characterization of 10-Minute Wind Variability for The 30% HSBO Scenario ... 58
Figure 1-64: Statistical Characterization of 10-Minute Wind Variability for The 30% LOBO Scenario ... 59
Figure 1-65: Statistical Characterization of 10-Minute Wind Variability for The 30% LODO Scenario ... 59
Figure 1-66: Statistical Characterization of 10-Minute Wind Variability for The 30% HOBO Scenario ... 60
Figure 1-67: Statistical Characterization of 10-Minute PV Variability for The 2% BAU Scenario ... 61
Figure 1-68: Statistical Characterization of 10-Minute PV Variability for The 14% RPS Scenario ... 62
Figure 1-69: Statistical Characterization of 10-Minute PV Variability for The 20% HSBO Scenario ... 62
Figure 1-70: Statistical Characterization of 10-Minute PV Variability for The 20% LOBO Scenario ... 63
Figure 1-71: Statistical Characterization of 10-Minute PV Variability for The 20% LODO Scenario ... 63
Figure 1-72: Statistical Characterization of 10-Minute PV Variability for The 20% HOBO Scenario ... 64
Figure 1-73: Statistical Characterization of 10-Minute PV Variability for The 30% HSBO Scenario ... 64
Figure 1-74: Statistical Characterization of 10-Minute PV Variability for The 30% LOBO Scenario ... 65
Figure 1-75: Statistical Characterization of 10-Minute PV Variability for The 30% LODO Scenario ... 65
Figure 1-76: Statistical Characterization of 10-Minute PV Variability for The 30% HOBO Scenario ... 66
Figure 1-77: Characterization of 10-Minute Wind Variability for Lower Penetration Scenarios ... 67
Figure 1-78: Characterization of 10-Minute PV Variability for Lower Penetration Scenarios (Note: 2% BAU 71MW Nameplate Capacity) ... 67
Figure 1-79: Characterization of 10-Minute Wind Variability For 20% Penetration Scenarios ... 68
Figure 1-80: Characterization of 10-Minute PV Variability For 20% Penetration Scenarios (LOBO, LODO and HOBO Have Identical PV Sites) ... 68
Figure 1-81: Characterization of 10-Minute Wind Variability For 30% Scenarios ... 69

Figure 1-82: Characterization of 10-Minute PV Variability For 30% Scenarios (LOBO, LODO and HOBO Scenarios Have Identical PV Sites) ... 69
Figure 1-83: Mean-Absolute-Error for Day-Ahead Wind + Solar Forecast, All Scenarios All Hours ... 71
Figure 1-84: Day-Ahead Wind + Solar Forecast Accuracy for Each Scenario by Season ... 71
Figure 1-85: Day-Ahead Forecast and Actual Wind and PV Generation For Selected Weeks from Each Season: 20% HOBO Scenario ... 73
Figure 1-86: Distribution of 1-Hour Persistence Forecast Error for Wind In 20% Scenarios ... 74
Figure 1-87: Expected 1-Hour Persistence Forecast Error as Function of Current Wind Production Level For 20% Scenarios ... 75
Figure 1-88: Expected 1-Hour Persistence Forecast Error as Function of Current PV Production Level For 20% Scenarios (Note LOBO, LODO and HOBO Scenarios Use Same PV Sites) ... 75
Figure 1-89: 14% RPS Seasonal Average Day Profile for Wind All Years ... 77
Figure 1-90: 30% LOBO Seasonal Average Day Profile for Wind All Years ... 78
Figure 1-91: Smoothing of Plant-Level 10-Minute Variability over PJM's Footprint, June 14, 30% LOBO ... 80
Figure 2-1: PJM Operating Reserves ... 82
Figure 2-2: Metered Regulation for July 10, 2011 with 2 Second Deviations from a 20-Minute Trend ... 86
Figure 2-3: 2-Second Load Data Plotted with 20-Minute Rolling Average and 10-Minute Average Load ... 86
Figure 2-4: Deviations of PJM 2-Second Load from (l) Trend and (r) 10-Minute Average ... 87
Figure 2-5: Short-Term Persistence Forecasting for 10-Minute Wind Generation. ... 90
Figure 2-6: 10-Minute Wind and Solar Variability as Function of Production Level for 2% BAU, 14% RPS, and 30% LOBO Scenarios ... 91
Figure 2-7: 10-Minute Variability of Illustrative Renewable Scenarios with Hourly Average Production Level: Empirical Data in MW ... 92
Figure 2-8: 10-Minute Variability of Illustrative Wind Scenarios with Hourly Average Production Level: Empirical Data, Per-Unit of Aggregate Nameplate Capacity for Each Scenario ... 93
Figure 2-9: Quadratic Approximations to Empirical Variability Curves for Study Scenarios ... 95
Figure 2-10: Sample Day Showing 10-Minute Periods That Exceed Ramp-Up or Ramp-Down Limits ... 99
Figure 2-11: Sample Day Showing 10-Minute Periods That Exceed Range-Up or Range-Down Limits ... 100
Figure 3-1: Load Net Renewables for the Average Day of January 2026 ... 105
Figure 3-2: Load Net Renewables for a Day in January 2026 with the Largest HSBO LnR Range ... 105
Figure 3-3: Load Net Renewables for the Average Day of February 2026 ... 106
Figure 3-4: Load Net Renewables for a Day in February 2026 with the Largest HSBO LnR Range ... 106
Figure 3-5: Load Net Renewables for the Average Day of March 2026 ... 107
Figure 3-6: Load Net Renewables for a Day in March 2026 with the Largest HSBO LnR Range ... 107
Figure 3-7: Load Net Renewables for the Average Day of April 2026 ... 108
Figure 3-8: Load Net Renewables for a Day in April 2026 with the Largest HSBO LnR Range ... 108
Figure 3-9: Load Net Renewables for the Average Day of May 2026 ... 109
Figure 3-10: Load Net Renewables for a Day in May 2026 with the Largest HSBO LnR Range ... 109
Figure 3-11: Load Net Renewables for the Average Day of June 2026 ... 110
Figure 3-12: Load Net Renewables for a Day in June 2026 with the Largest HSBO LnR Range ... 110
Figure 3-13: Load Net Renewables for the Average Day of July 2026 ... 111
Figure 3-14: Load Net Renewables for a Day in July 2026 with the Largest HSBO LnR Range ... 111
Figure 3-15: Load Net Renewables for the Average Day of August 2026 ... 112
Figure 3-16: Load Net Renewables for a Day in August 2026 with the Largest HSBO LnR Range ... 112
Figure 3-17: Load Net Renewables for the Average Day of September 2026 ... 113
Figure 3-18: Load Net Renewables for a Day in September 2026 with the Largest HSBO LnR Range ... 113
Figure 3-19: Load Net Renewables for the Average Day of October 2026 ... 114
Figure 3-20: Load Net Renewables for a Day in October 2026 with the Largest HSBO LnR Range ... 114

Figure 3-21: Load Net Renewables for the Average Day of November 2026 115
Figure 3-22: Load Net Renewables for a Day in November 2026 with the Largest HSBO LnR Range 115
Figure 3-23: Load Net Renewables for the Average Day of December 2026 116
Figure 3-24: Load Net Renewables for a Day in December 2026 with the Largest HSBO LnR Range 116

List of Tables

Table 1-1: Renewable Scenario Descriptions with Wind and Solar Installed Capacity 15
Table 1-2: Summary Statistics for PJM 2026 Load and Renewable Energy Production by Scenario 16
Table 1-3: Load and LNR Statistics over all 3 Years of Data 16
Table 1-4: Maximum and Minimum Net Load by Profile Year and Hour 18
Table 1-5: Hour of Day Alignment 21
Table 1-6: Summary of Each Scenario Renewable Resource By Resource Type 27
Table 1-7: Variable Generation Summary for Each Scenario by Including Wind and All PV Resource Types 27
Table 2-1: Regulation Schedule for Selected Days in Month (MW) 84
Table 2-2: Approximate Equations for 10-Minute Variability 94
Table 2-3: Estimated Regulation Requirements for Study Scenarios 97
Table 2-4: 10-Minute Periods Exceeding Ramp-Up or Ramp-Down for Selected Scenarios 99
Table 2-5: Number of 10-Minute Periods Exceeding Dispatched Resource Operating Range 100

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 Statistical Analysis of Load and Renewable Data

1.1 Objectives of Statistical Analysis

In this section, the report provides information in charts and tables that describe and characterize the PJM system load data and renewable resource data. Renewable resources analyzed consist of Wind and PV generation where PV consists of Single Axis Solar PV, Commercial Fixed Axis Solar PV, and Distributed Residential Rooftop Solar PV. Wind generation is variable across time scales ranging from second to seasons and cannot be perfectly forecast over any horizon. PV generation like wind is variable across a smaller time scale, i.e., daylight hours, and is influenced by numerous factors such as cloud cover, haze, humidity, aerosol and others. Balancing Area load also exhibits variability and uncertainty across many operational time frames. Renewable resource variability and uncertainty increase the overall variability and uncertainty of net load (system load net of renewable generation).

The main purpose of the analysis provided in this section is to convey familiarity to the reader of the chronological load and renewable (Wind and PV) data which are the primary inputs to the technical analysis described in the report. In general it is not possible to extract quantitative conclusions about operating impacts directly from statistics of wind, PV and load data. While certain features may stand out from a system operations perspective – such as a difference in time when peak and net load peak occur – several other factors must be considered to determine the magnitude of the impact. Production simulations take many of these other factors into account as they seek to mimic the actual operation of the system against the array of operating constraints, and therefore are the better framework for drawing operational conclusions.

Renewable generation scenarios consisting of different penetrations of wind and PV were defined for the study and are shown in Table 1-1. Scenarios were defined in consultation with PJM[1], and renewable wind and PV sites were selected from the data available in the NREL databases. Chronological production data at 10-minute intervals over the calendar years of 2004, 2005 and 2006 were extracted and aggregated by generation type for this analysis.

In the GE MAPS production simulations, individual sites were assigned to existing or planned network buses in the PJM model. The statistical analysis and characterization of the renewable resources examine the aggregate production i.e. the total generation of all wind and PV sites in each scenario.

[1] Please see PJM PRIS Task 2 Report: "Scenario Development and Analysis"

PJM provided 5-minute resolution load for the same calendar years as the renewable production data, since system load can be affected by weather conditions and renewable generation is also weather related. The load data was escalated with PJM guidance to make the data sets representative of the future study year.

Table 1-1: Renewable Scenario Descriptions with Wind and Solar Installed Capacity

Scenario	Abbreviation	Installed Capacity
2% Business as Usual	2% BAU	5,193
14% Renewable Portfolio Standard	14% RPS	40,188
20% High Offshore Best Onshore Wind	20% HOBO	62,704
20% Low Offshore Distributed Onshore Wind	20% LODO	64,284
20% Low Offshore Best Onshore Wind	20% LOBO	62,794
20% High Solar Best Onshore Wind	20% HSBO	73,278
30% High Offshore Best Onshore Wind	30% HOBO	103,939
30% Low Offshore Distributed Onshore Wind	30% LODO	105,812
30% Low Offshore Best Onshore Wind	30% LOBO	102,357
30% High Solar Best Onshore Wind	30% HSBO	108,903

The first row of Table 1-2 summarizes the PJM load for 2004, 2005 and 2006 profiles, scaled for the study year. The remaining rows show statistics pertaining to renewable generation for each scenario. Load Net of Renewable generation (LNR) is summarized in Table 1-3. Both tables present the aggregate annual energy statistics, contribution of renewable energy during peak load hours for each scenario, and the minimum net load.

Table 1-2: Summary Statistics for PJM 2026 Load and Renewable Energy Production by Scenario

Scenario	Abbreviation	Maximum (MW)	Minimum (MW)	Average (MW)	Std. Deviation (MW)	Average Annual Energy (TWh)
Load	Load	200,278	66,583	110,684	19,762	969,596
2% Business as Usual	2%BAU	4,894	29	1,956	1,139	17,132
14% Renewable Portfolio Standard	14%RPS	34,444	802	13,864	6,991	121,445
20% High Offshore Best Onshore Wind	20%HOBO	51,705	685	20,456	8,632	179,199
20% Low Offshore Distributed Onshore Wind	20%LODO	53,203	1,198	20,579	9,673	180,273
20% Low Offshore Best Onshore Wind	20%LOBO	52,095	1,042	20,432	10,025	178,984
20% High Solar Best Onshore Wind	20%HSBO	60,598	883	20,574	10,659	180,230
30% High Offshore Best Onshore Wind	30%HOBO	85,643	1,026	32,634	13,933	285,878
30% Low Offshore Distributed Onshore Wind	30%LODO	87,687	1,728	32,558	15,314	285,204
30% Low Offshore Best Onshore Wind	30%LOBO	85,706	1,473	32,539	16,209	285,039
30% High Solar Best Onshore Wind	30%HSBO	91,152	1,218	30,715	16,278	269,061

Table 1-3: Load and LNR Statistics over all 3 Years of Data

Scenario	Abbreviation	Maximum (MW)	Minimum (MW)	Average (MW)	Std. Deviation (MW)	Net Average Annual Energy (TWh)
Load	Load	200,278	66,583	110,684	19,762	969,596
2% Business as Usual	2%BAU	198,082	65,183	108,729	19,967	952,464
14% Renewable Portfolio Standard	14%RPS	182,294	47,251	96,821	21,200	848,151
20% High Offshore Best Onshore Wind	20%HOBO	170,399	37,322	90,228	20,783	790,397
20% Low Offshore Distributed Onshore Wind	20%LODO	169,571	36,202	90,105	21,575	789,323
20% Low Offshore Best Onshore Wind	20%LOBO	169,504	37,548	90,252	21,758	790,612
20% High Solar Best Onshore Wind	20%HSBO	171,033	30,876	90,110	20,075	789,366
30% High Offshore Best Onshore Wind	30%HOBO	160,917	9,117	78,050	22,421	683,718
30% Low Offshore Distributed Onshore Wind	30%LODO	156,136	9,387	78,127	23,690	684,392
30% Low Offshore Best Onshore Wind	30%LOBO	159,229	7,010	78,146	24,368	684,557
30% High Solar Best Onshore Wind	30%HSBO	164,967	1,927	79,970	22,319	700,535

Operationally, the load net of renewable generation (i.e., LNR) will drive the decisions and algorithms for deployment of controllable resources (e.g., conventional generating units, energy transactions with neighboring markets and areas, and demand response). The LNR analysis does not consider energy transactions with neighboring markets and systems, so the minimum hourly LNR values for each scenario cannot be used directly to assess implications for the PJM generation fleet. The price of the excess energy during these periods would be very low, and therefore presumably attractive to outside purchasers; energy sales could add significantly to the demand served by PJM resources.

Table 1-4 depicts the maximum and minimum LNR hours by year. The minimum net load hour mentioned above (i.e. changing the minimum load from 66.6 GW to 30.9 GW of LNR) occurs for the 20% HSBO scenario for load and renewable generation based on calendar year 2005 profiles. With profiles from other calendar years, the minimum LNR for this scenario is higher (35.9 GW and 36.5 GW). It is interesting to note that these absolute minimum net loads have occurrences in the spring and fall seasons while the maximum net loads trend to the summer mostly around July 28, 29 and August 4 for profiles 2005, 2006 and 2004 respectively.

Maximum net loads are also of interest. Looking at the maximum net load hour, it can be seen from the tables that renewable generation in all of the scenarios reduces the PJM peak net load (i.e., the portion of the load that must be served by generation other than wind and solar). The amount of this reduction varies by scenario and year as would be expected from the differing portfolios of wind and solar resources in each scenario and the variability between years in terms of load, wind and PV resources. Scenarios with a greater proportion of offshore wind do not reduce system peak load as much as the LOBO and LODO scenarios. It should also be noted that a shift in the peak net load hour from noon to 2 PM to later in the day (5-6 PM) occurs as penetration levels increase. This may be attributed to the effects of solar PV being able to provide generation during the daylight hours.

Table 1-4: Maximum and Minimum Net Load by Profile Year and Hour

LNR - 2004 Profile Year				
Scenario	Maximum (MW)	Maximum Hour	Minimum (MW)	Minimum Hour
Load	170,758	08/04/2026 14:00	70,163	04/19/2026 1:00
2%BAU	170,420	08/04/2026 14:00	66,961	04/19/2026 1:00
14%RPS	163,364	08/04/2026 14:00	47,986	04/20/2026 0:00
20%HOBO	152,386	08/04/2026 15:00	37,322	09/20/2026 2:00
20%LODO	156,276	08/04/2026 15:00	37,189	04/20/2026 0:00
20%LOBO	157,205	08/04/2026 15:00	38,137	04/20/2026 0:00
20%HSBO	154,650	08/04/2026 17:00	35,899	04/19/2026 11:00
30%HOBO	143,827	08/04/2026 17:00	13,333	03/29/2026 12:00
30%LODO	150,470	08/04/2026 17:00	16,966	04/20/2026 0:00
30%LOBO	150,772	08/04/2026 17:00	11,820	03/29/2026 12:00
30%HSBO	151,154	08/04/2026 17:00	6,054	04/19/2026 11:00
LNR - 2005 Profile Year				
Scenario	Maximum (MW)	Maximum Hour	Minimum (MW)	Minimum Hour
Load	182,076	07/21/2026 12:00	66,583	05/25/2026 1:00
2%BAU	179,514	07/29/2026 13:00	65,183	05/25/2026 0:00
14%RPS	170,147	07/28/2026 13:00	47,251	11/01/2026 2:00
20%HOBO	161,057	07/28/2026 14:00	37,431	04/18/2026 1:00
20%LODO	160,433	07/28/2026 14:00	36,202	11/11/2026 1:00
20%LOBO	160,374	07/28/2026 14:00	37,548	11/11/2026 1:00
20%HSBO	157,986	07/28/2026 17:00	30,876	04/26/2026 11:00
30%HOBO	153,800	07/28/2026 17:00	17,457	11/05/2026 0:00
30%LODO	152,228	07/28/2026 17:00	9,387	04/26/2026 12:00
30%LOBO	153,336	07/28/2026 17:00	7,010	04/26/2026 12:00
30%HSBO	154,216	07/28/2026 18:00	1,927	04/26/2026 11:00
LNR - 2006 Profile Year				
Abbreviation	Maximum (MW)	Maximum Hour	Minimum (MW)	Minimum Hour
Load	200,278	07/29/2026 13:00	69,178	04/12/2026 1:00
2%BAU	198,082	07/28/2026 13:00	66,282	04/12/2026 1:00
14%RPS	182,294	07/28/2026 13:00	49,870	03/28/2026 1:00
20%HOBO	170,399	07/27/2026 15:00	40,047	03/28/2026 1:00
20%LODO	169,571	07/28/2026 13:00	39,980	03/28/2026 1:00
20%LOBO	169,504	07/28/2026 11:00	40,767	04/12/2026 0:00
20%HSBO	171,033	07/29/2026 18:00	36,523	04/26/2026 11:00
30%HOBO	160,917	07/29/2026 18:00	9,117	04/26/2026 11:00
30%LODO	156,136	07/29/2026 18:00	13,312	10/24/2026 12:00
30%LOBO	159,229	07/29/2026 18:00	10,125	04/26/2026 11:00
30%HSBO	164,967	07/29/2026 18:00	6,253	04/26/2026 11:00

The section presents numerous statistical characteristics related to the wind and solar resources for each of the study scenarios. However, it does not address capacity value, which requires its own specialized analysis based on LOLE and ELCC methods. Capacity value of wind and solar resources are discussed in detail in another chapter of this report.

The initial part of this section examines the system load, its development for the study, and how it is modeled to be representative of the system study period. Next, the focus is on the variability of wind and PV (renewable) generation as defined by the study scenarios, and how it combines with the inherent variability of PJM load. The analysis will look at hourly data over the entire three years of the available wind, PV and load profile data. Variability and uncertainty are then examined with the 10-minute interval data. Finally the uncertainty and error characteristics of various forecasts available for the chronological wind and PV production data are analyzed including the day-ahead forecasts. Other techniques important to the analysis and presented later in the report, such as persistence forecasts, are also examined.

The analysis here is conducted on an aggregate basis for the entire PJM footprint; that is, the total generation for each time interval (10-minute, 1-hour, as appropriate) is considered, independent of where the individual wind and solar resources may be located. Differences stemming from alternate locations of wind and PV generation for scenarios of similar penetration are used to compare locational/diversity effects. The transmission infrastructure assumed for the study scenarios was not a factor in this analysis; this analysis relates only to load, wind, and solar data.

1.2 Load Analysis

Renewable resources by nature are variable and uncertain. Weather plays a significant role. Load variability, while perhaps having uncertainty to a lesser degree, is also affected by weather. For this reason the project team determined that it would use coincidental load and renewable data (i.e., chronologically synchronized load and renewable data from the same calendar years). PJM provided 5-minute chronological load data from October 2004 through December 2006. Hourly load data for 2004, 2005 and 2006 for each PJM area was obtained and aggregated to create the PJM total system load. Each year of load data was escalated to the project study year 2026. Throughout this report, load magnitudes for 2026 will be shown; and to distinguish the origin of the study data, a reference to the profile used (i.e., 2004, 2005, or 2006) will also be shown.

Load data has inherent weekly patterns. For example when full weeks of load data are plotted, a trained eye can identify the weekday and weekend trends. For this reason it is important to align, by day of the week, the load data from the profile years with the load data of the study year. January 1, 2026 is a Thursday and January 1, 2004 is also a Thursday, and hence, there is no adjustment to the 2004 profile to align the days of the week. Since January 1, 2005 is a Saturday and January 1, 2006 is a Sunday, profile shapes for these years of study data are shifted. Accordingly, to align day of the week between these profile years, January 1, 2026 is mapped to January 6, 2005 and to January 5, 2006. To maintain the chronology of data for the study year, December 31, 2026 profile 2005 maps to January 6, 2006. December 31, 2026 profile 2006 exceeds the end of the 2006 profile so the last four days repeat the 2006 profile days from December 25 through December 28. Figure 1-1, Figure 1-2 and Figure 1-3 show plots of each profile year and the mapping to the escalated system load for the 2026 study period. The blue traces are the raw load data from 2004 and the green traces are the scaled and time-adjusted profiles for 2026.

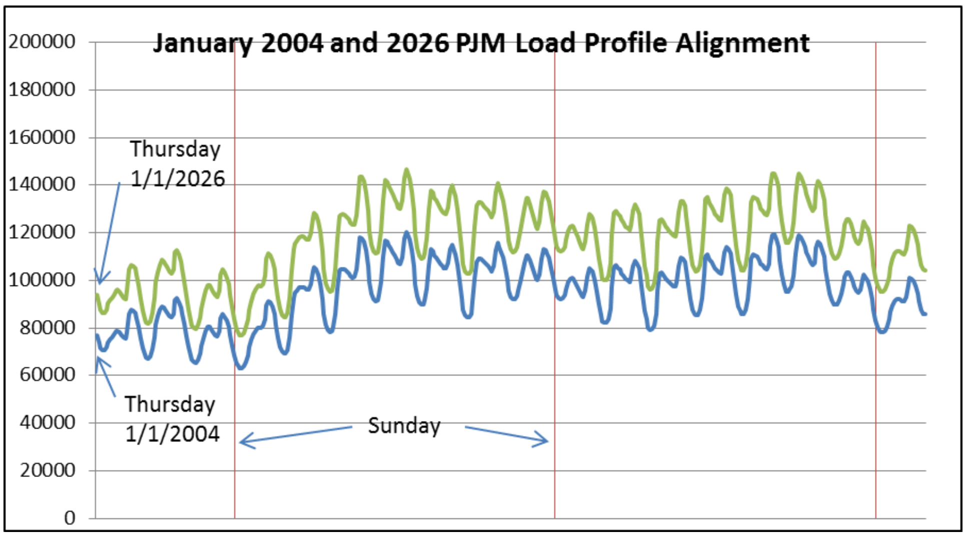


Figure 1-1: Weekday Alignment of 2004 Load Escalated to 2026 (MW)

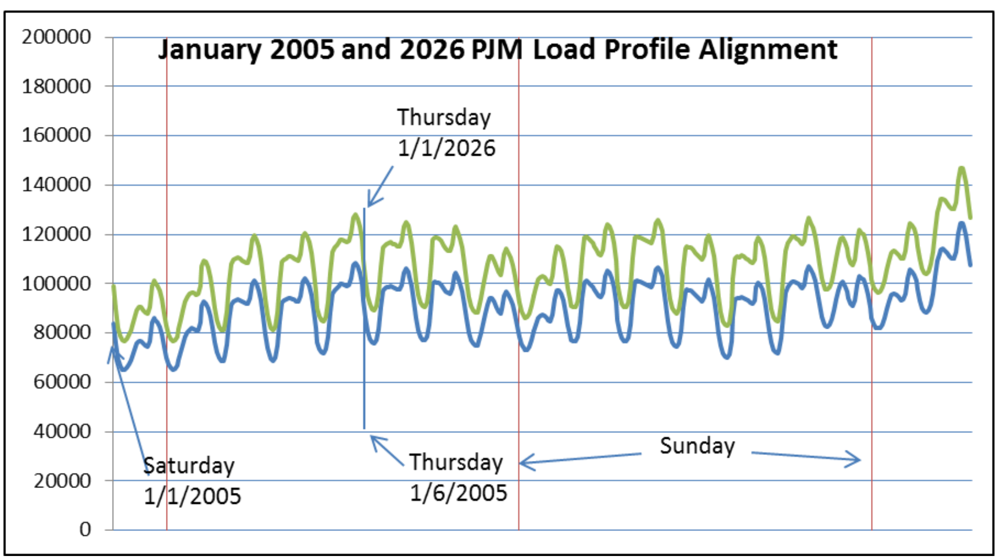


Figure 1-2: Weekday Alignment of 2005 Load Escalated to 2026 (MW)

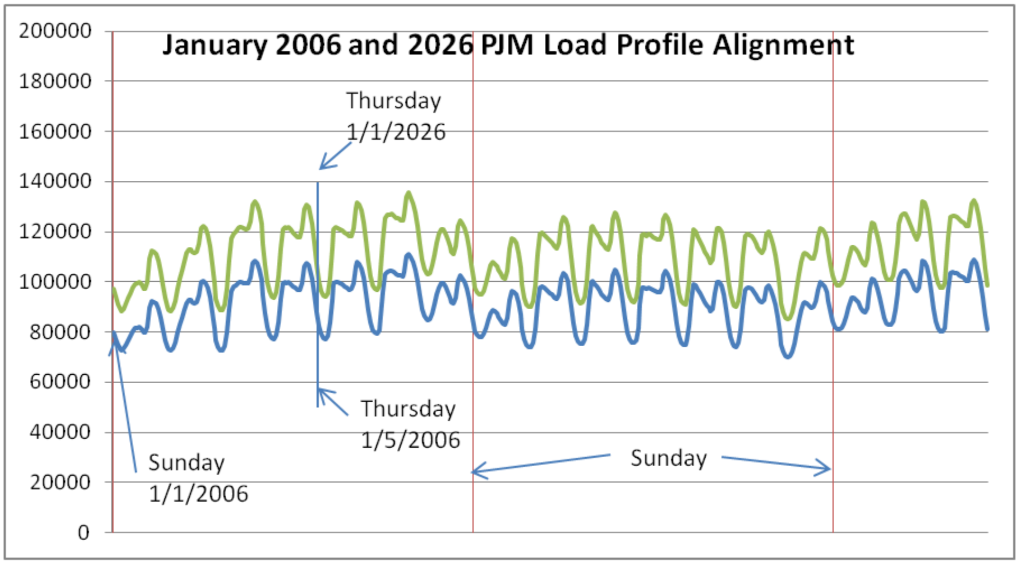


Figure 1-3: Weekday Alignment of 2006 Load Escalated to 2026 (MW)

The renewable chronological data is provided with Coordinated Universal Time (UTC) timestamp. This data is converted to Eastern Standard Time (EST) as shown in Table 1-5, below.

Table 1-5: Hour of Day Alignment

	EST Hour Ending	UTC Hour Ending
Study Period 2026	1/1/26 1:00	1/1/2026 6:00
Mapping to 2004 profile	1/1/2004 1:00	1/1/2004 6:00
Mapping to 2005 Profile	1/6/2005 1:00	1/6/2005 6:00
Mapping to 2006 Profile	1/5/2006 1:00	1/5/2006 6:00

Figure 1-4, Figure 1-5 and Figure 1-6 show seasonal, monthly and weekly energy for the study load for each profile year. When examining the seasonal variability, it is noted the largest difference in seasonal energy demand is approximately 60 TWh between the spring and summer of the 2005 profile. Examining the monthly energy in Figure 1-5, it can be observed that January, June, July, August and December have the highest energy demand, with differences no more than 20 TWh. Looking closer at the weekly demand in Figure 1-6, there is an observable change from week to week that trends toward the expected seasonal behavior.

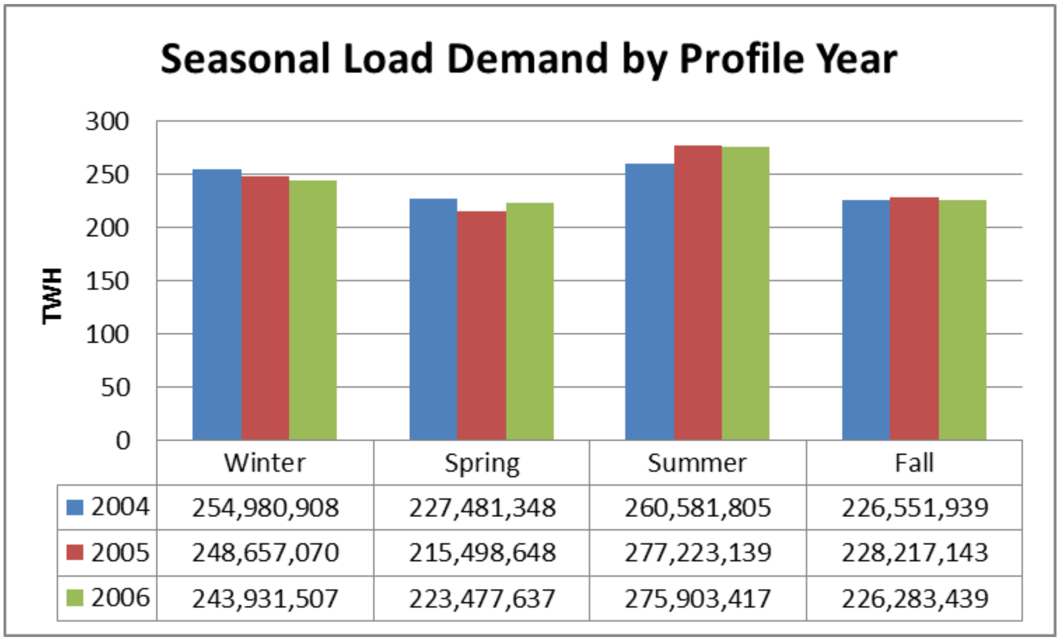


Figure 1-4: Seasonal Load Energy by Profile Year

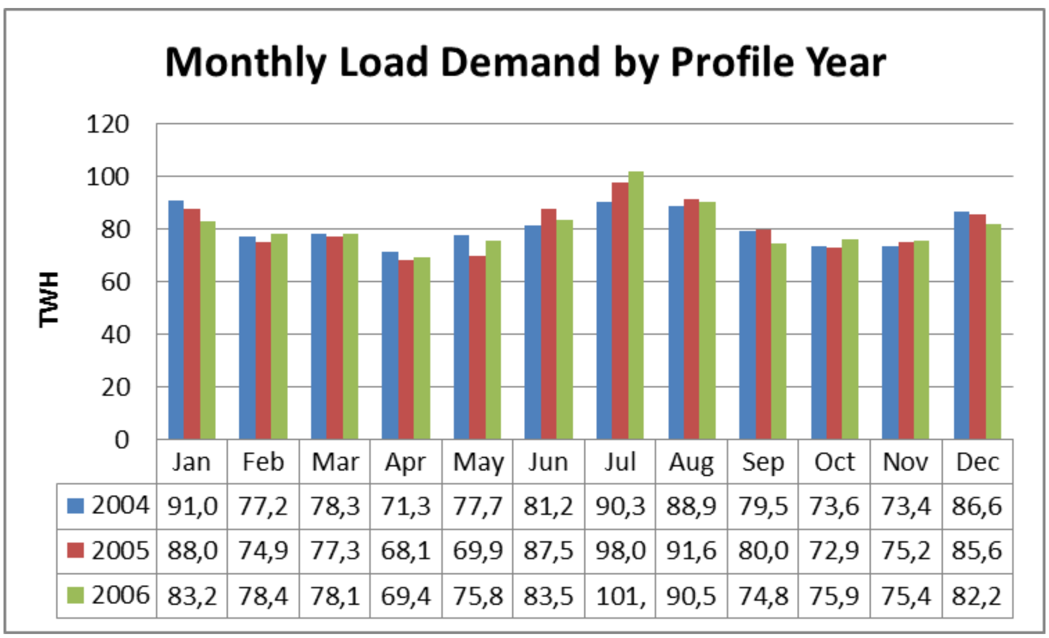


Figure 1-5: Monthly Load Energy by Profile Year

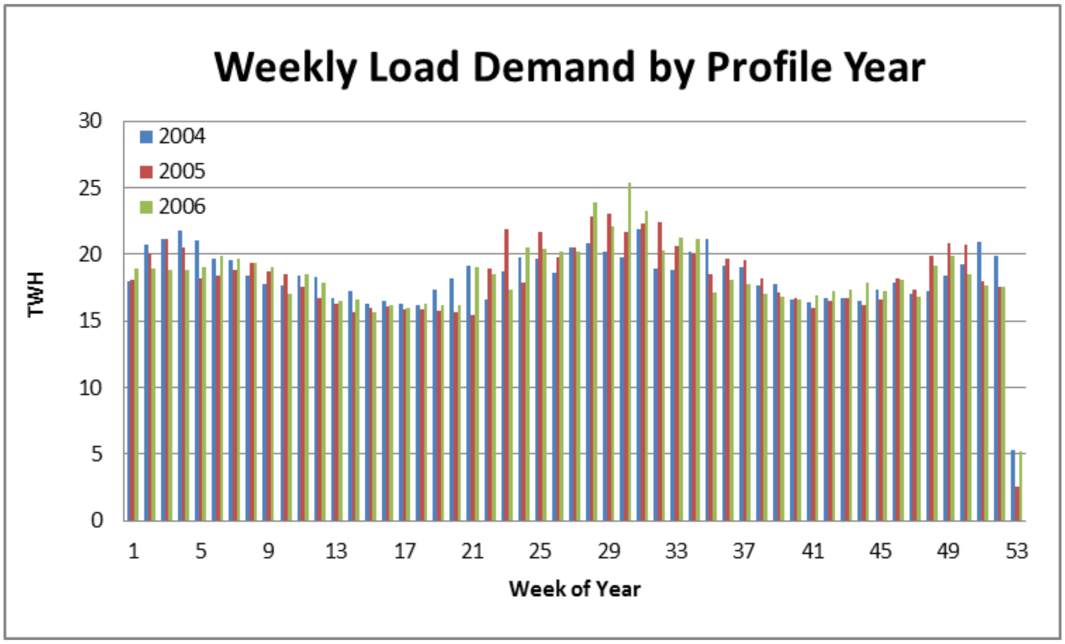


Figure 1-6: Weekly Load Energy by Profile Year

Another way of examining load is by plotting a Load Duration Curve (LDC). LDC provides a visual means of looking at the hourly load values non-chronologically so that one can view over the full 8760 hours in the year limits of loads that can be challenging, such as the peak or low load periods. Plotting the three study profile loads on the same graph shows periods that may be of particular interest. As depicted in Figure 1-7, it can be seen that different years being analyzed in the study have a comparable LDCs. This does not mean that the chronological loads are the same between profile years. It just shows that the load profiles have different hourly values of load throughout the year.

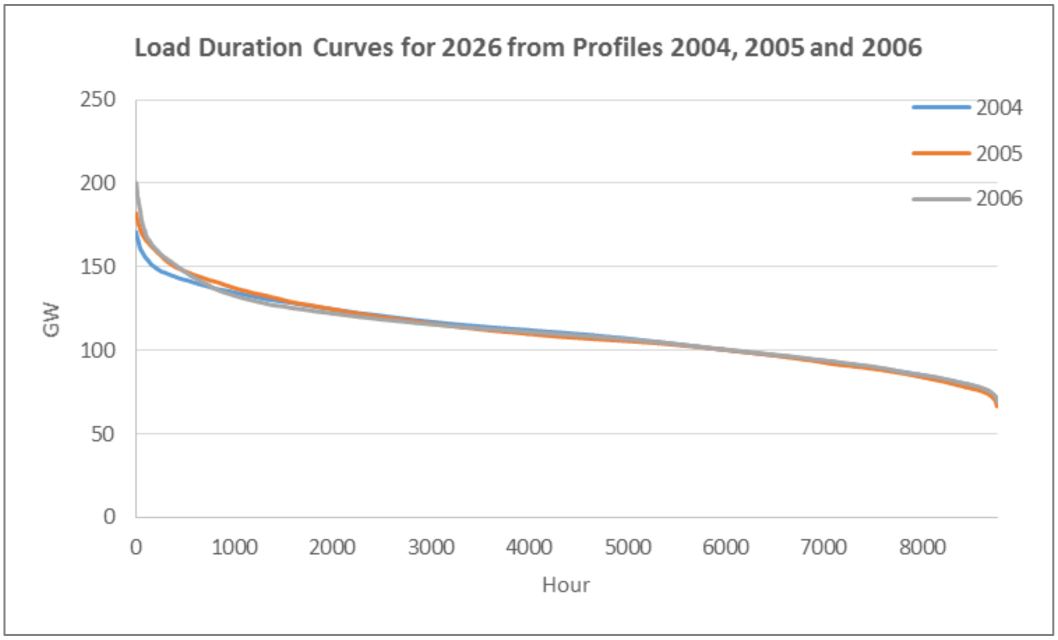


Figure 1-7: Load Duration Curves of Study Year for Each Annual Profile

Load magnitude varies from hour to hour. This variability can be examined by looking at the hourly change, and ranking the changes from high to low. This curve, similar to LDC, provides a way of examining the hourly up-ramps and down-ramps in load magnitude for the three profile years. Figure 1-8, Figure 1-9, and Figure 1-10 plot the hour to hour change in load and provide the values of the largest up-ramp and down-ramp for each annual load profile. The largest up-ramps and down-ramps can be identified along with a sense of the number of hours in the year that have large up-ramps or down-ramps. The majority of hourly ramps in each profile fall within the band of +/- 5,000 MW.

