Chapter 10

Financing Solar PV Projects: Energy Production Risk Reduction and Debt Capacity Improvement

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Chapter 10

Financing Solar PV Projects: Energy Production Risk Reduction and Debt Capacity Improvement

Romeo Pacudan[37]

Abstract

Various risks influence the decision in obtaining financing and determining the cost of financing for utility-scale solar photovoltaic (PV) projects in many developing countries. One of the risk areas is in the estimation of solar PV energy production, which is significantly derived from the uncertainty in solar resource data and measurement. Due to the lack of ground-measured data sets, the solar PV industry mainly relies on satellite-derived irradiation data to estimate on-site solar energy resource, but modelled data often lacked the accuracy to mitigate energy production risks. The use of multiple data sources has been increasingly employed and emerging to be the best practice in the solar industry. One of the methodologies that combine various sources of data is the measure-correlate-predict (MCP) approach, which correlates short-term measured data with long-term reference data sets. The study, using the proposed 27 megawatt peak (MWp) solar PV project in Brunei Darussalam, evaluates the impact of using correlated irradiation data sets on energy production and capital structuring of utility-scale solar PV projects. The study results confirm the outcome of other studies—that correlated solar irradiation data sets generate superior, high-confidence energy estimates (probability of exceedance at P90 and P99 levels) than those using satellite-derived data sets. With assumed financial parameters, the high-confidence energy estimates from MCP-derived data comfortably satisfy the debt-service coverage ratios (DSCRs) set by lending institutions and credit rating agencies, as well as generate lower levelised production cost of electricity. Also, the study shows that to achieve the minimum target DSCR of 1.3x and 1.2x for P90 and P99 energy production levels, the share of debt on the overall project capital structure could be further increased by around 7% for both cases from a reference debt share of 70%. The use of high-quality data sets therefore reduce project risks, increase project financial leverage, and enhance financial competitiveness. The government's support measures that address the issue on resource data uncertainty and establishing best practice in data measurement and use in project analysis would be crucial in developing solar PV industry in developing countries.

Keywords: Solar irradiation data sets, measure-correlate-predict, probability of exceedance, capital structuring

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1. Introduction

Solar photovoltaic (PV) power generation started to emerge recently in the national energy mix of a number of Association of Southeast Asian Nations (ASEAN) countries. This development is due to the improvement of solar PV cost competitiveness at the international market and the introduction of policies and regulatory frameworks that promote the deployment of renewable energy technologies in these countries. This is particularly evident in countries that have introduced reforms allowing private sector participation in the generation segment of the power industry. Also, due to increasing sizes of solar PV projects being planned and implemented in some of these countries, project financing or non-recourse financing has been increasingly used as one of the main mechanisms to finance utility-scale solar PV projects.

There exist, however, a number of project risks inherent to solar PV project planning, construction, and operation that inhibit the full development of solar energy resource potential in these countries. These can be broadly categorised into regulatory, market and operational, and technological risks (Lowder et al., 2013; Cleijne and Ruijrok, 2004). These risks, as perceived by lenders and investors, could influence in obtaining and determining the cost of financing.

One of the main risk areas is in the estimation of the expected annual production of electricity from solar PV power plant at the pre-construction stage of the project (Vignola et al., 2013; Schnitzer et al., 2012)—the stage where mobilisation of financial resources is crucial. There is a risk that the expected annual production would be overestimated and that failure to achieve the target production compromises the project's ability to meet its debt obligations. This risk emanates from the uncertainty in solar resource data, which is the focus of this study, and in the models to forecast solar project performance used in the feasibility studies.

Banks and investors providing financing to solar PV projects, on the other hand, require higher production probability (higher level of confidence on actual energy production) to determine the associated risk with a project's ability to service its debt obligations and other operating costs.

Due to lack of available ground measurement data near identified project sites in many developing countries, project developers often rely on satellite-derived solar irradiation data in their feasibility studies. High-resolution satellite data have, however, high uncertainty due to difficulties in integrating key atmospheric parameters in the radiative transfer models (McMahan et al., 2013; Vignola et al., 2013; Stoffel et al., 2010).

To ensure accuracy in solar irradiation estimation and obtain high-confidence estimate of solar energy resource, there is an increasing recognition in the solar energy industry to analyse and use multiple data sources, instead of relying solely on modelled data. One of the measures used that take advantage of using various sources of solar data is the measure-correlate-predict (MCP) approach, which correlates short-term data measurements with long-term reference data sets (Vignola et al., 2013; Schnitzer et al., 2012). This methodology has been widely utilised in the wind industry to increase the confidence level and minimise uncertainty in long-term wind energy resource assessments (Rogers et al., 2005; Carta et al., 2013).

Thuman et al. (2012) have demonstrated that in the case of several sites in the United States (US), the MCP technique could generate data sets with lower uncertainty levels compared with satellite-derived irradiation data sets. Schnitzer et al. (2012), on the other hand, have shown that high-confidence energy estimates from MCP-derived data sets are higher than those from satellite-derived irradiation data.

This study further extends the analysis by looking into the implications of using MCP-derived data sets on the financial structuring of projects. Using the proposed expansion of 27 megawatt peak (MWp) solar PV project in Brunei Darussalam, the study combines the measured irradiation data on-site with satellite data through the MCP methodology, estimate the expected production of the proposed project for cases using satellite-derived data and correlated data sets, and compare the high-level confidence energy estimates of these cases. From these, the study further investigates capital structuring of the project by simulating combinations of project debt-to-equity ratio to satisfy the debt-service coverage ratio (DSCR) targets set by lenders and credit rating agencies for high-confidence energy estimates.

