Shine On, Shine On:
Persistence Analysis of New York State's Customer-Sited Solar PV Installations[1]

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ABSTRACT

NYSERDA's NY-Sun PV Incentive Program provides cash incentives and/or financing according to a megawatt block structure, with a goal of installing 10 GW of solar photovoltaic (PV) capacity by 2030. Solar installations are typically in place for 25+ years. Future grid planning requires knowing both the total solar capacity installed and the stability of its electricity generation over time. This study analyzed New York State solar production data to explore how generation from installed systems changes over time. The analysis's key metric is the performance loss rate (PLR), or the annual percent reduction in the amount of electricity produced.

This study estimates an average annual PLR of 0.83% ± 0.09% across New York State. Aggregated over time and the state's solar fleet, an 0.83% annual PLR would mean an over 20% reduction in annual solar production by 2050 from the 10 GW targeted under New York's Climate Act Scoping Plan. This represents a loss of around 2,200 GWh, underscoring the importance of incorporating solar production degradation into long-term energy planning.

The analysis reveals significant regional and system-level variation. Annual PLRs range from 0.5% in Long Island to 1.5% upstate. Purchased and power purchase agreement systems exhibit higher loss rates than leased systems, monocrystalline modules outperform polycrystalline, and systems using microinverters show lower PLR than string inverters and optimizers. Finally, systems in disadvantaged communities show higher loss rates.

Analysis results will help the state track progress on its decarbonization goals and identify opportunities to mitigate performance risks across the solar portfolio.

Introduction

This study presents a persistence analysis of solar photovoltaic (PV) assets installed in New York State from February 2012 through November 2021. Many of these assets were supported by NYSERDA's NY-Sun program. Prior evaluations and studies of that program examined program impact and first-year annual capacity factors. However, in planning for the grid of the future, an important question is to what extent the production levels of the installed systems hold up over time. This study directly addresses that question by examining the persistence of installed system production performance and its relationship to system characteristics.

The NYSERDA NY-Sun PV Incentive Program, open August 12, 2010, through December 29, 2025, provides cash incentives and/or financing according to a megawatt (MW) block structure. "Blocks," or specific MW targets per defined sector and geographic region of New York, are active on a rolling basis until fulfilled. The program expanded its original goal of installing 3 gigawatts (GW) direct current (DC) of PV capacity by 2023 to 6 GW DC by 2025, and NYSERDA's 2019 petition to extend the NY-Sun program and increase funding was approved in 2020. On September 20, 2021, Governor Kathy Hochul called to expand the NY-Sun Program, with a goal of 10 GW by 2030. NYSERDA and DPS developed the Solar Roadmap to propose a pathway to achieve the 10 GW target, filed December 17, 2021 (NYS DPS, 2021).

[1] The views expressed in this paper are those of the authors and do not necessarily reflect the views of the New York State Energy Research and Development Authority.

An April 2022 order adopted the roadmap recommendations. The order expanded funding for base incentives, the Solar Energy Equity Framework, and incentive adders.

A white paper by DNV (Hieslmair 2024) reviewed available studies of solar system performance over time. These studies examined various technologies, numbers of systems, system sizes, regions, and vintages. The system-level degradation determined from these studies ranges from 0.2% to 1.2% per year, with an average of 0.62%. In work serving solar system developers, DNV's assessment practice uses a standard value of 0.64% per year based on a key study among those reviewed in the paper, with exceptions for certain specific technologies. Following that practice, this paper treats 0.64% as a useful benchmark, while recognizing that different groups of assets may have different overall degradation rates, and individual systems vary even more. New York Green Bank, as a financing entity, recognizes the importance of persistence in a long-term investment strategy and incorporates an assumed loss rate between 0.5% to 0.75%. NY-Sun to this point has not focused on projecting long-term production levels and has not adopted a performance loss rate (PLR) assumption that could provide an alternative point of reference.

The present study (DNV 2025) is the first to focus specifically on assets in New York State, with New York's climate and PV system characteristics. This study uses empirical data from over 13,000 systems installed in the state over many years. The full study and its findings are described in detail below.

Approach

Overview

The overall study approach is illustrated in Figure 1.