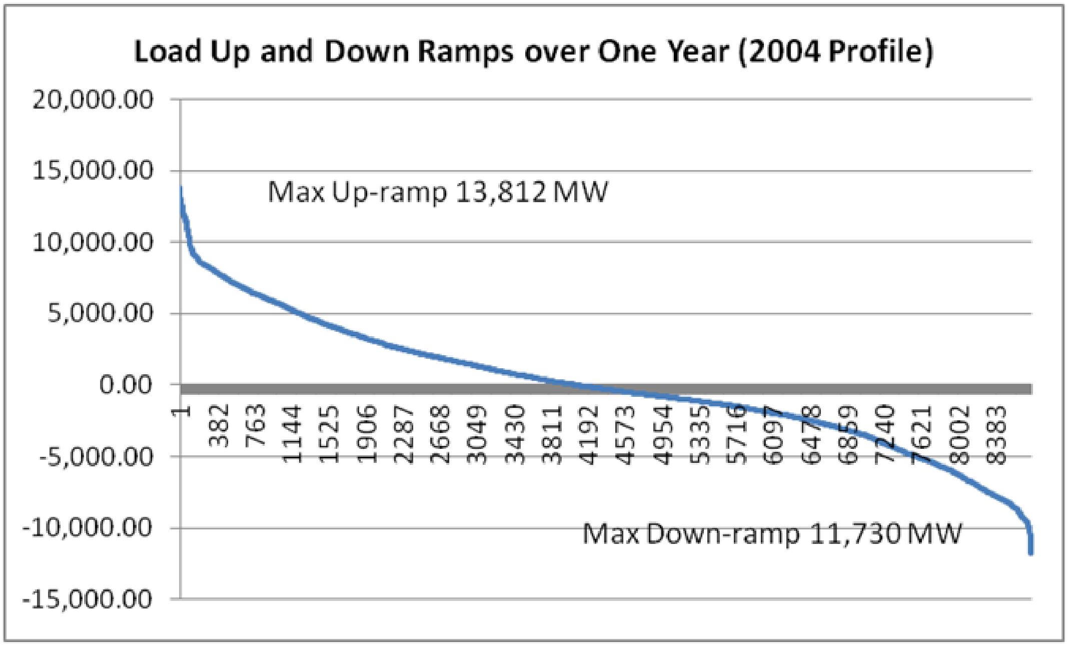


Figure 1-8: Hour To Hour Load Ramp Duration Curve for Study Year with 2004 Profile

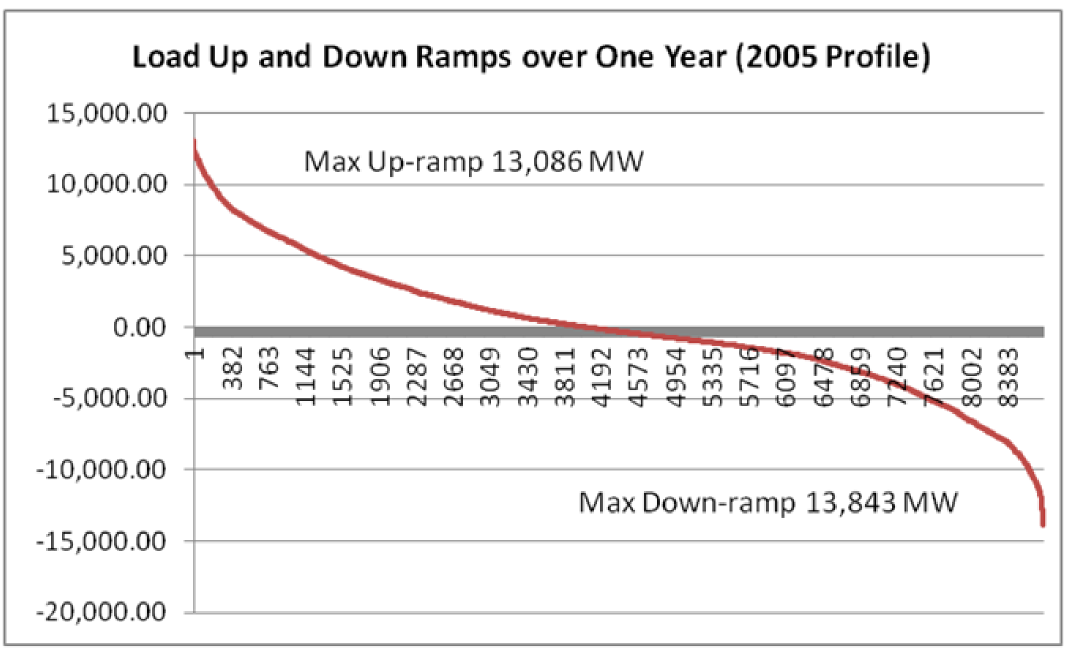


Figure 1-9: Hour To Hour Load Ramp Duration Curve for Study Year with 2005 Profile

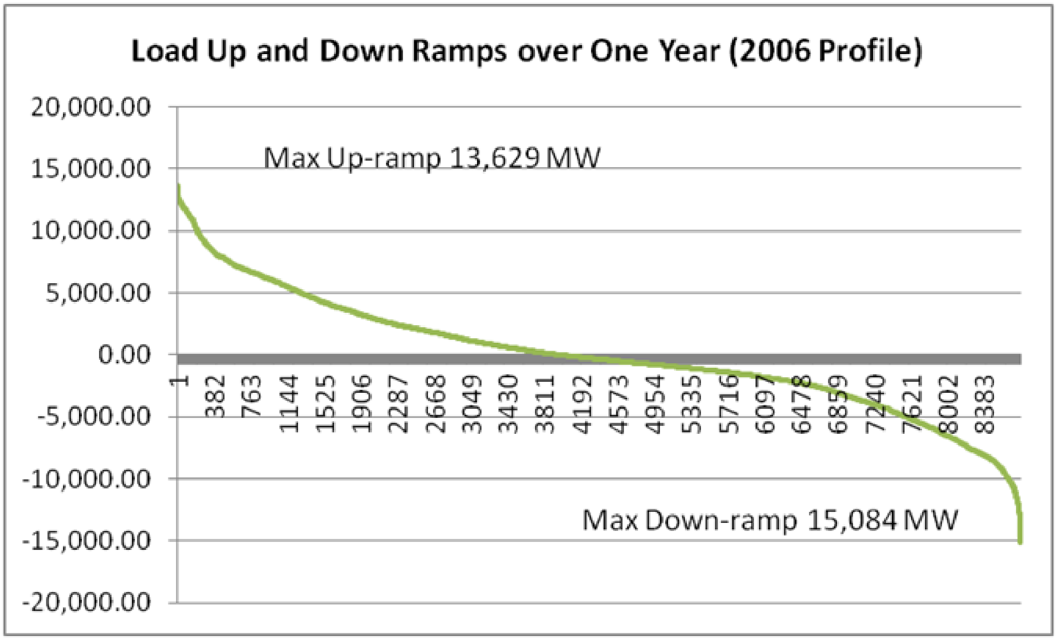


Figure 1-10: Hour To Hour Load Ramp Duration Curve for Study Year with 2006 Profile

1.3 Renewable Generation Variability

The time horizons - for which wind generation variability is important for power system operations - range from tens of seconds to seasons. Over shorter horizons, the variability appears as almost random due to the extremely large number of factors that can influence production over this time frame.

Nine scenarios plus a reference scenario are described in this section. Variable generation renewable resources consist of Wind, Central PV (with single-axis tracking), Distributed Commercial PV and Distributed Residential PV. Summary information for each resource type in each scenario is shown in Table 1-6 below[2]. This table shows the aggregated Wind, PV and Total Renewable as a single resource type providing the Reference capacity (i.e., installed capacity of that resource type), energy and capacity factor for each. In general for all of the scenarios the aggregated wind has a capacity factor in the range of 38% to 40%. Solar PV - which includes the single axis Central PV and Distributed PV (Commercial and Residential) - has capacity values ranging from 18% to 20%. When looking at all renewables as an aggregated resource, the capacity values of the combined wind and PV range from a

[2] It should be noted the data shown in this table is more recent than the task 2 report in that offshore wind energy was updated that resulted in reducing the number of offshore sites to satisfy the energy requirement for the 20% and 30% scenarios.

low of 28% to a high of 38% with the reference case having a capacity factor of close to 38%.

Table 1-6: Summary of Each Scenario Renewable Resource By Resource Type

2006 Profile	Wind			Total PV			Total Renewable		
Scenario	Ref Capacity MW	Energy GWh	Capacity Factor	Ref Capacity MW	Energy GWh	Capacity Factor	Ref Capacity MW	Energy GWh	Capacity Factor
Reference (BAU)	5,122	17,087	38.1%	71	124	19.8%	5,193	17,211	37.8%
14% Base (RPS)	**32,833**	**111,225**	**38.7%**	**7,355**	**11,782**	**18.3%**	**40,188**	**123,007**	**34.9%**
20% High Offshore Best Sites (HOBO)	44,213	150,067	38.7%	18,491	29,423	18.2%	62,704	179,490	32.7%
20% Low Offshore Dispersed (LODO)	**45,792**	**153,329**	**38.2%**	**18,491**	**29,423**	**18.2%**	**64,284**	**182,752**	**32.5%**
20% Low Offshore Best Sites (LOBO)	44,303	152,212	39.2%	18,491	29,423	18.2%	62,794	181,635	33.0%
20% High Solar Best Sites (HSBO)	**36,254**	**123,714**	**39.0%**	**37,024**	**58,896**	**18.2%**	**73,278**	**182,611**	**28.4%**
30% High Offshore Best Sites (HOBO)	68,294	228,556	38.2%	35,645	58,053	18.6%	103,939	286,609	31.5%
30% Low Offshore Dispersed (LODO)	**70,167**	**231,357**	**37.6%**	**35,645**	**58,053**	**18.6%**	**105,812**	**289,410**	**31.2%**
30% Low Offshore Best Sites (LOBO)	66,711	231,277	39.6%	35,645	58,053	18.6%	102,357	289,329	32.3%
30% High Solar Best Sites (HSBO)	**52,557**	**183,140**	**39.8%**	**56,346**	**90,664**	**18.4%**	**108,903**	**273,804**	**28.7%**

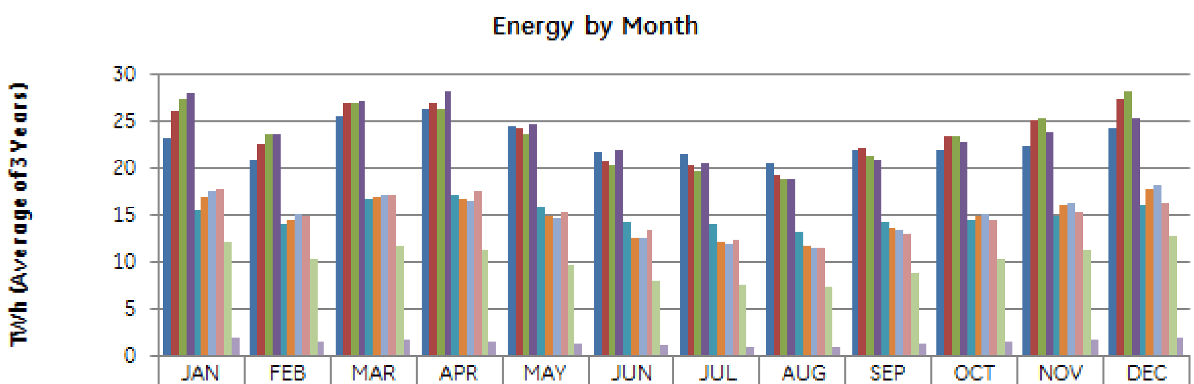
A similar table showing the specific breakdown of PV resources by type is shown in Table 1-7. As shown in this table, the central PV stations, which have single axis tracking, have capacity factors between 20% and 21%, while capacity factors of Distributed Commercial PV sites (fixed panels) are between 16% and 17%. Distributed Residential PV installations have lower capacity ratings and diversified locations with installation positions depending upon the slant and tilt of residential construction, which is why this resource type has the lowest capacity factor of the three PV resources - i.e., between 15% and 16%.

Table 1-7: Variable Generation Summary for Each Scenario by Including Wind and All PV Resource Types

2006 Profile	Wind			Central PV			Distributed Commercial			Distributed Residential		
Scenario	Ref Capacity MW	Energy GWh	Capacity Factor	Ref Capacity MW	Energy GWh	Capacity Factor	Ref Capacity MW	Energy GWh	Capacity Factor	Ref Capacity MW	Energy GWh	Capacity Factor
Reference (BAU)	5,122	17,087	38.1%	71	124	19.8%	-	-	-	-	-	-
14% Base (RPS)	**32,833**	**111,225**	**38.7%**	**3,253**	**5,770**	**20.2%**	**3,251**	**4,811**	**16.9%**	**851**	**1,202**	**16.1%**
20% High Offshore Best Sites (HOBO)	44,213	150,067	38.7%	8,078	14,774	20.9%	8,265	11,723	16.2%	2,148	2,927	15.6%
20% Low Offshore Dispersed (LODO)	**45,792**	**153,329**	**38.2%**	**8,078**	**14,774**	**20.9%**	**8,265**	**11,723**	**16.2%**	**2,148**	**2,927**	**15.6%**
20% Low Offshore Best Sites (LOBO)	44,303	152,212	39.2%	8,078	14,774	20.9%	8,265	11,723	16.2%	2,148	2,927	15.6%
20% High Solar Best Sites (HSBO)	**36,254**	**123,714**	**39.0%**	**16,198**	**29,598**	**20.9%**	**16,530**	**23,445**	**16.2%**	**4,296**	**5,853**	**15.6%**
30% High Offshore Best Sites (HOBO)	68,294	228,556	38.2%	18,290	33,637	21.0%	13,775	19,538	16.2%	3,580	4,878	15.6%
30% Low Offshore Dispersed (LODO)	**70,167**	**231,357**	**37.6%**	**18,290**	**33,637**	**21.0%**	**13,775**	**19,538**	**16.2%**	**3,580**	**4,878**	**15.6%**
30% Low Offshore Best Sites (LOBO)	66,711	231,277	39.6%	18,290	33,637	21.0%	13,775	19,538	16.2%	3,580	4,878	15.6%
30% High Solar Best Sites (HSBO)	**52,557**	**183,140**	**39.8%**	**27,270**	**49,316**	**20.6%**	**23,076**	**33,087**	**16.4%**	**6,000**	**8,261**	**15.7%**

1.3.1 Variability – Energy Production Summary

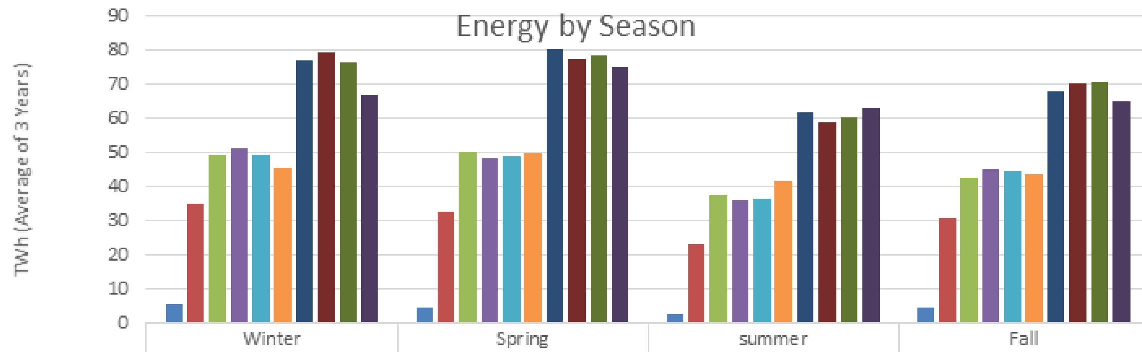
Figure 1-11 shows the energy delivery by month for all renewable generation scenarios. The monthly values reflect the average hourly production data from three profile years for the PJM system. It can be seen from this figure that the wind and PV generation in each scenario tend to somewhat balance out in each month such that when wind production is low, PV production is high, and when wind production is high, PV production is low. However, it is also evident that the spring and winter months have a higher renewable energy production than the summer months.



	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
30% HSBO	23	21	25	26	24	22	22	20	22	22	22	24
30% LOBO	26	23	27	27	24	21	20	19	22	23	25	27
30% LODO	27	24	27	26	24	20	20	19	21	23	25	28
30% HOBO	28	24	27	28	25	22	20	19	21	23	24	25
20% HSBO	15	14	17	17	16	14	14	13	14	14	15	16
20% LOBO	17	15	17	17	15	13	12	12	14	15	16	18
20% LODO	18	15	17	17	15	12	12	12	13	15	16	18
20% HOBO	18	15	17	18	15	13	12	11	13	14	15	16
14% RPS	12	10	12	11	10	8	8	7	9	10	11	13
2% BAU	2	2	2	2	1	1	1	1	1	1	2	2

Figure 1-11: Monthly Energy Production by All Renewable Resources (Average of 3 Years)

Figure 1-12, shows another way of displaying renewable production by scenario for each season.



	Winter	Spring	summer	Fall
2% Bau	5	4	3	4
14% RPS	35	33	23	31
20% HOBO	49	50	37	43
20% LODO	51	48	36	45
20% LOBO	49	49	36	45
20% HSBO	45	50	41	43
30% HOBO	77	80	61	68
30% LODO	79	77	59	70
30% LOBO	76	78	60	71
30% HSBO	67	75	63	65

Figure 1-12: Renewable Energy Production by Season and Scenario for 2006 Profile Year (3 Year Average)

In general, the scenarios are quite similar with respect to monthly and seasonal energy production characteristics. For the most part, the highest production occurs during spring, closely followed by the winter, with the lowest production in the summer. The composite nature of each scenario (different mixture of on and offshore wind plants, central and distributed PV plants, differing geographic characteristics, etc.) and averaging the seasonal production, are most likely responsible for attenuating the contrasts regarding energy production.

1.3.2 Capacity Factor

Average renewable resource capacity factors over the three years of data for each scenario is shown in Figure 1-13. The 2% BAU and 14% RPS scenarios have the largest capacity factors for total renewables at 38% and 35% respectively. Note that for the 2% BAU scenario, the renewable resource is nearly all wind, which explains the high capacity factor for that scenario. Other scenarios have significant PV solar in the mix. The lowest capacity factors (28% and 29%) are associated with the high solar (HSBO) scenarios. The high offshore scenarios did not exhibit any additional benefit with regard to capacity factor that might be attributed to the geographical location of the offshore sites (lower latitude sites tend to have lower average wind speeds than higher latitudes on the east shore). Another factor is that the scenarios selected with high offshore wind also included the best onshore wind sites.

Capacity factors for the 30% scenarios tend to be lower than their 20% counterparts since the site selection process selected the best sites first for the 20% scenarios with lower capacity factor sites available for selection in the 30% scenarios. The difference of about 1% in capacity factor between the 20% and 30% penetration levels can be attributed to the site selection process and the increase of PV sites.

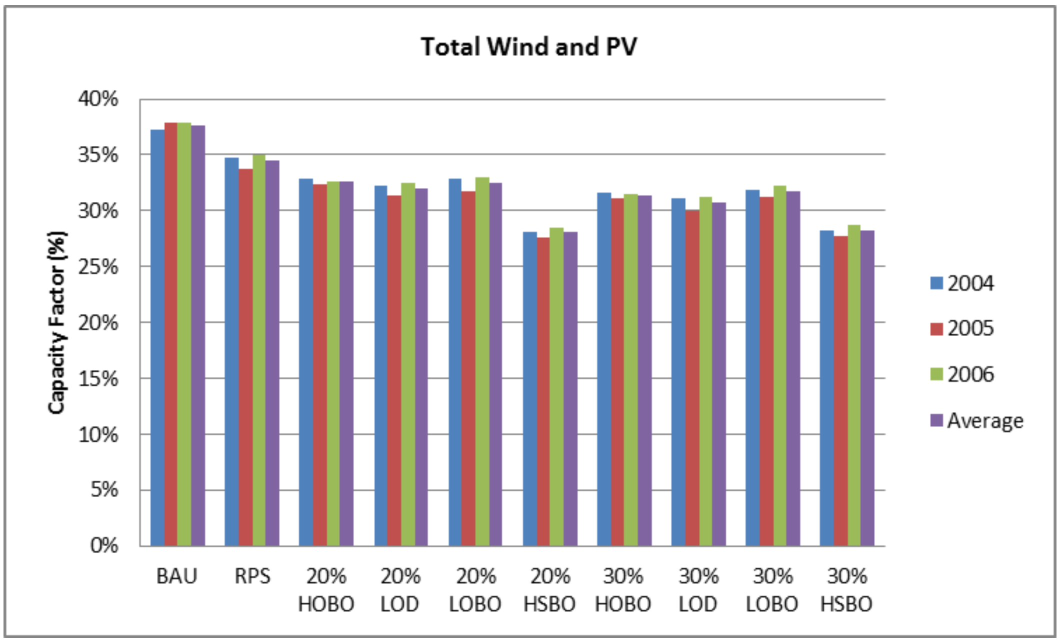


Figure 1-13: Average Annual Capacity Factor for Each Scenario and By Year

Figure 1-14 shows the capacity factor breakdown between off-peak (00:00 – 04:499) and on-peak (5:00 – 11:59). The 2% and 14% RPS scenarios have larger off-peak capacity factors than on-peak because of the greater proportion of wind in these two scenarios. This is consistent with wind having greater generation in the early morning hours of the day. Larger amounts of Solar PV included in the 20% and 30% scenarios increase the on-peak capacity factors. In particular, the High Solar scenarios have a greater difference between the on-peak and the off-peak capacity factors, indicative of an increase in Solar PV sites, reduction in wind, and shifting of energy production from off-peak to on-peak.

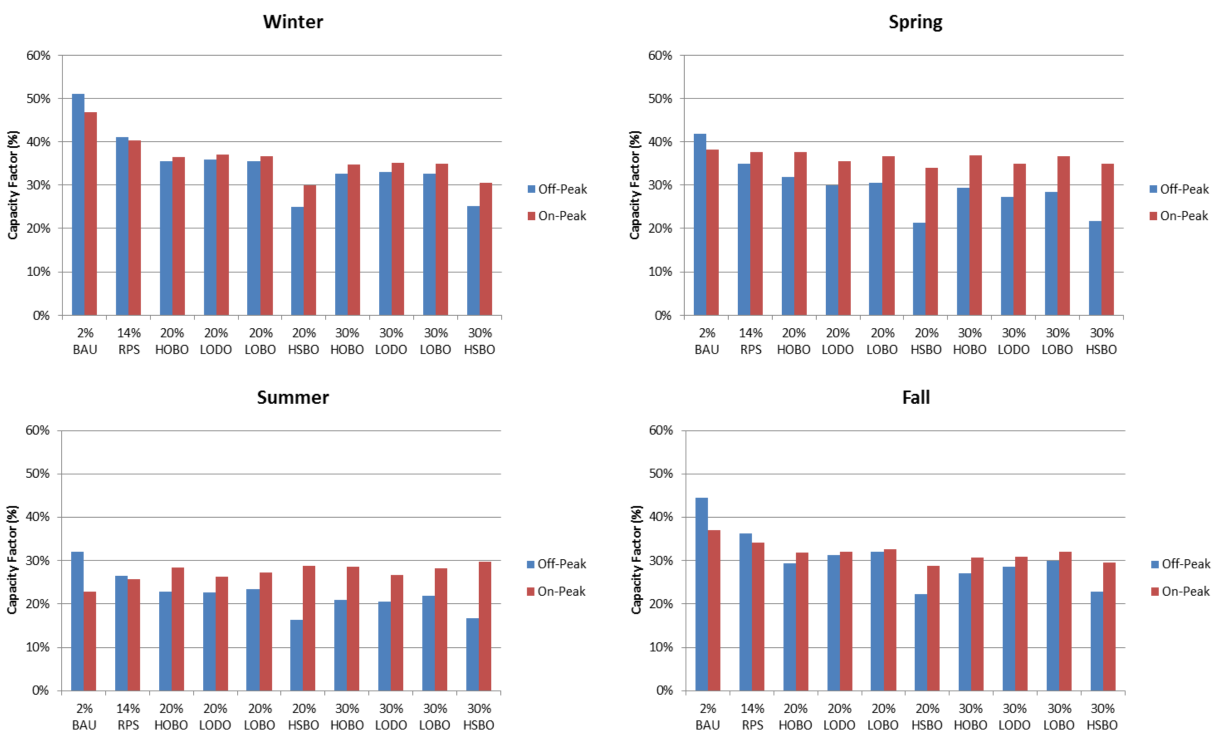


Figure 1-14: Off-Peak and On-Peak Capacity Factor by Season for All Scenarios (Average Over 3 Years)

1.3.3 Hourly Variability – Diurnal Characteristics

The large-scale meteorological phenomena that drive wind and PV generation, exhibit cycles that are non-integer multiples of 24 hour days. In addition, other wind generation drivers, such as sea breezes or atmospheric mixing can correspond to diurnal cycles in certain seasons. Averaging by hour of the day over an extended period such as a season can help reveal these patterns. Figure 1-15 through Figure 1-18 show the average daily profiles of the aggregated Wind and PV generation for each scenario by season.

The winter profile shown in Figure 1-15 shows lower generation from midnight until about 10 a.m. at which time the PV generation begins to ramp up until the afternoon when PV generation starts to ramp down. By 7 p.m. to 8 p.m. Wind generation becomes the primary resource that serves load. The geographical span of PJM from the east coast to mid-west (multiple time zones) provides an extended period of day light hours for PV generation. This can be seen in each of the seasonal plots when the PV "bump" begins and ends.

The average spring profiles in Figure 1-16 show the increase in wind that contributes to more exaggerated peaks in the 20% and 30% HSBO scenarios. The increase in daylight period compared to the winter season also contributes to the increasing daytime profiles.

The average summer profiles in Figure 1-17 show a much lower contribution of wind in the early morning and late evening hours, while PV provides generation for more hours in the day during this season.

The average fall profile in Figure 1-18 is similar to the spring profile. As a side note, the similarity of the LOBO and LODO profiles in this analysis is the result of averaging the data over many hours. However, noteworthy observation here is that LOBO and LODO have the same amount of wind energy but in different locations. From an overall PJM point of view, the profiles are similar. Differences in impacts would be related to regional issues within portions of the PJM network.

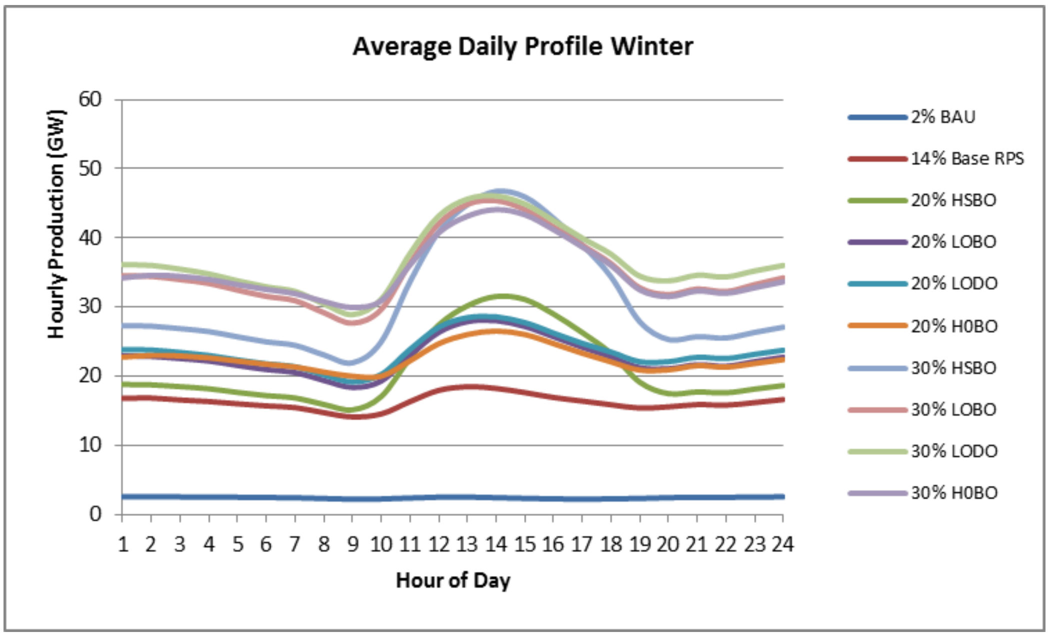


Figure 1-15: Average Daily Wind and PV Generation – Winter Profile (3 Years of Data)

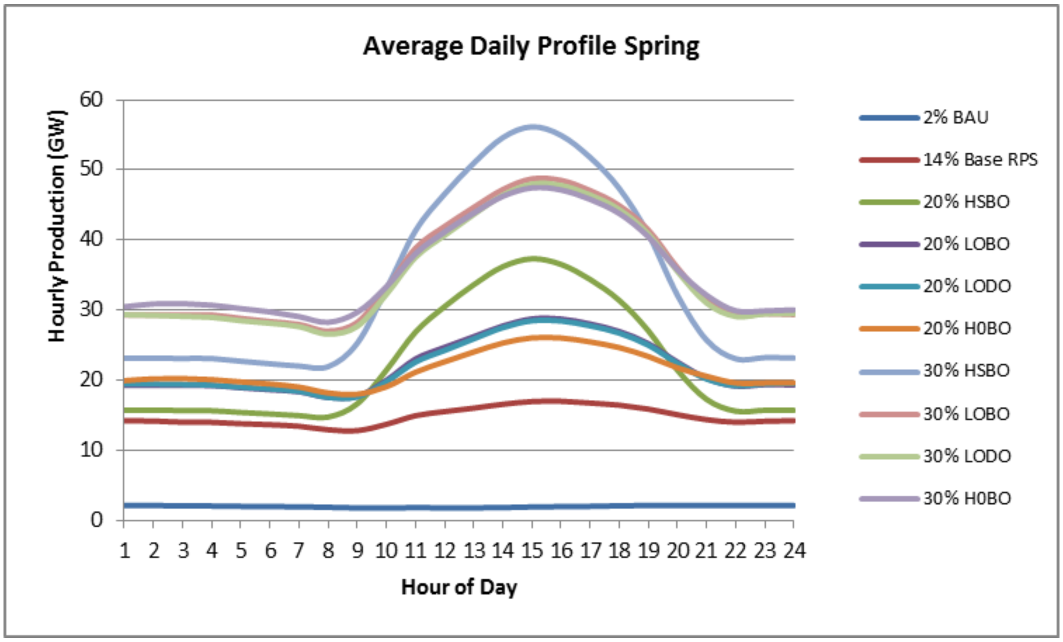


Figure 1-16: Average Daily Wind and PV Profile – Spring Profile (3 Years of Data)

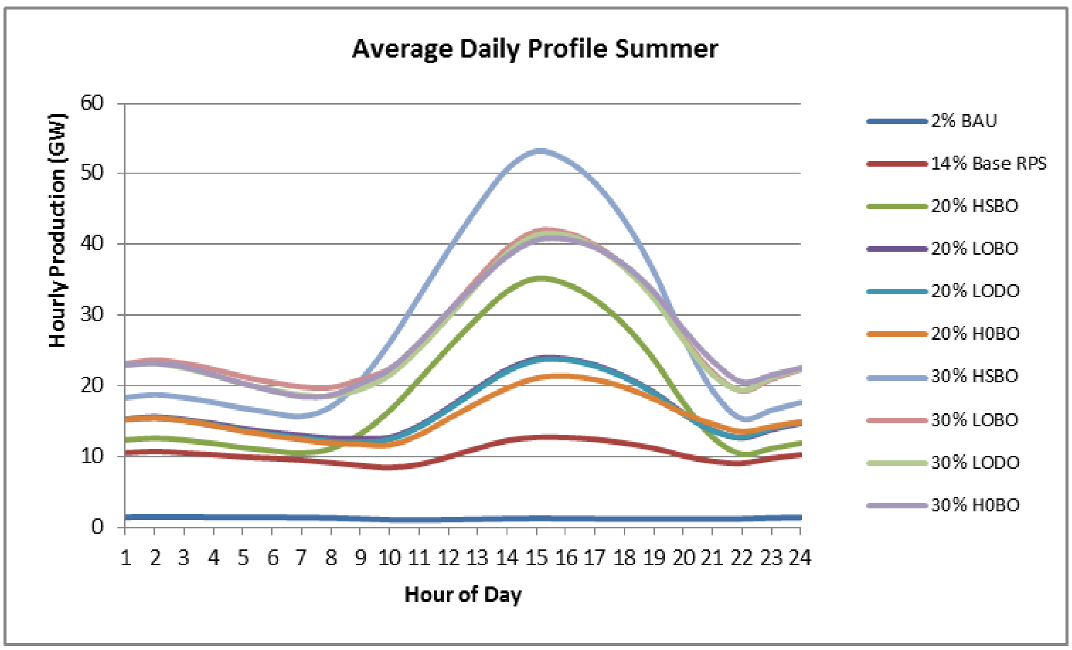


Figure 1-17: Average Daily Wind and PV Generation – Summer Profile (3 Years of Data)

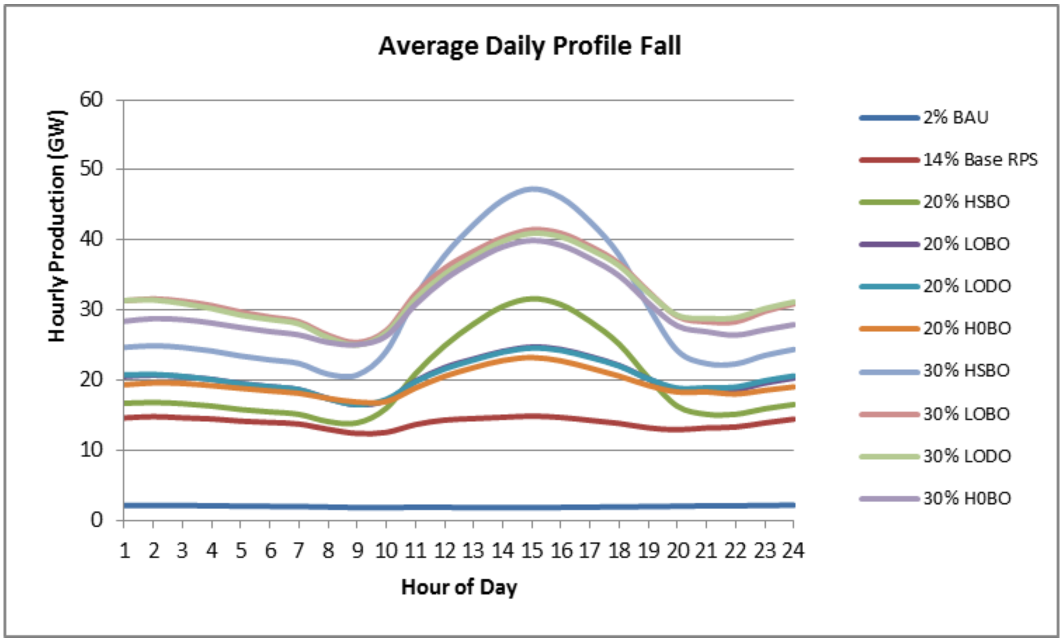


Figure 1-18: Average Daily Wind and PV Profile – Fall Profile (3 Years of Data)

To reveal more details about the behavior of the aggregate renewable production, each scenario was examined for each month over the three year profile periods. Figure 1-19 through Figure 1-28 show the hourly average daily production by month for each scenario along with the maximum and minimum values for each hour. Each trace is a series of twelve daily profiles, one 24-hour profile for each month of the year.

The trends noted previously are again evident here, with the highest production in the winter and spring seasons, and the lowest production in the summer. The 2% BAU scenario does not have an apparent PV influence (only 71 MW PV compared to 5122 MW wind) while the penetration of the PV increase in the 14% scenario begins to show a more defined daily generation contribution. Daily PV production is most observable in each month when penetration increases as shown in the 20% and 30% scenarios. The diurnal behavior of wind is apparent in the 2% and 14% and can be observed in the higher penetration cases however the PV contribution to the aggregate is beneficial since it generally increases while wind trends down and decreases while wind trends up. This is also true when making a month to month comparison since PV has lower generation in the winter months when wind is largest and highest in the summer months when wind is lowest.

In general for the 20% and 30% scenarios, wind and solar PV complement each other where the PV contribution is greatest during the daytime hours when sun is highest in the sky.

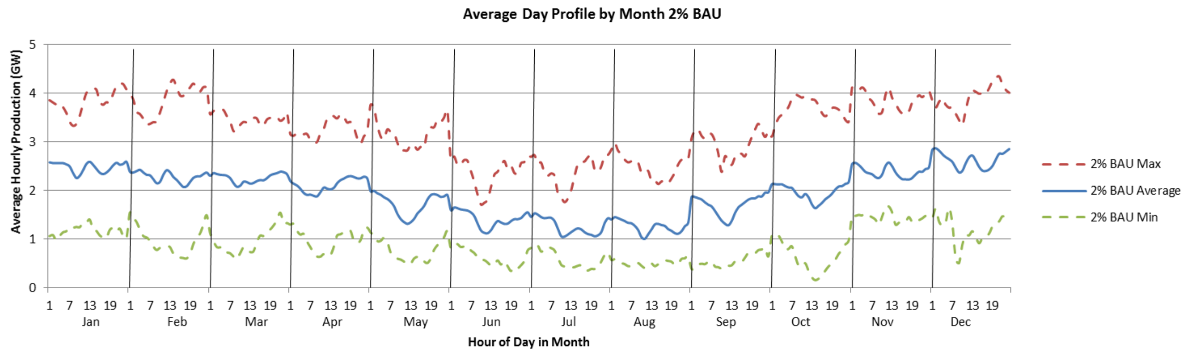


Figure 1-19: Average Daily Patterns by Month For 2% BAU Scenario; Maximum and Minimum Values Indicated By Dashed Lines

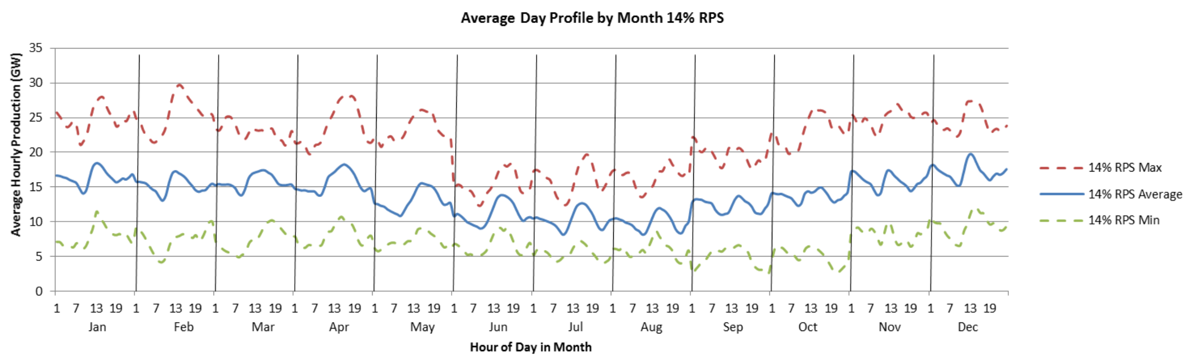


Figure 1-20: Average Daily Patterns by Month for 14% RPS Scenario; Maximum and Minimum Values Indicated By Dashed Lines

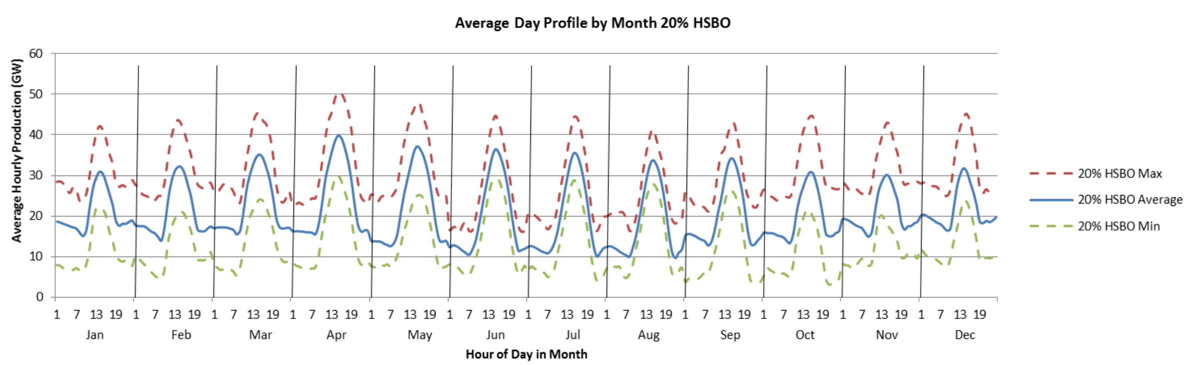


Figure 1-21: Average Daily Patterns by Month For 20% HSBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

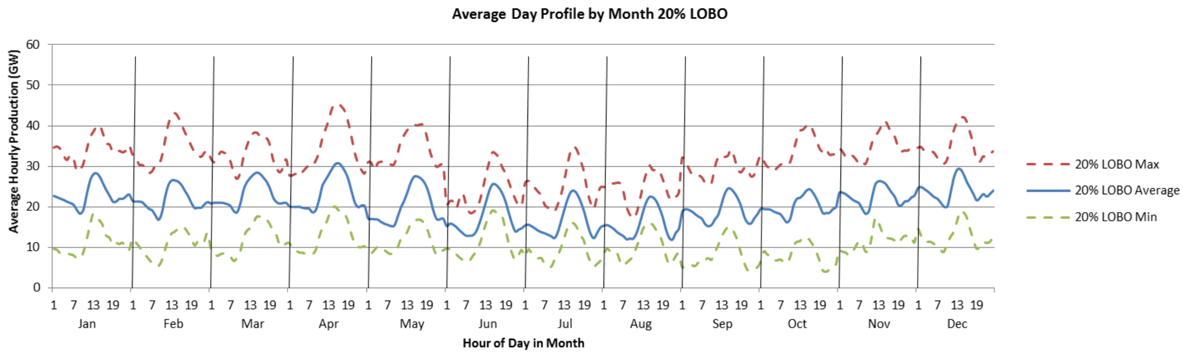


Figure 1-22: Average Daily Patterns by Month For 20% LOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

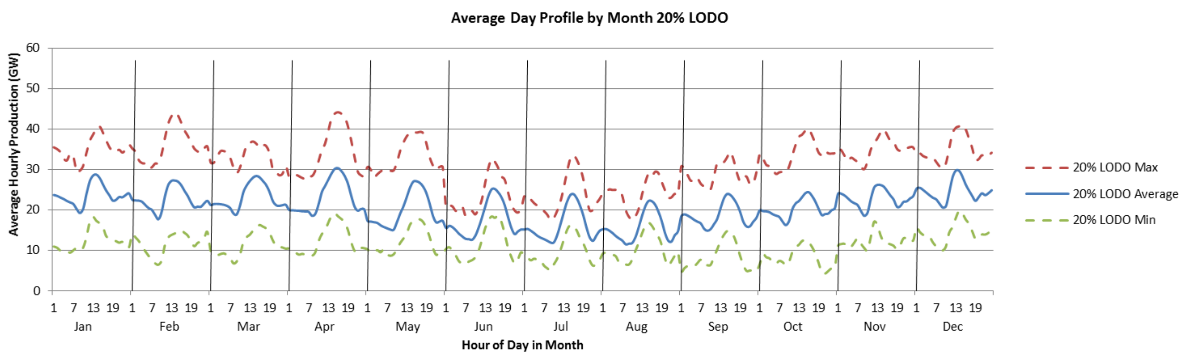


Figure 1-23: Average Daily Patterns by Month For 20% LODO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