The study results could strengthen the case for policymakers to introduce—in addition to policy and regulatory frameworks such as feed-in tariff, net metering, renewable portfolio standards, and tradable certificates that promote renewable energy deployment in general—other support mechanisms that address the lack of information and awareness related to energy resource data.

2. Methodology and data

In quantifying the impact of using a bankable solar radiation data set on solar PV project's financial leverage, the study carried out the following methodological approach: (i) establishment of solar irradiation data sets, with on-site measured data as the base and satellite-based data as reference data sets in deriving a forecast data derived from MCP methodology, as well as quantification of their associated resource measurement uncertainties; (ii) estimation of the energy yield of the solar PV project case studies with these two data sets; (iii) estimation of energy production at higher confidence levels based on the overall project uncertainty levels; (iv) estimation of the potential improvement of the project's debt capacity based on a target DSCR for the two data sets using a simple cash flow model. These are further explained in the following subsections.

2.1. Project case study

The above methodological approach is applied to the 27 MWp expansion study of the Tenaga Suria Brunei (TSB) project. The TSB s a 1.2 MWp solar PV power generation demonstration project, which is jointly implemented by the Government of Brunei Darussalam and Mitsubishi Corporation. The project is situated in Seria, Belait District with global coordinates of 4.61°N, 114.34°E, and an altitude of 4.6 metres above mean sea level.

One of the core objectives of the TSB project is to identify the most suitable and high-performance PV technologies that are suited for local meteorological conditions (Mitsubishi Corporation, undated). This project was interconnected to the grid and commenced operation in May 2010. The demonstration phase was performed in May 2010 and October 2013 in which the Mitsubishi Corporation and the Department of Electrical Services jointly carried out the operation and maintenance services, data collection, and analysis (Pacudan, 2015a). At present, the project is being operated by the Department of Electrical Services with continued technical support from the Mitsubishi Corporation.

The Brunei National Energy Research Institute carried out a study to assess the potential expansion of the TSB project. The study identified a total land area of more than 24 hectares in three plots adjacent and within close proximity to the sites that are suitable and available for solar PV development. Using polycrystalline solar PV modules, a minimum of 27 MWp capacity could be potentially developed and added to the existing TSB project

(Pacudan, 2015b).

2.2. Solar irradiation data sets

The radiant power from the sun is known as the total solar irradiance, which is estimated at the mean earth–sun distance to be 1,366 ± 7 W/m^2 with the variation attributed to the 11-year sunspot cycle, while on the other hand, due to the earth's elliptical orbit, the solar radiation reaching at the top of the atmosphere also varies annually between 1,415 W/m^2 to 1321 W/m^2 (Stoffel et al., 2010; Paulescu et al., 2013). The solar irradiance that is available at the top of the earth's atmosphere is known as the extraterrestrial solar radiation. When the solar radiation passes through the earth's atmosphere, its spectral distribution is modified by absorption and scattering processes, and separated into different components (Stoffel et al., 2010). The direct normal irradiance is the part of the solar radiation that directly reaches the earth's surface and normal to the sun's position; the diffuse horizontal irradiance is the part of the radiation scattered in the atmosphere as measured on a horizontal surface. The sum of the direct and diffuse irradiation is known as the global horizontal irradiance (GHI). Energy production from solar PV power facilities are estimated using engineering simulation tools and GHI data sets (Coimbra et al., 2013; Stoffel et al., 2010).

At present, there are various sources of GHI data used by project developers in solar PV project preparation stage, and these are (i) modelled data, (ii) reference station data, and (iii) on-site data. Modelled data consist of a combination of satellite-modelled, numerically modelled, and back-filled data sets; reference station data are data sets collected from international, national, regional, and state level surface-based measurements; while on-site data are those collected through on-site solar measurement and monitoring campaigns (Schnitzer et al., 2012; McMahan et al., 2013).

On-site measurements are the most accurate data set for project analysis because they provide site-specific data with known technical details and management scheme, and the level of measurement uncertainty is relatively low (Stoffel et al., 2010; Vignola et al., 2013). Most on-site measurements, however, have shorter record period and do not capture the long-term historical climate trend. Surface reference stations have also higher accuracy and may have longer period of data record. These stations are sparsely distributed and, in most cases, they are not located within close proximity to project sites. In addition, some reference stations have also poor maintenance practices. Modelled data have the highest measurement uncertainty. To establish bankable data sets, the objective is to combine different data sources to create a reliable, long-term record of irradiances at the project site (Vignola et al., 2013).

2.2.1. On-site measured data

Meteorological parameters were monitored and analysed during the demonstration phase of the TSB project. Two first class pyranometers were installed together on-site with other sensors to measure other meteorological variables. On-site data were collected by the Department of Electrical Services and analysed by the Mitsubishi Corporation for the period 2010-2014. An independent review and analysis were carried out by Pacudan (2015a). The data is collected during a short period of time and do not encapsulate long-term trends.

The measured global solar irradiation in terms of daily average for each month is shown in Figure 10.1. The global solar irradiation pattern reflects the trend of the weather pattern of Brunei Darussalam, which is affected by two monsoon seasons—the northeast monsoon, which starts in December; and the southwest monsoon, which begins in June. The solar irradiation is lowest during the monsoon seasons and highest during the dry seasons.

The daily solar irradiation has the highest peak of 5.7 kWh/m^2 (kilowatt-hour/square meters) in March, then it goes down to around 5 kWh/m^2 in June, before it goes to another peak of 5.3 kWh/m^2 in August. From August, the irradiation starts to fluctuate downward until reaching the lowest level in January. The average daily irradiation for the period is 5.1 kWh/m^2 with an average annual sum of 1,857.4 kWh/m^2.