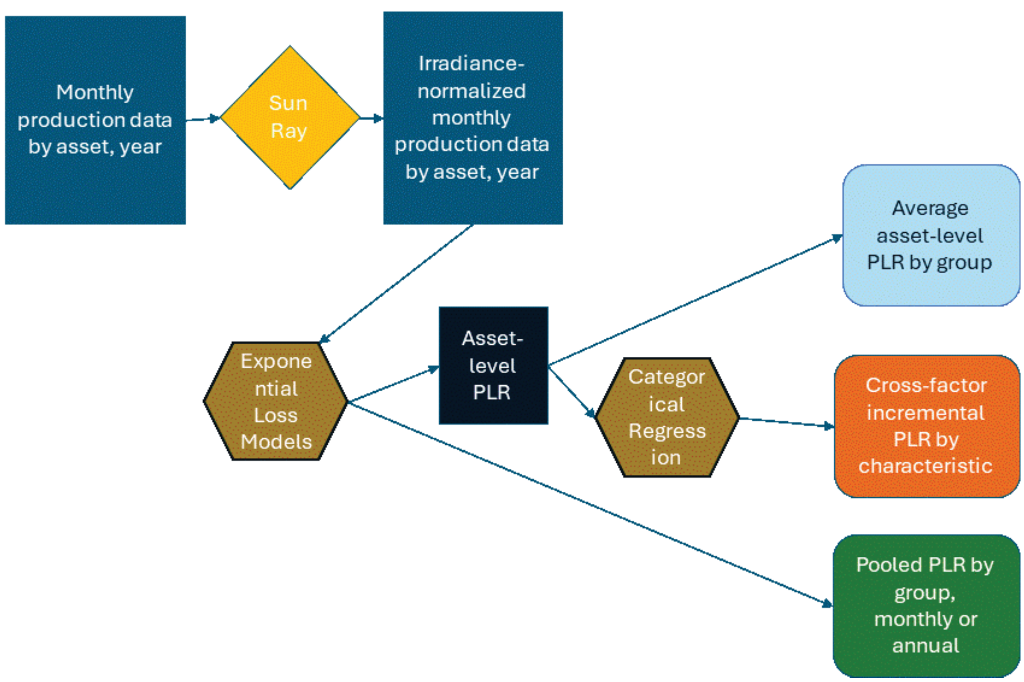

Figure 1. Study approach

Data. The study used monthly production data for a sample of NY-Sun assets. This data was compiled over time for a sample of 386 assets assessed in prior NY-Sun impact studies of first-year PV production (DNV for NYSERDA, 2024), and supplemented by similar data for a set of 13,587 NY residential solar PV assets that DNV's solar assessment practice has reviewed for other clients.

The production data for each asset and month was expressed as a capacity factor (CF). The CF is defined as a fraction of the production that would occur if the asset could produce at full capacity for all hours of the month.

Irradiance normalization. The monthly production data for each asset was adjusted to the production that would have occurred in a year with typical irradiance for each month, using DNV's SunRay™ tool.

PLR. The PLR was calculated as the year-over-year percent reduction in capacity factor, controlling for the month of the year. Multiple model specifications were explored, with results fairly similar across these specifications. Two primary methods were used to produce PLR by subgroup, for subgroups defined by geography or by technical characteristics of the asset.

1. ***Asset-level PLR,*** estimated separately for individual assets, averaged over subgroups. This approach is the most straightforward, and allows segmentation by any characteristics of interest. However, this approach can't provide separate PLR estimates by month of the year, since an individual asset has only a few observations for a given month.

2. ***Pooled PLR by subgroup, individual months*****,** with a single PLR value estimated across all assets in the subgroup. The subgroup annual PLR was then calculated as the CF-weighted average of the monthly PLRs. This approach provides separate PLR by month of the year, for each selected subgroup as a whole.

Incremental PLR effects. The effect of various asset characteristics on PLR was estimated:

a) As the difference in averages of the asset-level PLR between different subgroups

b) As the difference in the subgroup PLR estimates from the pooled models

c) Via a categorical regression that estimated the incremental PLR associated with each characteristic while holding the other characteristics constant.

The pooled PLR estimates and cross-factor analysis generally corroborated the indications from the simpler comparisons of asset-specific averages, with the cross-factor analysis providing additional insights in key cases.

Irradiance normalization

The irradiance normalization required acquisition of local irradiance data for the period covered by the production data, as well as corresponding Typical Meteorological Year (TMY) irradiance data for the same location. To limit data acquisition costs, assets were clustered geographically, with irradiance data purchased for 29 locations, indicated in Figure 2.

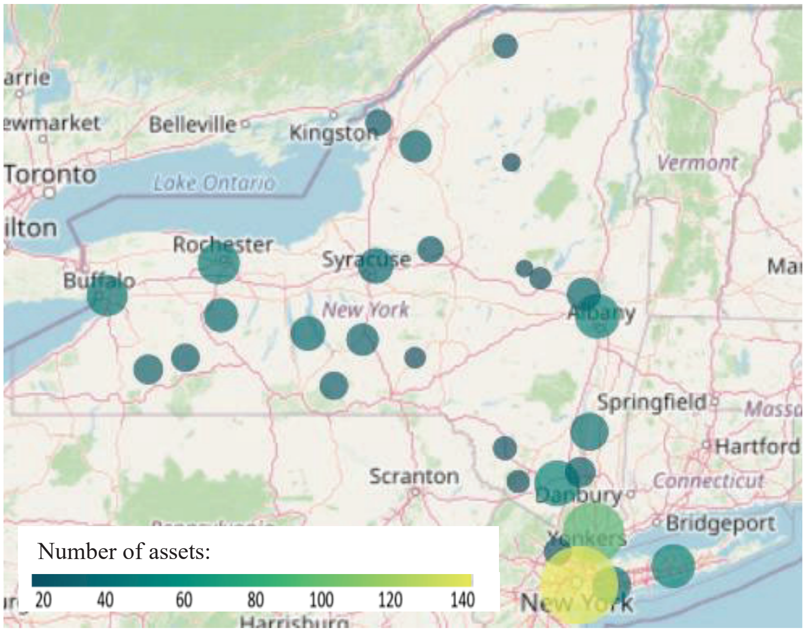

Figure 2. Irradiance clusters

Irradiance adjustments were made with DNV's SunRay tool. For each month of each year, the tool calculated the irradiance adjustment factor as the ratio of the actual irradiance for that specific month to the TMY irradiance. The irradiance-normalized production for each site and month is the observed production quantity for that site and month divided by the adjustment factor.