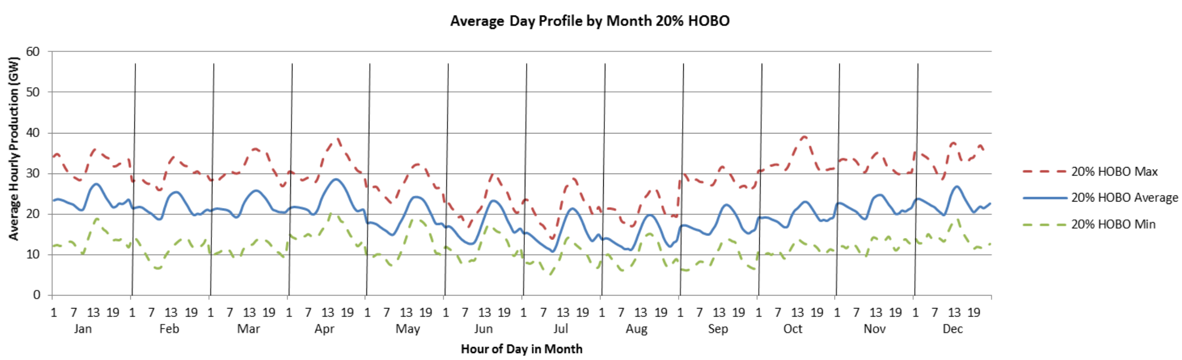


Figure 1-24: Average Daily Patterns by Month For 20% HOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

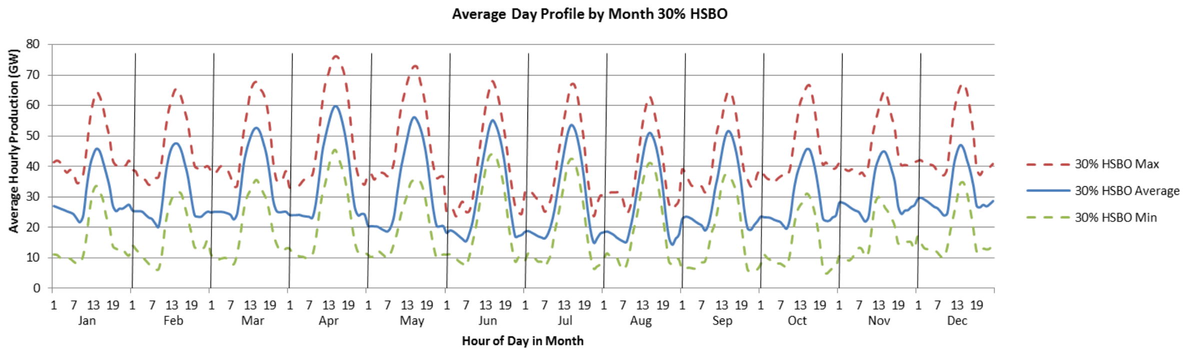


Figure 1-25: Average Daily Patterns by Month For 30% HSBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

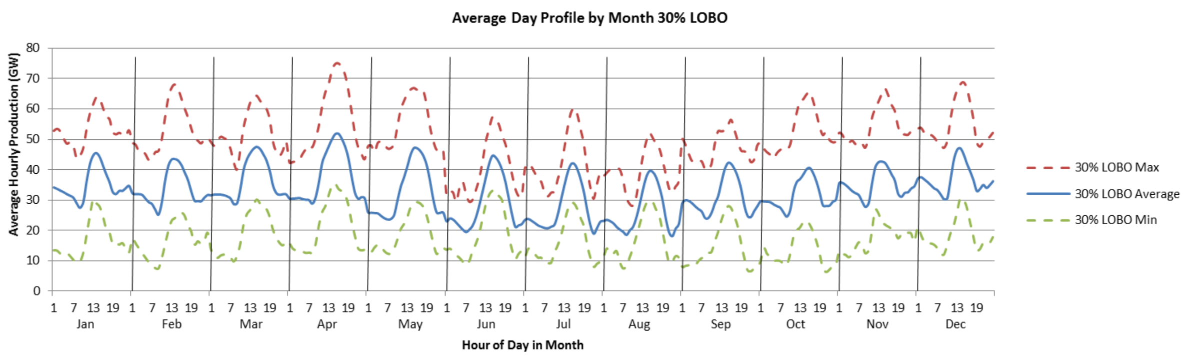


Figure 1-26: Average Daily Patterns by Month For 30% LOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

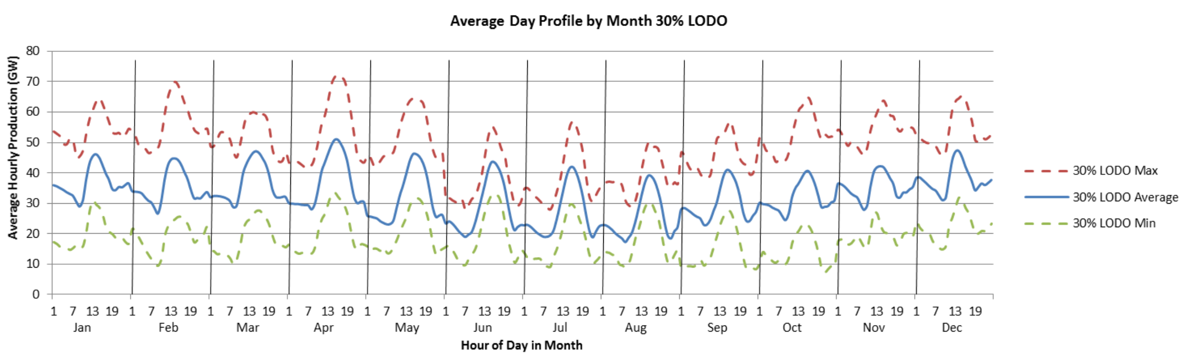


Figure 1-27: Average Daily Patterns by Month For 30% LODO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

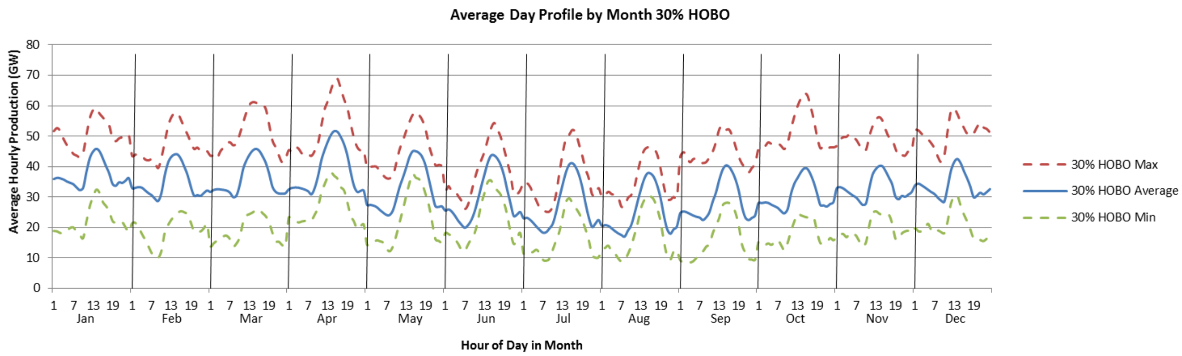


Figure 1-28: Average Daily Patterns by Month For 30% HOBO Scenario; Maximum and Minimum Values Indicated By Dashed Lines

1.3.4 Daily Variability –Load net of Renewable Generation

The average daily patterns of renewable generation for each scenario reveal some of the driving forces behind renewable generation. Operationally, though, how renewable generation patterns combine with those of load is perhaps a more pertinent issue. Figure 1-29 through Figure 1-32 combine the daily renewable generation patterns above with average PJM load for each hour and season. The seasonal characteristics of wind and PV can be seen in these figures. Looking at the winter season, the trend for higher wind generation and lower PV generation can be seen when comparing the general shape of the 2% BAU scenario (very little PV) to the other scenarios. The hours when PV generation contributes to the system show a larger dip in net load during the middle of the day.

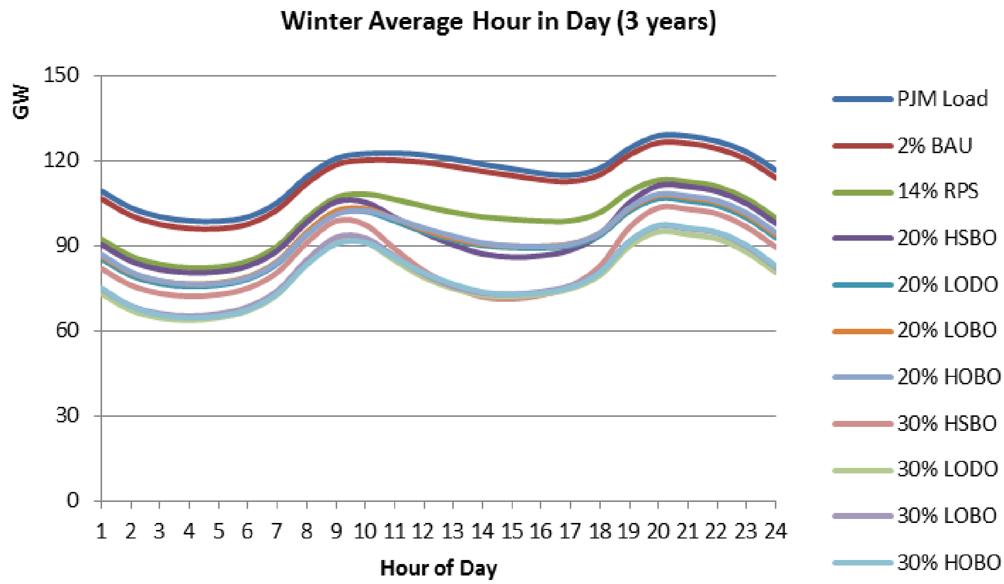


Figure 1-29: Average Daily PJM Load and Net Load for Each Scenario - Winter Season

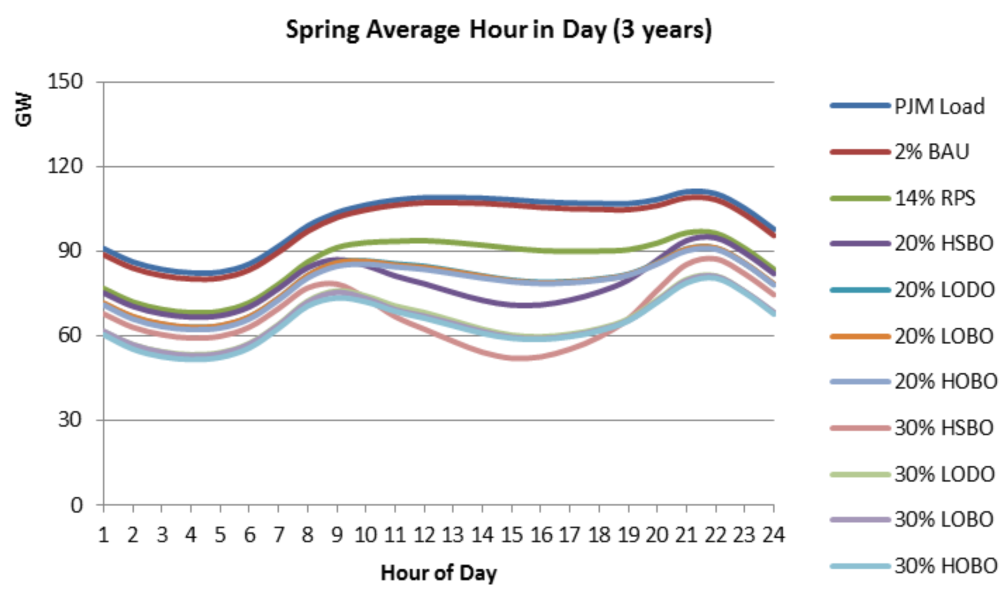


Figure 1-30: Average Daily PJM Load and Net Load for Each Scenario, Spring Season

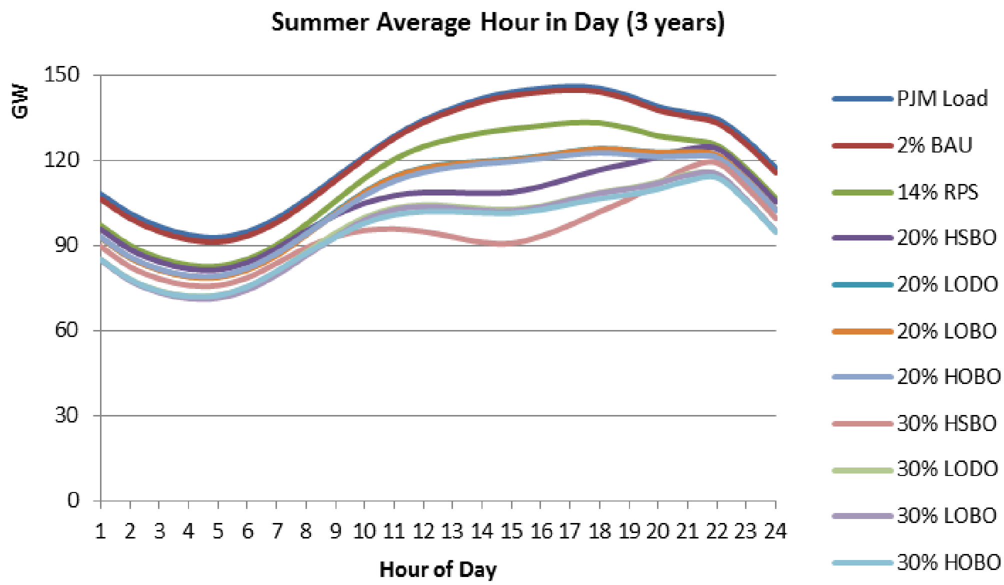


Figure 1-31: Average Daily PJM Load and Net Load for Each Scenario, Summer Season

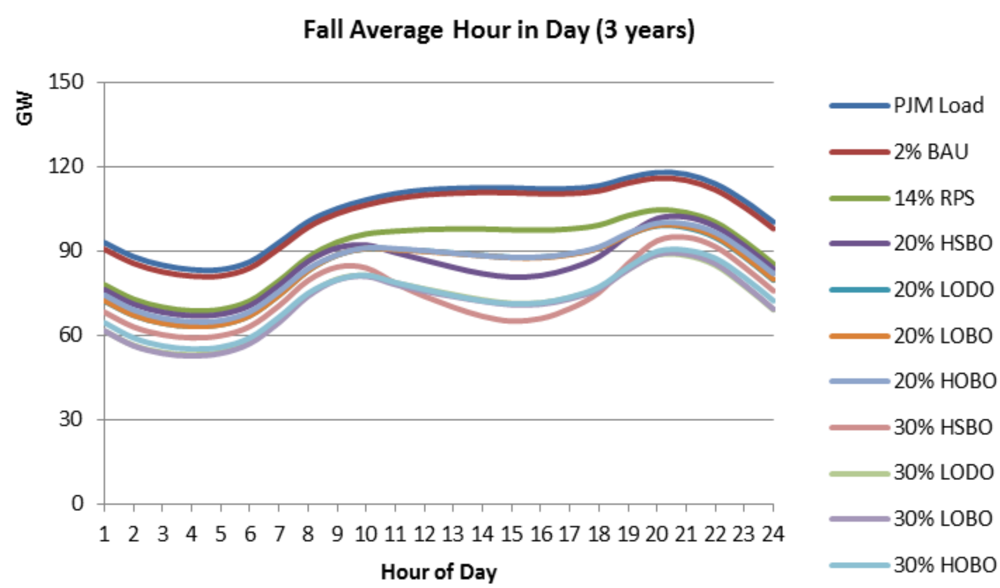


Figure 1-32: Average Daily PJM Load and Net Load for Each Scenario - Fall Season

Figure 1-33 shows duration curves of load-net-renewables (wind + solar), which indicated the portion of the PJM load that must be served by non-renewable generation resources. The right-hand portions of the curves show that in the higher penetration scenarios, renewables serve about half of total system load during low-load periods.

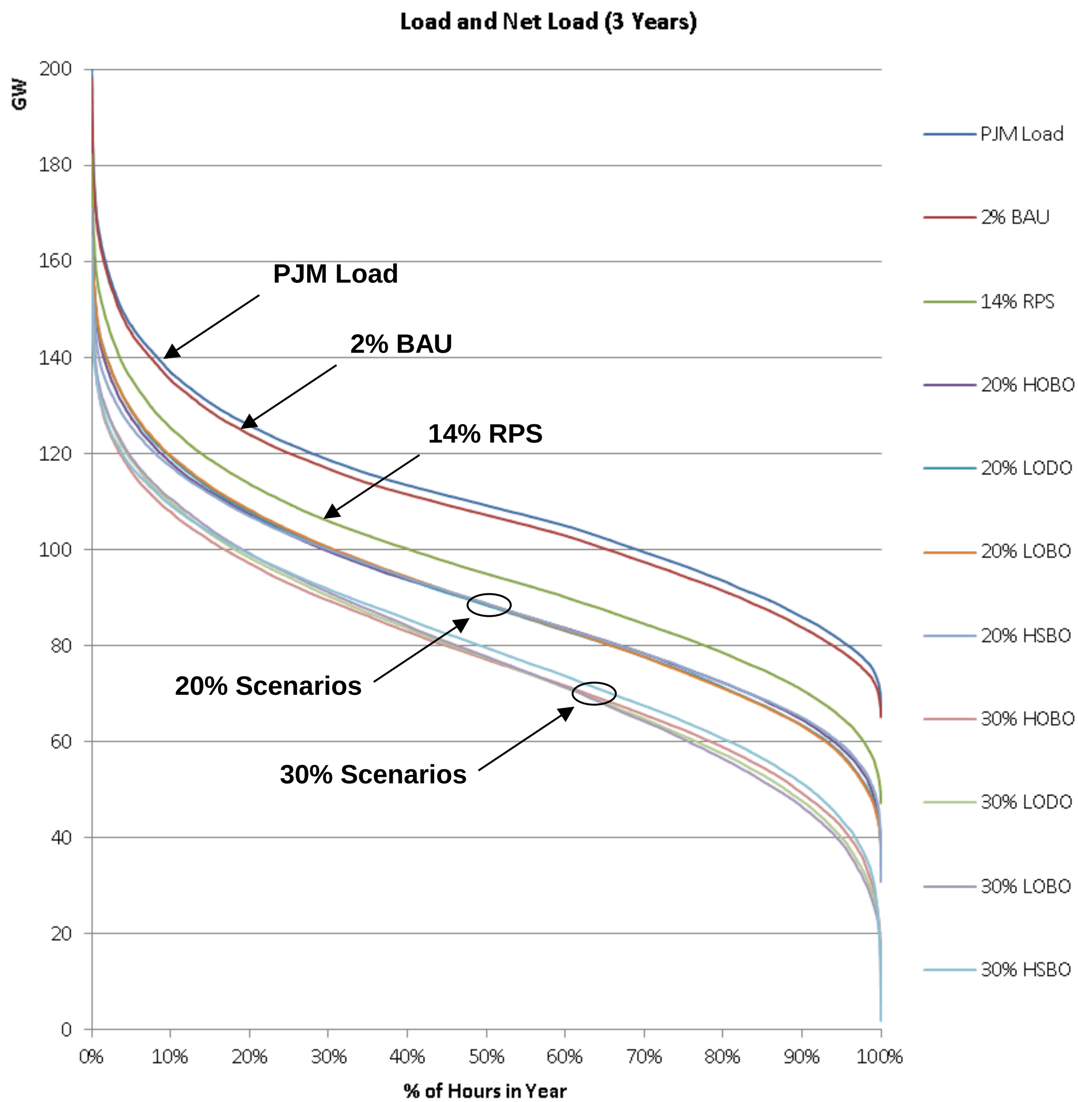


Figure 1-33: Duration Curves for Load and Load Net Renewables, All Scenarios, All Years, All Hours

Figure 1-34 shows the hourly changes in PJM load for all three years of data. Hourly changes in renewable generation are shown for all scenarios in Figure 1-35 through Figure 1-38. It is apparent from the respective distributions that the lower penetration scenarios would not have much effect on the aggregate changes when combined with load. Their impact increases as the penetration grows. Again, the specific impacts must be evaluated through chronological production simulations, as the ability of the PJM fleet to respond to changes in demand will depend on other factors beyond wind and load variability.

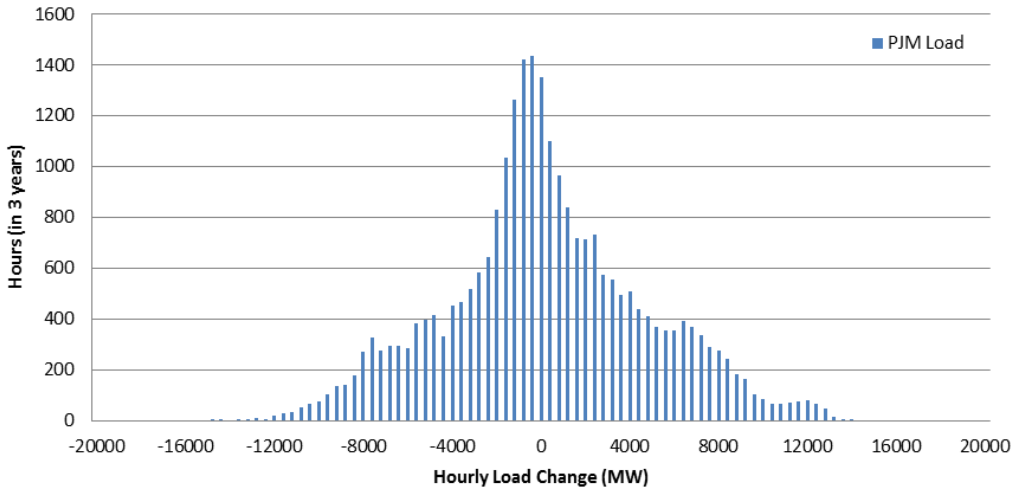


Figure 1-34: Distribution of Hourly PJM Load Changes (3 Years of Data)

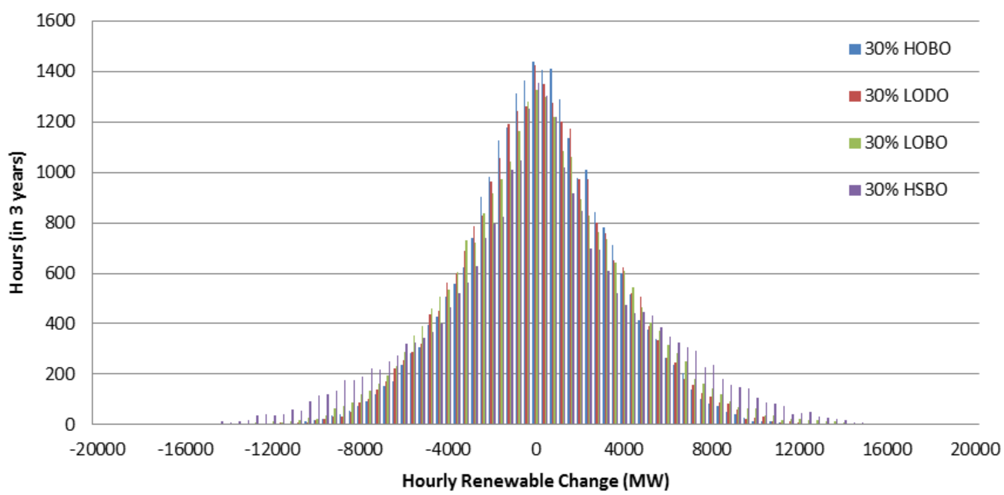


Figure 1-35: Hourly Changes in Renewables For 30% Penetration Scenarios

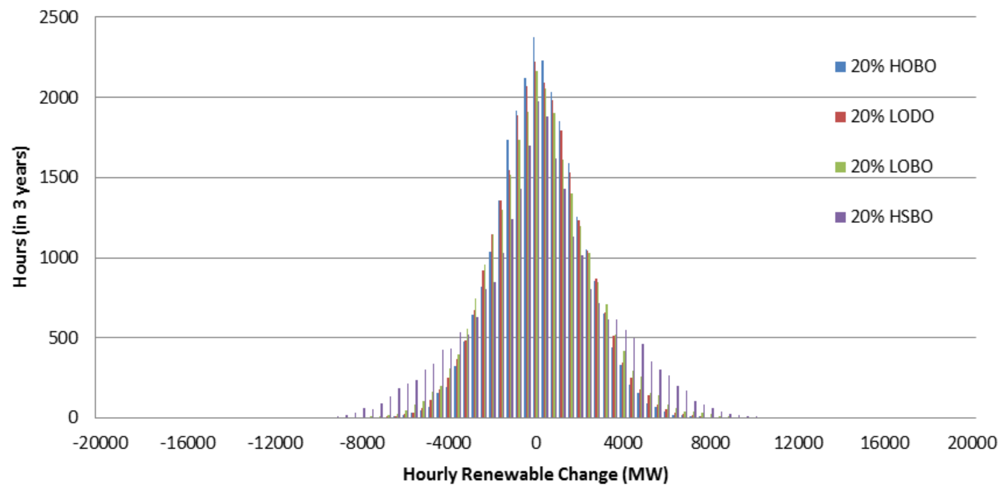


Figure 1-36: Hourly Changes in Renewables For 20% Penetration Scenarios

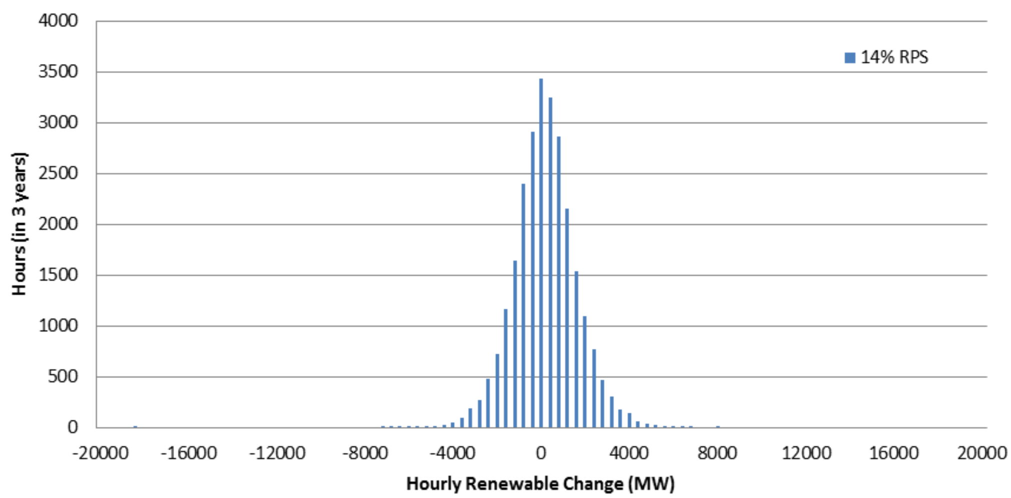


Figure 1-37: Hourly Changes in Renewables For 14% RPS Scenario

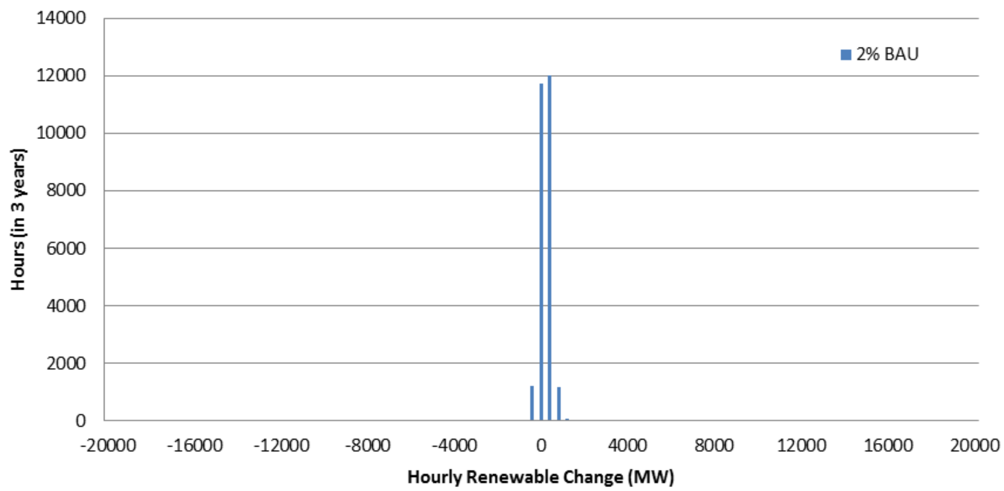


Figure 1-38: Hourly Changes in Renewables For 2% BAU Scenario

General operational impacts are better viewed as a comparison of the distribution of hourly changes in PJM load to those of the net load in the scenarios. These comparisons are shown in Figure 1-39 through Figure 1-44 for the 2%, 14%, 20% and 30% scenarios, respectively. These histograms show, from an operational perspective, the percent of hours over a three year period that fall within 400 MW bin range. As can be readily seen from the histogram, the number of hour to hour changes around the 0 MW range are the greatest, while the percent of hourly changes diminish as the magnitude of the hourly change increases, either as up-ramp or down-ramp.

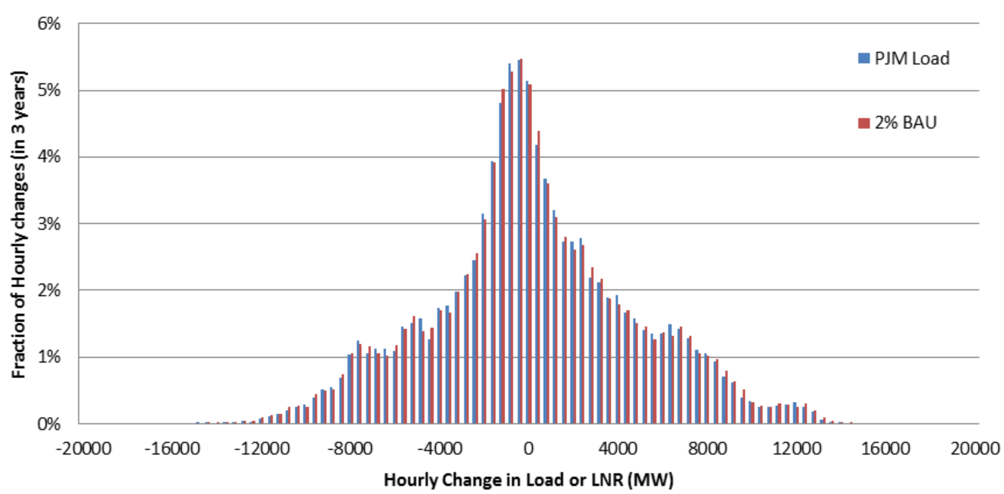


Figure 1-39: Hourly Change in PJM Load and Net Load For 2% BAU Scenario (3 Years of Data)

When renewable penetration is increased to 14%, it can be seen in Figure 1-40 that the hour to hour changes begin to spread across the ramp spectrum along the x-axis, reducing the % of changes around the 0 MW bin. Figure 1-41 shows the 20% HOBO scenario where the spread increases such that the changes around the 0MW bin is less than 4% of all the hours examined. The HSBO scenario shown in Figure 1-42 demonstrates an increased spread in the histogram indicating an increased variability in PV. Figure 1-43 shows the 30% HOBO scenario with greater spread and less than 3% of hourly changes around the 0 MW bin. It is interesting to observe the 20% HSBO scenario spread in Figure 1-42 approaching the 30% HOBO scenario in Figure 1-44; another indication of increased variability with higher penetrations of PV. This trend is confirmed in the 30% HSBO scenario in Figure 1-44 when compared with the 30% HOBO scenario. The percentage of hours around the 0 MW bin is noticeably less.

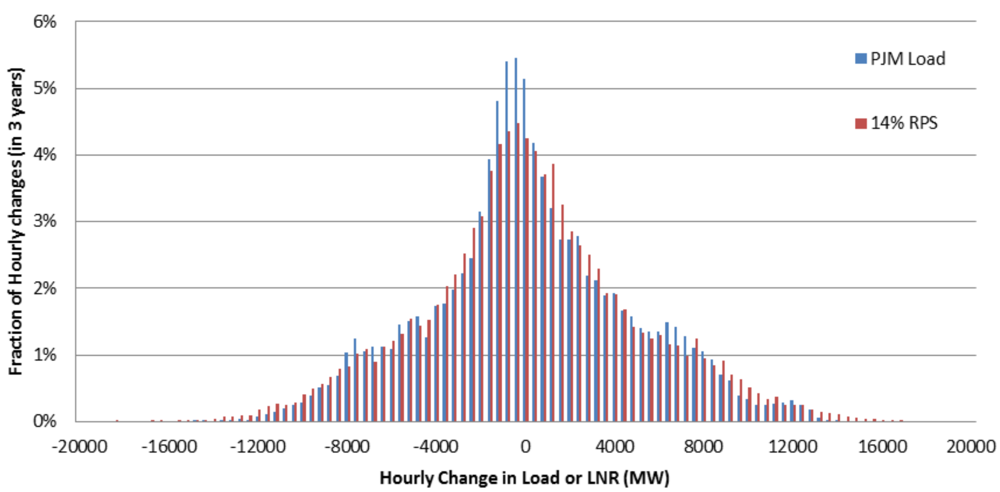


Figure 1-40: Hourly Change in PJM Load and Net Load For 14% RPS Scenario (3 Years of Data)

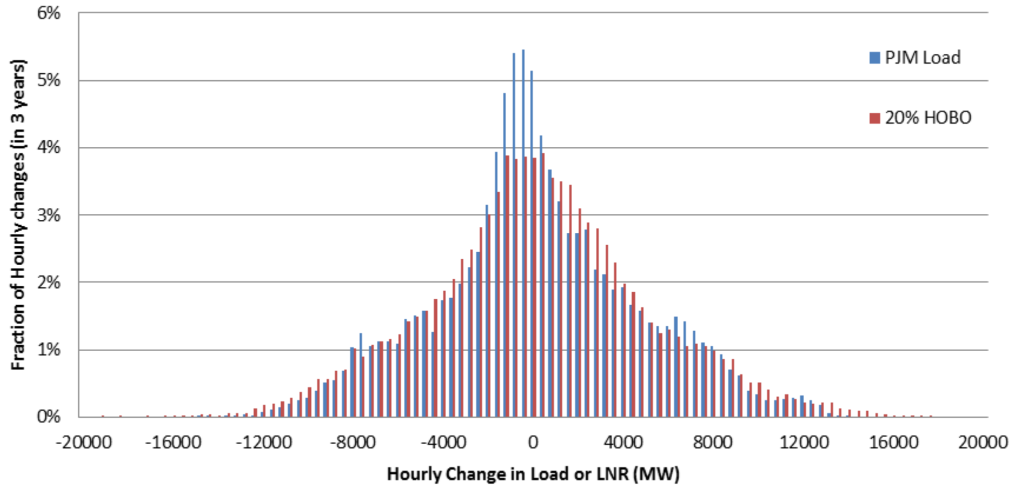


Figure 1-41: Hourly Change in PJM Load and Net Load For 20% HOBO Scenario (3 Years of Data)

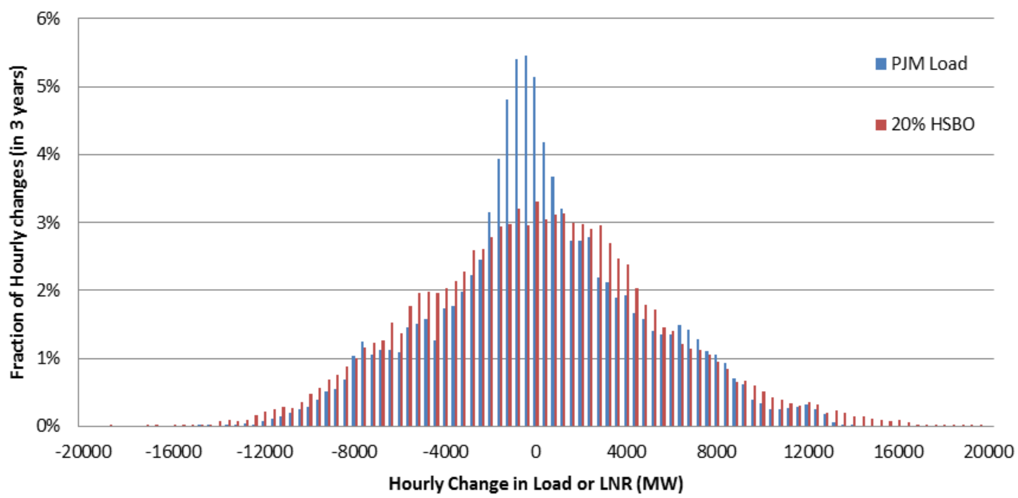


Figure 1-42: Hourly Change in PJM Load and Net Load For 20% HSBO Scenario (3 Years of Data)

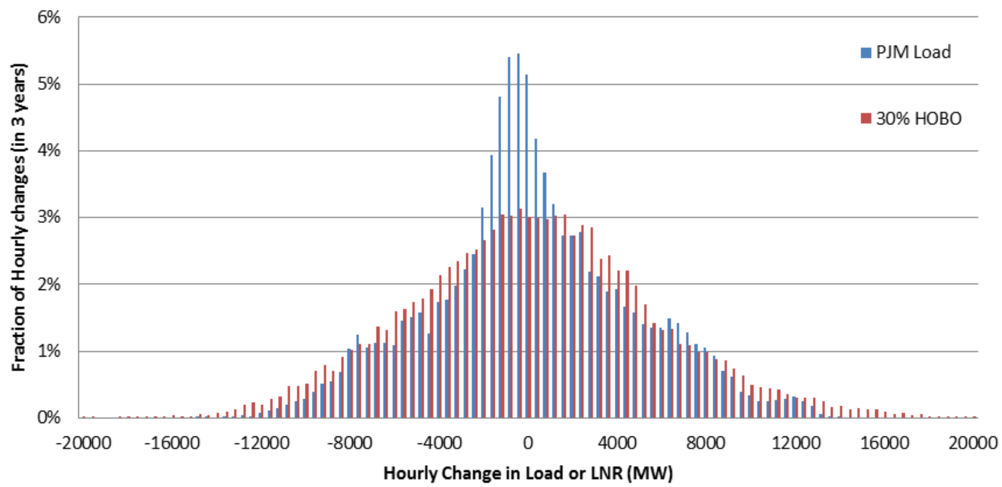


Figure 1-43: Hourly Change in PJM Load and Net Load For 30% HOBO Scenario (3 Years of Data)

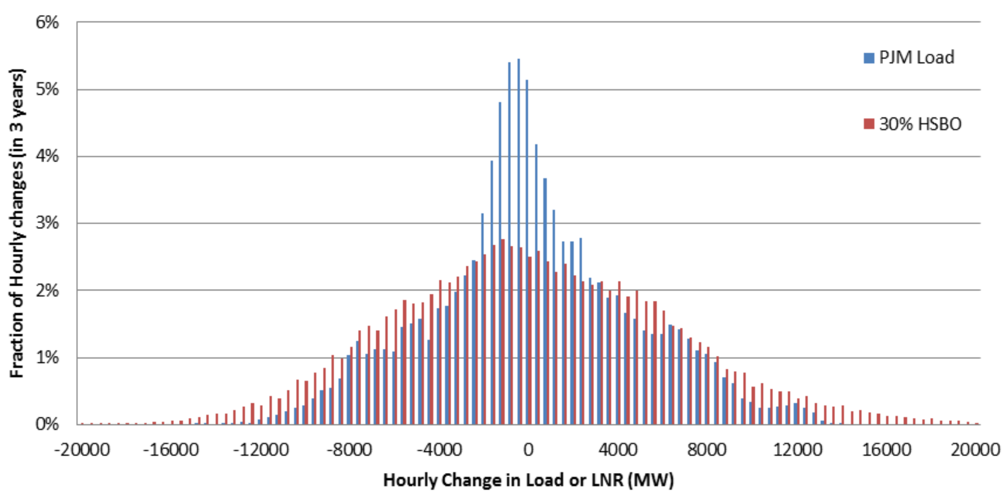


Figure 1-44: Hourly Change in PJM Load and Net Load For 30% HSBO Scenario (3 Years of Data)

The differences between the load only and net load case is relatively slight for the 20% HOBO scenario. Expanding the view on the tails of the distribution for the 20% HOBO scenario helps to reveal the impact of renewable generation. Expanding the view for the 20% HSBO scenario demonstrates the increased variability resulting from higher PV concentration.

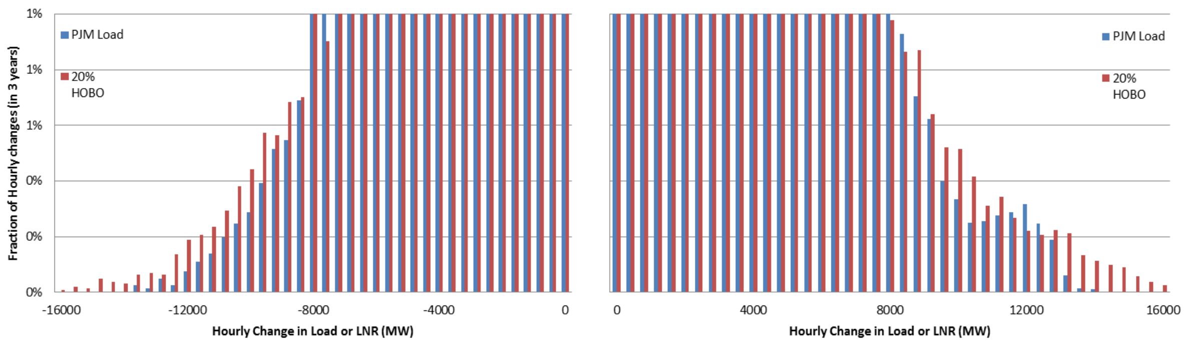


Figure 1-45: Distribution Tails of Hourly Changes for PJM Load and Net Load for 20% HOBO Scenario

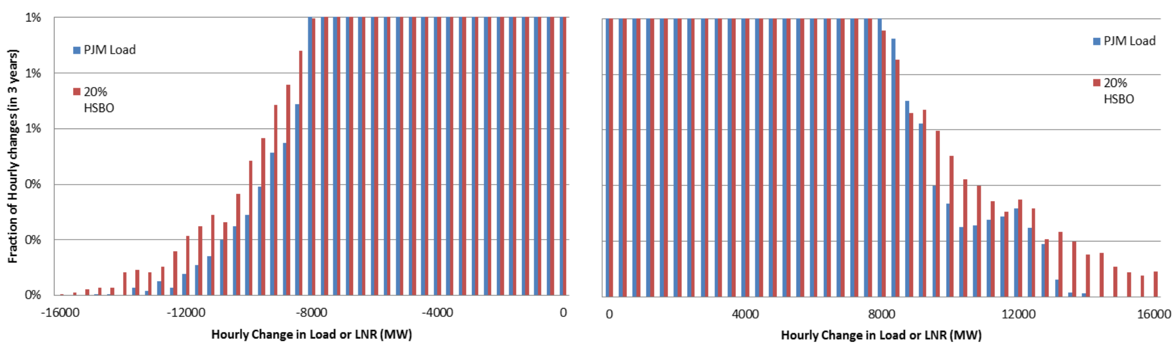


Figure 1-46: Distribution Tails of Hourly Changes for PJM Load and Net Load for 20% HSBO Scenario

Any increase in the number or magnitude of extreme hourly changes is important operationally. Views through comparison of hourly load and net load data can confirm their size and existence, but reveal little about specific impacts on the PJM system. The hourly production simulations are where the real operational impacts are assessed and quantified. The extreme events that can be identified in the statistical and quantitative characterizations are evaluated in the appropriate context of the entire power system, its individual elements, and the full range of operating constraints.

