Reducing uncertainty in PV yield assessments

PV yield modelling | When estimating the expected yield of a PV plant for financial risk assessment purposes, understanding the uncertainties of any model is crucial. Mauricio Richter of 3E investigates some of the emerging practices for obtaining and interpreting data to ensure the most accurate results

The EU-funded Solar Bankability Project together with the IEA PVPS Task 13 group have analysed current practices of PV cost and energy yield modelling and the corresponding risk assessment [1] [2]. Present-day models were analysed to identify gaps in how technical assumptions are accounted in the various photovoltaic (PV) cost elements. This enables stakeholders to identify hidden technical risks and their potential impacts.

Project developers, banks and asset managers use PV financial models to evaluate the profitability of a PV project. The capital expenditure (CAPEX) is strongly influenced by the construction costs. In a few cases, the considered technical assumptions are clear before the final CAPEX value is determined. Furthermore, financial models normally only make use of a single number for the CAPEX value and it is not a common practice to account for the inherent uncertainties of the CAPEX value in the financial model.

Technical assumptions are also important when determining the operational expenditure (OPEX). OPEX values should reflect the expected wear-out profile of the individual components. Such expenditures should be calculated using technical parameters that describe the technical lifetime profile of the equipment instead of the financial lifetime of the project, as these can often differ significantly. Regarding the monitoring of the plant, this typically focuses on the performance ratio (PR) and technical availability as these key performance indicators are of high importance in ensuring the overall profitability of the project.

When estimating the expected yield of a PV plant for financial risk assessment purposes, the correct identification and quantification of uncertainties is crucial. The estimation and evaluation of the PV energy yield comes with large uncertainties introduced by the different elements in the PV energy conversion chain. It is also essential when comparing the measured versus expected values as indicators for O&M decisions. For both purposes, reliable uncertainty measures are essential.

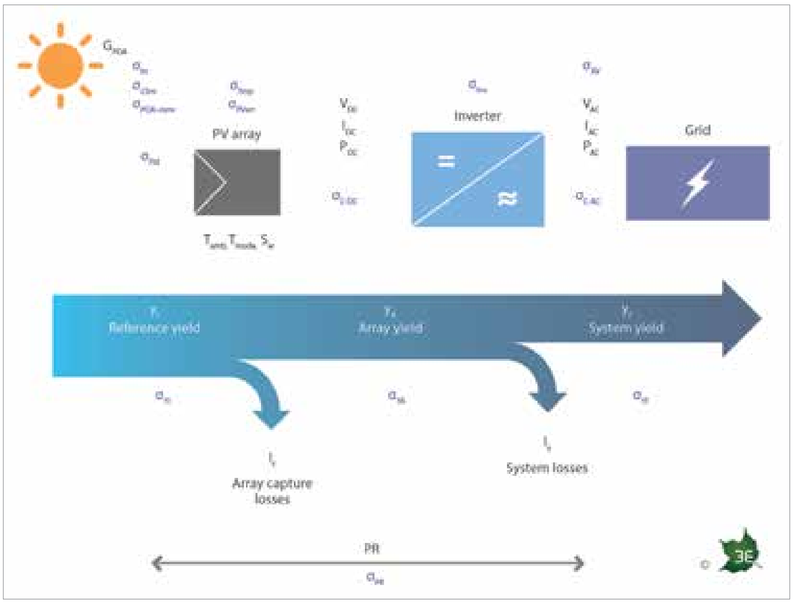


Figure 1. Energy flow diagram in a grid-connected photovoltaic system; in black, the measured/calculated parameters and in blue the related uncertainties

An overview of the energy flow in a grid-connected PV system with the uncertainties related to each conversion step is shown in Figure 1 as presented in [2]. The illustration highlights the importance of the correct uncertainty quantification when calculating the different performance indicators of a PV system. In general, the measured/expected electricity production or system yield is reported together with the PR, which quantifies the overall efficiency of energy conversion of the PV system under operating conditions. The PR is the ratio of the system yield Y_f to the reference yield Y_r. It should always be accompanied by an uncertainty, which in turn depends on the uncertainty in the final yield Y_f and reference yield Y_r quantification/estimation. Detailed explanation and examples of how these uncertainties are calculated and combined are available in the EU-funded Performance Plus Project report, "Best Practice Guide On Uncertainty in PV Modelling" [3] and further developed and complemented in [1] and [2].