Asset-Specific PLR

PLR was calculated for each asset that had at least 24 months of production data, not counting months excluded for zero or low production. The fitted model is an exponential decay relative to a different underlying CF for each month. A single decay rate is estimated across all months of the year. The model form is:

$$(1)\ \ln\left(CF_{j\,t}\right) = b_{0,j} + \sum_{m=1}^{12} b_{1,m,j}\, M_{mjt} + b_{PLR,j}\, t + \epsilon_{jt}$$

Where:

$\ln\left(CF_{j,t}\right)$ = the natural log of the CF for asset *j* in elapsed month *t*
$b_{0,j}$ = regression intercept for asset *j*
$b_{1,mj}$ = fixed effect for calendar month *m*
M_{mjt} = 0/1 indicator variable equal to 1 if the observation month *t* is calendar month *m* for asset *j*
t = months elapsed since installation date
$b_{PLR,j}$ = monthly production change for asset *j* (percent per month)
ϵ_{jt} = residual regression error.

Multiplying the coefficient $b_{PLR,j}$ by -12 gives the annual PLR. This PLR is a positive value for assets with declining production over time, and a negative value if the production is increasing over time.

Pooled PLR by Category and Month

The pooled estimation by category and month calculated the PLR by type within a subgroup or category, across all assets in that type, producing a separate PLR for each month of the year. The formulation is similar to the asset-level estimation, but estimated the PLR across all assets within a group, and allowed a separate PLR coefficient for each calendar month. Thus, the log-linear regression model incorporates both fixed effects for each month and interaction variables between the elapsed time since the installation date, the category, and the month, to produce separate PLR by category type and month. The fitted equation was:

$$(2)\ \ln\left(CF_{j,t}\right) = b_j + \sum_{m=1}^{12} b_{1,m,j}\, M_{mjt} + \sum_{m=1}^{12} \sum_{r} b_{PLR,mr}\, Cat_{rj} \quad M_{mjt} \times t + \epsilon_{jt}$$

where:

b_j = fixed effect for asset *j*

Cat_{rj}= 0/1 indicator variable equal to 1 if asset *j* belongs to category *r*

$b_{PLR,r}$= monthly production change for category *r* and calendar month *m*

Other terms are as defined for the asset-specific estimation (1).

In this model, the interaction term $Cat_{rj}M_{mjt} \times t$ is the product of the category-specific dummy variable and the calendar-month dummy variable. The product equals 1 if asset *j* is in category *r* and the calendar month (for asset *j*'s elapsed months *t*) is *m*, and 0 otherwise.

To produce an annual PLR from these results, the monthly PLR values were weighted by the average CF for each month. Each month's CF corresponds to its relative contribution to annual production. Hence this weighting of monthly values avoids overvaluing the PLR from winter months. Production, and therefore CF, is lowest in the winter and highest in the summer months.

Another model explored was similar to model (2), but estimated a single PLR across all months. We moved to the month-specific PLR version (2) because the single-PLR pooled model, as well as the simpler analysis represented by Equation (1) produced unusually high PLR for the Upstate region. The monthly PLR estimates indicated that the high overall Upstate values produced when all months were weighted equally were related to unusually high PLR estimates for two winter months. By appropriately downweighting these months, the CF-weighted average of monthly PLRs mitigated that effect.

The primary regional and statewide estimates are therefore produced using method (2), the pooled monthly estimates, CF-weighted. However, this more complex analysis was not conducted for all characteristics of interest. Instead, comparisons of effects of different characteristics rely on the simpler analysis from model (1), while recognizing that differences in regional mix could affect some of these comparisons.

Cross-Factor Analysis

Any comparison of averages across distinct subgroups defined by one characteristic reflects not only differences related to that characteristic, but also the effects of differing mixes of other characteristics across the subgroups. For example, even if there were no concern that one region's PLR may be overstated, differences by equipment type could reflect regional differences as well as the effects of the equipment itself.

To attempt to isolate the contributions of various asset characteristics to PLR, a cross-factor analysis in the form of a multiple regression analysis was used. This analysis estimated the incremental difference in PLR associated with particular asset characteristics while controlling for the other characteristics. The analysis was an unweighted categorical regression across all assets. For this analysis, we regressed the asset-specific PLR values on asset characteristics.

A few variants of the model were explored, testing for effects of most of the characteristics variables available in the data set. Program staff were interested in whether there were differences in decay rate by region (Upstate, Downstate, or Long Island), by whether the asset was in a DAC, by technical characteristics of the asset, by purchase or lease arrangement, by sector, by size, or by equipment manufacturer. The final version of the model excluded terms that were not found to be significant. Many of these terms turned out not to be statistically significant in the tested models.