1.3.5 Faster variations in renewable generation

The discussion thus far has focused on variations in wind and PV generation, PJM load, and net of wind and PV generation on an hourly basis. Chronological production simulation at one-hour time steps is the primary analytical technique for this renewable generation integration study. Via these simulations, each actual day which contributes a small amount to the hourly averages above, will be examined in detail. Consequently, the preceding discussion is intended to provide an overview of the major impacts of wind and PV generation on the net demand against which PJM generating resources will be committed and dispatched. The chronological production simulations will provide the quantitative detail regarding wind and PV generation impacts on PJM operations.

Variations of load, wind and PV generation on smaller time scales are also important operationally. Because these cannot be directly evaluated through hourly production simulations, characterizations of the faster variations in load, wind, and PV are necessary to establish additional operation impacts such as incremental regulation needs and operating reserve impacts.

The data used for this analysis consists of 10-minute resolution wind and PV data from the renewable generation data set. A first measure of the variability within the hour can be made by simply looking at the magnitude change from one interval to the next.

Figure 1-47 through Figure 1-56 display scatter plots of the aggregated wind and PV generation variability from one 10-minute interval to the next for each scenario. Changes in production to the next interval are plotted on the vertical axis against the current production level on the horizontal. The spread from top to bottom across each "cloud" is a measure of the within-hour volatility, and illustrates directly how the aggregated wind and PV generation can increase the range of maneuverable generation necessary to balance supply and load.

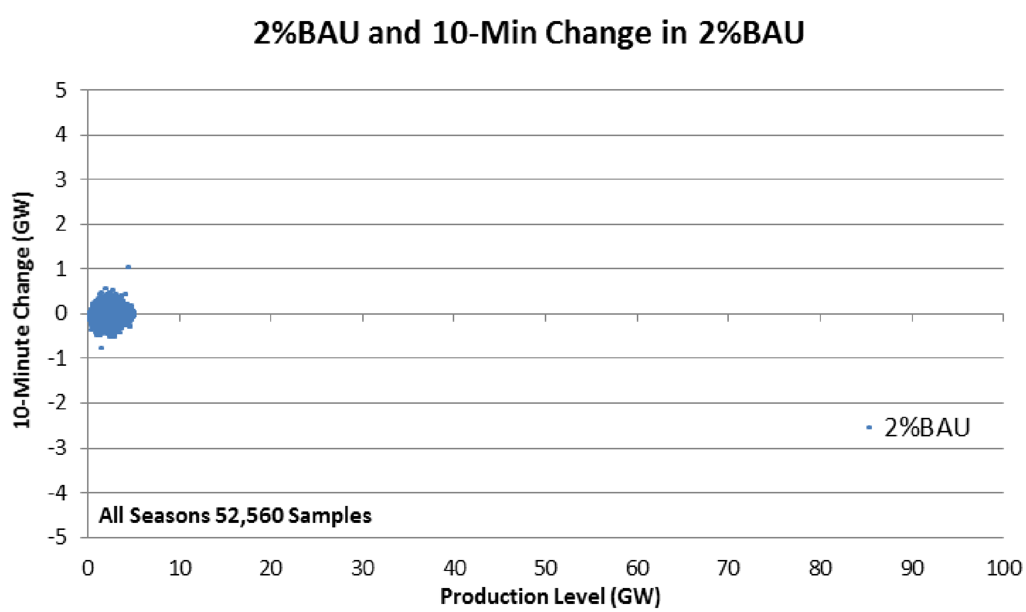


Figure 1-47: 10-Minute Wind + Solar Variability as a Function of Production Level For 2% BAU Scenario

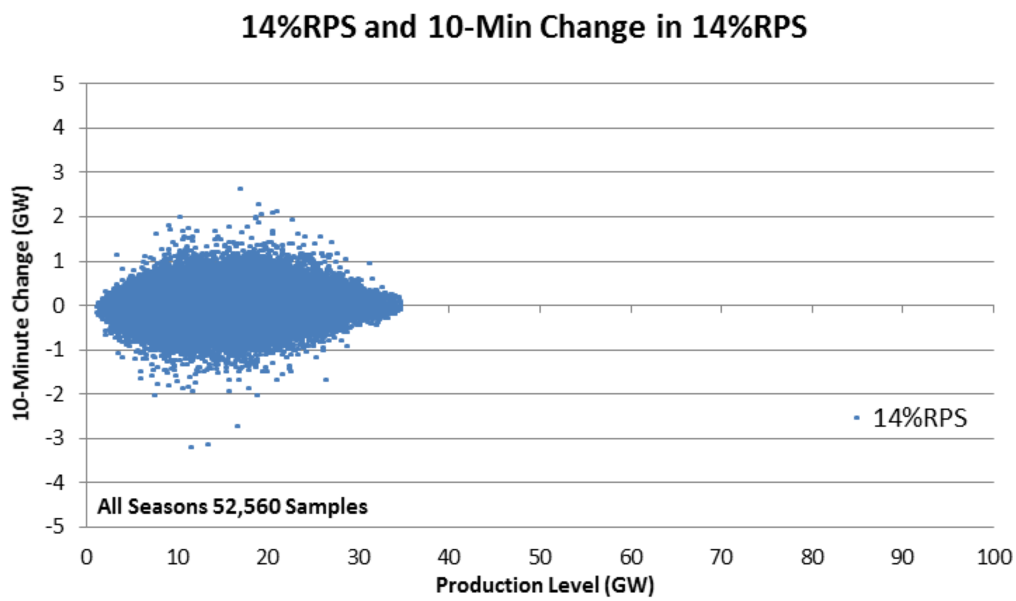


Figure 1-48: 10-Minute Wind + Solar Variability as a Function of Production Level For 14% RPS Scenario

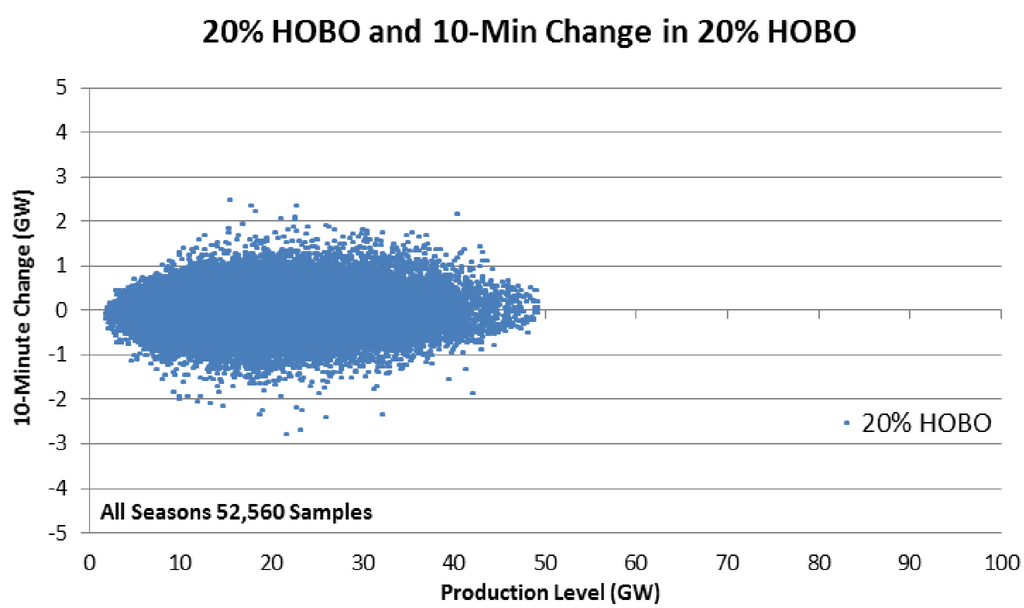


Figure 1-49: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% HOBO Scenario

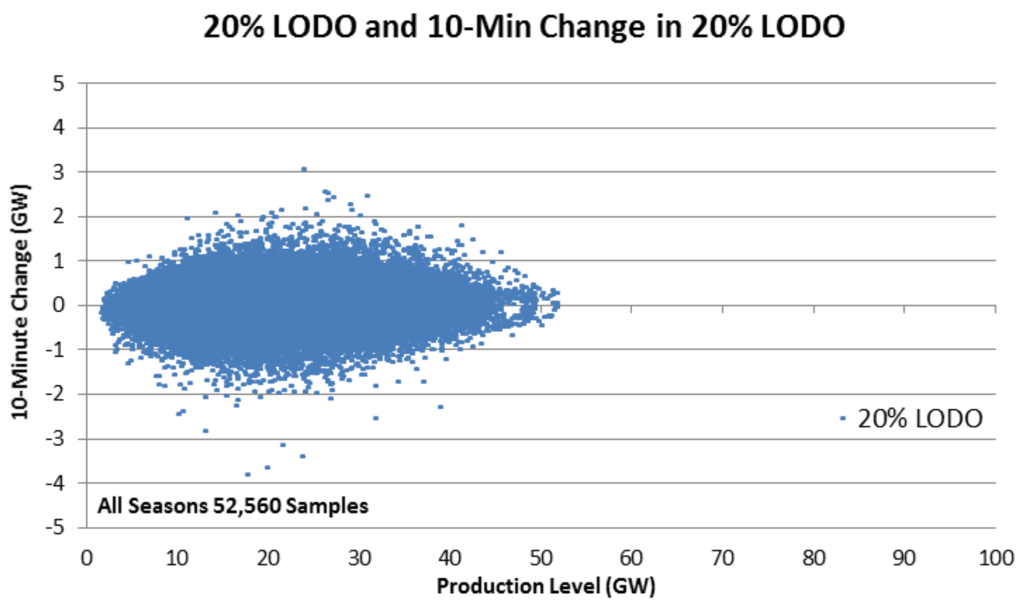


Figure 1-50: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% LODO Scenario

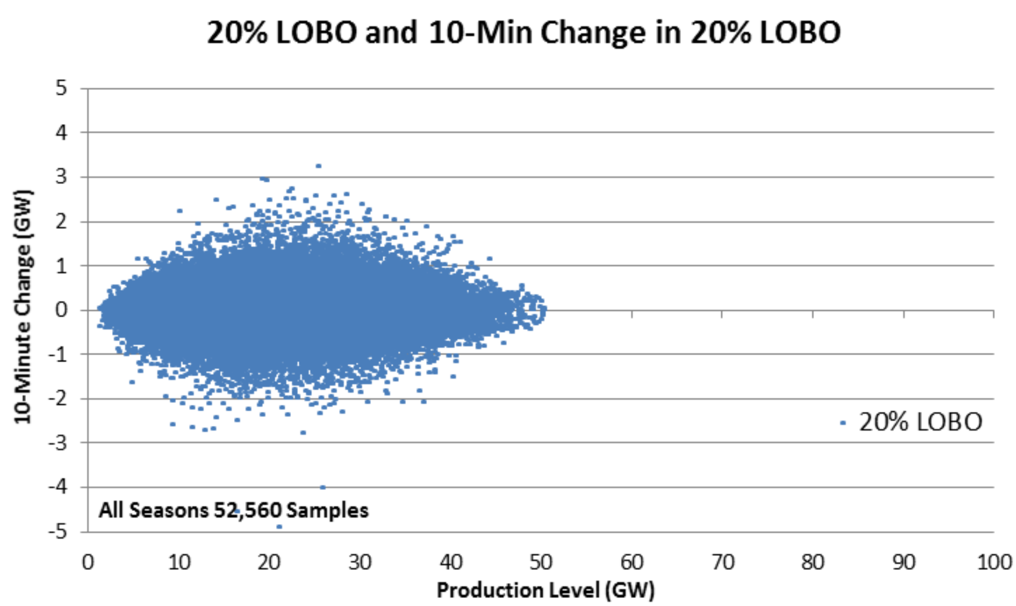


Figure 1-51: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% LOBO Scenario

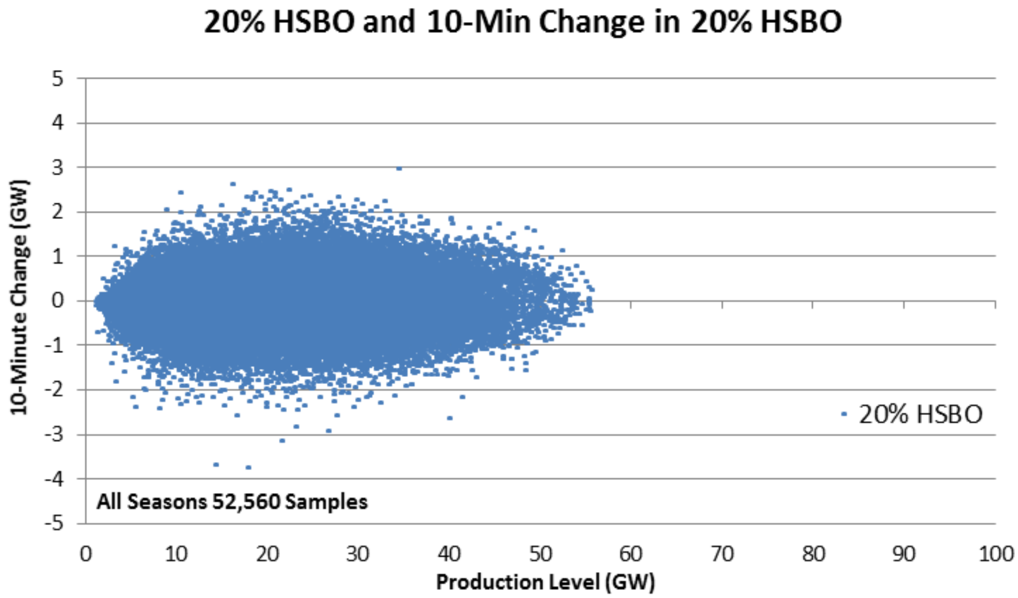


Figure 1-52: 10-Minute Wind + Solar Variability as a Function of Production Level For 20% HSBO Scenario

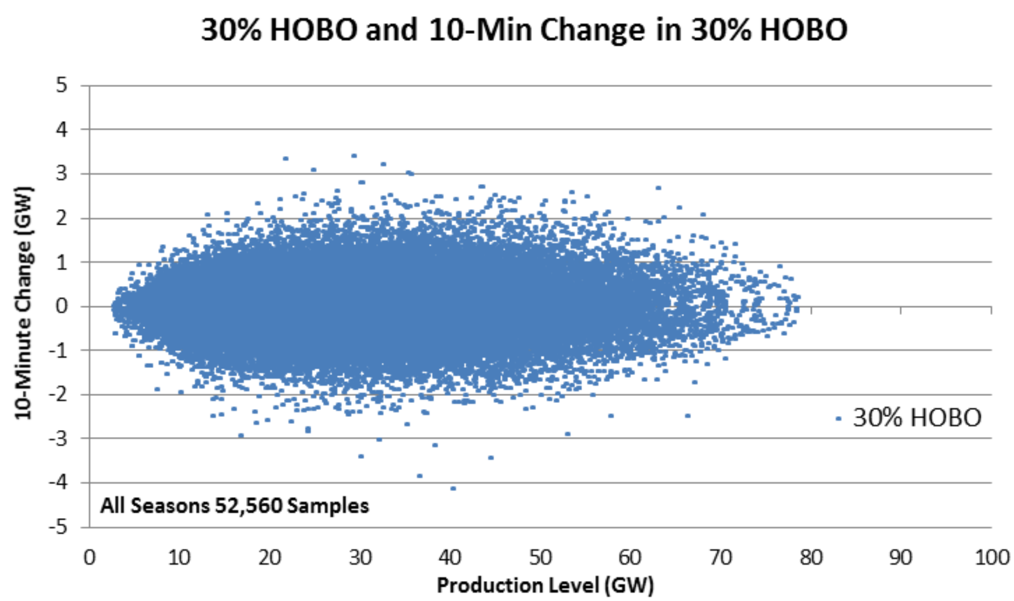


Figure 1-53: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% HOBO Scenario

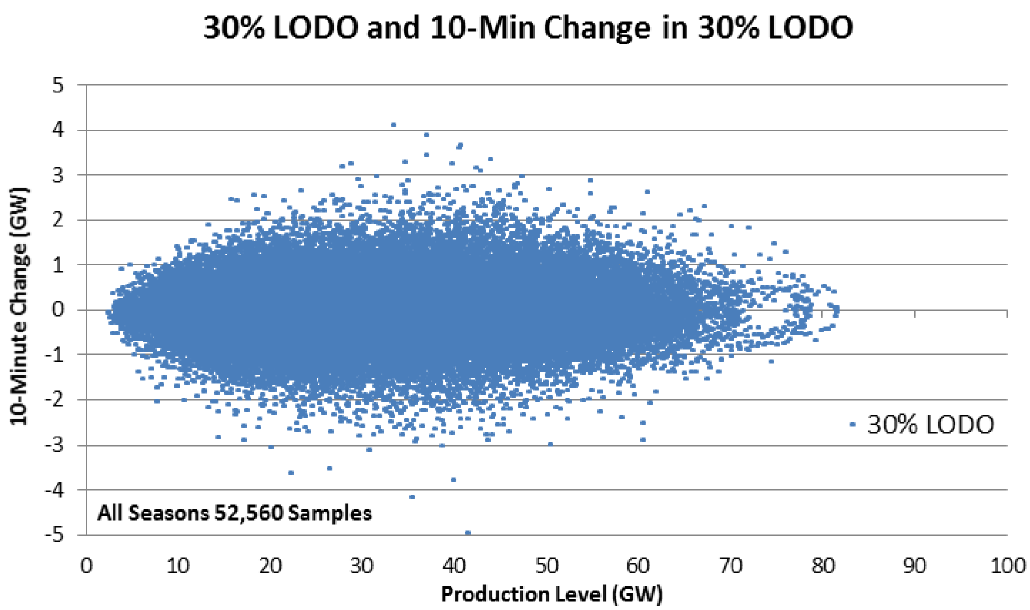


Figure 1-54: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% LODO Scenario

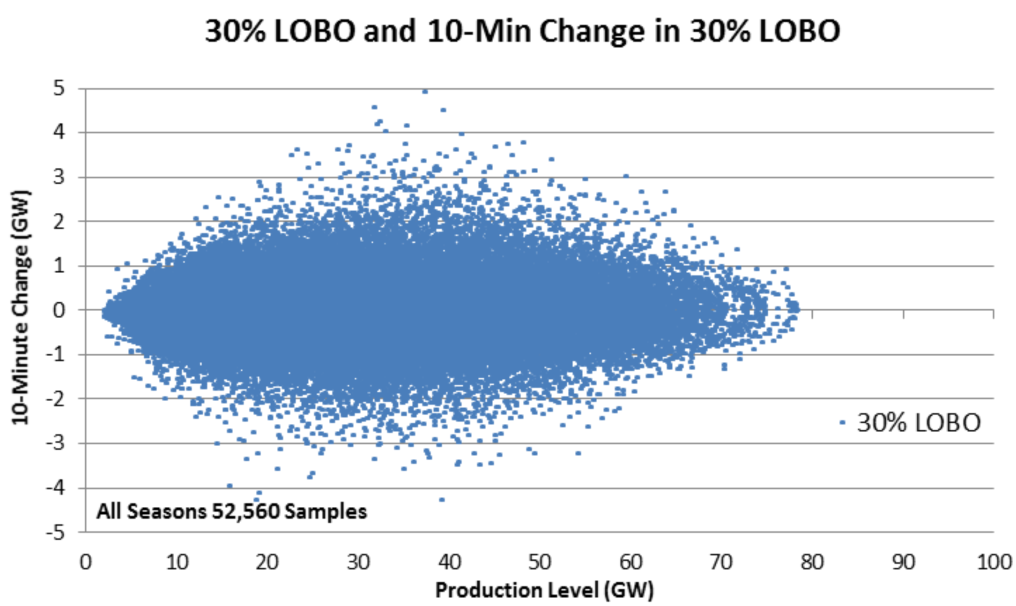


Figure 1-55: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% LOBO Scenario

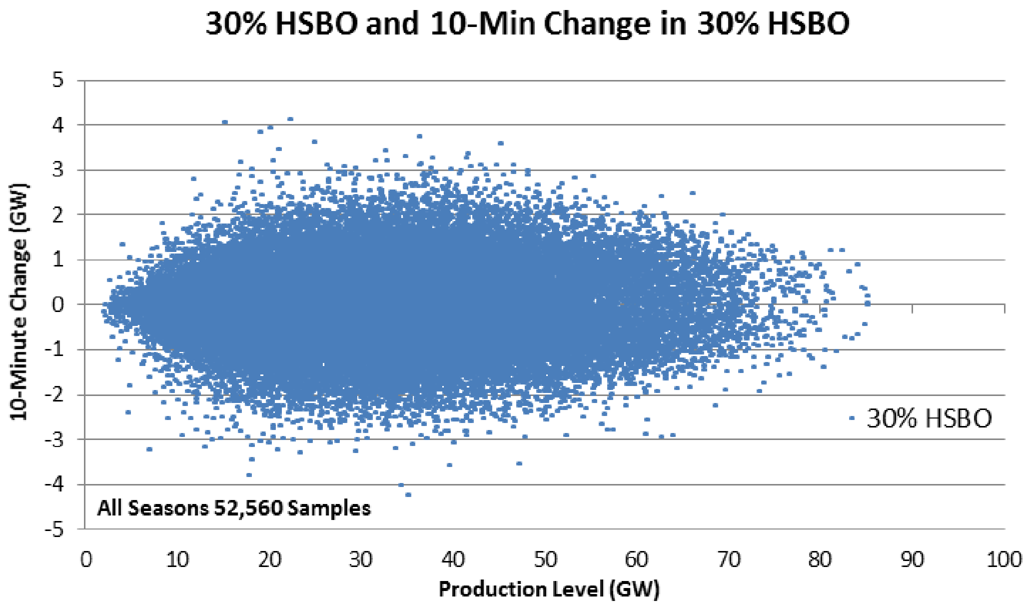


Figure 1-56: 10-Minute Wind + Solar Variability as a Function of Production Level For 30% HSBO Scenario

The aggregated variability illustrated in the previous figures is representative of the aggregated wind and PV generation. Separating the aggregated wind and aggregated PV from the total aggregated renewables provide additional statistics of the 10-minute variability and is a useful characterization that will be used later in the quantitative analysis of regulation needs and operating reserve impacts. Figure 1-57 through Figure 1-76 is a modification of the cloud charts. Ten-minute variations (changes from one data point to the next in the 10-minute dataset) are grouped by the average hourly production level during the time the variation occurred. Hourly production levels are then organized into "bins", where the 10% to 20% bin, for example, contains all of the 10-minute variations that occurred when the hourly production was between 10% and 20% of aggregated nameplate capacity.

Once sorted, the standard deviation of the variations in each bin is computed, and plotted against production level, as shown by the blue squares in Figure 1-57. Three years of 10-minute data result in over 150,000 samples. Because of the large sample size, the distributions in each bin are quite Gaussian, so the standard deviation becomes a useful metric for calculating the expected magnitude of variations.

The shape of the curve in Figure 1-57 merits some explanation. At low levels of wind generation, the expected variations are small, mainly due to low wind speed levels. The expected variations are highest near 50% of nameplate production; because wind speeds are such that each turbine is operating on the steepest portion of the power curve (power is a function of the wind speed cubed). As the aggregate production level increases further, winds are more vigorous and more of the individual turbines in the fleet are operating above rated wind speed. In this region, variations in wind speed have little to no impact on production, i.e. the power output of the turbine remains constant as wind speed varies. Consequently, the expected variation from one interval to the next is much smaller than at lower production levels.

It must be kept in mind that these statistical characterizations of variability are applied to all of the wind turbines in the scenario as a whole. They are useful here because of the large amounts of wind generation assumed for each scenario. In practice, a similar approach might be used to look back at actual operation of wind power in the PJM system. Wind plant production data from EMS archives – which would be of much higher resolution (e.g. SCADA scan periodicity, about 4 seconds) than what is available for this study – can be periodically extracted and analyzed in a manner similar to what is shown here. The result would be statistical characterizations of the actual wind generation fleet that could be fed into analysis of regulation and operating reserve needs going forward.

Figure 1-57 through Figure 1-66 show characterizations of 10-minute variations for ten wind generation scenarios, using three years of data. The red lines on each chart are approximations of the empirical data represented by the blue squares. The shape suggested by the empirical data provides for a simple curve fit using a quadratic expression.

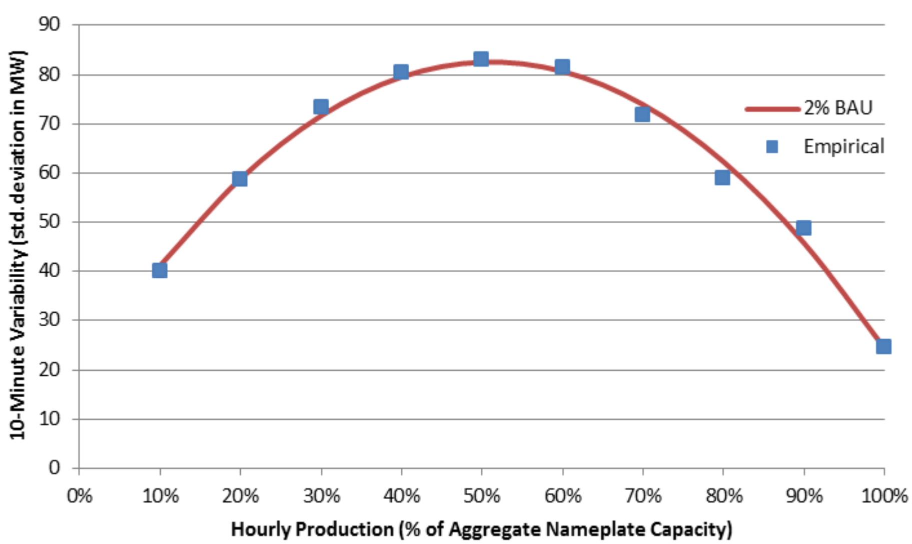


Figure 1-57: Statistical Characterization of 10-Minute Wind Variability for The 2% BAU Scenario

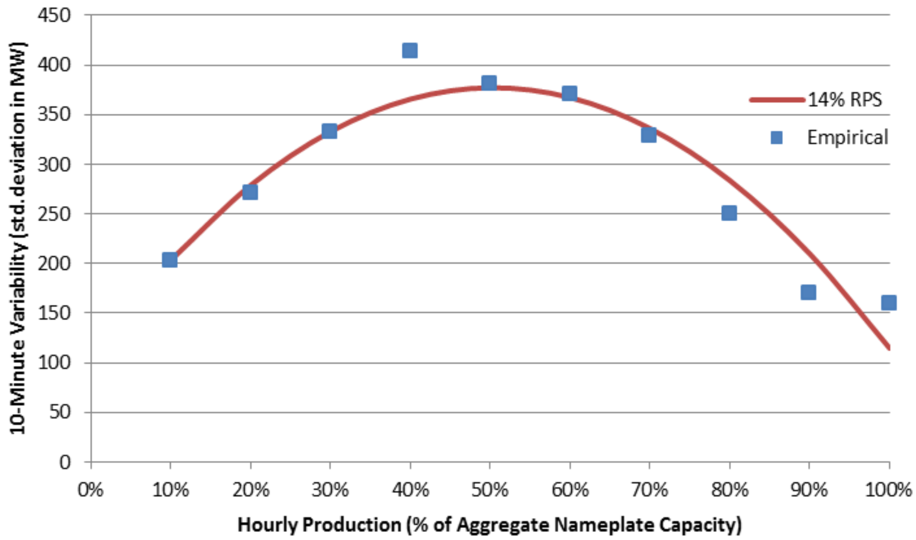


Figure 1-58: Statistical Characterization of 10-Minute Wind Variability for The 14% RPS Scenario

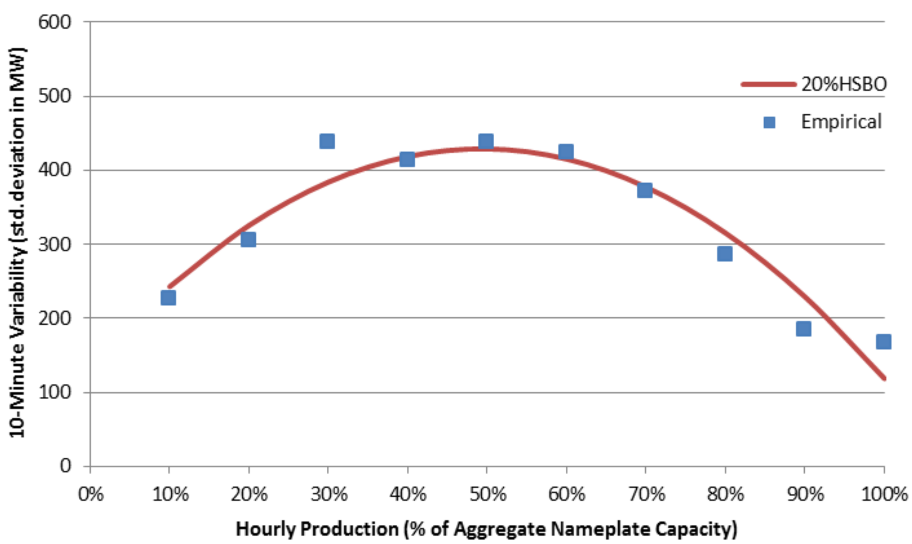


Figure 1-59: Statistical Characterization of 10-Minute Wind Variability for The 20% HSBO Scenario

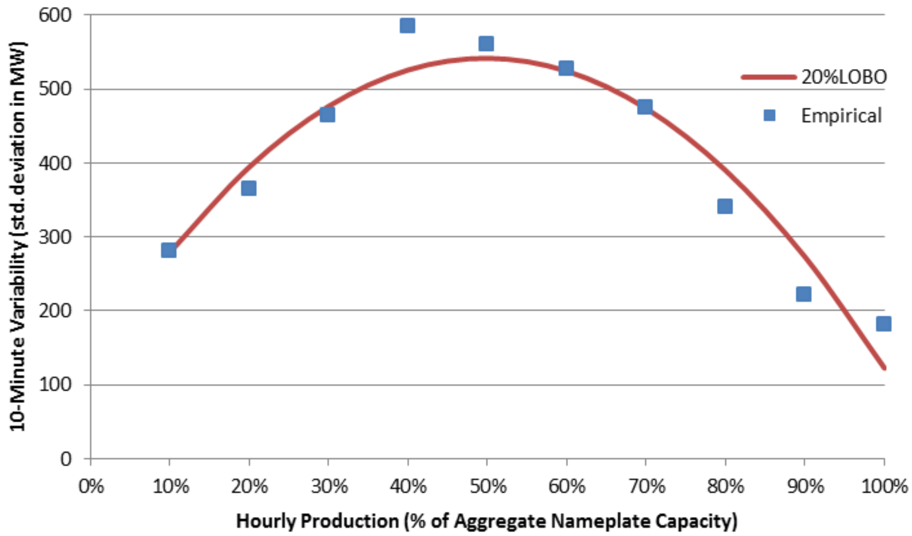


Figure 1-60: Statistical Characterization of 10-Minute Wind Variability for The 20% LOBO Scenario

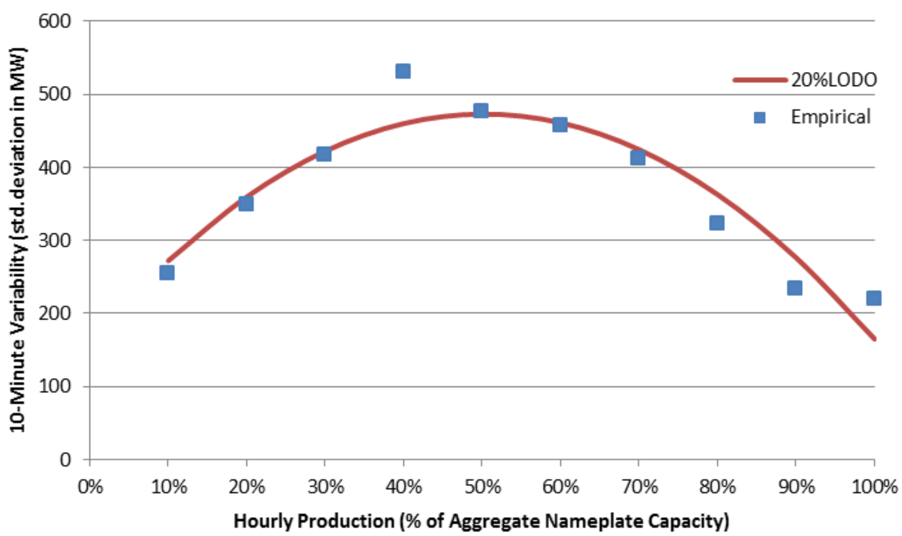


Figure 1-61: Statistical Characterization of 10-Minute Wind Variability for The 20% LODO Scenario

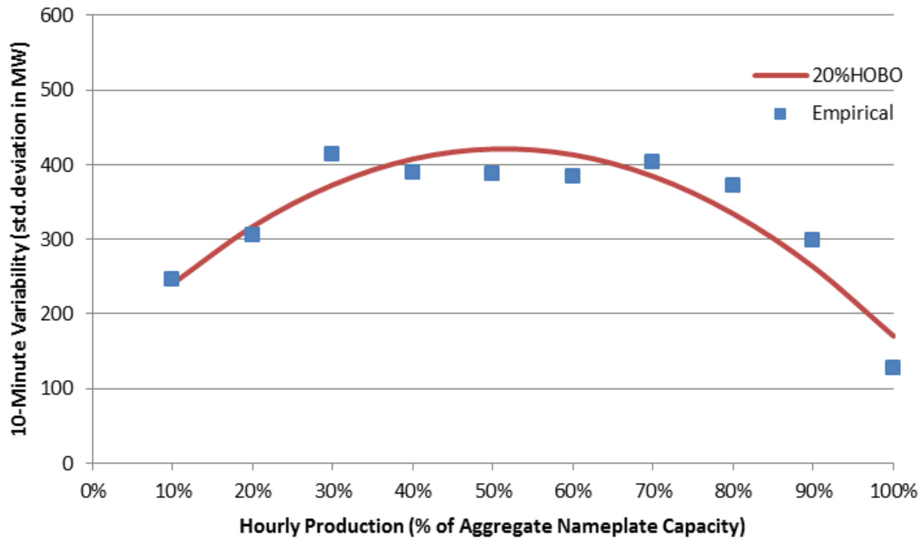


Figure 1-62: Statistical Characterization of 10-Minute Wind Variability for The 20% HOBO Scenario

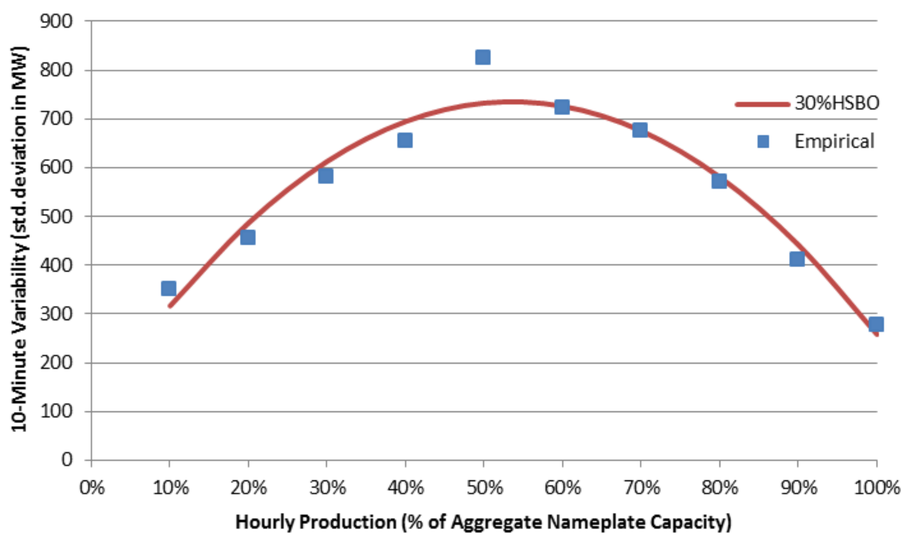


Figure 1-63: Statistical Characterization of 10-Minute Wind Variability for The 30% HSBO Scenario

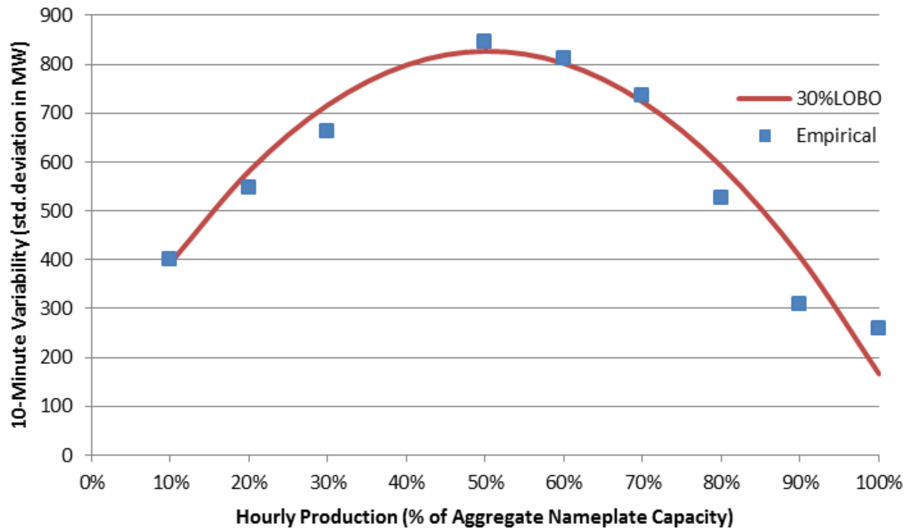


Figure 1-64: Statistical Characterization of 10-Minute Wind Variability for The 30% LOBO Scenario

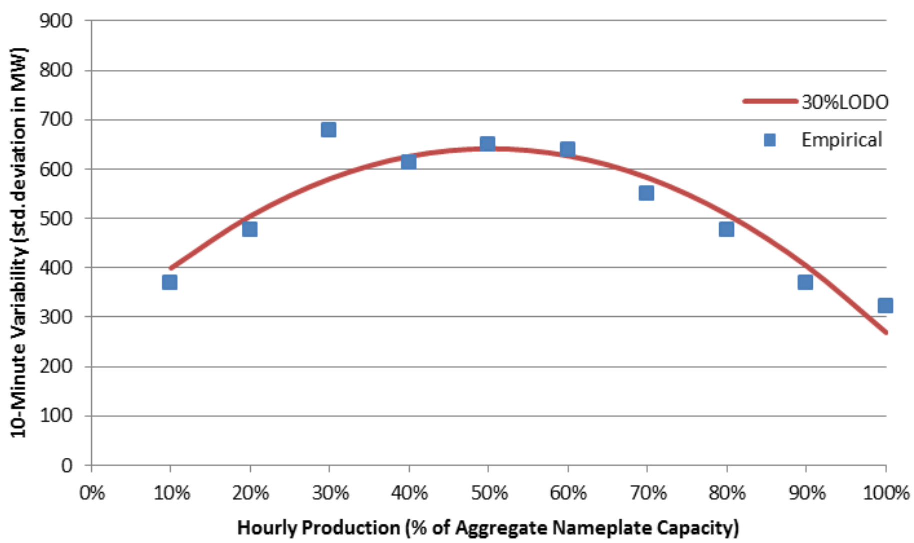


Figure 1-65: Statistical Characterization of 10-Minute Wind Variability for The 30% LODO Scenario

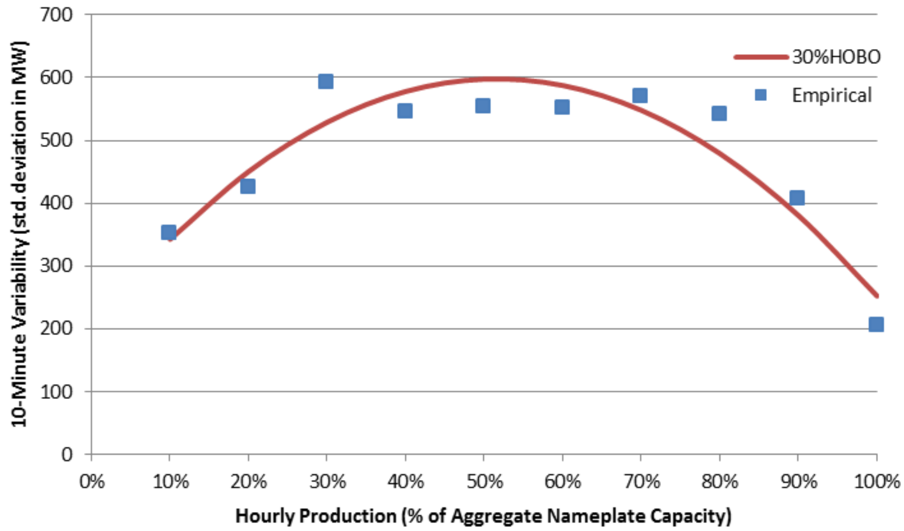


Figure 1-66: Statistical Characterization of 10-Minute Wind Variability for The 30% HOBO Scenario

Similarly the data for aggregated PV is assembled and sorted into bins as the wind data. The characterization of plotting the standard deviations of the 10-minute variations provides a useful metric to calculate the expected magnitude of variations. In Figure 1-67, the PV penetration in the 2% BAU scenario, although virtually small, with 71 MW reference capacity (nameplate) depicts a characteristic demonstrating largest variability when the PV plant operates in the midrange of its power output. It is more interesting to observe the remaining scenarios with larger PV penetration.