2.2.2. Reference irradiation data

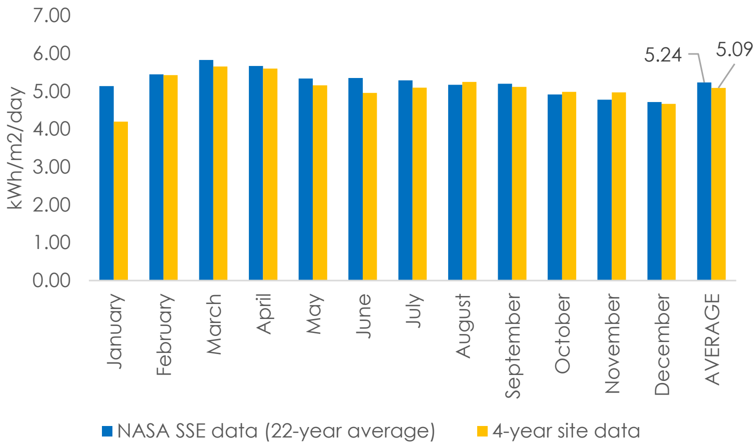
In most developing countries, including Brunei Darussalam, potential project sites are often not situated within close proximity to high-quality meteorological stations. Zelenka et al. (1999) have shown that satellite-derived solar radiation data provide a better estimate of the hourly solar resource than those extrapolated data from high-quality ground station if the site of interest is situated more than 25 kilometres from the measurement station. Project developers in developing countries therefore rely on modelled data for their solar project analysis.

Modelled data that are available and widely used in developing countries include the National Aeronautics and Space Administration (NASA) Surface Meteorology and Solar Energy (SSE) data and information, Meteonorm, Photovoltaic Geographical Information System (PVGIS), and others (Stoffel et al., 2010; Vignola et al., 2013; Yates and Hibberd, 2010). The NASA SSE data is publicly available and free of charge while other data sets are offered for a fee. This study uses the 22-year NASA SSE data set for the TSB site as the baseline data for the analysis.

The SSE data set is based on 1°×1° longitude latitude grid and provides estimates of global horizontal, direct normal, and diffuse horizontal mean monthly daily total irradiances and other meteorological parameters (Myers, 2009). While the 1° grid is relatively large for site analysis, project sites in the United States within the grid tend to follow the variations in solar resource and track closely with those from the National Solar Radiation Database of the National Renewable Energy Laboratory (Vignola et al., 2013). The NASA SSE used a physical model in estimating the solar irradiance, which is fairly accurate particularly when various atmospheric parameters are known (Vignola et al., 2013).

The site-specific solar irradiation data (4.61°N, 114.34°E) from NASA SSE were downloaded from the NASA website (https://eosweb.larc.nasa.gov/). NASA SSE's data sets tend to underestimate the solar irradiation during fall months while overestimate during the other seasons. The seasonal pattern is, however, similar to that of on-site data. This is shown in Figure 10.1. The average daily irradiation is 5.24 kWh/m^2, which is around 3% higher than the measured irradiation from TSB. The main implication is that using NASA SSE data for project planning would tend to overestimate the energy yield of a project.

Figure 10.1: Average Daily Global Horizontal Irradiation



kWh = kilowatt hour; NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy.
Source: Prepared by the author.

2.2.3. Correlated irradiation data

To increase accuracy, confidence, and reduce uncertainty, short-term ground-measured data are often validated using reference data sets, which in this case is the NASA SSE data. The method used in the study is the MCP technique. The MCP approach and its variants have been widely applied in the wind (Bass et al., 2000; Rogers et al., 2005; Carta et al., 2013) and solar industries (Meyer et al., 2008; Hidalgo and Mau, 2012; Thuman et al., 2012; Vignola et al., 2013; Gueymard and Wilcox, 2009). The MCP technique correlates short-term data with site-specific seasonal and diurnal characteristics with data set having a long period of record and consistent long-term annual trend so that a relationship between them is established.

Various MCP methods are used in wind and solar energy analysis. The most basic is the linear regression method, which is employed in this paper. Under this approach the predictor equation is given by the following:

$$\hat{I} = \beta_0 + \beta_1 I$$

Where; I is the reference GHI in kWh/m^2, $\hat{I}$ is predicted GHI also in kWh/m^2 at the target site, and β_0 and β_1 are the estimated intercept and slope of the linear relationship.

The linear regression used in the analysis is a model with a single independent variable x that has a relationship with a response variable y, which is a straight line. The simple linear regression model is given by

$$\hat{y} = \beta_0 + \beta_1 x + \varepsilon$$

Where the intercept β_0 and the slope β_1 are unknown constants and ε is a random error. The errors are assumed to have zero mean and unknown variance σ^2. The equation is also known as the least square regression equation since the criterion used to select the best-fitting line is the least sum of the squares of the residuals. The correlation coefficient evaluates the goodness of the fitting of data considered. This value can vary in the range of -1 and +1 for the strong correlation between the 2 variables x and y. The coefficient of determination, R^2, indicates the goodness of fit of the model. This is also called as the proportion of variation explained by the regressor x. R^2 value varies between 0 and 1.