The final regression model was specified as follows:

$$\widehat{b_{PLR,J}} = b0 + b1_{REGj} + b2_{DACj} + b3_{PURCHj} + b4_{MODj} + b5_{INVj} + b7_{INVMj} + \varepsilon_j$$

Where:

$\widehat{b_{PLR,J}}$= the average monthly decay rate for asset j estimated from the asset-specific regression

b0 = regression intercept

$b1_{REGj}$, $b2_{DACj}$, $b3_{PURCHj,}$ $b4_{MODj,}$ $b5_{INVj,}$$b6_{INVMj,}$ respectively, are the coefficients of the region, DAC status, purchase type, module family, inverter type, and inverter manufacturer that asset *j* belongs to.

ε_j = residual error of the regression.

Data

For the sites included in this study, NYSERDA required incentive recipients to provide production data for three years after installation. Recently, NYSERDA updated their requirements, and now incentive recipients must provide production data for two years after installation. The study team has worked with system operators to provide production data periodically for a sample of assets after the end of the three-year requirement. NYSERDA is considering ways to incentivize operators to provide data on an ongoing basis. Operator cooperation with these requests has been mixed. Table 1 indicates the number of assets installed in the state since 2012, and the number included in this study's analysis sample for each number of years since installation, by sector.

Table 1. Number of assets installed and in the analysis by years of data since installation

Size (kW)	NYS Total[2]	Study Sample											
		1	2	3	4	5	6	7	8	9	10	11	12
Non-Residential													
<200	1,884	63	63	56	49	39	19	10	6	2	2	1	0
200–750	360	139	139	135	120	99	90	66	42	24	13	3	0
≥750	110	79	79	76	74	67	60	38	17	7	2	0	0
Residential													
All	96,074	11,249	8,976	7,834	6,722	5,015	1,208	231	88	68	52	50	47
Total													
All	98,428	11,530	9,257	8,101	6,965	5,220	1,377	345	153	101	69	54	47

The table shows a solid set of assets in the study sample with up to six years of data, and smaller numbers with higher numbers of years of data. The large number of cases with four to six years of data provide for some clear insights into how production levels change over these first several years of the assets, as described below. The drop-off in the higher years reflects both the smaller number of assets installed earlier and the challenges of getting system operators to continue to provide data over many years. Given the more limited data available for systems older than six years, the results of this study don't necessarily indicate what the loss rates may be later in system life.

[2] These are NY Sun projects completed between 2011 and 2023 that overlap with the study group. The residential category includes 33, 271 projects from the Residential and Small Commercial Program that are unknown sector.

Results

Model fit

The pooled PLR model fit for all regions is illustrated in Figure . The heavy blue line is the average model fit for each month, given by the month effect, the region-specific trend, and the average of the asset effects across all assets with data in that month. The light blue line is the average of the actual observations across the same assets. Also indicated are the number of assets contributing to the regression in each month.

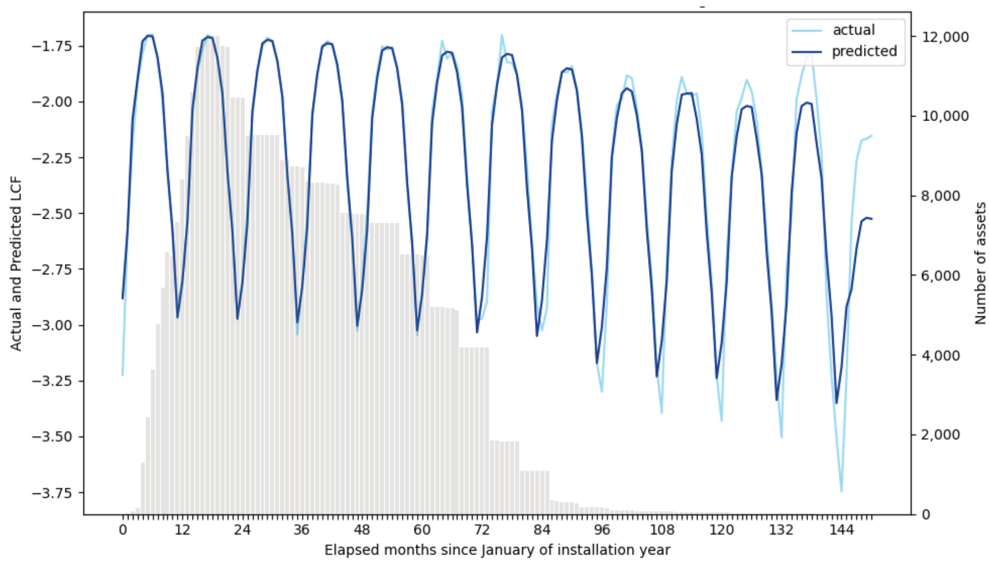

Figure 3. Actual vs predicted log of CF and number of assets – all regions, pooled PLR by region, across months

Across the first five to six years, the model fit tracks actual CF very closely. After that point, the fit is less tight. There are also very few assets with data this far out. Through the more stable first five to six years, the production cycle each year is clearly visible in both the actual and fitted data, along with a general declining trend. The more erratic ups and downs in the later years reflects the effects of different assets being included; because of the asset-specific term in the model, the average fit continues to track the average actual usage even in these years when the group of assets being averaged is different month to month. Because there are very few observations in the later period, these points have little effect on the overall fit and PLR estimate.