In Figure 1-68, the steep rise in the curve (i.e., rise in variability) in the 10% to 20% operation range indicates the largest change in variability for PV generation. This can be attributed to PV behavior when the sun rises and sets. In these hours PV can be more variable for several reasons. The steepness occurs during the low production periods when the sun is rising, setting or clouds cover exists. During sunrise and sun set PV moves rapidly from 0 MW and in the evening moving to 0 MW. This occurs daily and is captured by the steepness of the PV variability in the low output production periods. This inherently creates large 10-minute changes over the hour in these periods. The operational impact of PV is greater during this operating range. As PV operations increase to 100%, the variability due to cloud cover tends to be the primary cause of variability. As production reaches 100% only downward variability exists and approaches the same variability as the 10% operating range.

Considering the large geographical area in the PJM system the solar day for PJM spans multiple time zones thus extending the period when PV contributes to serving system load. In other words when the sun is rising in the eastern most region of PJM other areas of PJM remain dark while when the PV generation in the east is ramping down at the end of the day the western region of PJM continues to provide PV generation to the system. The aggregate of all PV sites across the full PJM geographical area is evaluated in this analysis.

Figure 1-67 through Figure 1-76 show characterizations of 10-minute variations for ten PV generation scenarios, using three years of data. The red lines on each chart are approximations of the empirical data represented by the blue squares. Because of the sharp ramp in the 10% to 20% range two quadratic curve fits are applied to the empirical data, one in the 10% to 30% operating range and the second from the 20% to 100% operation range.

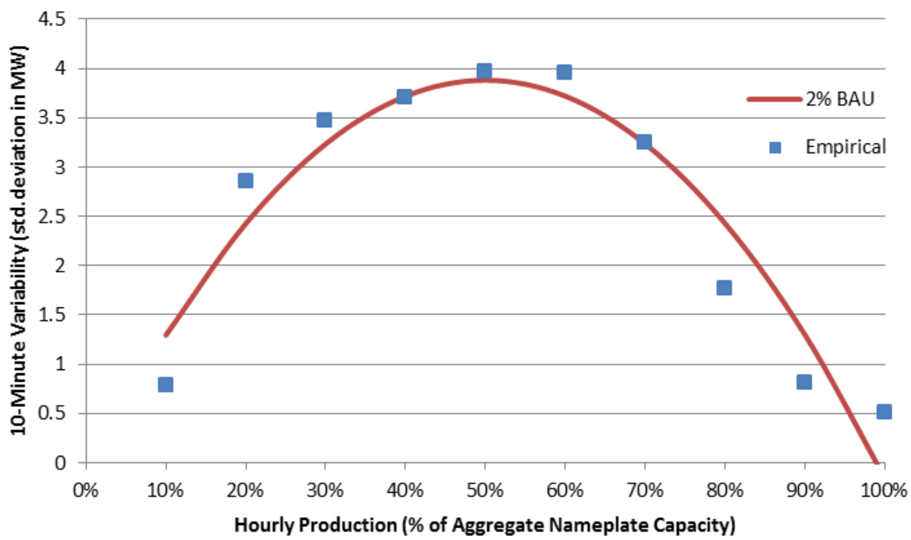


Figure 1-67: Statistical Characterization of 10-Minute PV Variability for The 2% BAU Scenario

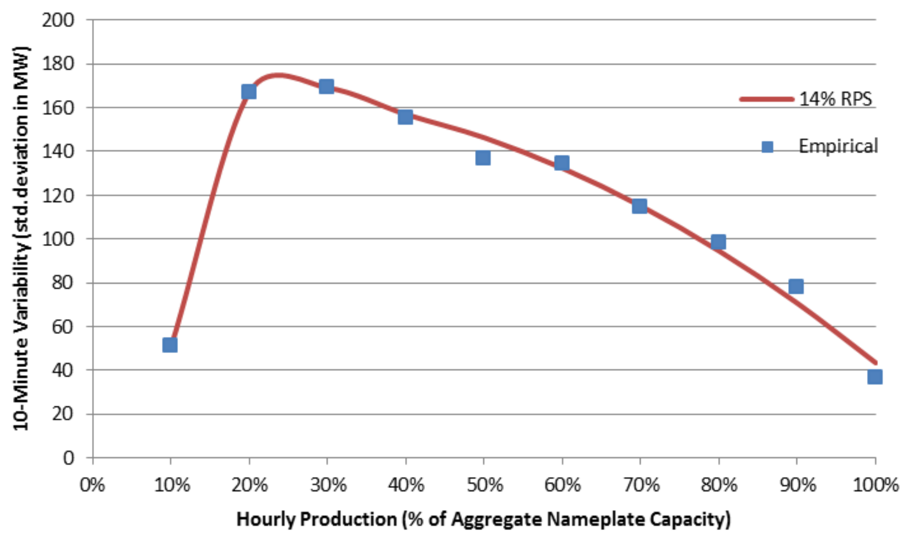


Figure 1-68: Statistical Characterization of 10-Minute PV Variability for The 14% RPS Scenario

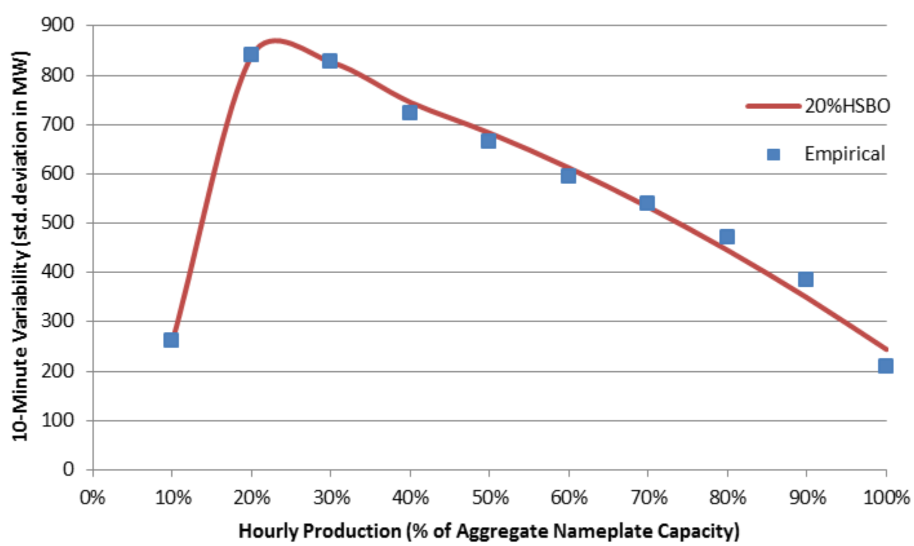


Figure 1-69: Statistical Characterization of 10-Minute PV Variability for The 20% HSBO Scenario

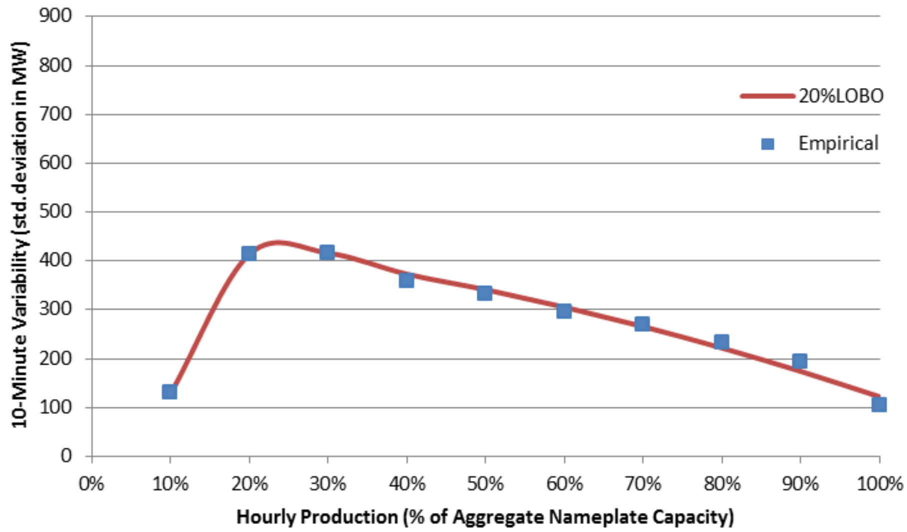


Figure 1-70: Statistical Characterization of 10-Minute PV Variability for The 20% LOBO Scenario

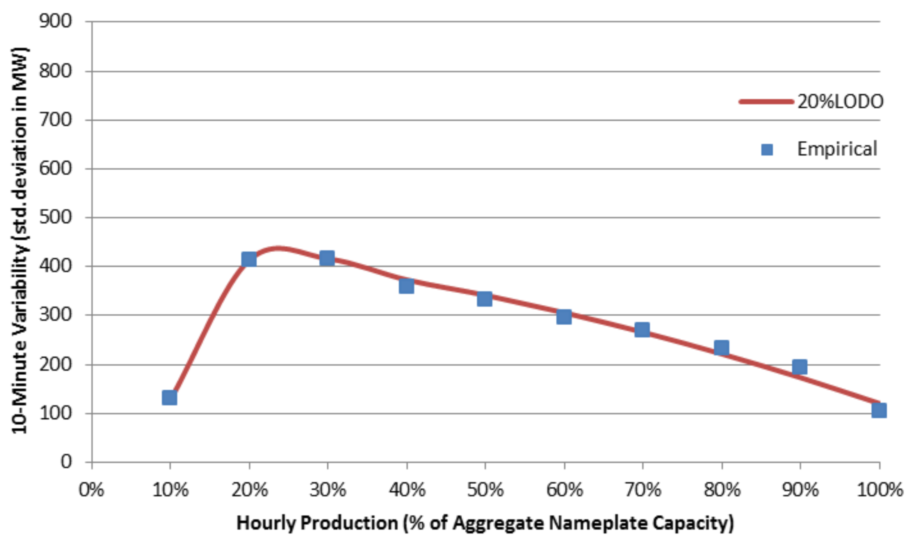


Figure 1-71: Statistical Characterization of 10-Minute PV Variability for The 20% LODO Scenario

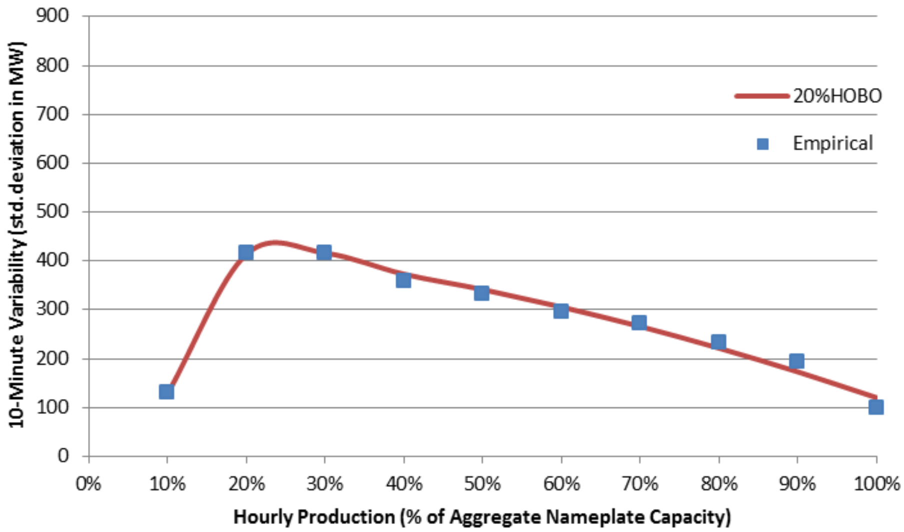


Figure 1-72: Statistical Characterization of 10-Minute PV Variability for The 20% HOBO Scenario

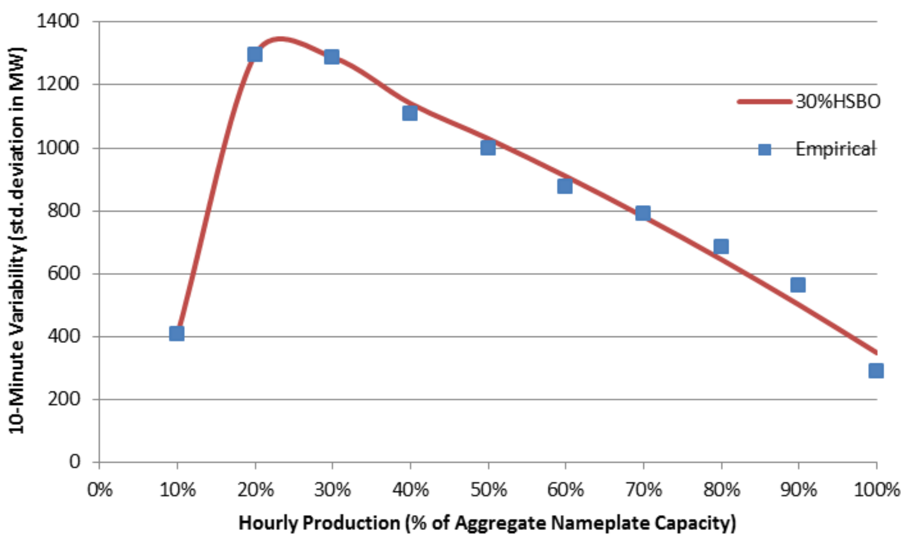


Figure 1-73: Statistical Characterization of 10-Minute PV Variability for The 30% HSBO Scenario

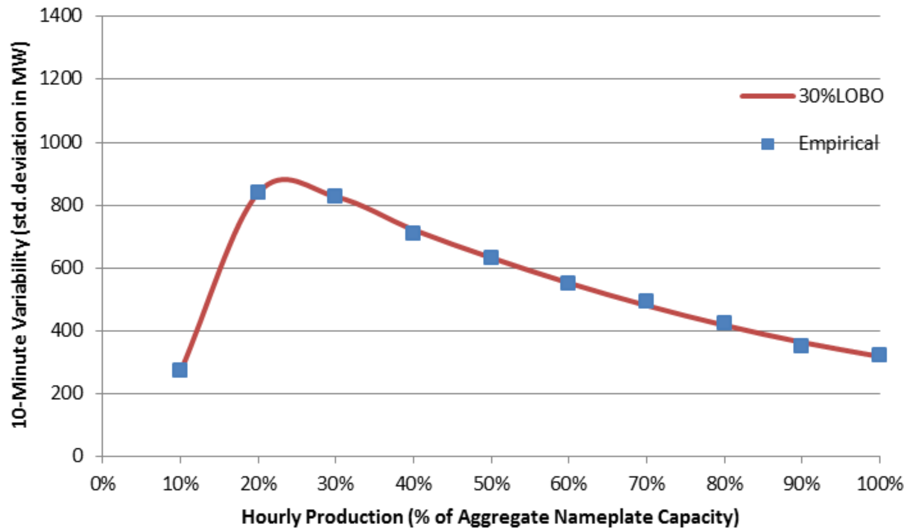


Figure 1-74: Statistical Characterization of 10-Minute PV Variability for The 30% LOBO Scenario

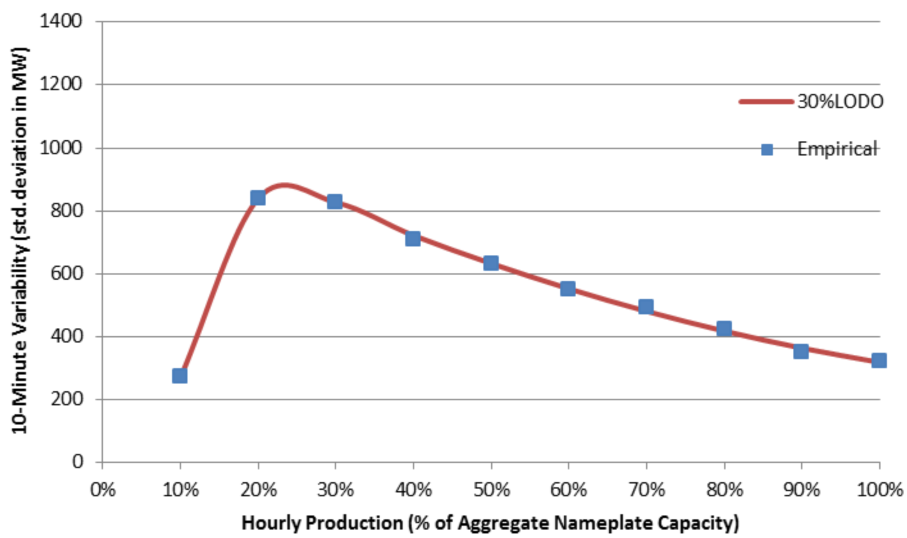


Figure 1-75: Statistical Characterization of 10-Minute PV Variability for The 30% LODO Scenario

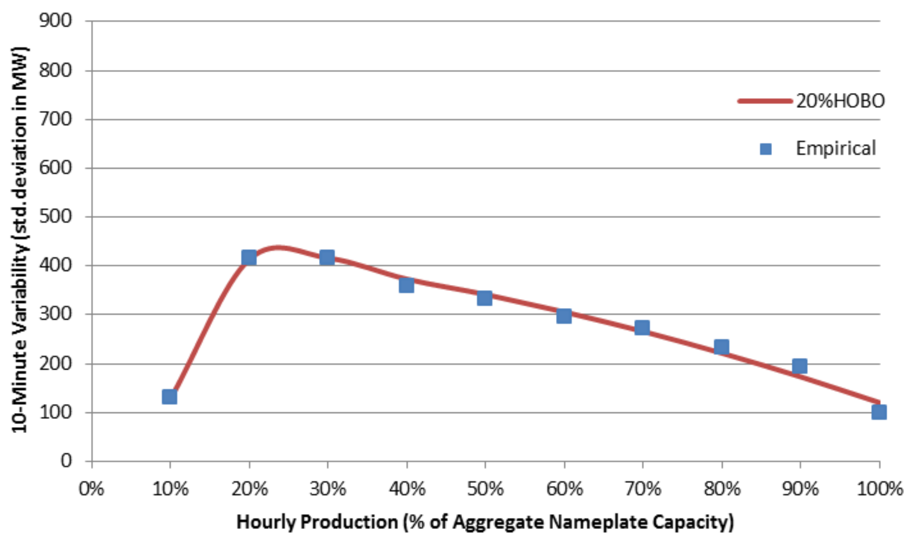


Figure 1-76: Statistical Characterization of 10-Minute PV Variability for The 30% HOBO Scenario

Characterizations of the wind and PV generation's 10-minute variability for all ten scenarios are shown in Figure 1-77 through Figure 1-82. All curves are plotted on the same vertical scale to emphasize relative variability. As the installed capacity is increased, so does the expected variability. There are some subtle differences, however. Processing the 10-minute variability in this way actually captures some unique aspects of each scenario. For example PV generation in Figure 1-80 and Figure 1-82 show substantial differences in the maximum expected variability between the solar and high solar scenarios. The differences however are reasonable realizing that the PV capacity for the 20% HSBO curve is 37 GW while the capacity for the 30% HOBO, LODO and LOBO scenarios is 36 GW. This comparison shows that the PV variability relationship between the 20% HSBO and the three 30% solar scenarios are similar.

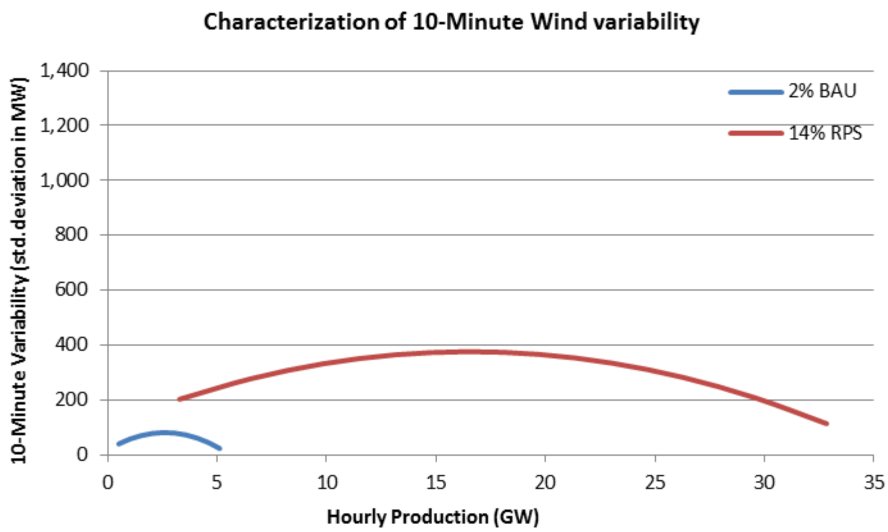


Figure 1-77: Characterization of 10-Minute Wind Variability for Lower Penetration Scenarios

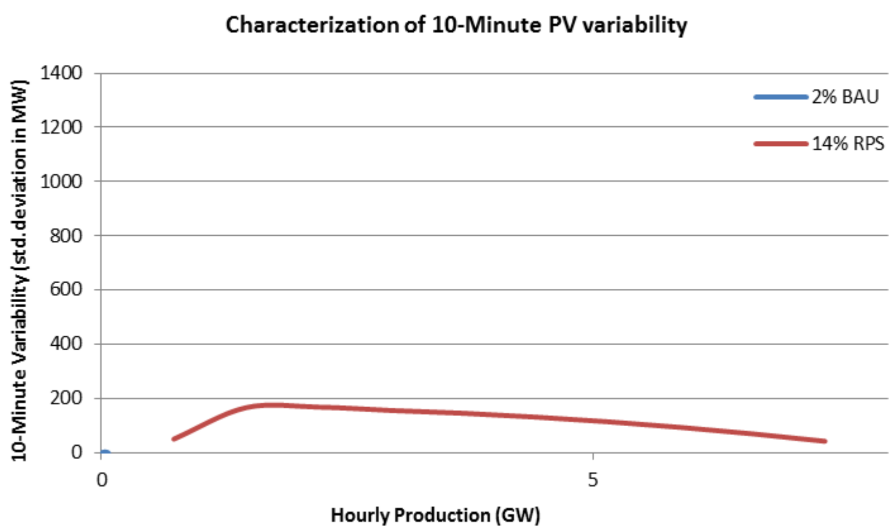


Figure 1-78: Characterization of 10-Minute PV Variability for Lower Penetration Scenarios (Note: 2% BAU 71MW Nameplate Capacity)

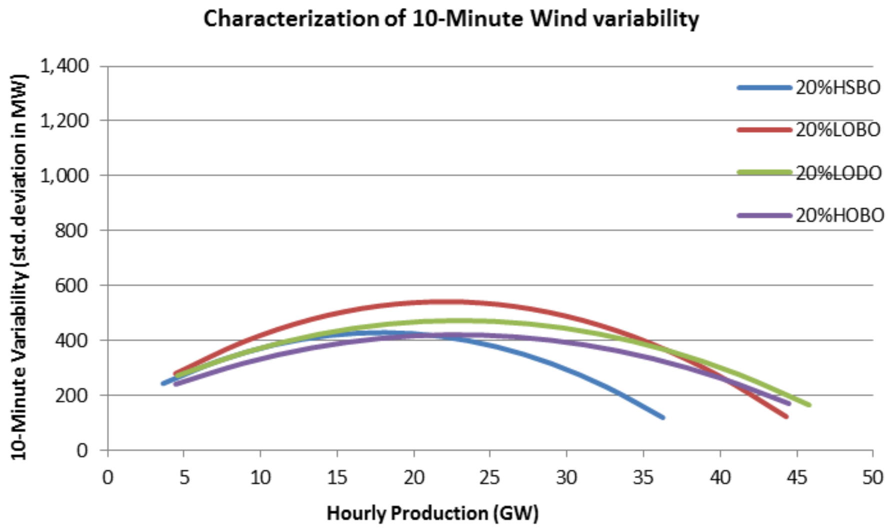


Figure 1-79: Characterization of 10-Minute Wind Variability For 20% Penetration Scenarios

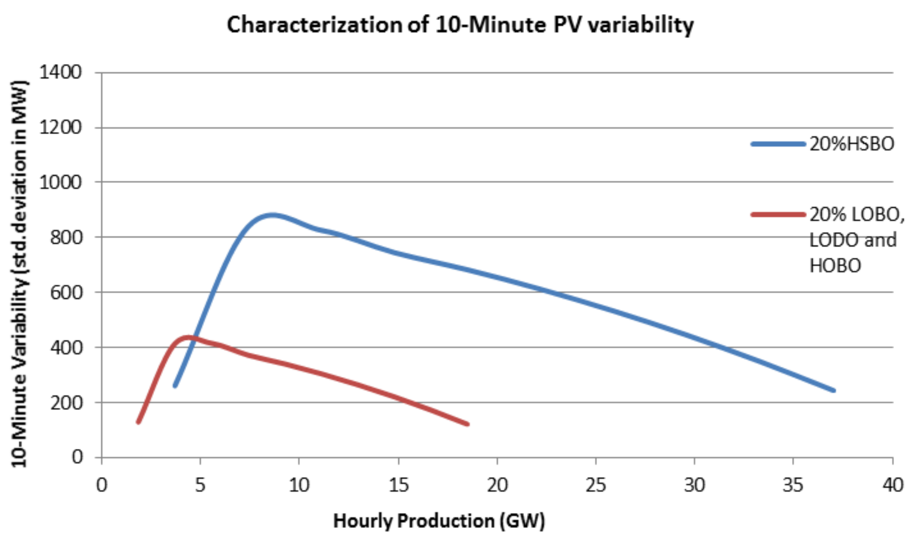


Figure 1-80: Characterization of 10-Minute PV Variability For 20% Penetration Scenarios (LOBO, LODO and HOBO Have Identical PV Sites)

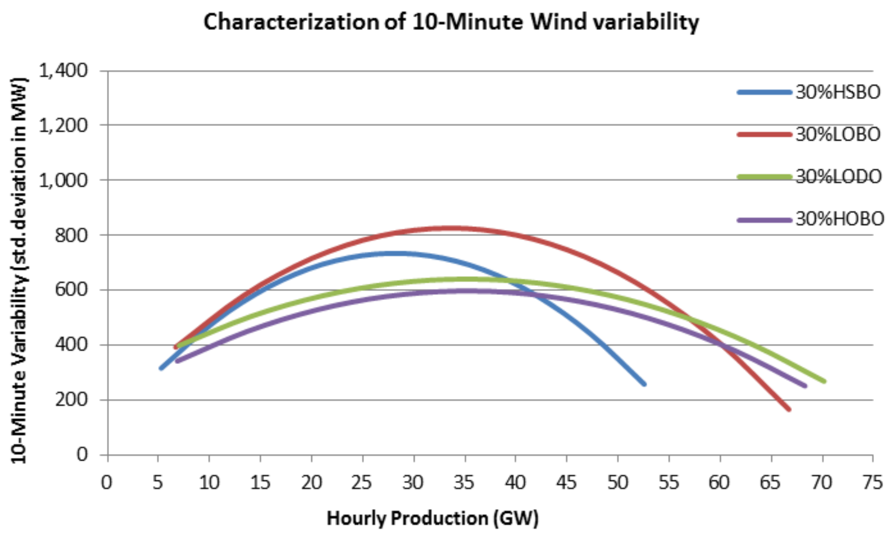


Figure 1-81: Characterization of 10-Minute Wind Variability For 30% Scenarios

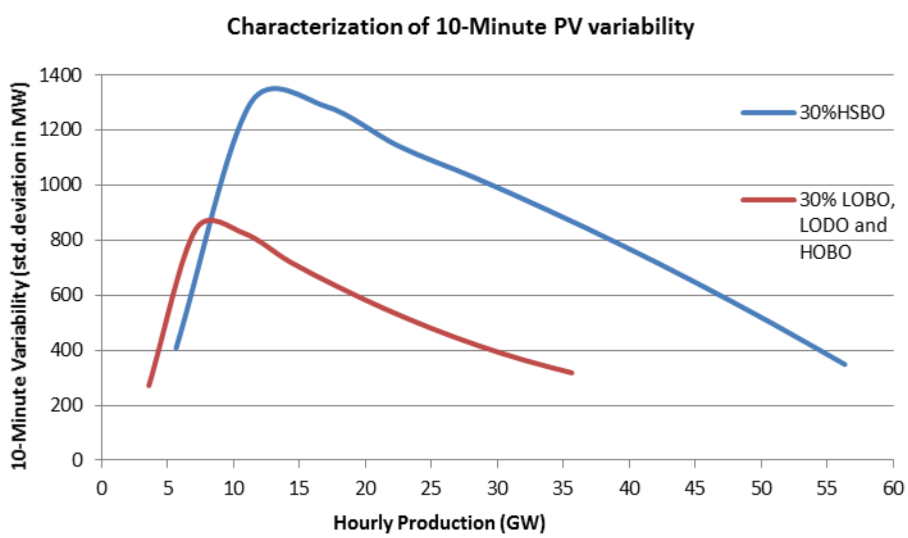


Figure 1-82: Characterization of 10-Minute PV Variability For 30% Scenarios (LOBO, LODO and HOBO Scenarios Have Identical PV Sites)

1.4 Renewable Generation Forecasting and Uncertainty

The accuracy with which renewable generation can be predicted varies with the forecast horizon. Beyond a week or so, it is nearly impossible to predict hourly production with any reasonable accuracy: forecasts based on empirical or historical data, as presented here previously, would likely be as accurate as the much more sophisticated methods.

Fortunately, forecast accuracy for load, wind, and PV generation will increase as the horizon is shortened.

In power system operations, the critical horizons are those used by operators to commit, schedule, and dispatch generation. The day-ahead forecast, meaning a forecast of hourly production over the 24 hours of the next day and generated about 12-24 hours prior to the start of the target day, is a critical input to processes that optimize the economic efficiency of the system within security and reliability constraints. Errors in the forecast quantities (load, wind, and PV generation) that drive the commitment and dispatch processes can have consequences for the economic efficiency and/or reliability of the system. Under-forecasting of wind and PV generation can result in commitment of too much conventional generation leading to excess uplift charges; over-forecasting may lead to depletion of reserves and very high locational marginal prices (LMPs).

Even shorter horizons are also important, as "looking ahead" is a fundamental part of power system operation. These horizons range from an hour to four or more hours into the future.

The dataset used in this study includes forecasts of production for each hour that represents a prediction made during the previous day, based on state-of-the-art wind and solar forecasting methods.

The objective of this analysis is to characterize wind and PV generation forecast accuracy for the horizons integral to the study:

- The day-ahead forecast used in unit commitment,
- An hour ahead forecast that factors into operating reserve considerations, and
- A very short term forecast (10-minute ahead) that is used to assess incremental regulation needs, as will be described in the reserve section.

1.4.1 Day-ahead

Mean-Absolute-Error (MAE) is the chosen metric for forecast accuracy. It is calculated by dividing the difference between the actual and forecast value each hour by the aggregate nameplate capacity, taking the absolute value, summing over all the hours, then dividing by the number of hours. The day-ahead forecast accuracy over all three years of the dataset is shown in Figure 1-83. The values are consistent with the current state-of the commercial art forecasts having MAEs in the 4% and 8% range. Diversity of renewable generation over the large PJM area contributes to a low aggregated forecast error (MAE). While one region of PJM may be over forecasting another under forecasts, and extremes of large over or under forecasts for the entire PJM footprint are less probable.

Forecast accuracy varies seasonally as shown in Figure 1-84. Errors are lowest in the summer when wind production is at its lowest and PV at its highest. This may be attributed to more consistent summertime weather across the PJM system and lower wind production in general during the summer months.

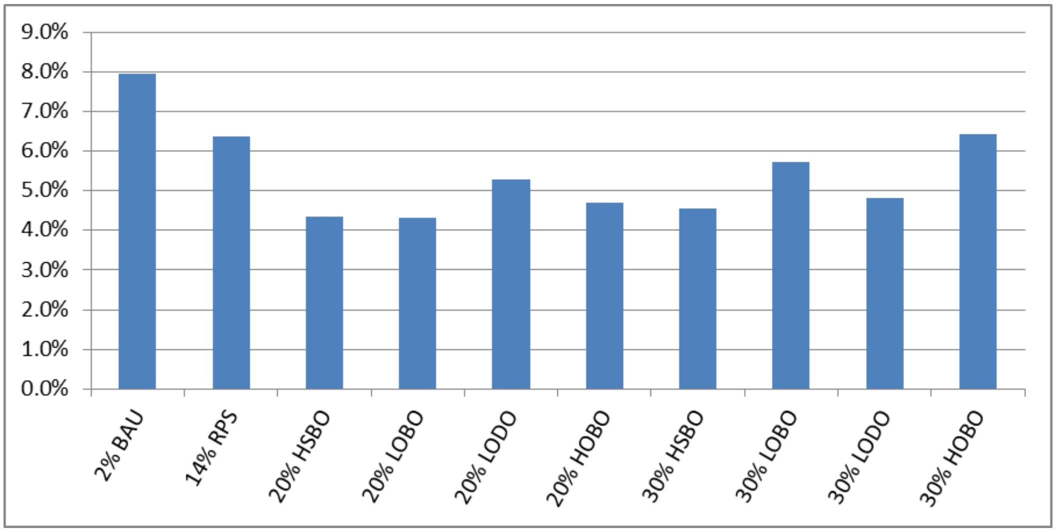


Figure 1-83: Mean-Absolute-Error for Day-Ahead Wind + Solar Forecast, All Scenarios All Hours

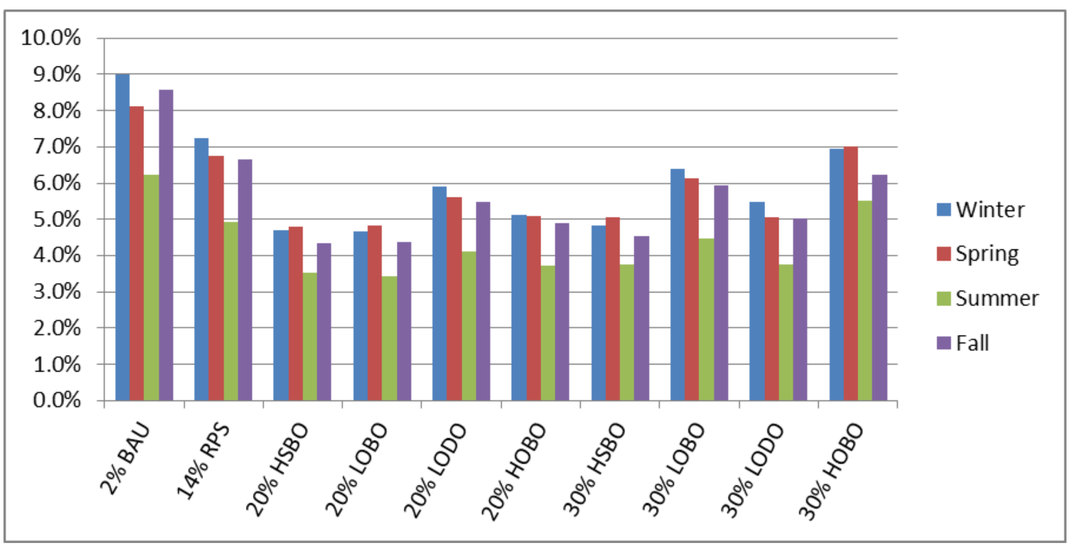


Figure 1-84: Day-Ahead Wind + Solar Forecast Accuracy for Each Scenario by Season

Although commonly used by forecast providers, MAE is sometimes a misleading statistic as it normalizes all error to the nameplate capacity. Large differences between actual and forecast wind generation at lower levels of production are reduced in “appearance” when divided by nameplate capacity. In absolute terms, there will be many hours with significant differences between forecast and actual wind. Figure 1-85 illustrates hourly forecast and actual wind and PV generation for randomly selected seven-day periods for the 30% HSBO scenario.

The graphs show that the day-ahead forecasts provided with the mesoscale production data and representing the state of the commercial art for wind and PV generation forecasting, track the trends in the actual wind and PV generation quite well. Closer inspection, though, shows some hours with very large forecast errors. On the chart for the week in April, for example, actual wind and PV generation is above the forecast by 20GW for a few hours just prior to April 7th. In November the renewable generation is over-forecast by over 5 GW for a few hours just prior to November 17th. During the August chart the forecast and actual track closely.

The production simulations can help reveal the significance of these errors with respect to system reliability an economics. Going forward, there are some significant outstanding questions regarding use of wind and PV generation forecasts in the various operational contexts. In wholesale energy markets, for example, wind and PV generation scheduled only in real-time or in short-term markets have the effect of ensuring over-commitment in the day-ahead market. On the other hand, over-forecasting of wind and PV generation in the day-ahead reliability commitment may pose risks to system security.

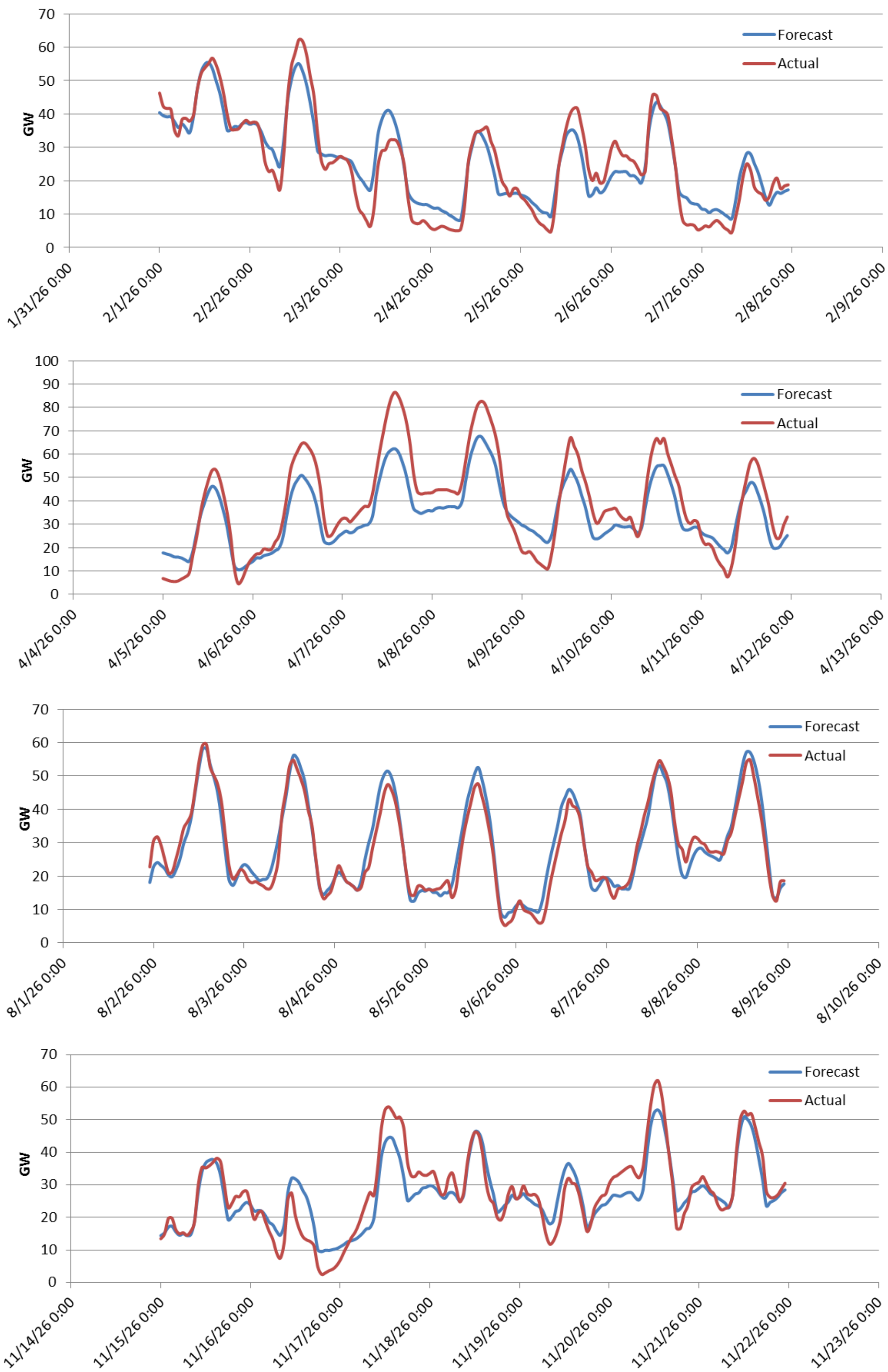


Figure 1-85: Day-Ahead Forecast and Actual Wind and PV Generation For Selected Weeks from Each Season: 20% HOBO Scenario

1.4.2 Hour-Ahead

At one-hour horizon, “persistence” forecasts have been shown to be as statistically accurate as those based on more sophisticated techniques or atmospheric modeling. Persistence forecasts simply assume that things will not change – the forecast for the next interval is what is measured in the current interval.