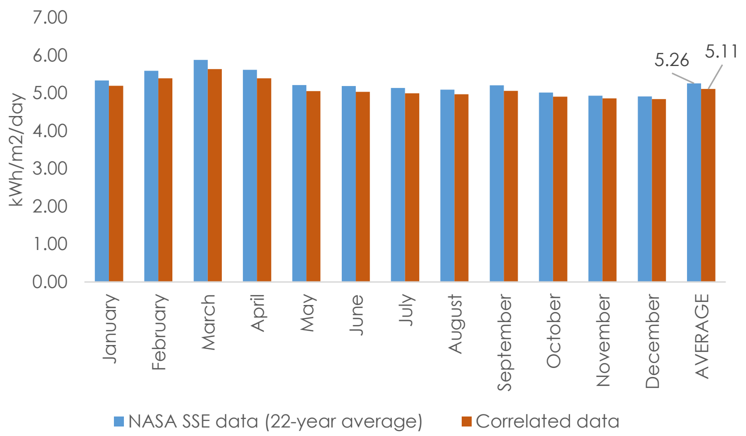
The values of β_0 and β_1 were determined from the simple linear regression of the short-term target site measurements (TSB site) against the reference data (NASA SSE). The derived coefficients are the following: β_0 = 0.7259 and β_1 = 0.8336.

The reference data are then used in the regression equation to predict the historical climate at the TSB site. Both strengths of the two data sets are being captured and that the uncertainty of the long-term irradiation estimate is being reduced.

Results of the analysis also confirm the findings of Rogers et al. (2005) that when using linear regression, the predicted mean irradiation at the target site will be close to the value of the measured mean. In this case, the predicted mean of correlated data and measured data have the same value at 5.1 kWh/m^2.

Figure 10.2 shows both the NASA SSE and predicted solar irradiation data. The data shown are for the incident global radiation on the collector plane with a tilt angle of 5° since solar PV modules at TSB site are inclined at an angle corresponding to the site's latitude. The satellite data is 2.8% higher than the correlated data.

Figure 10.2: Average Daily Incident Global Irradiation at 5° Inclined Plane



kWh= kilowatt hour; NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy.
Source: Prepared by the author.

2.3. Solar resource uncertainty and measurement uncertainty

Solar resource uncertainty comprises the following four main components (with uncertainty value ranges shown in the parenthesis): (i) spatial variability (0%–1%), (ii) representativeness of monitoring (0.5%–2%), (iii) inter-annual variability (2%–5%), and iv) measurement uncertainty (2%–15%) (Schnitzer et al., 2012). The focus of this study is the measurement uncertainty which represents the highest source of solar resource uncertainty. Modelled data have measurement uncertainties ranging from 8%–15% while on-site measurement have uncertainty range between 2% and 7% (Schnitzer et al., 2012; Vignola et al., 2013; Myers, 2009; Remund and Mueller, 2012).

On-site data have lower measurement uncertainty since they depend mainly on the quality and the frequency of on-site maintenance, while for modelled data, the uncertainty stems from the limitations of the computer-intensive radiative transfer models particularly during cloudy or partially cloudy periods (Schnitzer et al., 2012; Vignola et al., 2013).

Based on Myers (2009), the NASA SSE data has a measurement uncertainty of ±15% in global horizontal irradiation and ±20% in direct beam data. As mentioned earlier, the uncertainty for ground measurements is influenced by the quality and calibration of the pyranometer as well as the frequency of the field maintenance. The application of best practices in on-site measurement would help in reducing uncertainty in the measurements. Following Vignola et al. (2013) and Thuman et al. (2012), the measurement uncertainty for the validated GHI data used in this study is ±5%.

Table 10.1: Solar Resource Uncertainty

Uncertainty	NASA SSE	Correlated Data
Spatial variability*	0.50	0.50
Representativeness of monitoring period*	1.25	1.25
Inter-annual variability*	3.50	3.50
Measurement uncertainty**	15.00	5.00
TOTAL	15.46	6.25

NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy.
Notes: * Taken as mean value from Schnitzer et al. (2012).
Sources: Myers (2009) for NASA SSE data and Vignola et al. (2012).

To determine the impact of using a highly accurate data set, only the measurement uncertainties were changed in the two cases analysed in this study. The average values of the three other sources of uncertainties were used in the analysis and that these values were unchanged in both cases. The solar resource uncertainty for each case is taken as the sum of individual uncertainty components. The total estimated solar resource uncertainty for satellite-based irradiation data is 15.5% while that of correlated data is 6.3% (Table 10.1).

To calculate the total uncertainty, all single uncertainties were considered to be stochastically independent. The approach to estimate the joint uncertainty of independent (un-correlated) uncertainties is to calculate the root-mean-square value. Single uncertainties of the energy level are merged by the root-mean-square function (Abel et al., 2000).

2.4. Estimating energy production

2.4.1. Energy production modelling tools

The energy production of the 27 MWp TSB solar PV expansion plant was estimated for both two cases discussed above using a solar PV production modelling tool. Based on the review and assessment by Yates and Hibberd (2010), Cameron et al. (2008) and Klise and Stein (2009), solar PV production modelling tools available in the market could be broadly characterised to comprise two main algorithms: the first determines the amount of sunlight that falls on the array, and the second estimates the amount of electricity that could be produced with that given sunlight.

The first algorithm consist of modules that contain site-specific meteorological data, translate the radiation into inclined surfaces (radiation models), take into account the shading effect of distant objects, obstructions, and the system itself, and factor in the decrease of the amount of sunlight due to soiling. The second algorithm includes modules that predict the power output of different PV technologies (PV performance models), discount the losses in direct current (DC) production and in the conversion of DC power into alternating current (AC), and take into account the performance of inverters. Solar PV production software packages used by industry stakeholders vary in model system complexity. Some models have simplified assumptions related to system components and ratings while complex models consider manufacturer parameters, derived parameters, and empirically derived data (Klise and Stein, 2009; Yates and Hibberd, 2010; Cameron et al., 2008).