Performance loss rates by region

Table 2 shows the PLR by region and overall. The results are well determined, with standard errors between 9% and 32% of the estimate. The overall PLR of 0.83% per year is statistically significantly different from the benchmark of 0.64% at the 10% significance level. For comparison, a study of degradation rates of systems up to 8 years old in California found a rate of 1.5% to 2% while using a different analysis approach (Verdant, 2021). The table shows a much higher PLR for the Upstate region, and a much lower value for Long Island. Reasons for these differences are not clear, but may be related to more severe weather conditions Upstate causing a higher level of equipment degradation.

Table 2. PLR by region and overall, CF-weighted pooled PLR by region and month

Region	Number of assets	Avg capacity	Avg CF	PLR (percent per year)	Standard error of PLR (% per year)
Downstate	1,670	22	12.9%	0.87%	0.19%
Long Island	4,946	10	13.2%	0.41%	0.13%
Upstate	2,365	81	12.0%	1.67%	0.15%
All	8,981	31	12.7%	0.83%	0.09%

PLR Comparisons Across Subgroups

For most comparisons across subgroups, the average of the asset-specific PLRs in that subgroup is used for the comparative discussions, as a more intuitive basis for comparisons. However, the pooled monthly estimates weighted by CF are more meaningful at the regional level.

The asset-specific averages provide the first look at the factors associated with higher and lower PLR. The cross-factor analysis allows a look at the differences in PLR associated with various factors, while controlling for the other factors. This cross-factor analysis helps mitigate the effects of the overstated Upstate PLR in the simple averages. In most cases, the cross-factor analysis corroborates the simple comparisons.

Table 3 presents the average asset-level PLR by various subgroups. Table 4 shows the results of the cross-factor analysis.

Table 3. PLR by subgroup (percent production loss per year), average asset-level PLR, across months

Category	Type	Number of assets	Avg capacity (kW)	Median number of months	Avg. CF	Mean PLR	Std err
All	All	8,981	31	59	12.7%	1.17%	0.10%
Region	Downstate	1,670	22	60	12.9%	0.96%	0.23%
Region	Long Island	4,946	10	58	13.2%	0.42%	0.13%
Region	Upstate	2,365	81	62	12.0%	2.89%	0.21%
Sector	Non-residential	277	792	72	11.8%	1.02%	0.41%
Sector	Residential	8,704	7	59	13.0%	1.18%	0.10%
Size	< 200 kW	8,766	7	59	13.0%	1.17%	0.10%
Size	200 - 750 kW	136	423	76.5	11.7%	1.30%	0.65%
Size	> 750 kW	79	1,970	79	11.9%	0.98%	0.46%
DAC	Non-DAC	6,040	32	60	12.8%	1.25%	0.12%
DAC	DAC	2,941	29	58	13.1%	1.01%	0.18%
Purchase Type	Lease	7,337	7	60	12.8%	0.91%	0.10%
Purchase Type	PPA	1,380	82	49	13.2%	2.63%	0.35%
Purchase Type	Purchase	88	380	57.5	12.0%	2.69%	0.74%
Purchase Type	Unknown	176	461	59	11.9%	-0.19%	0.71%
Module Family	Monocrystalline	3,031	7	42	13.2%	-0.12%	0.19%
Module Family	Polycrystalline	2,131	8	61	13.1%	1.95%	0.19%
Module Family	Unknown	3,819	63	60	12.4%	1.76%	0.15%
Microinverter	Microinverter	6,750	7	60	13.0%	1.46%	0.11%

Category	Type	Number of assets	Avg capacity (kW)	Median number of months	Avg. CF	Mean PLR	Std err
Microinverter	Optimizer	1,675	7	51	12.7%	0.17%	0.30%
Microinverter	String	272	182	73	12.1%	0.21%	0.50%
Microinverter	Unknown	284	606	67	11.9%	1.00%	0.38%

Table 4. PLR increment associated with each asset characteristic holding other characteristics constant