Persistence forecasts are used in this study as a proxy for short-term wind and PV generation forecasts. While the overall accuracy, as mentioned above, is good relative to other methods, they are of limited use in volatile weather conditions that may lead to large ramps in wind and PV generation. Research is ongoing on special techniques for forecasting these conditions and better predicting large changes in wind and PV generation.

For 1-hour persistence, the forecast for the next hour is equal to the actual value for the current hour. The forecast error for the current hour is therefore the change in wind + solar output relative to the previous hour. Therefore, analyses of the hourly changes presented in a previous section of this report are also characterizations of the 1-hour persistence forecast error. The chart in Figure 1-86 (which is identical to the chart in Figure 1-36) shows the distribution of all hourly persistence forecast errors for the 20% scenarios.

A more useful representation of persistence forecast errors is shown in Figure 1-87 and Figure 1-88. In these charts the errors are grouped by hourly production level, as with the 10-minute data earlier in this section.

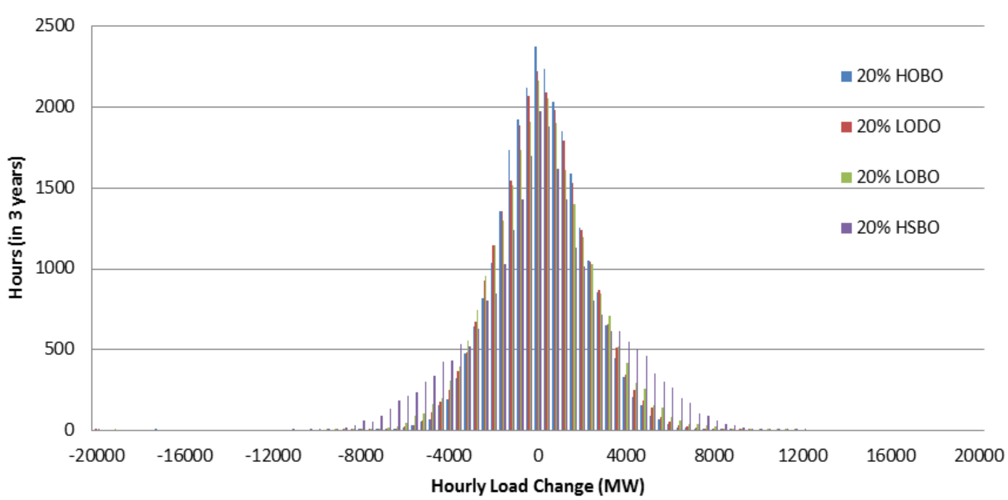


Figure 1-86: Distribution of 1-Hour Persistence Forecast Error for Wind In 20% Scenarios

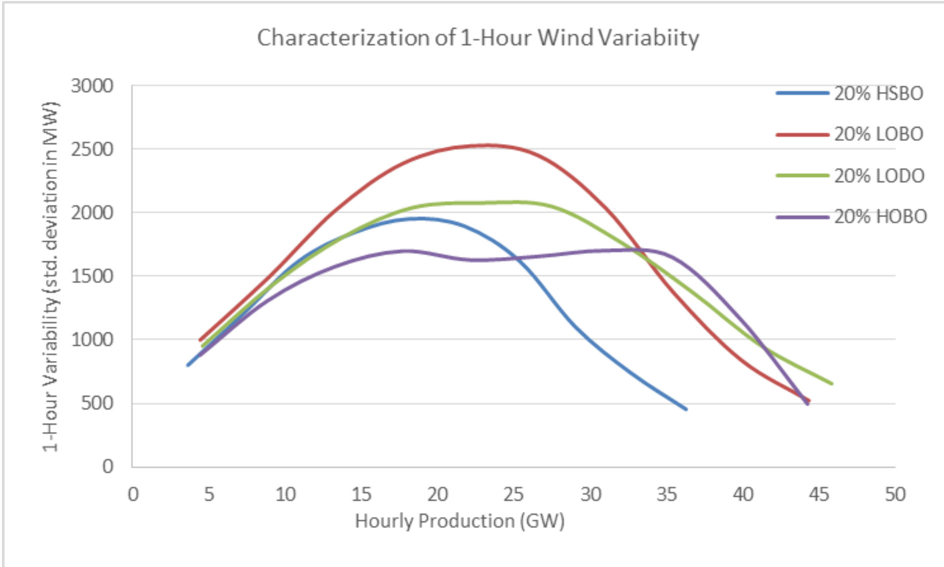


Figure 1-87: Expected 1-Hour Persistence Forecast Error as Function of Current Wind Production Level For 20% Scenarios

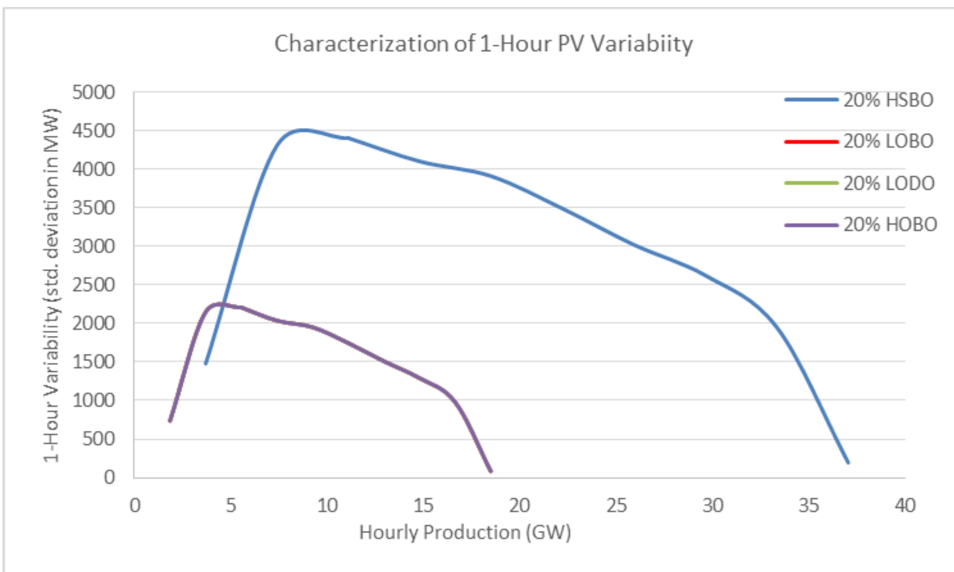


Figure 1-88: Expected 1-Hour Persistence Forecast Error as Function of Current PV Production Level For 20% Scenarios (Note LOBO, LODO and HOBO Scenarios Use Same PV Sites)

1.4.3 Very Short Term

Persistence forecasts over very-short term intervals are statistically more accurate than those over an hour. The charts characterizing wind and PV generation changes over 10-minute intervals, appearing earlier as Figure 1-78 through Figure 1-82 in the discussion of variability, also characterize the expected forecast error over a 10-minute interval as a function of production level. These will be used later in the examination of incremental regulation and sub-hourly flexibility requirements.

1.5 Statistical Characterization Observations and Conclusions

The observations and conclusions here are made on the basis of three years of synthesized meteorological and wind production data corresponding to calendar years 2004, 2005, and 2006. In some senses, the sample size is very adequate, as the behavior of wind and PV generation under many types of weather regimes is embedded in the dataset. With a limited sample size in terms of the number of years represented, there is no way to tell from the dataset alone whether annual energy production, for instance, is lower, higher, or about equal to what might be expected annually over the life of a wind or PV project. Other resources, such as long-term meteorological records, would need to be consulted to provide insight into these types of questions.

The wind generation scenarios defined for this study have broad diversity across the PJM area show that the winter and early spring seasons is when the highest wind energy production can be expected. And as is the case in many other parts of the U.S., summertime is the “off-season” for wind generation.

On the other hand PV generation production is highest in the summer season and lowest in the winter season. In addition PV generation is provided during the daytime hours when wind trends at its lowest thus providing a beneficial supplement for the wind fleet.

Aggregated PV and wind resources are complementary, as previously mentioned, in that when in the morning hours the wind generation ramps downward, the PV generation ramps upward; and when in the evening hours the PV generation ramps downward, the wind generation ramps upward.

Capacity factors for the combined wind and PV generation are reduced as renewables are added to the generation fleet. The BAU scenario has the highest combined wind and PV capacity factor at 37%. This scenario has the smallest PV generation (almost negligible at 71MW). As PV generation is added to the mix in the 20% scenarios the capacity factors for renewable generation is reduced. The impact of PV on capacity factor is seen with the High Solar scenarios when the combined capacity factors are 27%.

When looking at capacity factors seasonally, the 2% BAU scenario with the greatest percentage of wind has an off-peak capacity factor approaching 50% in winter. The 14% RPS scenario has an off-peak capacity factor of 40% in winter. As PV is added along with wind in the 20% and 30% scenarios, the on-peak capacity factors get greater than the off-peak capacity factors. This can be attributed to the increase of PV generation at on-peak hours as well as the increased diversity of wind sites.

Based on averages over the entire dataset, seasonal daily patterns in both winter and summer seasons exhibit some diurnal behavior (i.e., variation by the hour of the day) by wind. Figure 1-89 and Figure 1-90 show average daily wind profiles by season for two scenarios. The trends show lower power output during the midday hours, especially during the summer season. This trend is complementary to solar profiles which naturally peak during midday and have higher production during the summer season. The energy provided by PV being only in the day time hours, results in a bump in the combined generation profile observed in the daylight hours. In the winter, wind production is at its greatest and PV at its lowest. Summer patterns show a reduction in wind production while PV generation increases. The HOBO and LODO scenarios provide a combination of wind and PV that show the greatest consistency of production output. It is enticing to think that such patterns could assist operationally with morning load pickup and peak energy demand, but the patterns described here are averages of many days. The likelihood of any specific day ascribing to the long term average pattern is small.

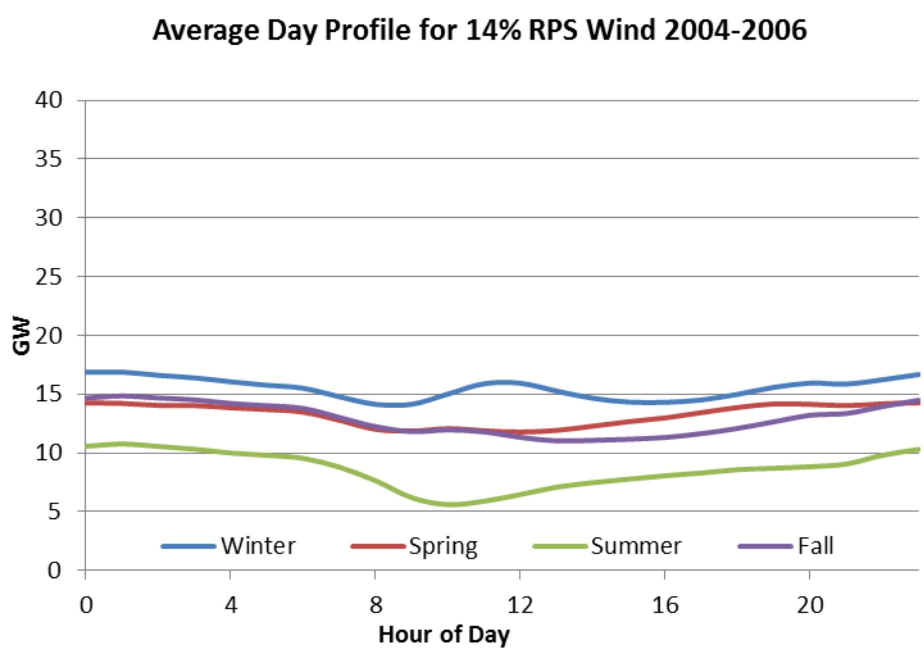


Figure 1-89: 14% RPS Seasonal Average Day Profile for Wind All Years

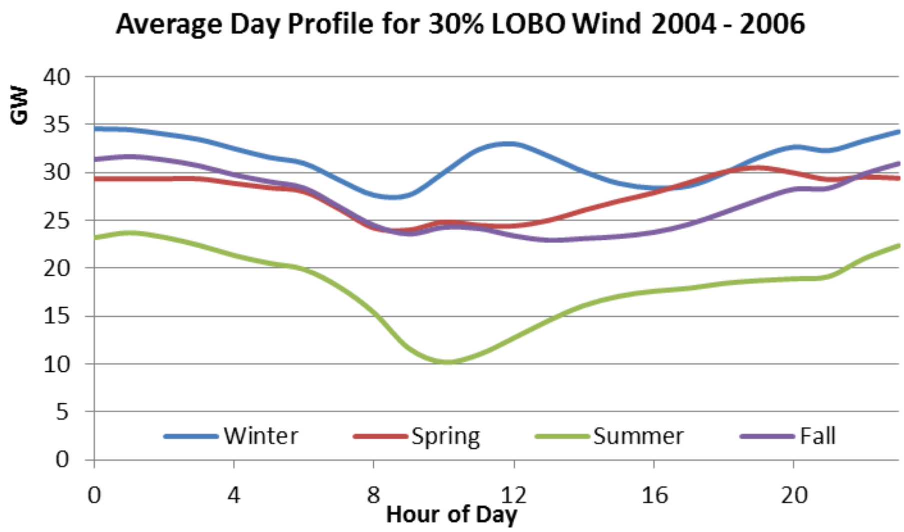


Figure 1-90: 30% LOBO Seasonal Average Day Profile for Wind All Years

The net load average patterns by season reveal increased reduction in net load during the midday hours as penetration increases resulting in a double peak in all but the summer season. The summer season exhibits an overall reduction in peak load with only the 30% HSBO showing enough load reduction to result in a slight load dip in the middle of the day.

The day-ahead forecasts developed for each scenario from information in the dataset show an overall forecast accuracy of 4% to 8% MAE. This is consistent with what is considered the state of the commercial art (for a large diverse operating area). Day-ahead forecasts for all scenarios are important since they will be used directly in the hourly production simulations, and represent the major source of uncertainty attributable to wind generation.

Shorter-term forecasts also factor into operations. For reserves, the most important of these are the short-term hour ahead and 10-minute ahead forecasts. The process for generating these normally uses persistence, which assumes that there will be no change in wind or PV generation over the forecast horizon. Persistence has been shown to be as statistically accurate as forecasts based on skill and sophistication (though skill-based forecasts may be much better during periods of predictable changes, as when weather fronts move through a region). The various statistical characterizations developed to portray the variability and short-term uncertainties of the aggregate wind and PV generation in each scenario are also critical inputs to the analysis of operating reserve impacts.

Figure 1-91 illustrates how the variability of individual wind and solar PV plants is reduced when all wind and PV plants are aggregated over PJM's footprint. The upper traces show the high variability associated with individual plants. The next traces below show the aggregate profiles for all wind and solar plants within the states of New Jersey, Pennsylvania, and Illinois. The lower traces show profiles for all wind plants in PJM, all PV plants in PJM, and the combination of all wind and PV plants in PJM. Short-term variability is dramatically reduced. Values shown are in terms of per units of capacity ratings. PJM's large geographic footprint is of significant benefit for integrating wind and solar generation, and greatly reduces the magnitude of variability-related challenges as compared to smaller balancing areas.

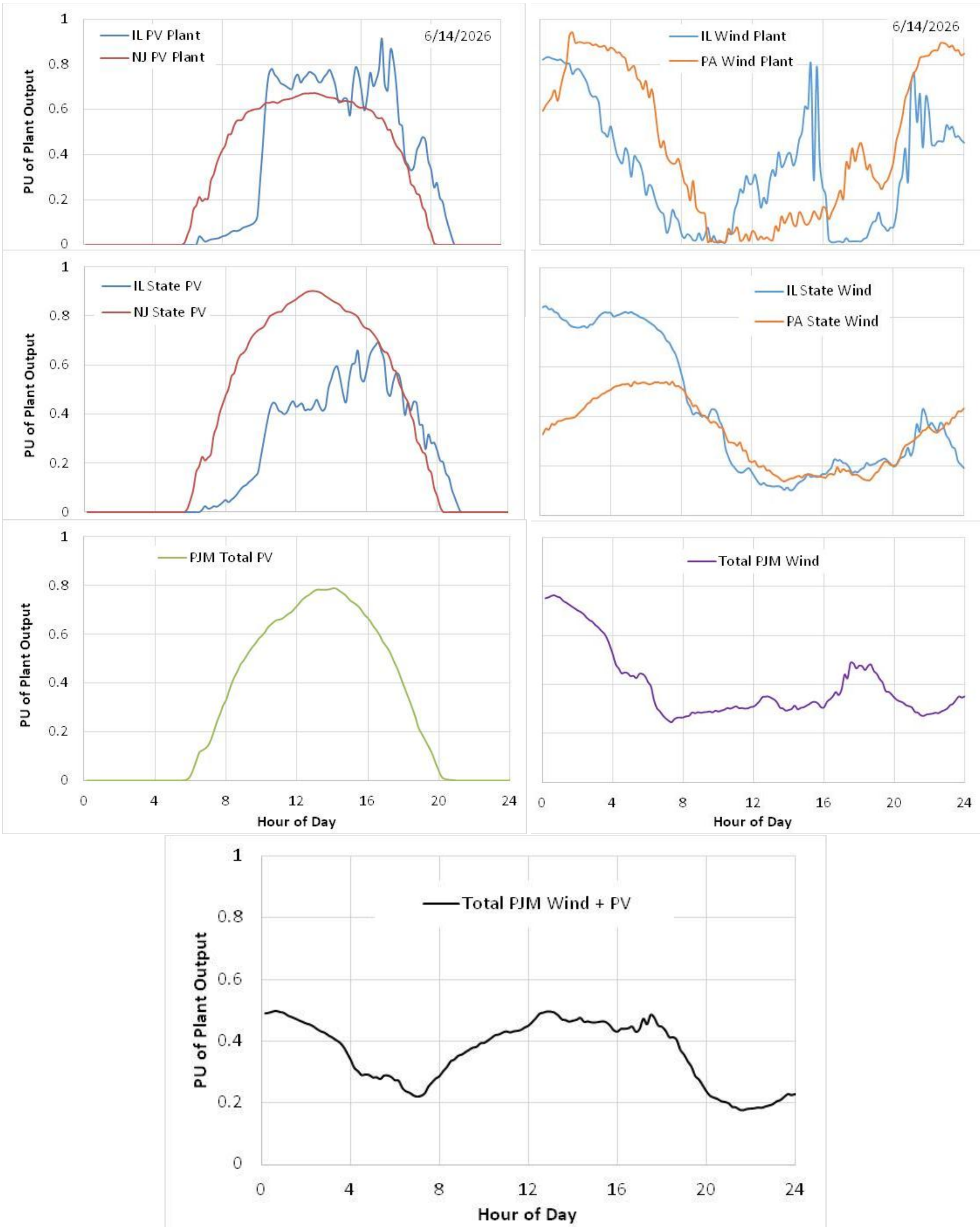


Figure 1-91: Smoothing of Plant-Level 10-Minute Variability over PJM's Footprint, June 14, 30% LOBO

2 Regulation and Operating Reserves

2.1 Reserve Analysis Overview

With increasing levels of wind and solar generation, it will be necessary for PJM to carry higher levels of regulation to respond to the inherent variability and uncertainty in the output of those resources.

Statistical analysis of wind, PV and load data was employed to determine how much additional regulation capacity would be required to manage renewable variability in each of the study scenarios. The regulation requirement for wind and solar was combined with the regulation requirement for load (a percentage of peak or valley load MW, per PJM rules) to calculate a total regulation requirement value. It was determined that due to the size and geographic spread of the PJM system, no additional primary reserve (synchronized or non-synchronized) or secondary reserves would be required to cover the forecast uncertainty.

Currently PJM has four categories of ancillary services:

- Regulation, which include generating units or demand response resources that are under automatic control and respond to frequency deviations,
- Reserves, which include Contingency (Primary) Reserve (combination of Synchronized and Non-Synchronized Reserves), and Secondary Reserve,
- Black Start Service, which include generating units that can start and synchronize to the system without having an outside (system) source of AC power, and
- Reactive Services, which help maintain transmission voltages within acceptable limits.

Regulating consists of on-line synchronized generation, typically by Automatic Generation Control (AGC) that provide a balance with load and generation to maintain an interconnection frequency of 60 Hz. These generating resources assist in the control of moment to moment changes in load. Additionally demand side response resources can be used along with regulating resources for frequency control.

Operating Reserves (OR) consist of generation resources that can be counted on to serve load during different time intervals within the hour. Operating reserves are categorized as follows:

- Contingency/Primary reserves
    - Synchronized Reserves
        - Spinning on-line generation
        - Customer demand response/Interruptible load

  - Quick-Start Reserves
- Supplemental reserves

Contingency Reserves (CR) consist of synchronized reserves and quick-start reserves. Synchronized reserves are spinning on-line generation or customer demand response. Spinning reserves must be at least 50% of the Contingency Reserve while customer demand response can be no more than 25% of the Contingency Reserve[1].

Quick start reserves consist of resources that can be brought on-line and synchronized within a 10-minute period.

Combined synchronized reserve and quick start reserve resources can be no less than the largest contingency.

Supplemental Reserves (SR) are available resources that can be brought on-line and provide energy to the PJM system within a 10 to 30 minute period. Figure 2-1 provides a pictorial representation of operating reserves.

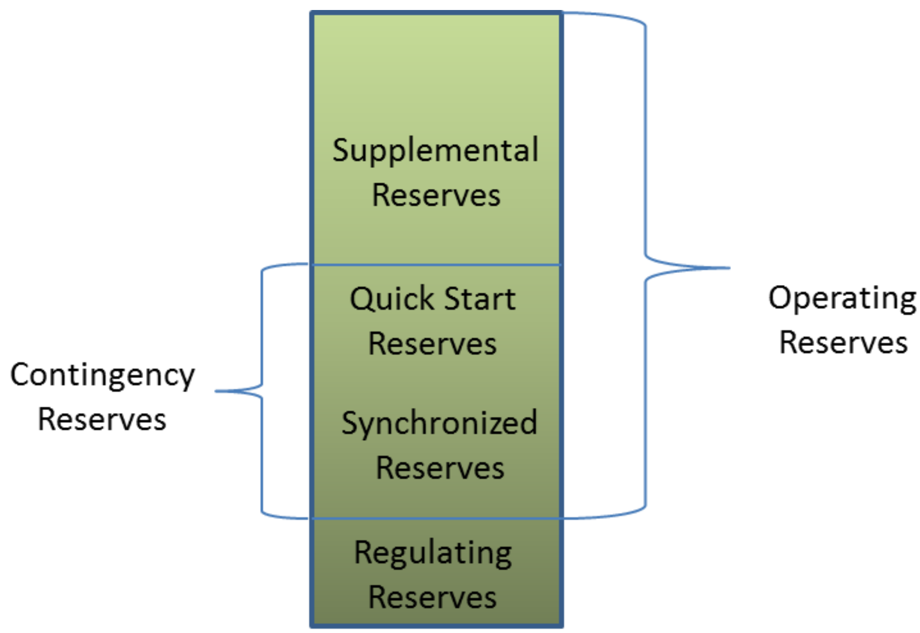


Figure 2-1: PJM Operating Reserves

The dynamic nature of the PJM regulation requirements was modeled in the production simulations using approximation methods described in this section. For the calculations here, and in the production simulations later, procurement of reserves is assumed to be a function of day type and time of day as follows:

- 05:00 – 23:59 Weekdays (on-peak hours)

- 00:00 – 04:59 Weekdays and all hours Weekends and specified holidays (off-peak hours)

A previous study titled the "KERMIT Study Report[3]" provided analysis of the PJM frequency regulation market and how the PJM AGC practice effectively controls fast and conventional resources. The PJM regulation requirement at the time of the study was 1% of the on-peak load for peak hours and 1% of the minimum load for the off-peak hours (Note: A reduction to the regulation requirement to 0.70% of the on-peak load during peak hours and 0.70% of the minimum load during the off-peak hours was made effective on 10/1/2012 when PJM implemented performance based regulation in compliance with FERC Order 755[4]). The study demonstrates that this level of regulation requirement provides PJM with sufficient regulation to stay above the CPS1[5] compliance requirement score of 100% by providing an average CPS1 value of 143%. The study indicated that the PJM regulation requirement could be reduced to a value below 1% while maintaining the CPS1 value above 100%. The project team considered reducing the 1% regulation requirement for this study; however, decision was made to keep the existing practice for this study, recognizing there may be changes at some future date. Consequently, the regulation values calculated for use in the production costing used a 1% regulation requirement to account for load and renewables in each scenario.

In the KERMIT Study, twelve selected days with 2-second resolution load values were examined. These sub-hourly values provide a basis for determining a foundation for the statistical analysis used in the regulation calculations to be described later. An illustration of regulation values for the twelve selected days from the KERMIT study are shown below in Table 2-1.

[3] KERMIT Study Report, PJM Interconnection, LLC; Reference Number: Statement of Work 11-3099; Prepared by KEMA Inc. December 13, 2011

[4] http://www.pjm.com/~/media/training/core-curriculum/ip-dsr/dsr-in-the-ancillary-service-markets.ashx

[5] CPS1 is a statistical measure of Area Control Error (ACE) variability and its relationship to frequency error.

CPS2 is a statistical measure designed to limit unacceptably large net unscheduled power flows by providing an oversight function that bounds ACE.

Table 2-1: Regulation Schedule for Selected Days in Month (MW)

Hour	1/21 2011	2/18 2011	3/20 2011	4/11 2011	5/10 2011	6/15 2011	7/10 2011	8/15 2010	9/7 2010	10/28 2010	11/23 2010	12/13 2010
1	772	599	585	551	543	635	721	673	589	573	583	731
2	772	599	585	551	543	635	721	673	589	573	583	731
3	772	599	585	551	543	635	721	673	589	573	583	731
4	772	599	585	551	543	635	721	673	589	573	583	731
5	772	599	585	551	543	635	721	673	589	573	583	731
6	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
7	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
8	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
9	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
10	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
11	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
12	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
13	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
14	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
15	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
16	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
17	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
18	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
19	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
20	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
21	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
22	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
23	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123
24	1,060	791	758	812	818	988	1,246	978	1,103	818	838	1,123

Even though only 3% of days in the year are examined the regulation requirements fluctuate seasonally as well as month to month. Hourly regulation varies from a low of 543 MW on May 10 to 1,246 MW on July 10. The lowest regulation requirements trend in the spring and fall while largest are in the summer and winter. From this selection of data it one could conclude the average annual on-peak regulation is about 1000 MW while off-peak average is approximately 600 MW. Overall this provides an example of how regulation is dispatched on an hourly basis for different days over months of the year.

Wind and PV generation will increase the real-time variability and short term uncertainty of the net load against which other resources are scheduled and dispatched.

2.2 Methodology

Chronological production simulations at hourly resolution have become the standard approach for assessing wind and PV integration impacts. Effects of wind inside of the hour on regulation, balancing, and reserves in general cannot be directly evaluated at that granularity. Consequently, statistical techniques have been developed for application to hourly and higher resolution wind, PV and load data to estimate the impacts within the hour.

2.3 High-resolution analysis

Statistical analysis of wind, PV and load data is employed to determine how much additional regulation capacity would be required to maintain CPS1 metrics in each of the wind scenarios. As previously mentioned, the 2-second interval load data for one day of each month of the year is one benchmark of providing load variability metrics. Along with this data other data available for this analysis consists of high resolution (5-minute interval) load, compiled for the study from actual load data for 2004, 2005, and 2006, and synthetic wind and PV generation data (10-minute interval) for 2004, 2005 and 2006 from the NREL mesoscale database.

The first objective of the statistical analysis is to examine the fast fluctuations of wind and PV generation relative to similar variations in the load. Using the 2-second resolution load data as a reference, the fast variations are computed as the difference between the 2-second data and a twenty minute rolling average window of the 2-second data (600 samples from 20 minutes before and 600 samples from 20 minutes following). Figure 2-2, shows the off-peak and on-peak regulation (at 1%) and the metered RegA[6] and TReg[7] values at 2 second intervals. The RegA (red line) trace remains within the regulation bands (blue line) while the variation of the actual load from the 20-minute rolling average (purple line) is less than the TReg limits.

The graph in Figure 2-3 highlights hours 2 through 9 and shows the relative comparison of the 20-minute rolling average trend to the 2-second data. It also illustrates the difference between the 10-minute average data and the 2-second data. It can also be observed in this figure that the 2-second data has smaller period to period variability than the data that is averaged over longer periods (notice the step changes with the 10-minute data graph). We looked deeper into the 2-second data to develop the relationship between the short term (2-second) and hourly variability and how this information can appropriately be represented statistically.

[6] The traditional regulation signal, or RegA signal, is the regulation signal point that is used for traditional regulating resources with physical characteristics that limit ramp rate. This regulation signal takes into account the RTO frequency and tie error. RegA shown is the PJM metered regulation response to control frequency from the Automatic Generation Control pulses.

[7] TReg is the total MW on regulation, provided by PJM.

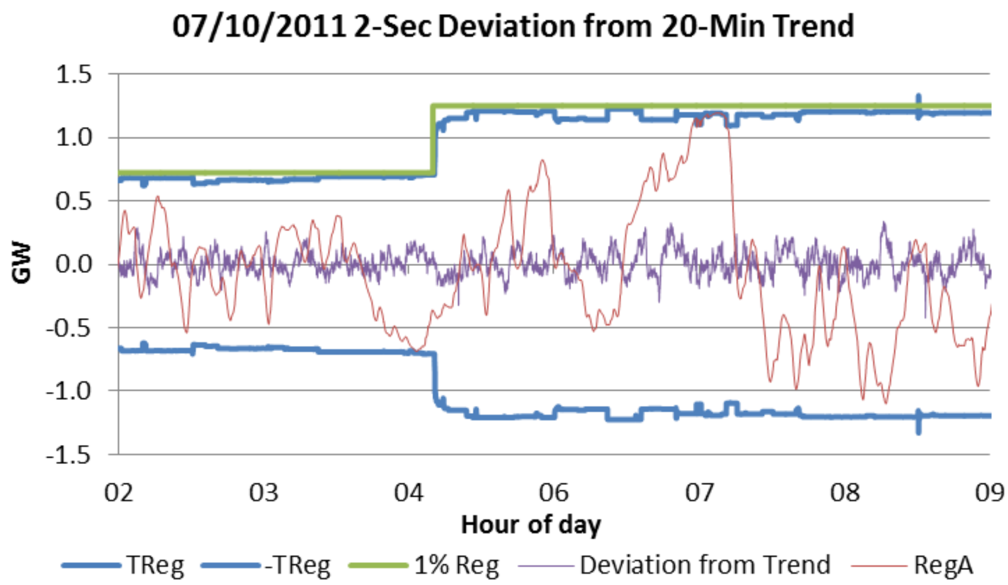


Figure 2-2: Metered Regulation for July 10, 2011 with 2 Second Deviations from a 20-Minute Trend

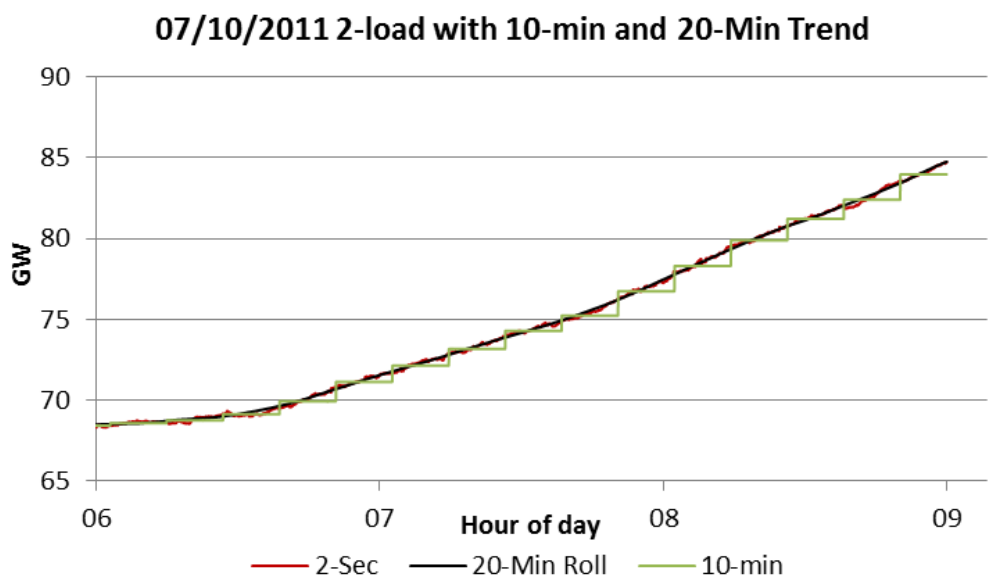


Figure 2-3: 2-Second Load Data Plotted with 20-Minute Rolling Average and 10-Minute Average Load

Of interest here is the deviation of the 2-second load data from the two curves, as shown in Figure 2-4. If the constructed curves are assumed to be proxies for the variability that is compensated for by movements of generation in the sub-hourly market, then the difference is what drives the need for additional regulation. The distribution of the differences over the requirement for regulation capacity has been approximated as a multiple of the standard deviation of the variability in this time scale. Previous studies have established that a statistically high level of confidence for reserve is achieved at about 3 standard deviations (or 3σ – or 3 sigma - in industry parlance) of 10-minute renewable variability. The 3σ criterion was also adopted for this study, which means that the regulation requirement is designed to cover 99.7% of all 10-minute variations. Using this factor, the regulation capacity inferred from the statistics is 300 MW to 1,100 MW (i.e., 3 times the values shown in Figure 2-4). Note that this accounts for the variability of the load only. Not included are additional deviations due to uninstructed generation movements, and ramping behavior of generation participating in the sub-hourly energy market. The regulation schedule described in Section 2.1 accounts for these factors as well as the changing variability of load with season, day, and hour.

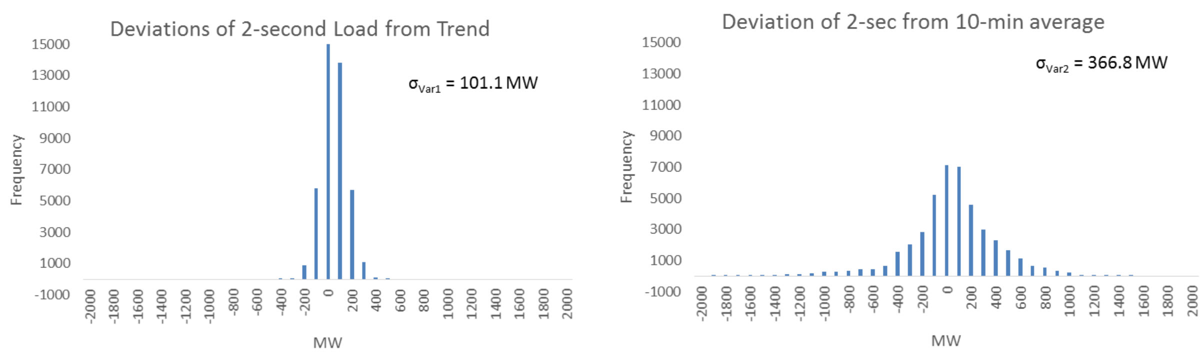


Figure 2-4: Deviations of PJM 2-Second Load from (l) Trend and (r) 10-Minute Average

The PJM simulated wind generation data used for this study is of 10-minute resolution, so it cannot be used directly to assess impacts of faster variations. However, extensive measurement data with time resolution down to seconds has been collected by NREL over the past decade and other high-resolution data for wind generation has been obtained from energy management systems (EMS) archives. Two observations are extracted from this measurement data for use here:

- Using the 20-minute rolling average window (used above), the standard deviation of the wind generation variations around this trend are around 1 to 2 MW for a 100 MW wind plant
- Using the 20-minute rolling average window (used above), the standard deviation of the PV generation variations around this trend are around 2.5 to 3.5 MW for a 100 MW PV plant.

- The fast variations from a wind or PV plant are statistically uncorrelated with similar variations from other wind or PV plants and with those from aggregate load, and therefore can be considered in this time frame as random independent variables.

The effect of the fast variations of wind generation can then be easily estimated. With 44,000 MW of wind generation, approximately the amount of the wind in the 20% scenarios (HOBO, LOBO and LODO), and the aggregate variability (i.e. deviation from the 20-minute trend) of the total wind generation can be calculated using the 2 MW assumption above:

$$\sigma_{wind} := \left(\sqrt{\frac{44000}{100}.2^2}\right) = 42.0\ MW \qquad Eq.1$$

And, because these variations are uncorrelated with those in load, using the standard deviation of load variations shown above in Figure 2-4, the standard deviation of the variability for net load (i.e. load net of wind generation) is calculated as:

$$\sqrt{\sigma_{Var1}^2 + \sigma_{Wind}^2} = 109.5\ MW \qquad \sqrt{\sigma_{Var2}^2 + \sigma_{Wind}^2} = 369.2\ MW \qquad Eq.2$$

Where the first equation uses the rolling trend approximation for sub-hourly market response to load and the second uses the 10-minute averages. In either case the effect of the fast fluctuations in wind generation is quite small: the standard deviation of variability is increased from 101.1 MW to 109.5 MW or from 366.8 MW to 369.2 MW

Similarly with 18,500 MW of PV generation, approximately the amount of PV in the 20% scenarios (HOBO, LOBO and LODO) and the aggregate variability of the total PV generation can be calculated using the 3 MW assumption above:

$$\sigma_{PV} := \left(\sqrt{\frac{18500}{100}.3^2}\right) = 40.8\ MW \qquad Eq.3$$

And, because these variations are uncorrelated with those in load, using the standard deviation of load variations shown above in Figure 2-4, The standard deviation of the variability for net load (i.e. load net of PV generation is calculated as:

$$\sqrt{\sigma_{Var1}^2 + \sigma_{PV}^2} = 109.0\ MW \qquad \sqrt{\sigma_{Var2}^2 + \sigma_{PV}^2} = 369.1\ MW \qquad Eq.4$$

The first equation uses the rolling trend approximation for sub-hourly market response to load and the second used 10-minute averages. In either case the effect of the fast fluctuations in wind generation is quite small: the standard deviation of variability is increased from 101.1 MW to 109.0 MW or from 366.8 MW to 369.1 MW

The aggregate variability of total Wind and PV can be calculated using the equation below:

$$\sqrt{\sigma_{Var1}^2 + \sigma_{Wind}^2 + \sigma_{PV}^2} = 116.8\ MW \qquad \sqrt{\sigma_{Var2}^2 + \sigma_{Wind}^2 + \sigma_{PV}^2} = 371.4\ MW \qquad Eq.5$$

The first equation uses the rolling trend approximation for sub-hourly market response to load and the second used 10-minute averages. In either case the effect of the fast fluctuations in wind generation is quite small: the standard deviation of variability is increased from 101.1 MW to 116.8 MW or from 366.8 MW to 371.8 MW

Over longer time scales –tens of minutes up to hours – wind and PV generation exhibits variations that are of markedly different character than that of load. In general, load changes over these time periods are relatively predictable, owing to both aggregation effects and a high level of familiarity based on history and heuristics. In this part of the analysis, it is assumed that short-term forecasts of load are nearly perfect, and that sub-hourly energy markets will dispatch the necessary capacity to balance load over these intervals.

The same notion is extended to wind and PV generation, except with recognition that short-term forecasts may exhibit appreciable error. Stated another way, sub-hourly markets will provide the necessary maneuverable capacity to balance forecast load and forecast wind and PV generation; but errors in these forecasts (for wind and PV, given the assumptions) will increase the regulation burden.

Figure 2-5 provides an illustration. The forecast for interval H2+20 is based on the observed wind generation during a previous interval or series of intervals, in this case the observed wind from H2+10. In the analysis here, it is assumed that the forecast for interval H2+20 is assimilated into the sub-hourly energy market clearing. The difference between the actual wind generation that appears in the interval and the forecast value will combine with the other deviations in load and generation. The aggregate of these deviations drives the requirement for regulation.