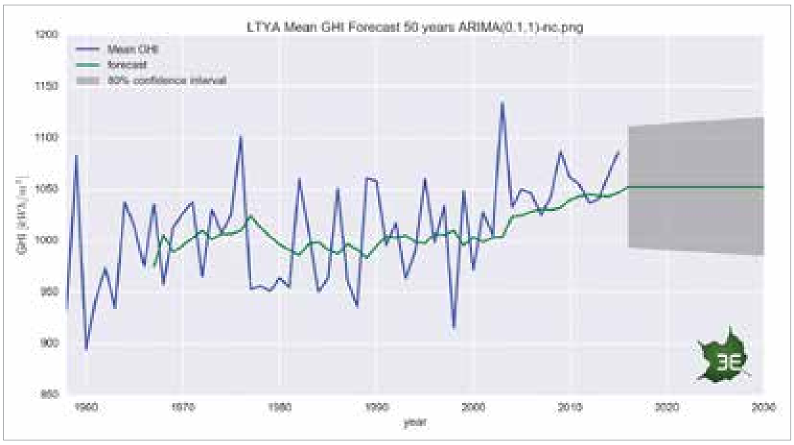
Solar resource quantification uncertainties

One of the main risks during the operational phase of a PV project arises from the uncertainty on the estimates of energy yield done during design phase. If the actual energy yield does not meet the initial estimates, the entire investment can be compromised as less revenue from energy sales will directly impact the servicing of the debt or the investment return. This scenario can result from, among other factors, long-term solar resource effects, component failures, defects, forced outages, higher degradation rates than expected, etc.

The bankability of a PV project largely depends on the uncertainty of the solar irradiation data obtained during the solar resource assessment phase. The uncertainty of long-term average solar irradiation is therefore a dominating parameter in risk assessment of PV projects. This uncertainty depends in turn on several aspects such as the quantification of the solar resource, the models used, the long-term solar resource variability and trends, etc. To a large extent, the long-term irradiation uncertainty depends on the source of the data and the reference period used. A recently published white paper by Kipp & Zonen and 3E presents in greater detail the benefits of both pyranometer and satellite irradiance data for utility-scale solar energy parks and recommends the use of both sources as these are complementary [4].

While on-site, ground-measured irradiance data from a high accuracy pyranometer correctly installed and maintained is the most accurate solution even over short periods of time (as little as a minute to an hour), data derived from satellite measurements comes very close to the on-site measurement uncertainty over longer time periods such as months and years. Satellite irradiance data is increasingly being used in both utility-scale solar parks and in smaller installations since it is easy to acquire; just a subscription to a service provides a high availability of data with good time resolution and spatial coverage. For most locations on earth, satellite data provides a useful historical database for site prospecting and for optimising the site-specific design of solar power plants. This data is often used as an input for long-term yield assessment and to calculate a reference yield for monitoring and business reporting.

Figure 3. Forecast of future long-term irradiation based on the average of 32 meteorological stations in the Netherlands using the ARIMA (0,1,1) model without trend



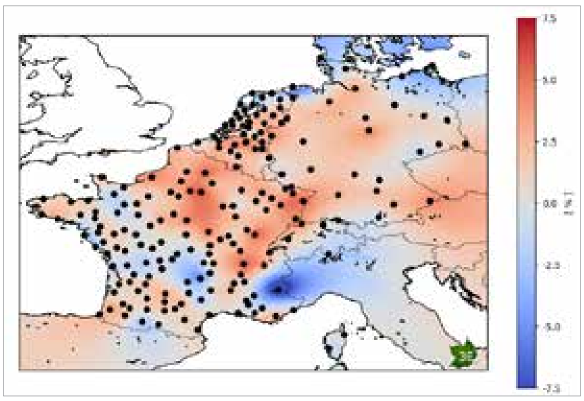


Figure 2. Percentage difference between state-of-the-art satellite irradiance data and ground station data in 2012 measured using high quality pyranometers maintained by the national public weather services