Characteristic	Type	Number of assets	Avg. capacity (kW)	Median number of months	Avg. CF	PLR increment (% per year)	
						Coeff	p-value
Intercept	All	8,981	31	59	12.68%	0.07%	0.798
Geography							
Region	Downstate	1,670	22	60	12.86%	0.00%	N/A
Region	Long Island	4,946	10	58	13.21%	-0.84%	0.009
Region	Upstate	2,365	81	62	12.00%	1.80%	0
DAC/non-Dac	non-DAC	6,040	32	60	12.83%	0.00%	N/A
DAC/non-Dac	DAC	2,941	29	58	13.13%	0.48%	0.064
Purchase Type							
Purchase type	Lease	7,337	7	60	12.84%	0.00%	N/A
Purchase type	PPA	1,380	82	49	13.17%	2.28%	0
Purchase type	Purchase	88	380	58	11.99%	3.36%	0
Purchase type	Unknown	176	461	59	11.94%	0.36%	0.703
Technical Characteristics							
Module family	Monocrystalline	3,031	7	42	13.15%	0.00%	N/A
Module family	Polycrystalline	2,131	8	61	13.10%	1.20%	0
Module family	Unknown	3,819	63	60	12.39%	1.44%	0
Inverter Type	Microinverter	6,750	7	60	13.01%	0.00%	N/A
Inverter Type	Optimizer	1,675	7	51	12.74%	-0.96%	0.002
Inverter Type	String	272	182	73	12.09%	-2.52%	0

Characteristic	Type	Number of assets	Avg. capacity (kW)	Median number of months	Avg. CF	PLR increment (% per year)	
						Coeff	p-value
Inverter Type	Unknown	284	566	78	11.87%	-3.12%	0

Notes: The results are for all assets with an asset-level PLR estimate. Light gray rows are the default characteristic; coefficients are the increment to PLR associated with each characteristic relative to the default. Dark gray cells indicate rows with coefficients not statistically significantly different from 0 at the 10% significance level.

In the table, the p-value indicates the smallest significance level at which the increment is statistically significantly different from 0. A p-value smaller than 0.1 indicates a PLR increment statistically significantly different from the neutral type at the 10% significance level, other characteristics held constant. Increments with higher p-values are marked out by dark gray highlight in the table.

PLR by DAC and non-DAC location

A direct comparison of average asset-level PLR found a significantly lower PLR in DAC than in non-DAC geographies. However, this difference appears to be related to the regions where the DAC and non-DAC assets fall. In the study pool, 82% of the DAC assets are in Long Island, where the PLR is low, and only 7% are Upstate, where the PLR is high. Non-DAC assets, by contrast, are 42% in Long Island and 36% Downstate. The cross-factor analysis found a higher PLR associated with being in a DAC location, when controlling for regional and other differences in characteristics. Program staff conjecture that this result may be related to the higher prevalence of flat rooves in the Long Island DAC areas.

PLR by purchase type

Most assets in the study data (81.7%) were leased. Power purchase agreement (PPA) systems exhibit much higher PLR than leased ones. Purchased systems are relatively few in the study data set and also have much higher PLR than leased. The cross-factor analysis confirmed these directional comparisons. While the study cases are heavily weighted towards leased assets, historically the NY-Sun Program has had about 27% leased, 10% PPA, and 63% purchased systems.

Our consultants to solar developers observed that purchased systems in the residential sector are likely to have less consistent maintenance, since owners may not realize the systems are not performing well, and may not call for repairs immediately. Thus, the higher PLR for these systems makes sense. The effects of ownership/management arrangements on maintenance are discussed further below under Longer-Term Persistence.

PLR by module family

Monocrystalline systems exhibit very low PLR, not statistically different from 0. By contrast, polycrystalline systems exhibit a PLR somewhat higher than the overall average. The polycrystalline systems are generally older, and there may be reasons other than the module type that they have higher performance loss rates. Over one-third of the systems have an unknown module type. These have a PLR similar to the polycrystalline systems. The very low PLR for monocrystalline systems observed in the asset-level averages was borne out by the cross-factor analysis.

PLR by inverter type

Microinverter systems appear to have higher PLR than those with optimizers or string inverters, even controlling for other characteristics. A possible explanation is that an individual microinverter failure within a system results in only moderate performance decline and may go undetected and unaddressed, whereas a string failure would bring production to zero, hence be more likely to be promptly repaired.

Effects of Temporary Disruptions

The primary analysis in this study assesses the PLR for operating, communicating assets. A monthly production value of zero could indicate that the solar production system is not operating, or could simply indicate a lapse of communications. An initial concern was that intermittent communications outages could result in large swings in CF that would add a lot of variability to the PLR estimates. To remove this potential contributor to variability, for each asset the analysis excludes months with 0 production, as well as the adjacent months. This exclusion avoids most temporary disruptions lasting more than a month. On the other hand, if the rate of low/no-production months is increasing over time, the exclusion of these months could lead to understated PLRs.

To assess whether there might be an additional source of increased production loss related to increasing frequency of outages, we reviewed the proportion of assets that had blank or low production as a function of system age in months. Low production for a month is defined as less than 5 kWh and greater than zero. For each month, an asset is included in the base of the percentage only if it has positive production data for later months. Results are shown in Figure 4.