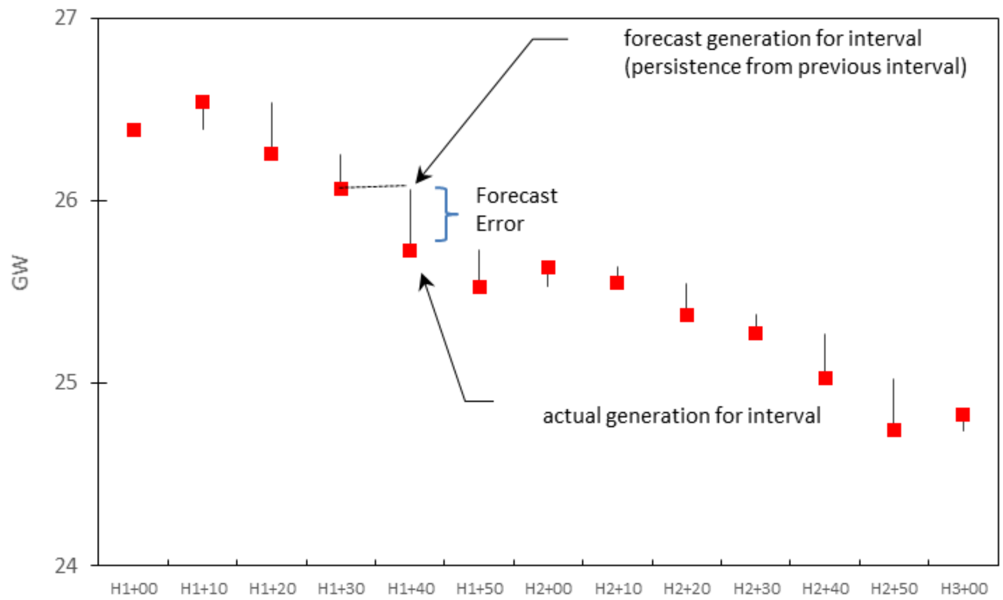


Figure 2-5: Short-Term Persistence Forecasting for 10-Minute Wind Generation.

Owing to the large sample of synthetic wind and PV generation data, the expected "errors" in the persistence forecast can be mathematically characterized.

Figure 2-6 shows 10-minute variability (i.e., the change in 10-minute renewable production from one 10-minute period to the next) as a function of total renewable production for three scenarios with increasing renewable penetration.

The charts are created by plotting x-y pairs of points where "x" is renewable (wind + PV) generation in the current interval "i", and the "y" value is equal to renewable generation in the next interval minus renewable generation in the current interval. The bold face numbers on the charts are the nameplate capacities.

One significant trend is that the maximum 10-minute variations occur when renewable production is about half of total capacity. Variability is lower near maximum production levels, partly because many wind plants are operating above the knee in the wind-power curve where changes in wind speed do not affect electrical power output. This characteristic of variability is relevant to the requirement for regulation, which is discussed later.

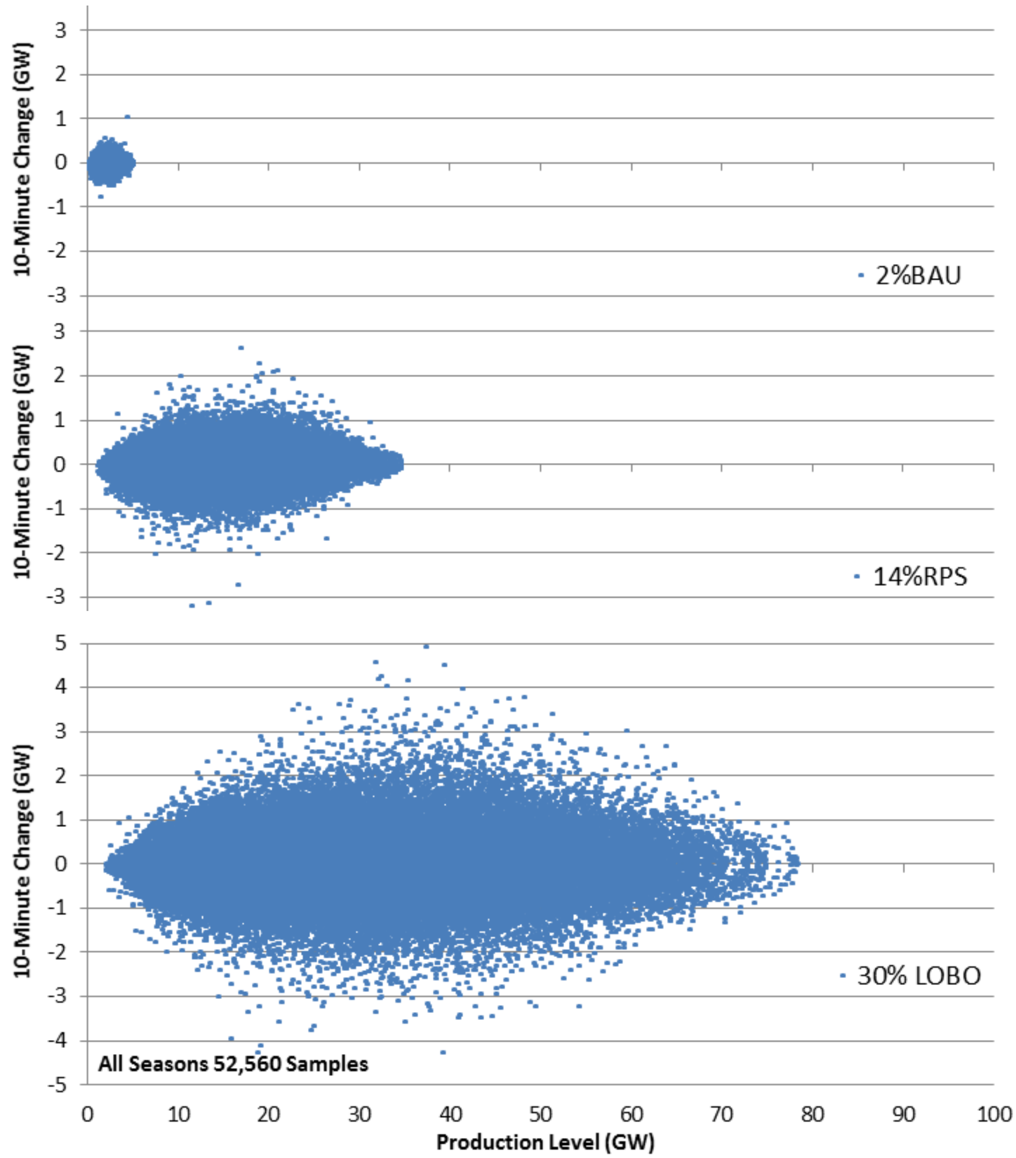


Figure 2-6: 10-Minute Wind and Solar Variability as Function of Production Level for 2% BAU, 14% RPS, and 30% LOBO Scenarios

The analysis illustrated that the variability of wind and solar power output is a function of the total production level, as shown in Figure 2-7. Here, each of the changes (or forecast errors) is grouped in ten "bins" or deciles of production from 0 to 1.0 per unit of nameplate rating. Then the standard deviation of the (normal) distributions in each of the deciles is computed and plotted. A key observation is that more regulation is needed when production is at mid-level, and less regulation is needed when production is very low or very high.

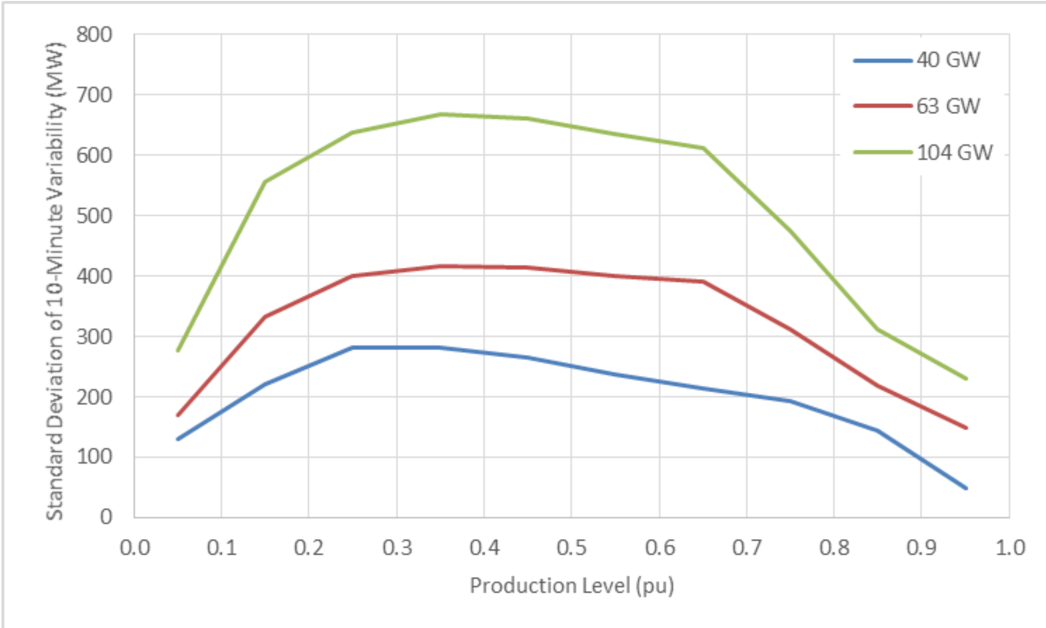


Figure 2-7: 10-Minute Variability of Illustrative Renewable Scenarios with Hourly Average Production Level: Empirical Data in MW

The scenarios analyzed above are for illustration, and are representative of the penetration levels examined in this study. In the analysis to come, the specific variability characteristics of each scenario are computed and then used in estimations of incremental regulation requirements. Characterization of the variability in this manner captures the uniqueness of each defined scenario: those with large concentrated wind or PV generation facilities will show more variability than scenarios with much more dispersed plants. Effects of geographic diversity, as another example can be seen in Figure 2-8, where the variability at 10-minute intervals, expressed as a percentage of total capacity, declines as the number of individual turbines in the scenario (and the total installed capacity) increases. In Figure 2-7 the standard deviations are in units of MW, but in Figure 2-8, the standard deviations have been normalized as per MW unit of capacity.

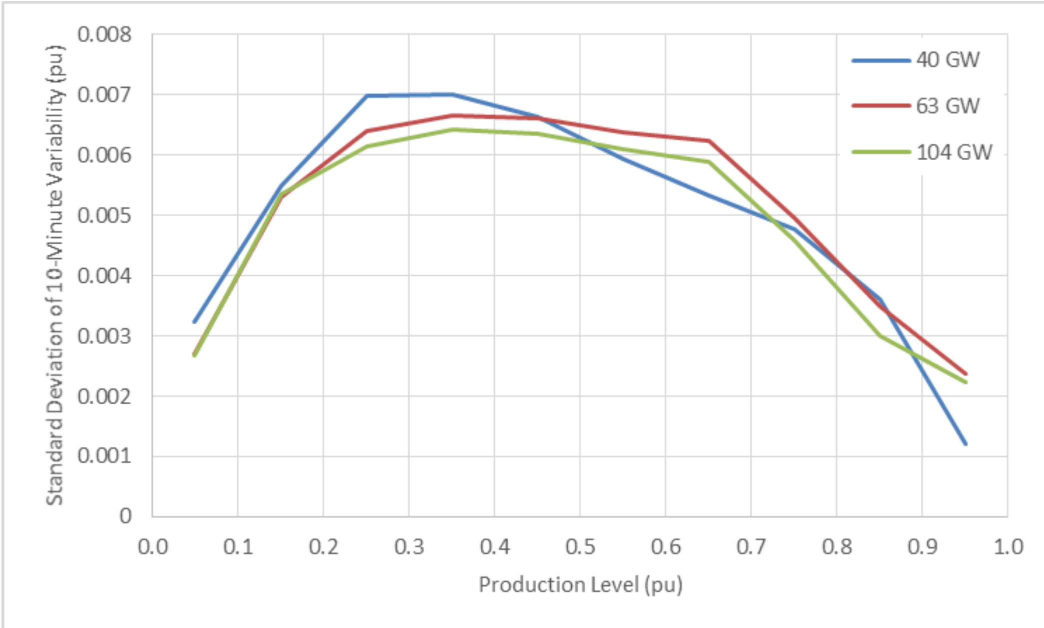


Figure 2-8: 10-Minute Variability of Illustrative Wind Scenarios with Hourly Average Production Level: Empirical Data, Per-Unit of Aggregate Nameplate Capacity for Each Scenario

The curves can be approximated well with a simple quadratic expression. The utility of this approximation is that the variability can be defined by the current or forecast production level. This provides a method to procure the appropriate amount of additional regulation as wind and PV generation varies over hours or days.

2.4 Results with hourly data: Regulation – Hourly Approximations

The estimated operating reserve requirements for each renewable generation scenario are described here. The previous discussions feed into the regulation analysis. Beyond regulation, other calculation techniques using 10-minute wind and load data along with production simulations results from GE MAPS are used to assess how the PJM operating reserve categories would be impacted by wind generation.

Incremental regulation requirements for each scenario are estimated as a function of the variability of PJM load as implied from the scheduled regulation (see Table 2-1) and the variability of the wind and PV generation as defined by the 10-minute "persistence forecast error" characterizations, as shown in Figure 2-9 for each of the study generation scenarios.

Equations which approximate the 10-minute variability as functions of hourly production level for wind and PV generation for each scenario in the study are shown in Table 2-2. These equations are graphically depicted in Figure 2-9. As shown in these figures, the shapes of PV curves are such that they cannot be accurately approximated by one quadratic equation. Hence, we have used two quadratic equations, PV1 for the ascending section in the left, and PV2 for the descending section on the right, as shown in Table 2-2.

Table 2-2: Approximate Equations for 10-Minute Variability

Scenario	Wind (W) Variability Approximation	PV Variability Approximation
2% BAU	σ_w = -9.32E-06 * $(W)^2$ + 0.049 * (W) + 18.39	σ_{pv1} = -3.21 * $(PV_1)^2$ + 0.23 * (PV_1) + 18.39
14% RPS	σ_w = -8.92E-07 * $(W)^2$ + 0.03 * (W) + 126.28	σ_{pv1} = 3.13E-05 * $(PV_1)^2$ + .14 * (PV_1) - 23.64 where $PV_1 \leq$ 1,471 σ_{pv2} =-7.65E-06 * $(PV_2)^2$ + .05 * (PV_2) + 63.10 where PV_2 >1,471
20% HOBO	σ_w = -5.42E-07 * $(W)^2$ + 0.02 * (W) + 135.10	σ_{pv1} = -4.13E-05 * $(PV_1)^2$ + 0.38 * (PV_1) - 437.20 where $PV_1 \leq$ 5,547 σ_{pv2} = -6.22E-07 * $(PV_2)^2$ - 0.01* (PV_2) + 456.71 where PV_2 > 5,547
20% LOBO	σ_w = -8.59E-07 * $(W)^2$ + 0.04 * (W) + 118.27	σ_{pv1} = -4.13E-05 * $(PV_1)^2$ + 0.38 * (PV_1) - 437.20 where $PV_1 \leq$5,547 σ_{pv2} = -6.22E-07 * $(PV_2)^2$ - 0.01 * (PV_2) + 456.71 where PV_2 > 5,547
20% LODO	σ_w = -6.03E-07 * $(W)^2$ + 0.03 * (W) + 148.79	σ_{pv1} = -4.13E-05 * $(PV_1)^2$ + 0.38 * (PV_1) - 437.20 where $PV_1 \leq$5,547 σ_{pv2} = -6.22E-07 * $(PV_2)^2$ - 0.01 * (PV_2) + 456.71 where PV_2 > 5,548
20% HSBO	σ_w = -1.06E-06 * $(W)^2$ + 0.04 * (W) + 79.33	σ_{pv1} = -1.06E-06 * $(PV_1)^2$ + 0.27 * (PV_1) - 532.04 where $PV_1 \leq$ 11,107 σ_{pv2} = -5.95E-07 * $(PV_2)^2$ + 0.01 * (PV_2) + 701.72 where PV_2 >11,107
30% HOBO	σ_w = -3.17E-07 * $(W)^2$ + 0.02 * (W) + 204.72	σ_{pv1} = -2.29E-05 * $(PV_1)^2$ + 0.40 * (PV_1) - 878.67 where $PV_1 \leq$ 10,694 σ_{pv2} = 3.43E-07 * $(PV_2)^2$ - 0.04 * (PV_2) + 1164.77 where PV_2 > 10,694
30% LOBO	σ_w = -6.00E-07 * $(W)^2$ + 0.04 * (W) + 151.18	σ_{pv1} = -2.29E-05 * $(PV_1)^2$ + 0.40 * (PV_1) - 878.67 where $PV_1 \leq$ 10,694 σ_{pv2} = 3.43E-07 * $(PV_2)^2$ - 0.04 * (PV_2) + 1164.77 where PV_2 > 10,695
30% LODO	σ_w = -3.05E-07 * $(W)^2$ + 0.02 * (W) + 264.19	σ_{pv1} = -2.29E-05 * $(PV_1)^2$ + 0.40 * (PV_1) - 878.67 where $PV_1 \leq$ 10,694 σ_{pv2} = 3.43E-07 * $(PV_2)^2$ - 0.04 * (PV_2) + 1164.77 where PV_2 > 10,696
30% HSBO	σ_w = -8.15E-07 * $(W)^2$ + 0.05 * (W) + 79.71	σ_{pv1} = -1.42E-05 * $(PV_1)^2$ + 0.40 * (PV_1) - 1,380.92 where $PV_1 \leq$ 16,904 σ_{pv2} = -1.28E-07 * $(PV_2)^2$ - 0.01 * (PV_2) + 1,507.74 where PV_2 > 16,904

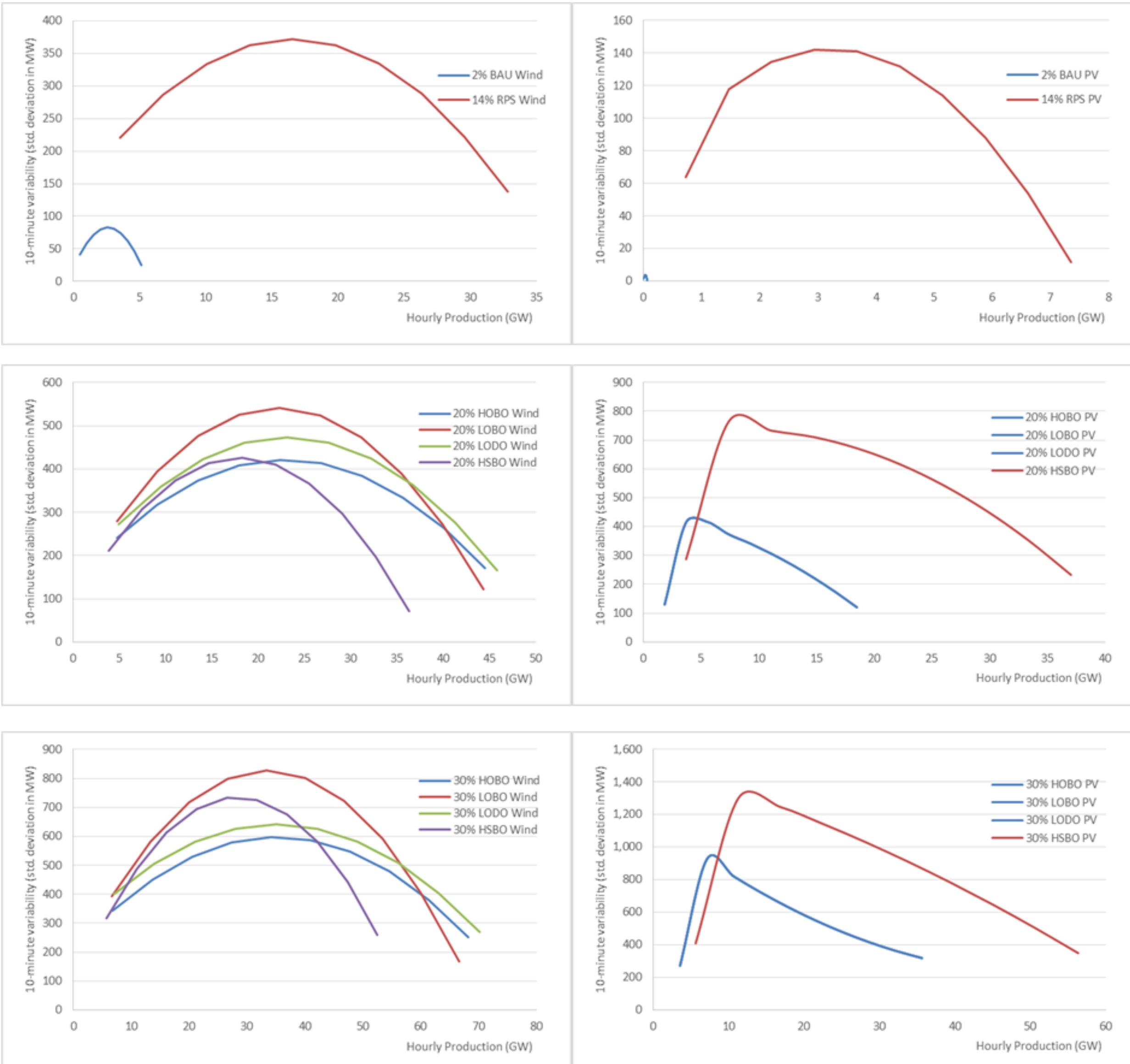


Figure 2-9: Quadratic Approximations to Empirical Variability Curves for Study Scenarios

As mentioned previously, the variability of wind and PV generation at this time scale is assumed to be uncorrelated with that of load, so a statistical combination of independent variables is appropriate. The calculation assumes that the total variability is the root mean square sum (RMS) of:

- The standard deviation of the load variability, assumed to be 1/3 of the regulation scheduled for the hour (as noted before, the appropriate required regulation is 3 times the standard deviation, which would encompass 99.7% of all variations in the normal sample).

- The fast wind variability, taken as 2 MW per 100 MW of installed capacity. For each scenario, the total fast variability is the root-mean-square sum of the installed capacity divided by 100 times 2 MW squared. This component is included for completeness, but a very small contributor to the incremental regulation (per Equation 1).
- The longer-term wind variability or the difference between the short-term persistence forecast and the actual wind 10 minutes into the future. This error is taken as the variability from one 10-minute interval to the next and is a function of the expected hourly production level, i.e. the expected error is largest in the middle range of the aggregate production level per curves in Figure 2-9 above and the equations in Table 2-2.
- The fast PV variability, taken as 3 MW per 100 MW of installed capacity. For each scenario the total fast variability is the root-mean-square sum of the installed capacity divided by 100 times 3 MW squared. This component is included for completeness, but a very small contributor to the incremental regulation (per Equation 3).
- The longer-term PV variability or the difference between the short-term persistence forecast and the actual PV 10 minutes into the future. This error is taken as the variability from one 10-minute interval to the next and is a function of the expected hourly production level, i.e. the expected error is largest during sun rise and sun set range of the aggregate production level per curves in Figure 2-9 above and the equations in Table 2-2.

Results of the calculations for all scenarios are shown in Table 2-3. The amount of additional regulation calculated for each hour depends on

- The amount of regulation carried for load alone. It should be noted that when more regulation is available, the incremental impact of wind and PV generation is reduced due to the statistical independence of the variations in the wind and PV generation and load.
- The aggregate wind and PV generation production level, since the statistics show that wind production varies more when production from 40 to 60% of maximum and PV production varies more when production is from 10% to 20% of maximum (Figure 2-9)

Table 2-3 summarizes the range of regulation required for each scenario. As can be seen, wind and PV generation penetration, the average regulation requirement is estimated to increase from approximately 1,204 MW without wind and PV to a high of approximately 2,737 MW with the 30% HSBO scenario. At lower penetration levels the incremental regulation requirement is smaller. The hourly analysis indicates average regulation requirements would increase to a high of approximately 1,958 MW with the 20% HSBO scenario. At the 14% RPS scenario the average regulation increases approximately 362 MW to 1,566 MW. Examining the average increase in regulation over a year is a way to compare scenario differences. Hourly on and off peak as well as monthly and seasonal values are included in these averages. In other words an increase in renewable penetration demonstrates a trend of increased regulation.

In the production cost and sub-hourly simulations, the amount of regulation was adjusted hourly as a function of the total renewable energy production in each hour.

Table 2-3: Estimated Regulation Requirements for Study Scenarios

Regulation	Load Only	2% BAU	14% RPS	20% HOBO	20% LOBO	20% LODO	20% HSBO	30% HOBO	30% LOBO	30% LODO	30% HSBO
Maximum (MW)	2,003	2,018	2,351	2,507	2,721	2,591	2,984	3,044	3,552	3,191	4,111
Minimum (MW)	745	766	919	966	1,031	1,052	976	1,188	1,103	1,299	1,069
Average (MW)	1,204	1,222	1,566	1,715	1,894	1,784	1,958	2,169	2,504	2,286	2,737
% Increase Compared to Load		1.5%	30.1%	42.4%	57.3%	48.2%	62.6%	80.2%	108.0%	89.8%	127.4%

From a contingency perspective, none of the wind or solar plants added to the PJM system was large enough such that their loss would increase PJM's present level of contingency reserves. And given the large PJM footprint for a single balancing area, the impacts of short-term variability in wind and solar production is greatly reduced by aggregation and geographic diversity.

The following approach was adopted to assess the need for additional operating reserves due to wind and solar variability:

- Simulate hourly operation using GE MAPS, with regulation requirement allocated per the criteria described above and contingency reserves per PJM's present practices.
- Using the hourly results of the GE MAPS simulations, compare the ramping capability of the committed units each hour with the sub-hourly variability of wind and solar production in that hour.
- Quantify the number of periods where ramping capability is insufficient.

2.5 Impacts on Operating reserves

As previously described, regulation is just one piece of the ancillary services PJM uses to maintain system reliability. The higher penetrations of wind and PV generation as defined by the study scenarios introduce additional regulation requirements.

PJM counts regulation resources separately from their operating reserves, as shown in Figure 2-1. Conceivably, regulation could be near the top of the aggregate range when a contingency occurs, thereby actually reducing the amount of operating reserves available for replacing lost generation. With additional regulation required by wind and solar generation, the amount of operating reserves available to respond to a contingency could be lower than the current minimum amounts.

In this study, contingency reserves consists of no less than the largest contingency where synchronized reserves consist of at least 50% of on-line generation and customer demand response can be no more than 25%[8]. Although variability and uncertainty exists for wind and solar resources, the generating capability of any single plant modeled in the study is less than the largest single generating contingency on the PJM system. For this reason the existing contingency reserves established for PJM were not changed when modeling reserves within the GE MAPS program. It is the very short intermittency of wind and solar generation variability that presents the challenge to operation modeling.

Hourly regulation requirements calculates as described in the previous sections were used in the GE MAPS program. A check to verify adequacy of the calculated reserves and to identify days when the PJM system is operationally stressed GE MAPS output depicting the hourly generation ramp and resource range capabilities were examined. The GE MAPS outputs represent remaining on line generation after meeting load and reserve (regulation and spinning contingency). This analysis employed the 10-minute aggregated wind and solar data to determine the 10-minute net load. The 10-minute change in LNR was compared to the hourly ramp limit from the GE MAPS output. The time when the 10-minute ramps were exceeded were identified and counted. The range of LNR within each hour was also calculated by noting the time and count of each period when LNR range exceeded the GE MAPS output value for range.

Figure 2-10 is an excerpt from the ramp analysis, showing a day with three 10-minute periods when the change in net load (red dots) exceed the ramp-up capability of the committed generators (green line). This day had the greatest number of LNR ramps exceeding ramp-up or ramp-down in the year. There were three 10-minute periods in the day when LNR ramp exceeded the ramp-up or ramp-down limit. For this case there were

---

[8] PJM Manual 10: Pre-Scheduling Operations, Revision: 27, Effective Date: February 28, 2013; and "Reserves – Scheduling, Reporting, and Loading presentation", PJM State & Member Training Department Operations 101, June 18, 2013.

five days with two periods exceeding ramp limits and 12 days with one period exceeding ramp limits. In all there were 25 LNR ramps exceeding ramp limits out of 52,560 ramps (.048%) examined in this case.

Table 2-4 summarizes the analytical results for several scenarios, and shows that there are relatively few periods in a year when renewable ramps exceed fleet ramping capability, and those few events would not likely cause an unacceptable decrease in PJM's Control Performance Standard (CPS) measures. There are comparatively few 10-minute periods when ramps exceed hourly limit based upon the GE MAPS commitment. It should also be noted the GE MAPS ramp-up and ramp-down values are specifically for committed resources and do not count offline quick start generation such as CT's.

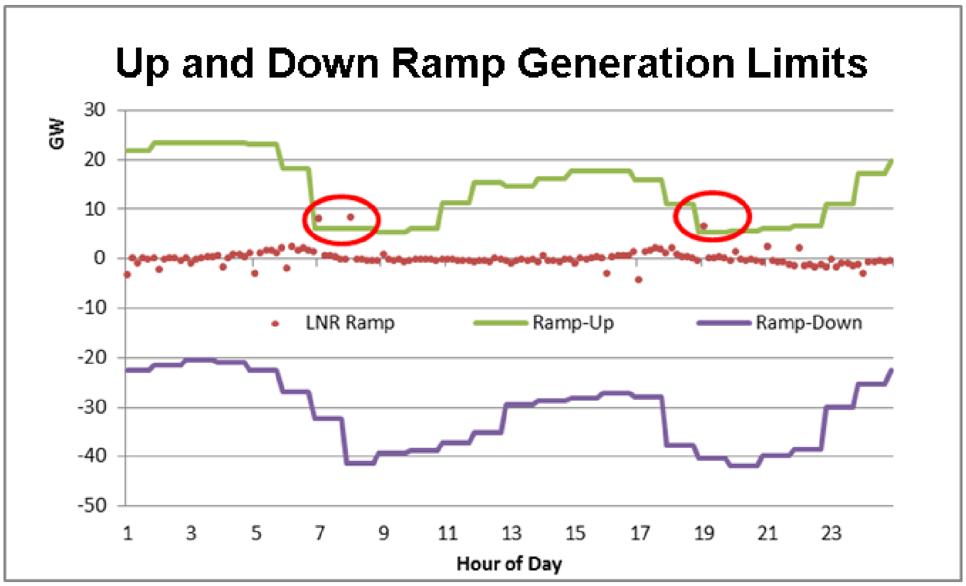


Figure 2-10: Sample Day Showing 10-Minute Periods That Exceed Ramp-Up or Ramp-Down Limits

Table 2-4: 10-Minute Periods Exceeding Ramp-Up or Ramp-Down for Selected Scenarios

52,560 Samples	2% BAU		14% RPS		30% HOBO		30% LODO	
Number of 10-Min samples exceeding dispatched ramp capability	Count	%	Count	%	Count	%	Count	%
Ramp-up	25	0.048%	32	0.061%	322	0.613%	19	0.036%
Ramp-down	0	0.000%	0	0.000%	5	0.010%	57	0.108%

When examining the LNR range limits for the same case there were more days with at least one LNR period exceeding the range limit. The day shown in Figure 2-11 is the day with the largest number of periods (8) that exceed the hourly range limit. Out of the 52,560 periods examined in the year there were 18 periods (0.034%) exceeding the range limit. Table 2-5 depicts the results of four scenarios at different penetration levels. It can be seen the number of periods exceeding the available resource range is approximately 1% for each scenario above the 2% BAU case. Most of the count is in the range-up indicating the 10-minute period when additional resources may be required. Since MAPS does not count the PJM quick start resources as on line spin it should be noted that this additional generation capability, storage resource or customer demand response could be employed to mitigate these periods.

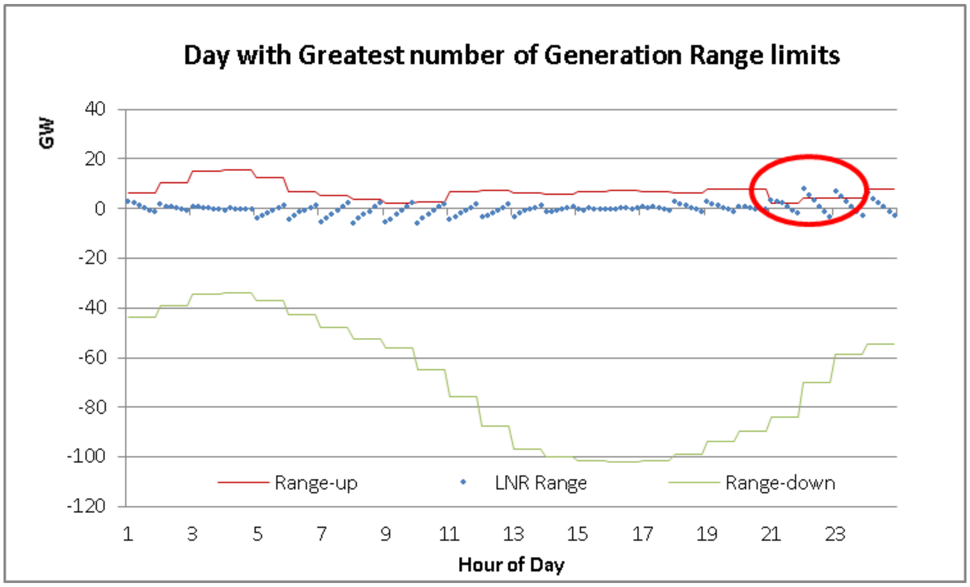


Figure 2-11: Sample Day Showing 10-Minute Periods That Exceed Range-Up or Range-Down Limits

Table 2-5: Number of 10-Minute Periods Exceeding Dispatched Resource Operating Range

52,560 Samples	2% BAU		14% RPS		30% HOBO		30% HOBO	
Number of 10-Min values exceeding dispatched resource operating range	Count	%	Count	%	Count	%	Count	%
Range-up	18	0.034%	489	0.930%	727	1.383%	398	0.757%
Range-down	0	0.000%	2	0.004%	2	0.004%	94	0.179%

The adequacy of the reserves was further confirmed by the "challenging days" simulated in the PROBE sub-hourly analysis reported in a separate section. The range and ramp analysis along with analysis of LNR data was used to determine the set of challenging days. The selection criteria specifically included days with low ramp-rate and ramp-range capability relative to wind and solar ramps.

The results of the combined analytical methods indicate that no additional operating reserves would be required for the study scenarios.

2.6 Observations and Conclusions

Conclusions regarding wind and PV generation impacts on PJM operating reserves along with other observations and recommendations are described here.

Significant penetration of wind and PV generation will increase the regulation capacity requirement and will increase the frequency of utilization of these resources. The study identified a need for an increase in the regulation requirement even in the lowest wind and solar penetration scenario (2% BAU), and the requirement would have noticeable increases for higher penetration levels. For example, the average regulation requirement for the load only (i.e. no wind or solar) case was 1,204 MW. This requirement increases to about 1,600 MW for the 14% RPS scenario, to a high of 1,958 MW in the 20% scenarios and then 2,737 MW in the 30% scenarios. Task 4 discusses

The primary driver for increased regulation requirements due to wind and solar power is the error in short-term power forecasting. The economic dispatch process is not equipped to adjust fast enough for the errors inherent in short-term wind and PV forecasting and this error must be balanced by regulating resources. (This error must be accounted for in addition to the load forecasting error.)

The post analysis of GE MAPS output hourly range and ramp limits indicate the statistically calculated regulating and contingency reserves were adequate for the GE MAPS production simulation. The PJM fleet has sufficient resource flexibility based upon the GE MAPS results to meet additional regulating and contingency reserve requirements for the scenarios examined in the study.

There are some differences in regulation impacts discernible amongst scenarios at the same energy penetration levels. This can be traced directly to the statistics of variability used in these calculations. Based on the PJM wind and solar generation mesoscale data, some scenarios exhibit higher variability from one 10-minute interval to the next than others. A number of factors could contribute, including the relative size of the individual plants in the scenario, and the impact on spatial and geographic diversity, the local characteristics of the wind and PV resources as replicated in the numerical weather simulations from which the data is generated, and even the number of individual turbines, wind plants and types comprising the scenario, as more plants of wind and solar would imply more spatial diversity.

At the same time, however, the differences may be within the margin of uncertainty inherent in the analytical methodologies for calculating regulation impacts. Given these uncertainties, it is difficult to draw concrete conclusions regarding the relative merits of one scenario over the others from the regulation viewpoint. For example, future developments in short-term wind and solar generation forecasting could result in a more variable but easier to forecast deployment of generation, and hence, reduce the burden on regulation, since a large proportion of the changes would be scheduled into the sub-hourly energy market.

PJM routinely analyzes regulation requirements (KERMIT study is an example) and makes adjustments. As wind and PV generation is developed in the market footprint, similar analysis will take control performance objectives and the characteristics of the operating wind generation through empirical data into account. At a minimum, high-resolution data for all wind and PV generation facilities should be collected and archived. When regulation needs are analyzed, approaches like those illustrated in this report or others developed by PJM staff can be used to augment the current methods for evaluation regulation requirements.

Analysis of these results indicates that assuming no attrition of resources capable of providing regulation capacity, there may be adequate supply to match the increased regulation requirements under the wind integration scenarios considered. PJM business process is robust and is designed to assure regulation adequacy as the required amount of regulation evolves over time and the needs of the system change.

From an Operating Reserve perspective, the analysis of 10-minute load and wind profiles against the backdrop of hourly production simulation results from GE MAP did not indicate operating reserves would need to augmented for the renewable penetration levels considered. While the analytical approach that employed GE MAPS results and 10-minute profile data was somewhat approximate, the number of intra-hour events that exceeded the system flexibility (as measured by GE MAPS range and ramp results) minus the contingency spinning and regulation was small.

This observation would initially seem to run counter to some previous integration study findings. There are a few aspects of this particular study and the PJM footprint that can be offered as support for this finding:

1. The geographic diversity inherent to the renewable generation scenarios considered in this study is very high. As geographic diversity increases the time frame over which significant changes in aggregate renewable product occur becomes longer.
2. The PJM generation fleet is the largest ever studied for a single Balancing Area Authority (BAA).
3. The time frame for operating reserves ranges from intra-hour intervals of several to tens of minutes. This is the time frame of interest for the analysis presented here. Renewable production changes over longer time frames, e.g. hour to hour, are effectively considered in detail in the GE MAPS production simulations. The production simulation results for all renewable generation scenarios indicate that

there was enough flexibility in the PJM fleet to manage the largest changes in renewable production, at least at hourly granularity.

The high-resolution PROBE simulations conducted as part of this study were also intended to address questions concerning the adequacy and deployment of operating reserves, as the process used to select days for these detailed simulations incorporated the results from the analysis described here.

3 Appendix: Load Net Renewables

The following figures present the Load net Renewables (LnR) for each month of the study year of 2026.

The LnR curves are provided for different levels of renewable energy penetration as defined in the PJM PRIS Study Scenarios.

For each month, the LnR is shown for an average day in the month, and also for a day in the month with maximum LnR range of the 30% High Solar and Best Onshore scenario.