State-of-the-art satellite irradiance data providers use advanced models which have increased significantly the accuracy of the data throughout the day and under complex cloudy conditions. However, as with any model, satellite irradiance data is subject to uncertainties. The yearly difference between state-of-the-art satellite irradiation data and on-site measured data collected by national weather services from over 200 meteorological stations is shown in Figure 2. The percentage difference between the satellite irradiation data and high accuracy on-site measured data over one year is in the order of ±2.5% to ±3% for many places across western Europe. Figure 2 also highlights the importance of having dense networks of high quality on-site measurements as this enables the continuous accuracy improvement of satellite irradiance data over complex conditions.

Reducing the uncertainty on long-term solar resource estimates by extrapolating short-term measured datasets

The use of long-term solar resource site adaptation techniques potentially mitigates the risk of an overestimation of the solar resource in the initial assessment during project development. An overestimation of energy yield will directly impact the estimated investment returns as the actual energy production may not meet the initial estimates.

The uncertainty of long-term satellite irradiation data can be further reduced with the help of high quality on-site measured irradiation, combining the data of a short period of record but with site-specific seasonal and diurnal characteristics with a data-set from a long period of record with not necessarily site-specific characteristics. Upon completion of the measurement campaign (typically one year), different methodologies can be applied between the measured data at the target site, spanning a relatively short period, and the satellite data, spanning a much longer period. The complete record of satellite data is then used in this relationship to predict the long-term solar resource at the target site, reducing the uncertainty on the long-term estimates.

Solar resource variability

The variability of the solar resource is defined as the ratio of the standard deviation to the average global horizontal irradiation over a long-term historical period of typically 10 to 20 years. For example, in Europe this can range from about ±4% up to ca. ±7% depending on weather conditions. This value is typically calculated from long-term databases providing yearly data over a historical period of at least 10 years.

Recent publications suggest the use of different methods to account for and to mitigate the impact of the long-term solar resource variability and trends in energy yield calculations [1]. For example, the proposed method in Figure 3 accounts for the effect of solar resource variability and a long-term trend as part of the uncertainty. This method is clear for cash flow analysis (uncertainty of single years). However, when assessing the risk of multiple year sums, the method still needs further development.

Independently of the statistical method used for the trend detection and future long-term irradiation prediction, the methodology must be clearly documented to allow the correct interpretation of the results, especially considering the increasing interest in financial models for PV plants beyond year 25.

Energy yield estimation

Further uncertainties arise from the estimation of the long-term yield of a PV

	Uncertainties	Range
Solar resource	Climate variability	±4% - ±7%
	Irradiation quantification	±2% - ±5%
	Conversion to POA	±2% - ±5%
PV modelling	Temperature model	1°C - 2°C
	PV array model	±1% - ±3%
	PV inverter model	±0.2% - ±0.5%
Other	Soiling, mismatch, degradation, cabling, availability, etc.	±5% - ±6%
Overall uncertainty on estimated yield		±5% - ±10%

Table 1. Typical uncertainties in the different conversion steps

plant during its financial lifetime. These uncertainties are related to the different modelling steps which rely on several user assumptions, often based on user experience or judgement. In general, technical project description parameters do not represent a significant uncertainty when the project is in an advanced design phase. However, some technical parameters, such as the nominal PV module power and tolerance, are based on approximations and therefore will have an impact on the overall uncertainty when calculating the expected energy yield of the PV plant.