Yates and Hibberd (2010), in their comparative performance assessment of the main models currently used by researchers, integrators, and project developers in North America, conclude that the radiation model components of the evaluated tools perform consistently and predicting similar plane-of-array irradiance from the same weather data. In terms of overall energy production, the difference between the estimates of the most aggressive and the most conservative modelling tool is 9%. The software packages evaluated were PV Watts, Solar Advisor Model, PV-Design Pro, PV*SOL, and PVsyst.

The study used the PVsyst software in simulating the energy production of the two cases of data sets. The software is one of the most powerful and accurate tools in PV or solar cell production. The model allows a very detailed definition of the PV plant, including special geometries, as near shading objects or tracking systems and permits monthly variations of soiling, which accurately reflect real world conditions (Yates and Hibberd, 2010; www.pvsyst.com). The software package also contains a huge database of technical and electrical properties of the most common PV components (modules and inverters) available in the market.

In estimating the solar PV power plant energy production, the study used a typical polycrystalline solar PV modules and inverter models available in the market. Key model input parameters are shown in Table A1 of the appendix. In the model, DC electricity is generated from PV modules and converted into AC electricity through central inverters.

In the simulation process, PV arrays are fixed to face south and inclined at 5°, which corresponds to the project location's latitude (NREL, 1990). Several methodologies exist in translating the horizontal radiation into plane-of-array irradiance. Among these models, the Perez et al. (1990) model was considered to be the most complex and most accurate

(Cameron et al., 2008; Yates and Hibberd, 2010; McMahan et al., 2013). The PVsyst model employs the methodology of Perez et al. in its solar irradiation module.

The PVsyst simulation model endogenously estimates the technical losses of the system based on the technical parameters specified in the case study. In addition to this, the study exogenously estimated the loss in production due to PV module degradation and plant availability. Annual degradation of 1% was used in the study following IRENA (2012) and DBRS (2014) and an average of 98% availability based mainly on average inverter manufacturers' guarantees.

2.4.2. Uncertainty in energy production

Electricity production estimate using satellite-derived irradiation data set has higher uncertainty than that of using ground-correlated data set. As discussed in the previous section, this is due to higher solar data uncertainty of the former compared with the latter. In addition to solar resource uncertainty, there exist other sources of uncertainty in the calculation of energy production, and these include the following (with the uncertainty value range shown in the parenthesis): (i) energy simulation and plant losses (3%–5%), (ii) transposition to plane of array (0.5%–2%), and (iii) annual degradation (0.5%–1%) (Schnitzer et al., 2012).

Table 10.2: Solar PV Energy Production Uncertainty

Uncertainty	NASA SSE	Correlated Data
Annual degradation*	0.75	0.75
Transposition to plane of array*	1.25	1.25
Energy simulation, plant losses*	4.00	4.00
Solar resource uncertainty**	15.46	6.25
TOTAL	16.04	7.56

NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy; PV = photovoltaic.
Notes: * Taken as mean value from Schnitzer et al. (2012).
Sources: ** Derived from Table 10.1.

In estimating the total energy production uncertainty, the study used the mean values of each of the above uncertainties. Also, since the focus of the study is on solar resource uncertainty (specifically measurement uncertainty), the same uncertainty values were used for both production estimates using satellite- and ground-correlated data sets. These were combined with the solar resource uncertainty estimated earlier for both sets of irradiation data. The total uncertainty of the electricity production using satellite-derived solar irradiation data set is 16% while that of ground- correlated data set is 7.6% (Table 10.2).

2.5. Debt structuring

2.5.1. Project risks and probability of exceedance

The uncertainty in energy production estimates translates to energy risk for the 27 MWp TSB expansion project. There is the risk that the expected production, hence project revenues, will not be achieved in actual condition. Project financial stakeholders rely on the probability of exceedance analysis to characterise and quantify risks related to energy production and, ultimately, revenues of solar PV projects (McMahan et al., 2013; Dobos et al., 2012). The exceedance probability is the likelihood of attaining or exceeding an energy production value.

Project lenders and credit rating agencies often require project developers to estimate the P50, P90, and even P99 of annual electricity generation of a given project. If a P50 annual generation value of a solar power plant is 10 megawatt-hours (MWh), this means that there is a 50% likelihood that the generation would be greater than 10 MWh. Similarly, a P90 value of 10 MWh would mean that the power plant would generate more than 10 MWh 90% of the time.

In estimating the probability of exceedance, the uncertainties related to solar resource measurement and other uncertainties related to energy production (uncertainties described in previous sections) characterise the source of statistical variations. Following Dobos et al. (2012) and McMahan et al. (2013), the normal distribution (Gaussian distribution) and the cumulative distribution function were constructed based on the mean annual yield and standard deviation (uncertainty values). The P90 or P99 values were calculated from the distribution's cumulative distribution function.[38]

[38] Following function (Dobos et al., 2012), cumulative distribution function is defined by the following function:

$$\Phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{2}[1 + \operatorname{erf}\left(\frac{x-\mu}{\sigma}\frac{1}{\sqrt{2}}\right)]$$

The value of P90 occurs when $\Phi\left(\left(\frac{x-\mu}{\sigma}\right)\right) = 0.1$. Setting $\gamma = (\frac{x-\mu}{\sigma})$, the following equation can be solved numerically.

$$\Phi(\gamma) = 0.1 \rightarrow \gamma = 1.282 = \frac{x-\mu}{\sigma}$$

Rearranging, this gives an expression for P90 value given the mean (μ) and standard deviation (σ) of the data set that is assumed to fit a normal distribution.

$$x = \mu - 1.282$$

2.5.2. Debt sizing

Lenders, particularly those involved in project finance or non-recourse financing, are conservative and would only provide an amount of debt that they are confident can be repaid from revenues generated by the project. To determine if borrowers can fulfil their financial obligations, banks rely on the DSCR measure (McMahan et al., 2013; Cleijne and Ruijgrok, 2004). DSCR is defined as the ratio of project cash flow (after all operating expenses are paid) to debt repayment during a given period. If the DSCR value is around 1, this means that the borrower would be able to meet its financial obligations. Banks, however, could require a higher DSCR if their perception of the project risk is high.