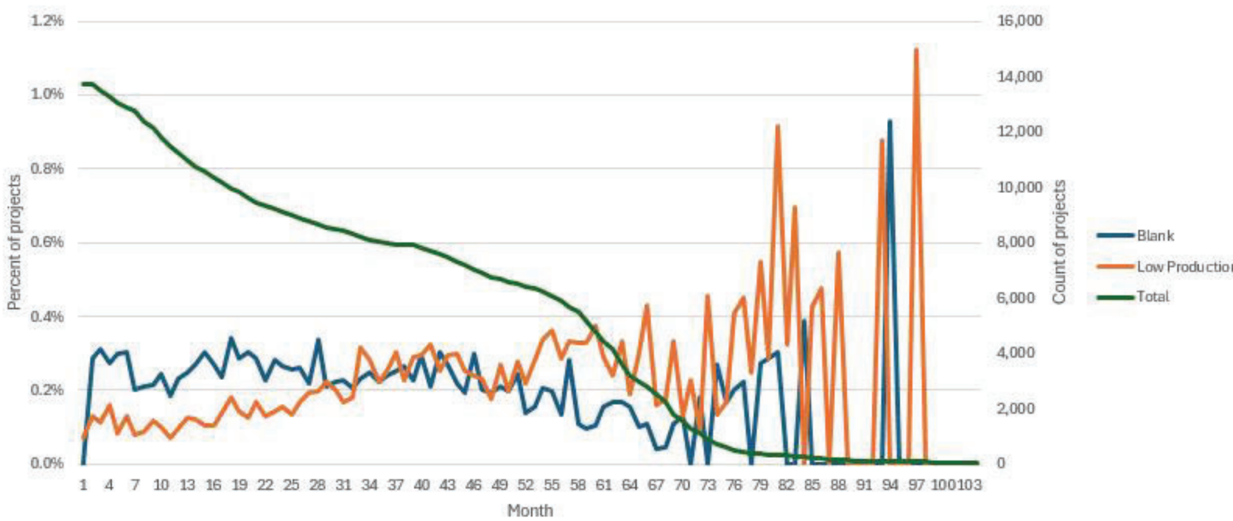

Figure 4. Percent of reporting assets with blank or low production versus months since installation
Note: Low production for a month is less than 5 kWh which indicates connectivity but not performing as expected.

The figure shows that for any age, around 0.5% of all assets have zero production (blank) and a similar fraction have low production, for a given month. The percentages become more erratic in later months, as there are fewer assets of that age, but there does not appear to be any overall increase in the rate of disruptions over time. Thus, effects of temporary disruptions are not a major omission in the PLR analysis.

What remains unaddressed by the analysis is the rate of full system shut-downs or abandonment over time. The data available to the study doesn't indicate if the end of a data stream is due to the system being discontinued or inoperable, versus a change in ownership or management. System shut-downs are likely to be more of an issue in later years than over the relatively early years examined in this study.

Longer-Term Persistence

The analysis presented above is based primarily on assets with five to seven years of production data. These empirical results give a useful look at how well solar system performance holds up over time, but provide little information on what happens later in the life of a system. In this section, we offer perspectives on what can be expected over solar system life, based on the evaluation contractor's experience as a consultant to system developers.

Overall system life. The evaluation contractor team expects residential PV systems to be able to last for 30 years with proper maintenance. While residential PV systems don't have moving parts, they are not immune to component failure. Modules, string inverters, microinverters, optimizers, and communications hardware can all fail with differing levels of impact to system production. The factors described below all suggest reasons that production loss rates could be expected to increase at system ages beyond those captured in the analysis in this study.

String inverter failures. The evaluation contractor team expects most string inverters to have a useful life of 10 to 15 years. Once a single inverter in a string system fails, the system (if it has only one string inverter) or that portion of the system (if it has multiple string inverters) is unable to convert DC electricity to AC electricity for delivery to loads and the grid, and is out of commission.

In systems that are owned by third parties (third-party owned, or TPO), the owner has a financial incentive to replace failed string inverters so the owner can continue collecting PPA or lease payments from the homeowner. The evaluation contractor team would expect that most TPO systems with failed string inverters will have inverters replaced fairly quickly in order to resume operation. For systems that are owned fully by the homeowner, it is possible that if a string inverter fails and is outside of the warranty period, which is typically about 10 to 12 years for string inverters, the homeowner may not opt to purchase a new string inverter at cost to them. The cost of a new inverter can be several thousand dollars. The evaluation contractor team does not have data to inform a reasonable rate of inverter replacement for cash/loan systems but expects that a portion of homeowners will not repurchase a replacement inverter to replace an inverter that has failed outside of its warranty.

Thus, some portion of purchased systems with string inverters are likely to become inoperable after roughly 10 to 15 years. For the most part, this effect is not reflected in the data used in this study, and permanently abandoned systems do not contribute to the estimated performance loss rates.

Microinverter and optimizer failures. Failures of microinverters and optimizers have a lesser impact on system performance since they are installed at the module level, and module-level power electronics (MLPE) systems are designed to bypass failures and maintain the optimal string performance. Enphase and SolarEdge are the leading providers of microinverters and optimizers in the US market respectively. Both have 25-year warranties on microinverters and optimizers. Failure of MLPEs will reduce the output of a PV system proportionally. For example, if a system has 10 modules, and one microinverter or optimizer fails, the system's output will be reduced by approximately 10%. In TPO systems, owners may or may not decide to replace a single failed MLPE component. The decision is likely dependent on the impact on revenue in a PPA, the ability of a technician to get to the site, and the potential impact of the reduced performance on a system's performance guarantee level.