Typical uncertainty ranges for the different elements involved in the overall estimation of the energy yield are summarised in Table 1. Further explanation and examples of how these uncertainties are calculated and combined are available in [1] and [3].

Several modelling steps, such as the calculation of the effective irradiance after reflection losses, thermal losses due to PV module physical characteristics and environmental conditions and conversion from DC to AC (i.e. inverter model), are well described and when using state-of-the-art models, the uncertainties of these modelling steps are rather small compared, for example, with the solar resource-related uncertainties. However, other additional losses occurring typically in the field, such as soiling, mismatch, degradation profile over time, snow effects and others, are often only partly simulated or accounted for by the simulation software. Therefore, users often have to estimate many of these losses and their effects based on the little information available and on their experience.

In general, it is not a simple task to evaluate several of the losses that occur in the field since they are often influenced by external parameters. Therefore, it becomes even more difficult to assess the uncertainty of these estimations. For example, when estimating soiling losses in addition to assessing the surrounding areas for the presence of potential soiling issues, one should also use models that account for monthly rainfall, humidity information and cleaning schedule, among others. Furthermore, a good alignment between the planning phase and the maintenance schedule during the operation phase can mitigate the risk of under/overestimating the effect of soiling losses considerably.

Table 2 presents some mitigation measures that can be applied to reduce the uncertainties, and therefore risks associated with the energy yield estima-

Mitigation measure	Impact/explanation
✓ Use state-of-the-art modelling software to calculate the expected energy yield of the system	Lower uncertainty in the overall energy yield estimation
✓ Verify nameplate power of the PV modules used in simulations with the flash test reports supplied with the modules	The uncertainty on the nominal PV module power and tolerance can be significantly decreased by performing flash tests. For example, independent test facilities typically guarantee the measured values to ±1.5 to ±2%.
✓ Use methods to account for the effect of different degradation behaviour over time (e.g. linear vs stepwise degradation)	PV module degradation over time may not always be linear. Using models to simulate the effect of different degradation profiles during the financial lifetime of the project can mitigate risks arising during the operation phase.
✓ When estimating soiling losses, use models that account for different factors including cleaning schedule, monthly rainfall profiles and humidity information among others	The use of models that account for monthly rainfall, humidity, and cleaning schedules can help to reduce significantly the uncertainty and to improve the OPEX during the operation phase. For example, for a PV plant located in a tropical desert climate (e.g. Dubai) the combination of the high occurrence of dust particles and high humidity may drastically reduce the yield, with soiling rates of up to 0.5%/day and up to 60% losses after a sand storm. The use of advanced models during the planning phase can help to determine a cost optimisation of the cleaning schedule.
✓ Use the expected overall unavailability for the calculation of the initial yield for the project investment financial model instead of the O&M guaranteed values	When calculating the financial income from electricity production of a PV plant, the availability assumption in the PV financial model should reflect the overall plant availability. This means an additional unavailability beyond the O&M service should be considered and added to the overall plant unavailability. This additional unavailability may be caused e.g. due to grid issues or other external factors that cannot be controlled by the operator, and thus may not be covered by guarantees.
✓ Take into account the technical lifetime of the devices as this can often be different than the financial lifetime of the project	The technical lifetime of some PV components may be shorter than the financial lifetime of the project. For example, PV inverters often have a technical lifetime of 10 years which in many cases would be shorter than the financial lifetime of the project.
✓ Use empirical methods for risk assessment calculations (e.g. P90) when possible	When calculating exceedance probabilities for risk assessment (e.g. P90), empirical methods based on actual available data should be used instead of assuming a normal distribution for all parameters. The assumption of a normal distribution does not necessarily apply to all parameters and assuming this behaviour can result in serious deviations.
✓ Consider re-assessing the long-term yield estimate of the plant using actual operational data	Using actual production once the PV plant is in operation can allow a very precise prediction of the long-term yield with a considerably reduced uncertainty. The adjustment of the financial models after e.g. one or two years of operation could potentially reduce the long-term estimation uncertainty by a factor of two.