Credit rating agencies also employ similar risk analysis method to major debt lenders to characterise credit risk (McMahan et al., 2013; Schnitzer et al., 2012). Fitch ratings and DBRS, for example, require a DSCR of 1.3x for P90 performance level and 1.2x for P99 (DBRS, 2014; Joassin, 2012). In sizing project debt, the DSCR targets specified by credit ratings were adopted in the study.

To estimate the project DSCR, the study established a simple cash flow model for each of the case studies. The financial parameters used in the analysis are shown in the Table A2 of the Appendix.

2.5.3. Levelised cost of electricity

One of the indicators used in the comparative analysis is the levelised cost of electricity (LCOE). LCOE is defined as the net present value of the unit cost of electricity over the lifetime of a generating asset. The levelised cost is that value for which an equal-valued fixed revenue delivered over the life of the asset's generating profile would cause the project to break even. This can be roughly calculated as the net present value of all costs over the lifetime of the asset divided by the total electricity output of the asset (IEA/NEA, 2010; Short et al., 1995).[39] The weighted average cost of capital (WACC)[40] is

[39]Following IEA/NEA (2010), LCOE was estimated using the following equation:

$$LCOE = \frac{\sum_{n=0}^{N} \frac{C_n}{(1+d)^n}}{\sum_{n=1}^{N} \frac{Q_n}{(1+d)^n}}$$

Where: C_n stands for total costs, in the year n; Q_n stands for energy generation, in the year n; n stands for year; N stands for the project life; and d stands for the discount rate.

[40]WACC was calculated using the following relationship:

used as the discount rate in estimating the LCOE.

3. Results and discussions

3.1. Energy production

The two data sets described in Section 2.2 were used in the energy production analysis. Energy production from solar PV power plant is a function of solar irradiation. As expected, the NASA SSE data result had a higher energy production compared with that from ground-correlated data set. Given the same power plant configuration, the energy yield on the first year from the case with satellite data is 3.5 % higher than that using the ground-validated data set.

Associated with this higher energy yield are better performance indicators. As shown in Table 10.3, the case of NASA SSE has higher yield factor and performance ratios, for both first year of operation and for the 20-year average, compared with the correlated data set case. For both cases, the performance indicators for the 20-year average are lower since an annual module production degradation of 1% was considered in the analysis.

Table 10.3: Comparative Performance Results of the 27 MWp Solar PV Project

Output	Unit	NASA SSE Data	Correlated Data
Peak power	kW_p	27,000	27,000
Irradiation on horizontal plane	kWh/m^2	1,911	1,859
Irradiation on inclined plane	kWh/m^2	1,918	1,864
Plant availability	%	98	98
First Year Performance			
Energy yield (after inverter)	kWh/year	41,928	40,457
Overall yield factor	$kWh/kW_p/year$	1,553	1,498
Overall performance ratio	%	81.0	80.4
Average Performance (20 years)			
Energy yield per year (average for 20 years)	kWh/year	38,174	36,835
Total yield for 20 years	kWh	763,483	736,700
Overall yield factor	$kWh/kW_p/year$	1,414	1,364
Overall performance ratio	%	73.7	73.2

kWh = kilowatt-hour; kWp = kilowatt peak; m^2 = square meter; NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy.

Note: Yield factor (YF) refers to the plant's specific performance in net kWh delivered to the grid per kW of installed nominal PV module power. This is also equivalent to the number of full load hours for the plant. Performance ratio (PR) is defined as the actual amount of PV energy delivered to the grid in a given period,

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$$WACC = \left[\frac{E}{D+E}\right] \times R_e + [\frac{D}{D+E}] \times (1 - corporate\ tax) \times R_d$$

Where: E = equity share; D = debt share; Re = return on equity (after tax); and Rd = debt interest rate.

divided by the theoretical amount according to standard test conditions (STC) data of the modules.
Source: Prepared by the author.

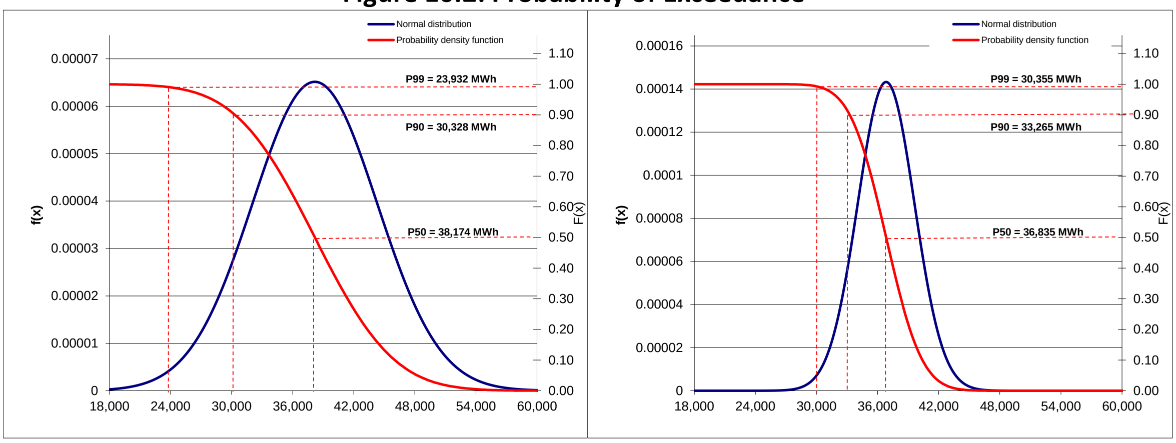
3.2. Uncertainty and project risks

While performance results from the simulation study using NASA SSE data set appear attractive and optimistic, bankers are cautious with these results since the key parameters in estimating the energy yield are fraught with higher uncertainty values. The overall energy production uncertainty for NASA SSE was estimated in the previous section to be 16.04% while that of ground-validated data was only 7.56%. These uncertainties are translated into project operational risks.