Figure 3-1: Load Net Renewables for the Average Day of January 2026

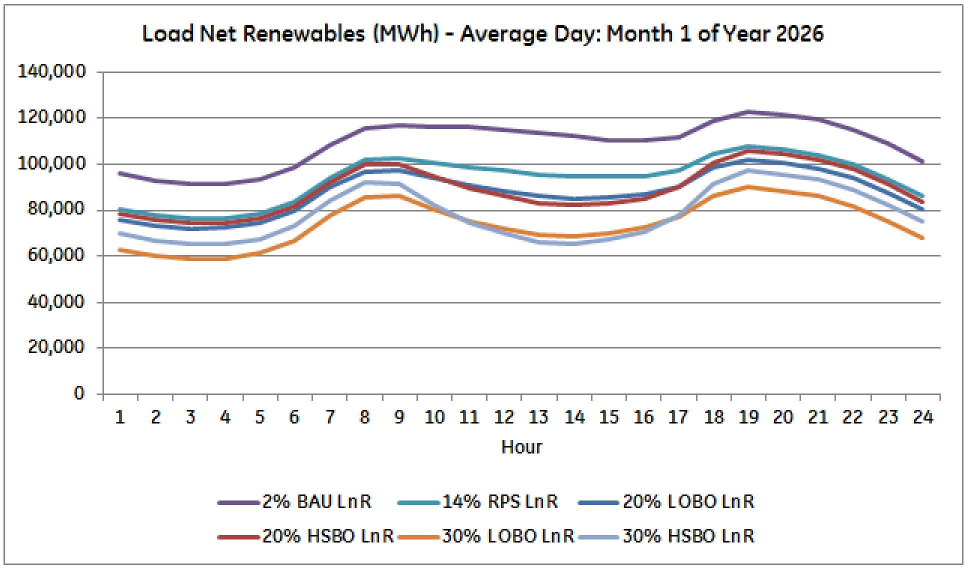


Figure 3-2: Load Net Renewables for a Day in January 2026 with the Largest HSBO LnR Range

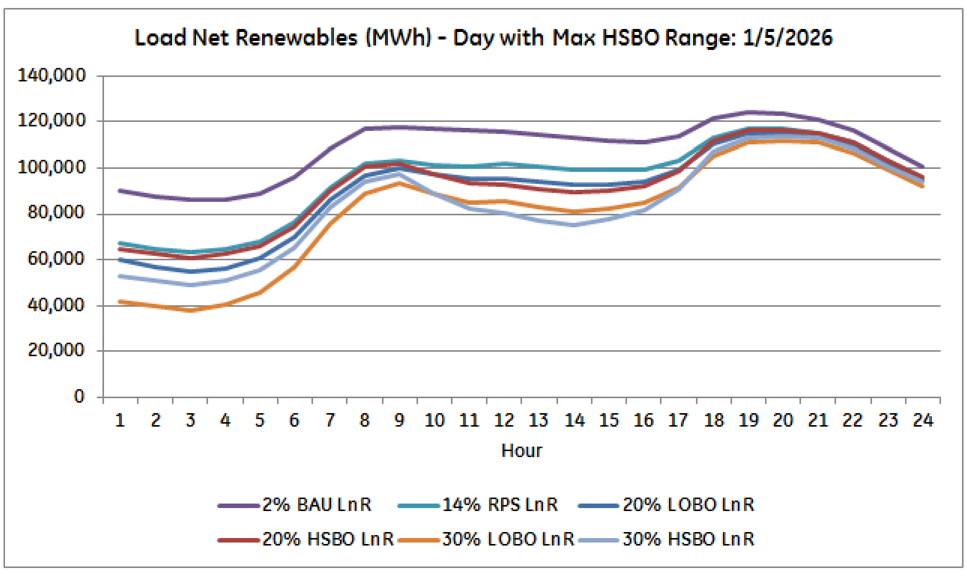


Figure 3-3: Load Net Renewables for the Average Day of February 2026

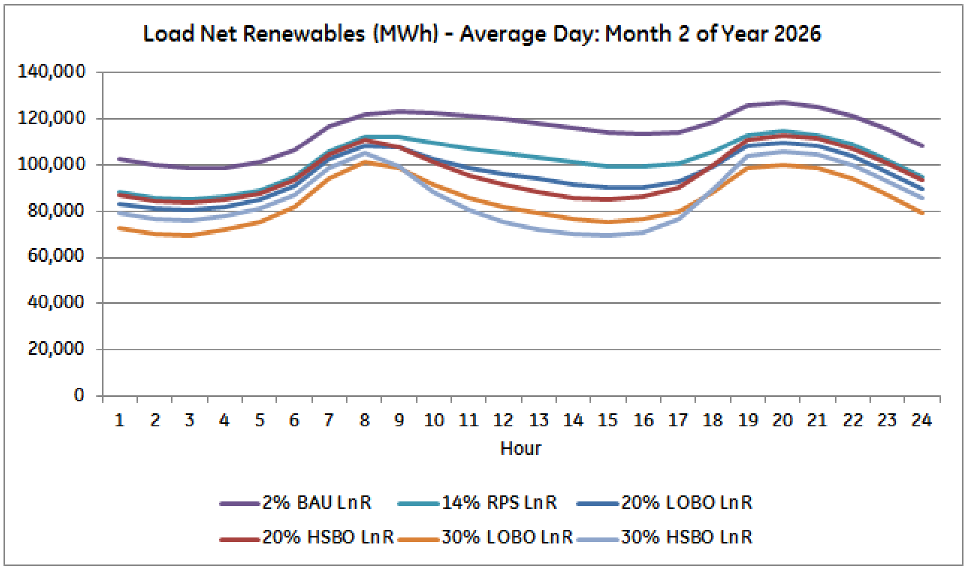


Figure 3-4: Load Net Renewables for a Day in February 2026 with the Largest HSBO LnR Range

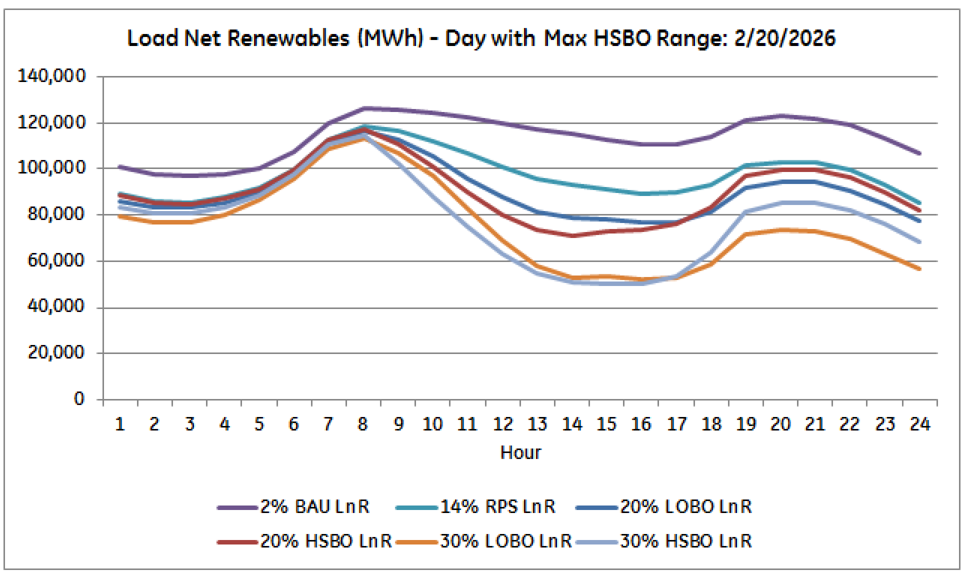


Figure 3-5: Load Net Renewables for the Average Day of March 2026

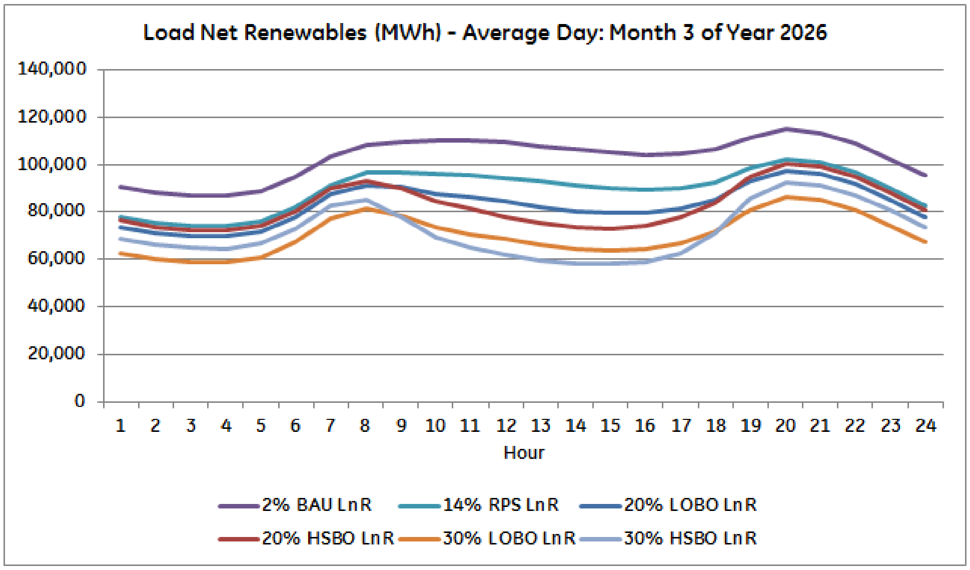


Figure 3-6: Load Net Renewables for a Day in March 2026 with the Largest HSBO LnR Range

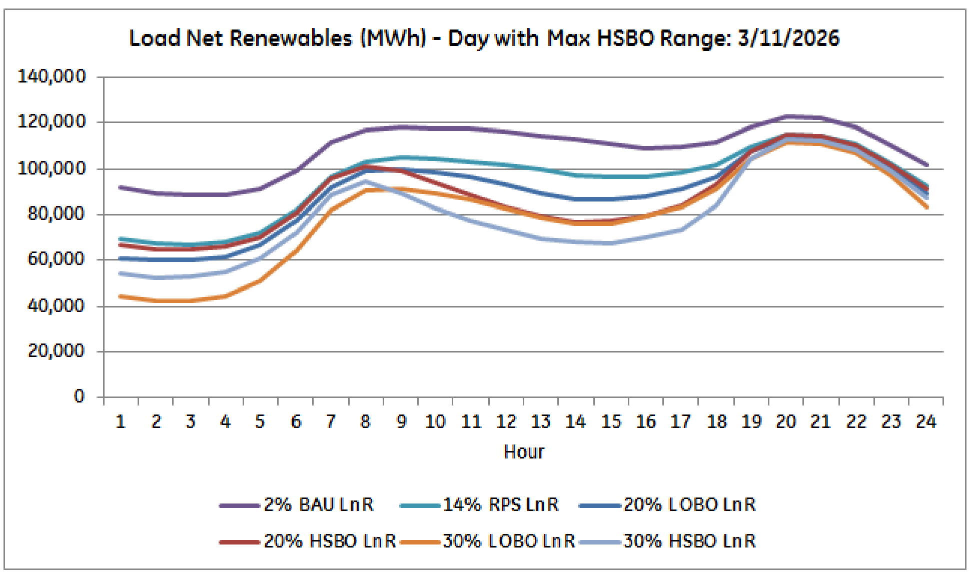


Figure 3-7: Load Net Renewables for the Average Day of April 2026

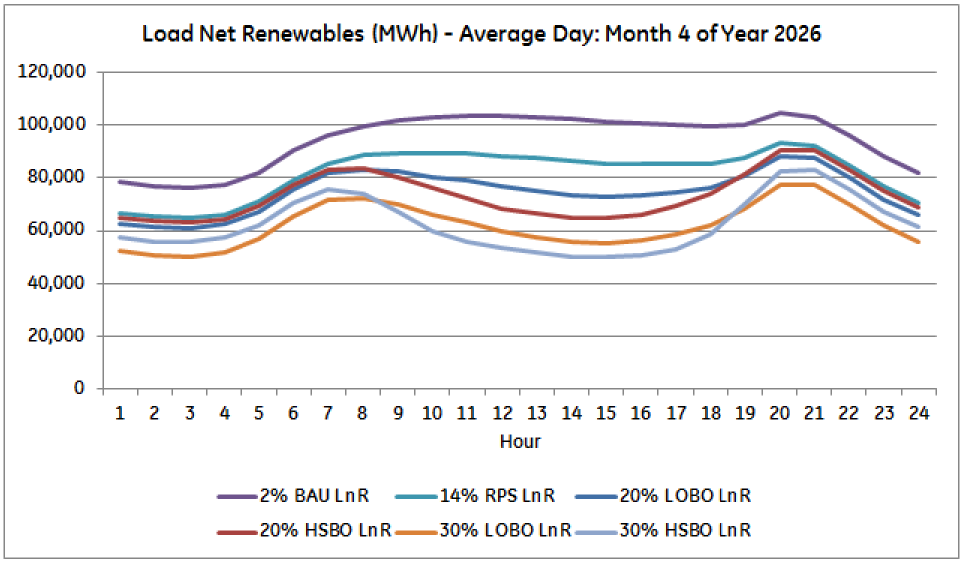


Figure 3-8: Load Net Renewables for a Day in April 2026 with the Largest HSBO LnR Range

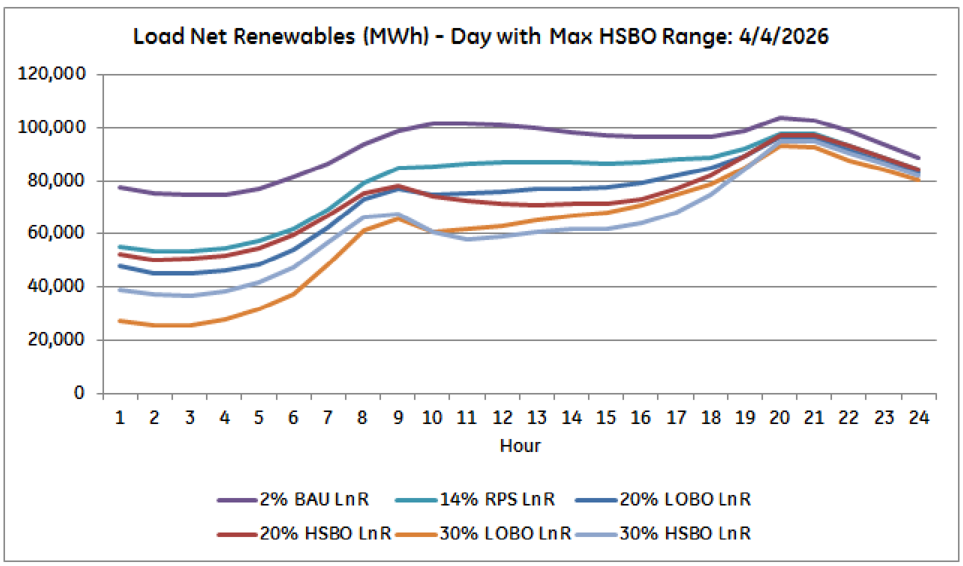


Figure 3-9: Load Net Renewables for the Average Day of May 2026

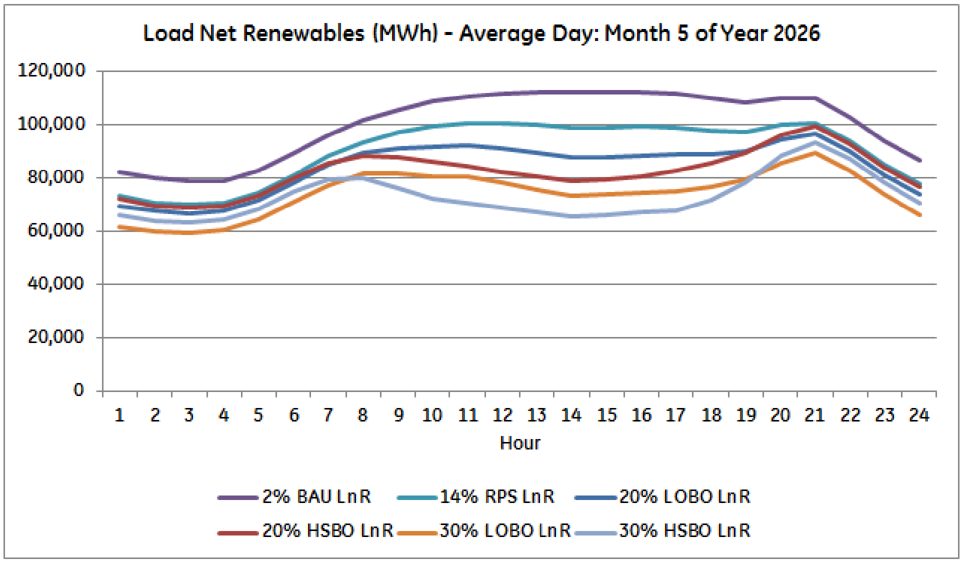


Figure 3-10: Load Net Renewables for a Day in May 2026 with the Largest HSBO LnR Range

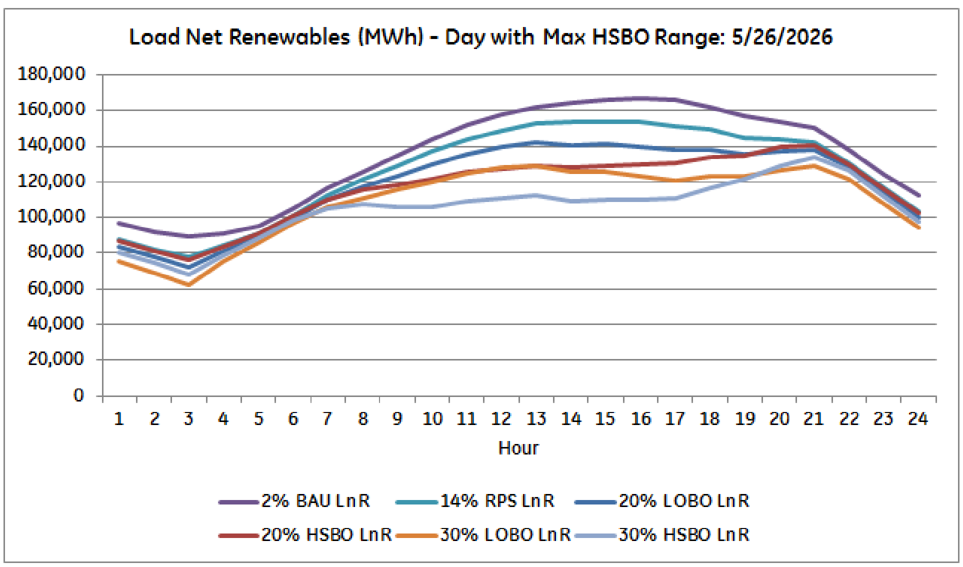


Figure 3-11: Load Net Renewables for the Average Day of June 2026

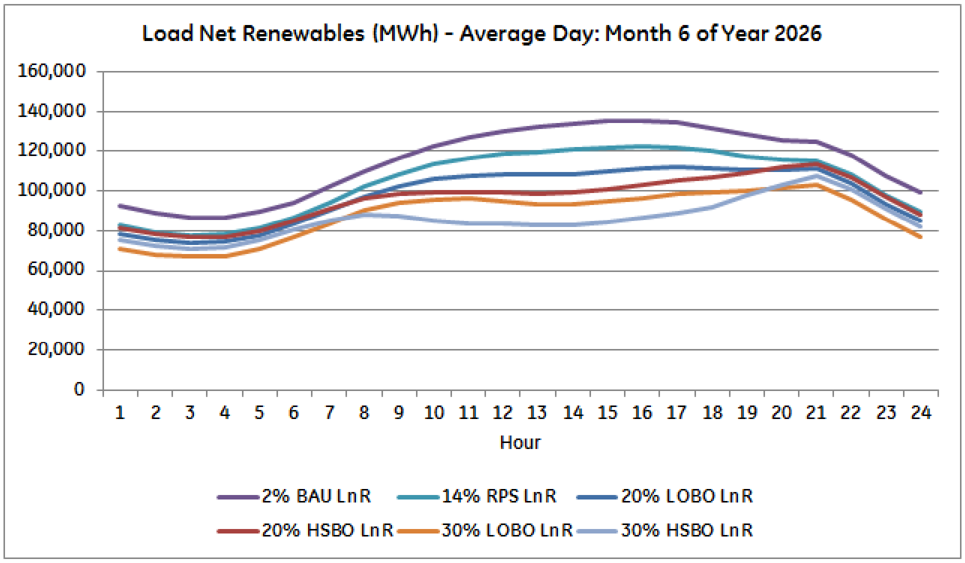


Figure 3-12: Load Net Renewables for a Day in June 2026 with the Largest HSBO LnR Range

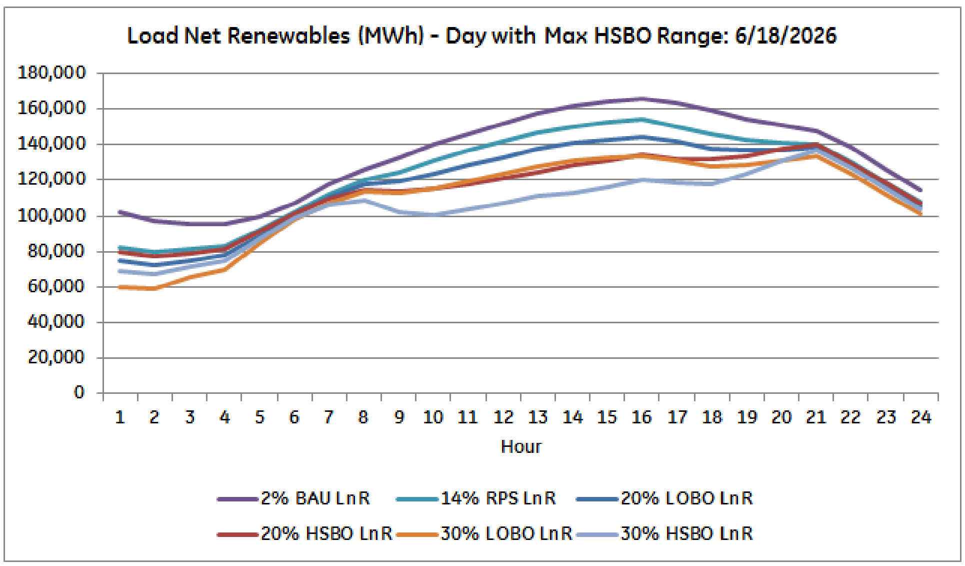


Figure 3-13: Load Net Renewables for the Average Day of July 2026

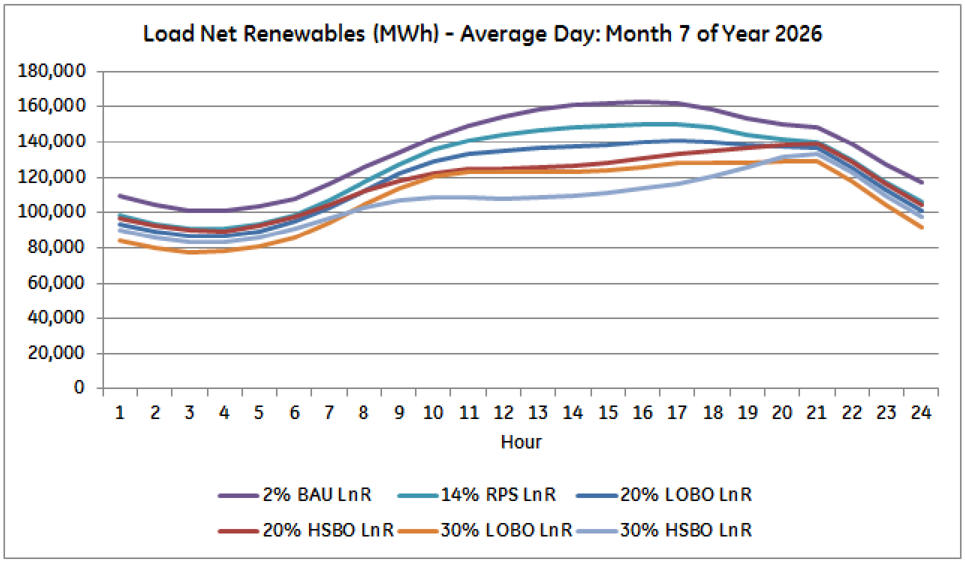


Figure 3-14: Load Net Renewables for a Day in July 2026 with the Largest HSBO LnR Range

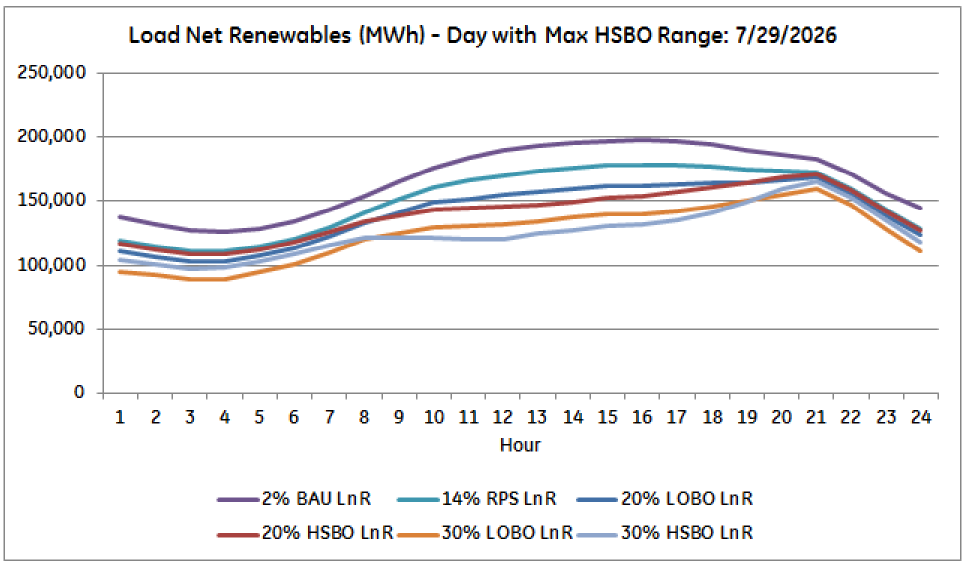


Figure 3-15: Load Net Renewables for the Average Day of August 2026

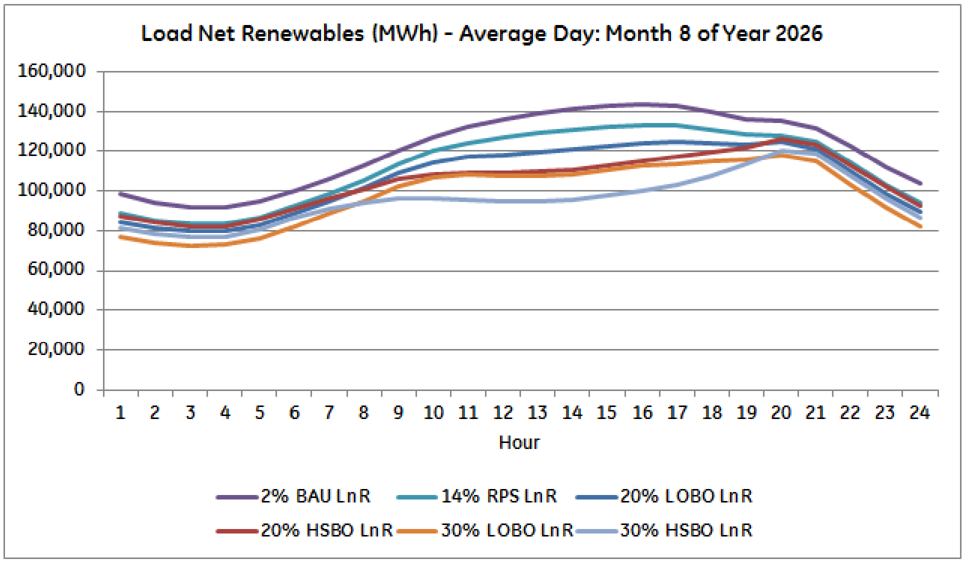


Figure 3-16: Load Net Renewables for a Day in August 2026 with the Largest HSBO LnR Range

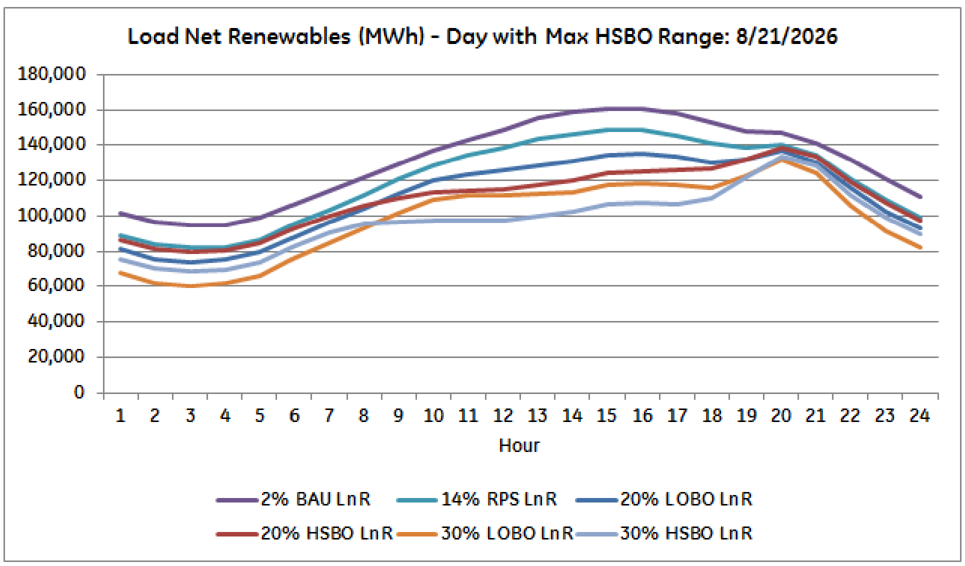


Figure 3-17: Load Net Renewables for the Average Day of September 2026

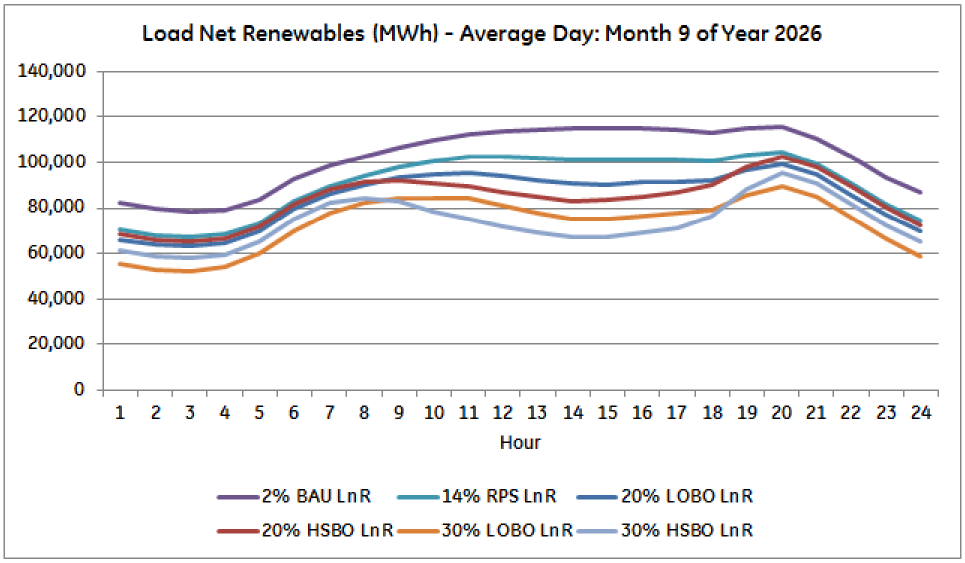


Figure 3-18: Load Net Renewables for a Day in September 2026 with the Largest HSBO LnR Range

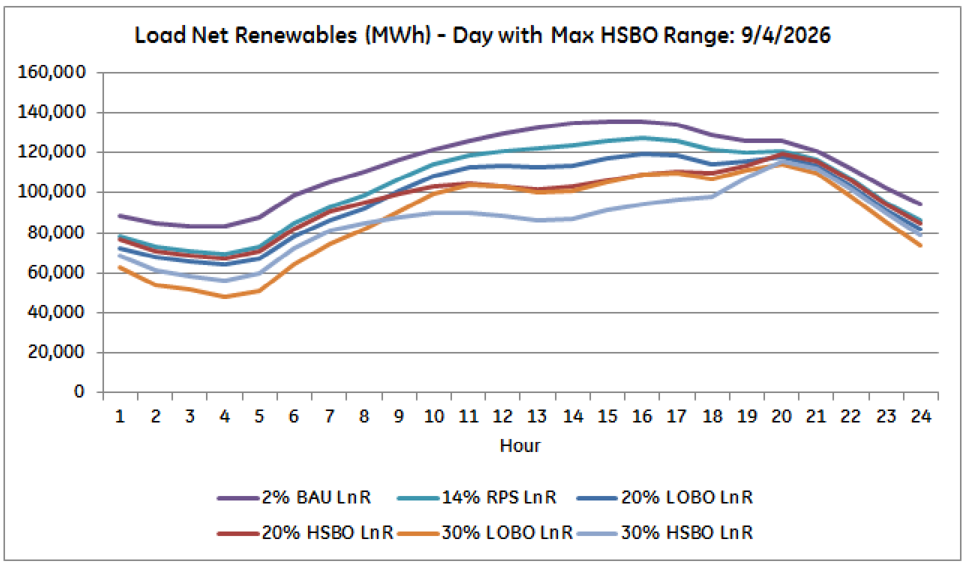


Figure 3-19: Load Net Renewables for the Average Day of October 2026

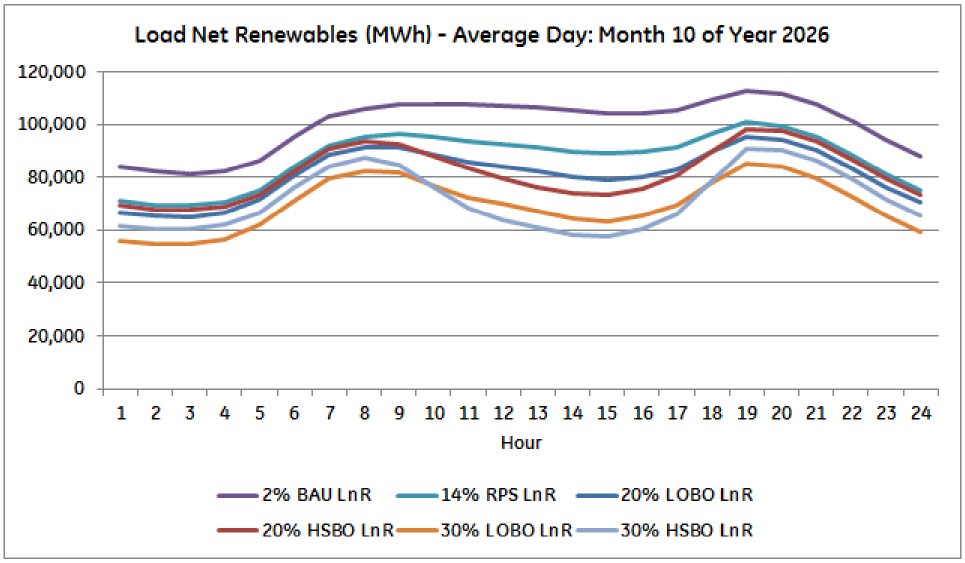


Figure 3-20: Load Net Renewables for a Day in October 2026 with the Largest HSBO LnR Range

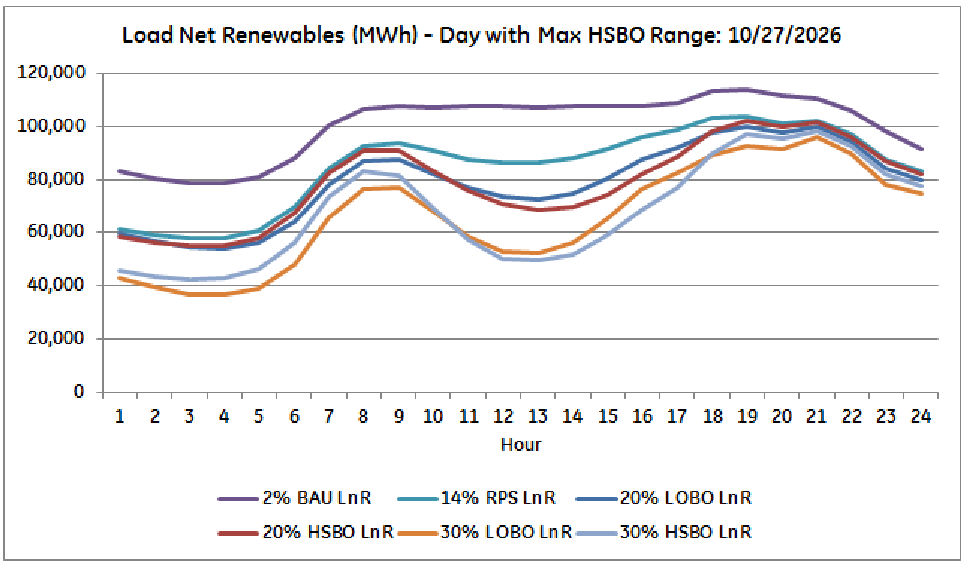


Figure 3-21: Load Net Renewables for the Average Day of November 2026

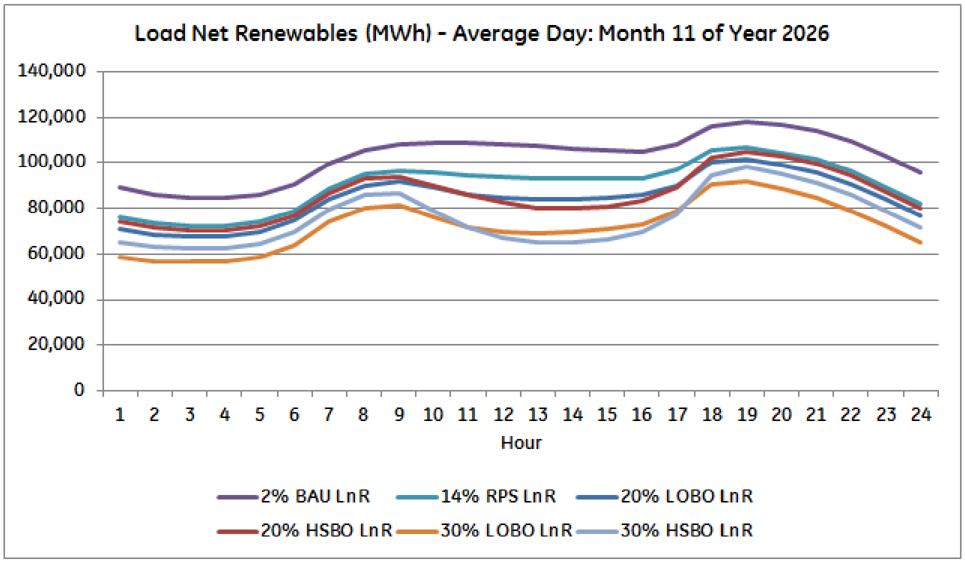


Figure 3-22: Load Net Renewables for a Day in November 2026 with the Largest HSBO LnR Range

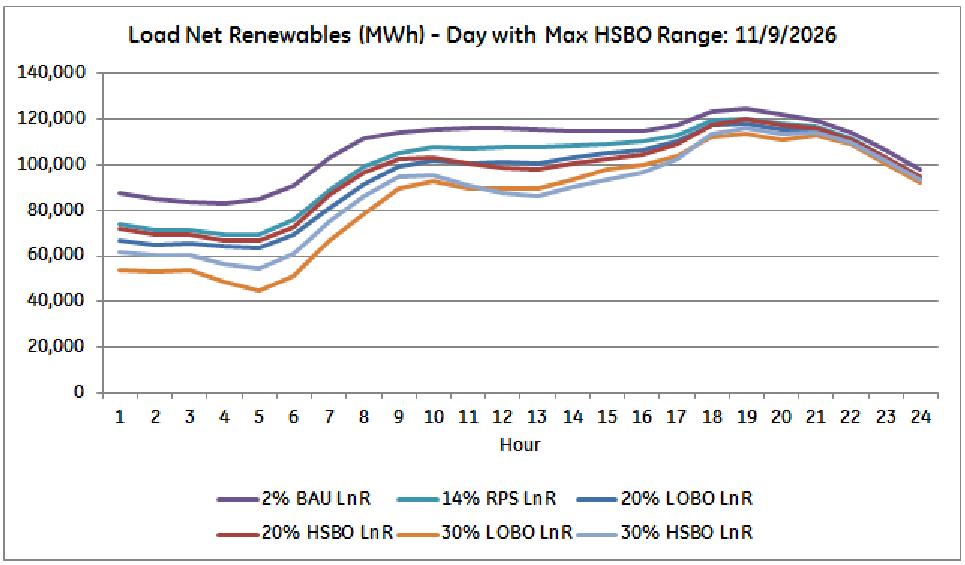


Figure 3-23: Load Net Renewables for the Average Day of December 2026

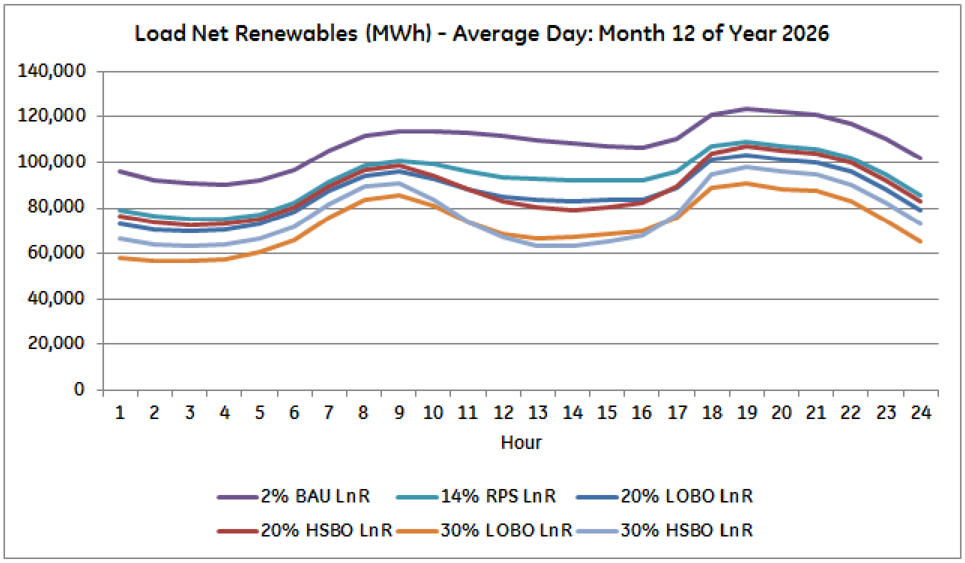
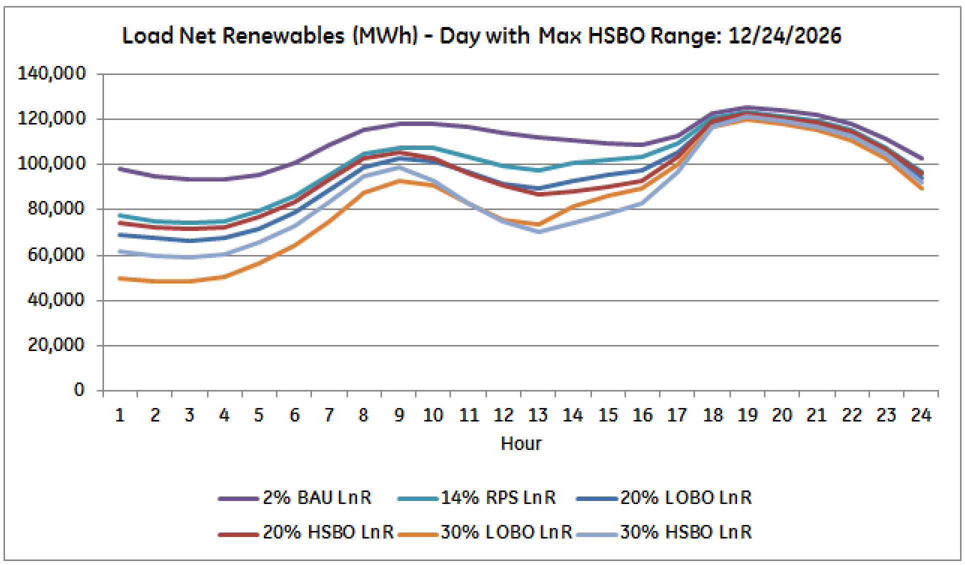


Figure 3-24: Load Net Renewables for a Day in December 2026 with the Largest HSBO LnR Range



imagination at work