Table 2. Mitigation measures for risks associated with the energy yield estimation during the planning phase of a PV project

tion during the planning phase as proposed by the IEA PVPS Task 13 group as presented in [2].

How accurate are PV yield estimates? Validation of long-term yield estimates and their level of confidence

The energy yield of a PV plant over its financial lifetime is estimated during the design phase with a long-term yield assessment. The long-term yield assessment usually returns the so-called P50 and P90 yields which represent the 50% and 90% exceedance probabilities, i.e., the energy yields that will be exceeded with a probability of 50% and 90%, respectively. These values are used as input for the financial model of the PV investment, and are usually evaluated for the first year of operation and for the overall financial lifetime of the plant. The correct calculation of the P90 considering all related uncertainties is essential for the evaluation of the PV investment. Moreover, when investing into larger portfolios of PV plants, the risk for the investor is finally expressed by the P90 yield of the portfolio rather than that of each individual plant. Up to now, for commercial projects little validated knowledge about the quality of their P50 and P90 yield estimates has been available in the public domain.

The Solar Bankability project together with IEA PVPS Task 13 group [1], [2] explored the quality of the initial P50 and P90 yield estimates on plant as well as on portfolio levels in order to further quantify the potential reduction of risk with larger portfolios. The purpose of this work was to validate the initial long-term yield estimates based on monitoring data over the first years under operation.

The correlation between P50 and P90 yield estimates and the actual electricity production were compared for a portfolio of over 40 PV plants. The sample comprises rooftop and ground-mounted systems and covers a wide range of plant size from 10kWp up to 12MWp. The data sets for the validation cover between one and four years of operational data. The PV plants with installation type and available data are listed in Figure 4.

Information on PV plant unavailability was collected for each individual plant and analysed. Figure 5 shows the actual percentage of unavailability (downtime) for most of the analysed PV plants. For most cases, the unavailability data comes directly from the detailed O&M reports. Moreover, when possible, the unavailability was calculated from measured 15-minute data. Unfortunately, it was not possible to determine the unavailability for all PV plants under study, since the detailed O&M report was not available for some plants and some plants only had monthly data available.

Figure 5 highlights that for some PV plants in the portfolio, the actual unavailability is very high compared with the initial expectations (e.g. PV plant number 28). Moreover, the mean yearly unavailability of the analysed portfolio is around 2%.

The main results are shown in Figure 6. The initial yield estimates for the first year of operation (P50) is represented by the zero line. The red and green background colours represent the initial P90 and P10 estimates, respectively. They are typically situated between ±7% and ± 9% from the P50 for a single site. The difference of the actual electricity production during the first year of operation from the P50 yield is represented by the blue bars. In this case, a negative blue bar means that less electricity was produced than initially expected. Statistically, eight out of 10 bars should lie

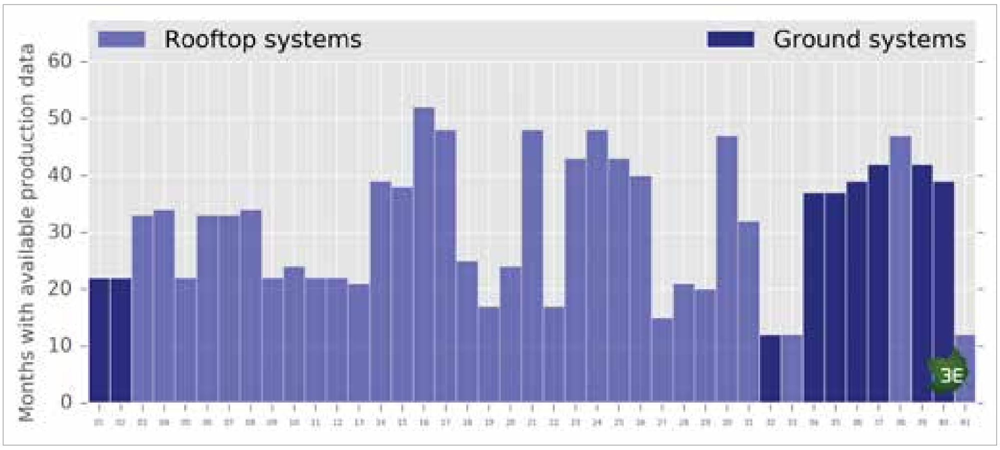


Figure 4. PV plants under study with available electricity production data and installation type