In typical residential PPAs, the revenue an owner earns is directly related to the output of the system. Replacing a failed MLPE component will typically come at a cost to the system owner even if the component is under warranty, so owners may balance the cost with potential recovered production.

In leased systems, revenue is not directly correlated to energy production. Lease contracts typically have a performance guarantee set between 85% and 95% of a system's forecast performance. On larger systems, if a single MLPE component fails, the performance of the system may only reduce by 5%. If performance guarantees are set conservatively, say at 85% of forecast production, the system owner may not elect to replace the failed MLPE component since they are still able to collect 100% of lease payments until the system performs below the performance guarantee threshold for a true-up period, which can be one to three years. In this case, the owner may wait for additional MLPE components or modules to fail before rolling a truck to replace.

Communication failures. Separately, lease contracts often allow for "billing on estimates" in cases where actual system production is not being communicated to the inverter provider's environment. It is best practice to replace failed communications equipment; however, this is not always done. When a system is not communicating, it is impossible to know whether the issue is specific to communications, in which case a system may be producing at normal levels, or if the system has failed in some capacity and is not producing. Given the structure of lease contracts, it is possible that failed systems can be billed on estimates and there may be a lag between when a system fails and when the system is repaired.

Roof repairs. It is best practice for residential PV installers to evaluate a home's roof prior to installing PV. The evaluation contractor team would expect installers to install PV systems on roofs that are no older than 10 years old. Otherwise, a reroof during the useful life of the PV system is nearly guaranteed. This requires the modules, racking, MLPEs and any conduit and wiring to be fully removed so the roof material can be replaced. Modules, racking, MLPEs, and conduit would then need to be reinstalled. Removal and reinstallation are typically at cost to the homeowner even in TPO systems. If a homeowner elected not to reinstall a TPO system, they would typically be required to buy the system from the owner at the fair market value of the system. Depending on the age of the system, this may be more or less than the cost to reinstall the system on a new roof. The likelihood that a homeowner would elect not to reinstall due to cost is unlikely in younger systems, but possible in older systems. Homeowners that own their systems may also elect to upgrade technology if newer technology exists at the time.

Shading. When residential PV systems are initially modeled, the site shade scene is captured either with onsite technology like a SunEye or by using 3D imagery and satellite data. Energy forecasts assume the shade scene will not change. In reality, trees, which are major factors in residential PV shade scenes, will grow. In TPO contracts, it is the homeowner's responsibility to maintain the original shade scene. In practice, there is likely foliage growth that is not managed by the homeowner. Increased shading on the PV array will decrease production. Systems with MLPE are better equipped to handle partial shading, whereas PV systems with string inverters are highly sensitive to shade: a small amount of shading can lead to a material reduction in output. It is likely that over the 20- to 30-year life of a residential PV system, the shade scene will change slightly which can impact production, usually negatively.

Effects of changes in shading are reflected in the performance loss rates estimated in this study. It is possible that shading could become worse at greater ages, since changes in shading farther out are harder to project at the time of the site assessment.

Conclusions

PLR Overall

An overall performance loss rate of 0.83% per year is estimated across assets in New York State. This rate is statistically significantly higher than the benchmark of 0.64% used by DNV's solar assessment practice, and somewhat higher than the range used by NY Green Bank. On the other hand, this rate is well within the range found in papers reviewed by Hieslmair (2024) and Verdant (2021).

If the overall loss rate of 0.83% per year were to continue over the life of the systems, it would result in a production decrease by about 20% in annual production by 2050 from the 10 GW of PV capacity targeted to be installed by 2030 under New York's Climate Act Scoping Plan. The production loss by 2050 would be on the order of 2,200 GWh per year, out of over 11,000 GWh of first-year production.

Performance Loss Accounted For in this Study

Performance loss rates estimated in this study represent the performance loss of operating and communicating systems, over roughly the first five to seven years of life. The rate of systems being disabled or abandoned on a permanent or long-term basis is not captured by this study.

Longer-Term and Expanded PLR Investigations

This study is based on analysis of production data over several years for a large number of assets. The study has identified a number of factors that appear to be associated with higher or lower PLR. While the specific PLR estimates from New York State may not apply in other areas, many of these directional findings are likely to.

Another type of study could investigate the proportions of incentivized systems that are still operational at different ages. Such a study could include working with the system managers to identify rates of data loss and reasons.

Also of interest could be a study to follow up with customers and owners of residential systems, to explore maintenance practices and approaches that might help improve these.

The majority of assets (65%) analyzed in this study had five or fewer years of production data. Only a handful had more than seven years. As a result, the performance loss rates developed in this study may not be indicative of loss rates after 10 or more years. In particular, if performance loss rates accelerate over time, or if systems are disconnected at increasing rates, the PLR estimated here is a rough lower bound on the capacity reductions in the later years. NYSERDA is continuing to collect production data, to establish a larger data set of longer production records that can be used for further study.

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