The probability of exceedance estimates the energy production values in relation to the given uncertainties. As shown in Figure 10.2, the probability distribution function of the case using ground-correlated data is slimmer compared with the case using NASA SSE data. This is mainly due to its lower value of statistical variation.

The energy production results presented in the previous section represent the expected value (the mean) or the P50 value. As shown in Figure 10.2, the NASA SSE case has higher P50 value than that of correlated data case. The situation appears to reverse when calculating energy production at higher confidence levels that are required by lenders. The ground-correlated case has higher production values for P90 and P99 than the satellite data case. For P90 and P99 values, the energy production with correlated data is 10% and 27% higher than those with NASA SSE data sets.

Figure 10.2: Probability of Exceedance



(A) NASA SSE Data **(B) Correlated Data**

NASA SSE = National Aeronautics and Space Administration Surface Meteorology and Solar Energy.
Source: Prepared by the author.

3.3. Impacts on debt financing

The study quantified the implications of the higher confidence values of energy production to debt financing. The project financial parameters, as mentioned earlier, are shown in Table A2 of the Appendix.

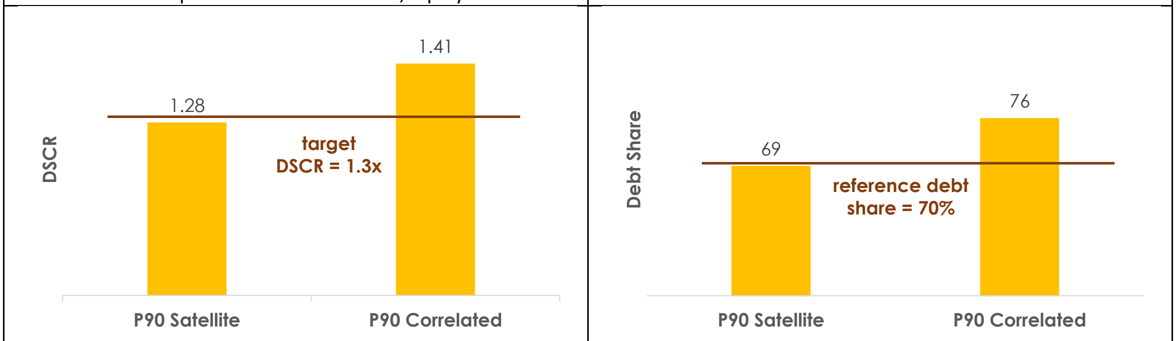
Taking reference from the criteria (target DSCR) used by banks and credit agencies, the DSCRs were estimated using the P90 and P99 energy production values. With constant capital structure of 70% debt and 30% equity, the P90 production value from satellite data results in a DSCR of 1.28x while that of correlated data resulted in a DSCR of 1.41x. The former is slightly below the 1.3x target by most financial institutions while the latter is comfortably higher than the target value. This is shown in (A) in Figure 10.3.

The study also analysed the effect on debt share to keeping the target of 1.3x DSCR constant (B in Figure 10.3). For the satellite data case, the debt share needs to be slightly reduced to meet the target DSCR. On the other hand, for the correlated data case, the debt share could be further improved from the reference share of 70% to 76%.

Improving (reducing) the share of debt also improves (degrades) the project's net present value (NPV), the equity NPV, and levelised cost of electricity. This can be seen by comparing the financial indicators shown in (A) and (B) in Figure 10.3. For the correlated data case, these improvements are attributed to the reduction of the WACC, which is used as the discount rate in the analysis. Similarly, the slight decline in the financial indicators for satellite data case is due to the reduction of debt share and to the corresponding increase of the WACC.

Figure 10.3: P90 Values, Target DSCR, and Debt Capacity Improvement

(A) Constant capital structure: debt=70%, equity=30%	**(B)** Constant DSCR: 1.3x



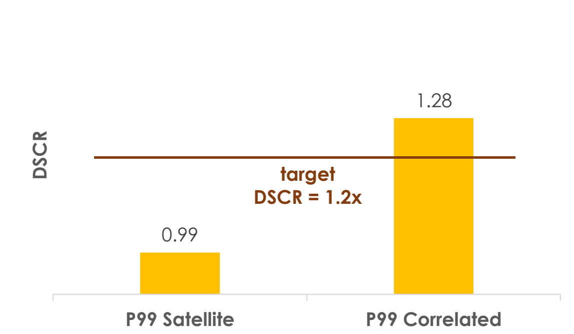
SATELLITE DATA	**CORRELATED DATA**	**SATELLITE DATA**	**CORRELATED DATA**
Project NPV = $7,650 Equity NPV = $657 Levelised cost = $0.2052/kWh	Project NPV = $13,561 Equity NPV = 4,773 Levelised cost = $0.1870/kWh	Project NPV = $7,418 Equity NPV = $557 Levelised cost = $0.2059/kWh	Project NPV = $15,157 Equity NPV = 5,371 Levelised cost = $0.1829/kWh

DSCR = debt-service coverage ratio; kWh = kilowatt-hour; NPV = net present value.
Source: Prepared by the author.