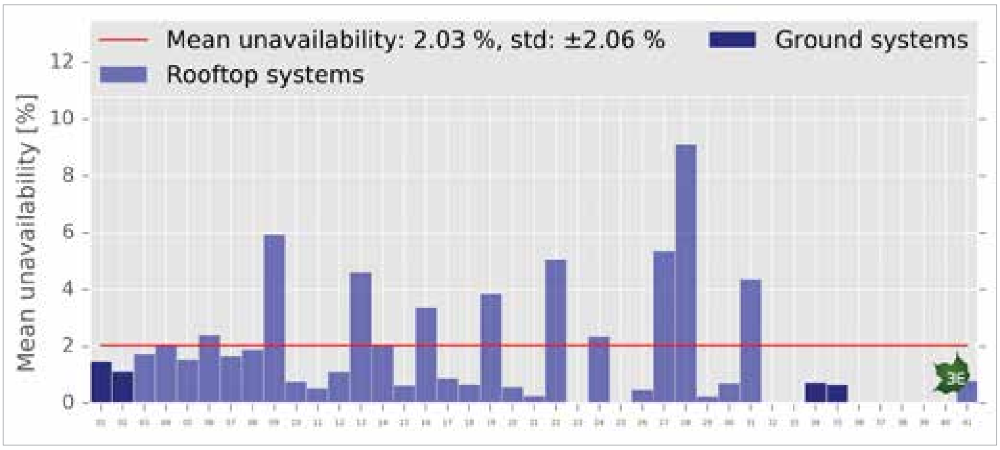


Figure 5. Actual time-based unavailability data from most of the PV plants in the portfolio

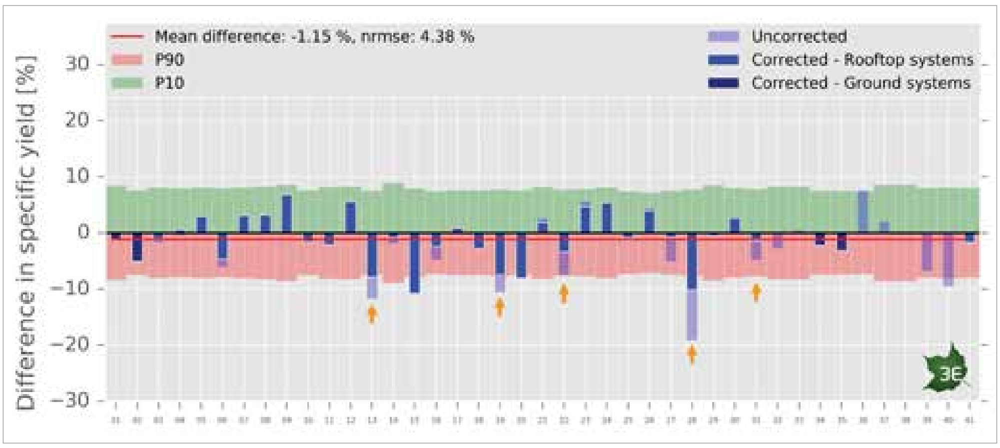


Figure 6. Difference in specific yield corrected for actual unavailability. The orange arrows highlight the effect of the unavailability correction for some examples

Figure 7. Violin plots for the difference in POA irradiation, PR and resulting specific yield between initial expected yield and actual yield for the analysed portfolio

within the red and green region, one should lie above and one below.

For most of the PV plants analysed across the portfolio, the actual electricity production during the first year of operation (blue bars) lies within the expected uncertainty range. At plant level, the yields are close to the ideal scenario but slightly biased negatively by -1.15%. However, while only one PV plant is situated above the P10 confidence interval , the portfolio contains six plants for which the actual production was below the P90 confidence interval. These deviations for some plants had to be further analysed to understand the gaps.

The orange arrows in Figure 6 point at the plants with significant durations of plant unavailability. When correcting the energy yield for the durations of unavailability, the actual electricity production for many of these plants remains within the anticipated confidence range. In other words, their initial long-term yield estimates did not account for the unexpectedly high losses due to the plants being unavailable. More generally speaking, the distribution of actual energy yields versus the initial long-term yield estimates is relatively narrow when excluding significant durations of unavailability and, hence, the initial long-term yield estimates were quite good.

At portfolio level, the overall (non-weighted) mean difference between initial long-term yield estimates and the actual yield over the portfolio is -1.15%. This means that, over the analysed portfolio, the yield is slightly lower than initially estimated during the design phase. Furthermore, as shown in Figure 7, the dispersion (NRMSE) is around 4.4% for the analyzed portfolio. These variations lie within the normal expected ranges as reported in scientific literature. These deviations are typically expected to be mainly due to the variability of the solar resource and other site-specific losses that are not precisely modelled during the design phase. Moreover, some overestimations are cancelled out with some other underestimations across the portfolio as shown in Figure 6.

The difference and its distribution for plane-of-array (POA) irradiation, performance ratio (PR) and specific yield for the entire portfolio are summarised in Figure 7. Such differences are represented using 'violin plots' which are a combination of box plots and kernel density plots. This kind of plot gives not only the valuable information of a box plot but also shows the probability distribution (density) of the data at different values.

As shown in Figure 7, the largest gap between initial expected and actual values comes from the performance ratio estimates. As previously highlighted, the initial estimates of system losses depend on several factors. In addition to the PV software modelling accuracy, several user estimates and assumptions affect the yield estimate. Regarding the POA irradiation, the results presented here are the outcome of comparing the initial estimate done during the initial yield estimation against the irradiation from state-of-the-art satellite-derived data for the first year of operation as, unfortunately, not all PV plants in the portfolio had good quality on-site solar irradiance sensor measurements.

In conclusion, the initial energy yield estimates for the portfolio under study generally agree quite well with the actual electricity production over the first years. The NRMSE across the analysed portfolio of over 40 PV plants is approximately 4.4%. By contrast, the uncertainty in long-term yield estimates for a single site is typically around ±5% to ±10%. The results of this PV portfolio use case show that this uncertainty range could decrease for a statistically meaningful portfolio of several PV systems down to around 4.4%. The outliers with energy yields below the P90 yield were largely caused by plant un-availabilities. Therefore, the risk of unavailability needs to be addressed next to the resource uncertainty and the uncertainty of the PV system model. This risk can be mitigated through good warranty conditions and operation and maintenance (O&M) contracts.

Investing in a big portfolio of PV plants may be seen as a risk mitigation strategy for investors through diversification of risks. For an entire portfolio of PV plants, the overall risk of not achieving the expected energy yield decreases with increasing size and spatial spread of the portfolio. Several variables such as the number of plants, their geographical spread, PV module technologies, the type of installations, system configuration, etc. will influence the resulting overall uncertainty. Nevertheless, the practices and potential sources of uncertainties highlighted in this text must be applied on a project-by-project basis to ensure best results.

Author

Mauricio Richter has worked as a PV expert in 3E's R&D team since 2012 and is currently the R&D product manager of 3E's data services. The scope of his work covers R&D topics in solar PV, with a focus on solar resource assessments, long-term yield estimates and performance analysis of PV systems. He is involved in several research projects including the recently finished EC FP7 funded project Performance Plus, the EC H2020 funded project Solar Bankability project and he is currently the activity leader in Subtask 1 of the IEA PVPS Task13.

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