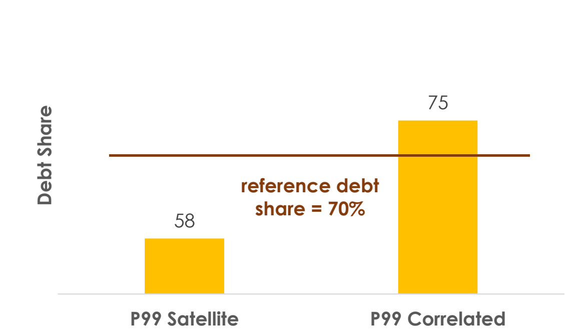
A similar stress test was carried out for P99 values with a target DSCR of 1.2x. The results indicate that the project case with satellite data fails to achieve the target DSCR. In addition, the calculation also shows that the project is not financially viable with key indicators showing negative project NPV and equity NPV. On the other hand, the DSCR value for the project case with correlated data is comfortably above the target limit while its financial indicators are positive. This is shown in (A) of Figure 10.4.

Figure 10.4: P99 Values, Target DSCR, and Debt Capacity Improvement

(A)
Constant capital structure: debt=70%, equity=30%



(B)
Constant DSCR: 1.2x



SATELLITE DATA	CORRELATED DATA	SATELLITE DATA	CORRELATED DATA
NPV = ($5,219) Equity NPV = ($8,308) Levelised cost = $0.2600/kWh	NPV = $7,705 Equity NPV = $695 Levelised cost = $0.2050/kWh	NPV = ($7,187) Equity NPV = ($9,504) Levelised cost = $0.2717/kWh	NPV = $8,890 Equity NPV = $1,193 Levelised cost = $0.2012/kWh

DSCR = debt-service coverage ratio; kWh = kilowatt-hour; NPV = net present value.
Source: Prepared by the author.

With DSCR value fixed at 1.2x, the debt share of the project using satellite data needs to be reduced to 58% (from a reference share of 70%) in order to achieve the target. In contrast, the project utilising the correlated data could be further increased to 75% as shown in (B) of Figure 10.4. The satellite data case results in higher WACC while the correlated data case generates a lower WACC value. This explains the slight increase and decrease of the levelised cost of energy for the project case with satellite data and the project case with correlated data. This can be observed by comparing (A) and (B) of Figure 10.4.

4. Conclusion and policy implications

The study has carried out a comparative analysis between a project using satellite-derived irradiation data (NASA SSE) and that using a bankable correlated data set, and their implications related to debt financing. The study results can be summarised as follows:

- Solar resource uncertainty of bankable correlated data set is relatively low and represents around 40% of NASA SSE data set uncertainty.
- The project using NASA SSE data set tends to overestimate energy production at P50 confidence level. On the other hand, energy production at higher confidence levels (P90 and P99) for the project using correlated data set is higher than those using satellite data.
- At constant capital structure, the project with satellite data set has DSCRs below the stress test targets of 1.3x for P90 and 1.2x for P99 production values. Conversely, the project using correlated data set has DSCR values higher than the reference DSCRs.
- To achieve the target minimum DSCR values, the debt share of the project that use correlated data set could be further increased by around 7% for both productions at confidence levels of P90 and P99. This results in a lower WACC, higher project NPV, and lower LCOE.
- The converse could be observed in the project using NASA SSE data set. At P90 confidence level, the debt share needs to be reduced by more than 1% while for P99, the share should be lowered down by 17%. In both production confidence levels, NPV values are negative, and the WACC as well as the LCOE are high.

The study shows that with a bankable solar data set, the overall project risks are reduced, project leverage is increased, and financial competitiveness of the solar PV project is enhanced. The availability of bankable solar irradiation data set reduces financial risks and eventually contributes to the rapid deployment of renewable energy technologies with overall benefits accruing to the society in general.

Governments of developing countries, in addition to introducing policy and regulatory frameworks (such as feed-in tariff, net metering, renewable portfolio standards, and tradable energy certificates) that promote and address economic barriers to renewable energy deployment, must also introduce support mechanisms that address the lack of bankable data and resource information. This could take in the form of (i) incentives or technical support to private sector activities related to resource measurements, or (ii) direct intervention by undertaking renewable energy resource measurements and making the information available to all project stakeholders.

Agencies responsible for renewable energy development could also support financing institutions in the form of awareness-raising activities and capacity building related to resource measurements, type of resource data used in project analysis, and risk analysis to increase their knowledge and understanding of the specific characteristics of renewable energy projects.

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Appendix

Table A1: Solar PV Power Plant Technical Parameters

Module Orientation	
Module inclination	5°
Azimuth	0°
Module-Inverter Configuration	
Installed module capacity	27,000 kW_p
Module type	Polycrystalline silicon
Number of modules	10,800
Nominal capacity of modules	250 W_p
Number of modules per string	18
Number of strings in parallel	6000
Inverter capacity	500 kW AC
Number of inverters	49
Installed inverter capacity	24,500 kW AC

kW_p = kilowatt peak; AC = alternating current.
Source: Prepared by the author.

Table A2: Cost and Financial Parameters

Cost Parameters Capital cost: US$2 million/MW Operating cost: 1% of capital cost	**Fiscal Parameters** Corporate tax rate: 18% Income tax holiday: 10 years Depreciation period: 20 years
Financing Parameters Debt share: 70% Interest rate: 8% Grace period: 2 years Loan term including grace period: 15 years Return on equity: 12%	**Others** Project useful life: 20 years Construction period: 1.5 years Feed-in tariff: $0.23 per kWh

kWh = kilowatt-hour; MW = megawatt.
Source: Prepared by the author.