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Analytical approach to quantitative risk assessment for solar power projects

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A B S T R A C T

Quantifying the economic risk associated with a solar power project is essential in order to secure financing. Quantitative risk assessment is often conducted by rerunning a model to calculate economic viability measures, including Internal Rate of Return (IRR) and Levelized Cost of Electricity (LCOE), for ranges of values of uncertain input parameters that determine capital cost, operating cost, energy yield and revenue. This paper provides an analytical approach that avoids this repetitive recalculation. The analytical approach is based on differentiating the economic viability measures with respect to the input parameters of interest. Using 20% changes in parameter values, the analytical approach is shown to agree within 0.875% for a behind-the-meter project. For an off-grid utility scale project the analytical approach is exact for five cost and energy yield parameters and agrees within 0.01% for degradation rate and 0.14% for discount rate. Moreover, the analytical approach is extended to provide differential importance measures that indicate which parameters are contributing most/least to the riskiness of the project. Results indicate that the ranking of parameters is identical for IRR and LCOE despite these being very different measures of economic viability, thus further supporting the analytical method provided in this paper.

1. Introduction

In order to attract investment to a solar project, risk assessment is essential, and there are many standards for mitigating and assessing risk, from the IEC system for renewable energy certification [1], which covers engineering aspects, through green/climate bonds certified by organizations such as the Climate Bonds Initiative [2], and Sustainalytics [3], to the rating of financial instruments by rating agencies such as Moodys [4], which covers business aspects. Equipment warranties and surety bonds can be used to reduce the risk of individual solar projects, and multiple projects can be securitized into a financial instrument suited to the needs of institutional investors.

Assessing the risks involved in individual solar projects is the basis of this standardization, certification and rating, and includes both qualitative and quantitative factors. Qualitative factors include equipment reliability, the quality of equipment warranties, and the possibility of future changes in electricity demand and government regulations. This paper focuses on quantitative factors including, solar and battery capital and operating costs, solar module degradation rate, trends in electricity prices and the discount rate.

Economic viability of solar projects is measured by Net Present Value (NPV), Internal Rate of Return (IRR) and Levelized Cost of Electricity (LCOE) and conventional risk assessment estimates the change in these measures due to variations in input parameters. For instance Ref. [5], calculates the change in IRR due to ±30% variation in system cost [6], gives the change in LCOE due to ±10% variation in systems cost and operating cost [7], assesses the change in IRR due to the timing of government incentives [8], estimates the change in IRR due to a 20% change in operations costs [9], estimates the change in LCOE due to a 20% change in operations costs, and [10] calculates the change in NPV due to ±30% variations in capital cost and discount rate. The impact of these changes in input parameters is obtained by rerunning the model for the corresponding range of parameter values.

There is also uncertainty due to the variability in the solar resource itself, and work in this area has quantified the probabilities of exceeding certain annual irradiance levels, see for example [11]. However, a Monte Carlo analysis in Ref. [12] has shown that the impact of variations in irradiance levels on IRR is negligible: a 13.8% coefficient of variation (CoV) in solar irradiance results in only 0.7% CoV in IRR. Although solar irradiance is variable, over the 25–32 year life of a solar project the variations almost cancel each other out, with minimal impact on IRR. In this paper, we do not therefore deal with risk due to variability in irradiance.

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Abbreviations

BTM	Behind-the-Meter
DIM	Differential Importance Measure
IRR	Internal Rate of Return (%)
LCOE	Levelized Cost of Electricity ($/kWh)
NPV	Net Present Value ($)
O&M	Operations and Maintenance
SAM	System Advisor Model

Risk assessment is important in attracting investors, and in particular institutional investors, who will invest on the order of $100m in solar projects bundled into tradable securities, [13,14]. A second benefit is that once the risk is quantified, it becomes insurable, [15,16]. However [17], states that "models for investment in the power sector rarely provide an explicit treatment of risk. Often it is assumed that, given a hurdle discount rate for the cost of capital, NPV positive investments will happen; sometimes the hurdle rates are increased for project risk, but these tend to be ad hoc suggestions."

In the past, many solar projects operated under feed-in tariffs which guaranteed a price for electricity over the life of the project. With the phasing out of feed-in tariffs in many jurisdictions, uncertainty about trends in electricity prices constitutes an additional source of risk. Thus, risk assessment today is even more important than it was in the past.

This paper provides an analytical approach to quantitative risk assessment for solar power projects. Instead of rerunning the model to calculate NPV, IRR or LCOE repeatedly for varying values of input parameters as in Ref. [5–10], we derive analytical results that can be used instead. The paper validates this approach using empirical data from a behind-the-meter project in Section 2, and a utility scale project in Section 3. Sections 4 and 5 provide discussion of the results and conclusions.

2. Risk assessment for behind-the-meter solar projects

We first deal with behind-the-meter (BTM) projects in which solar power is generated on the site of an electricity customer; some of the electricity generated is used by that customer and the rest is fed into the grid. In many jurisdictions, BTM projects can use net metering under which the customer receives a credit on their electricity bill for power fed into the grid so long as over the course of a year the net consumption of power from the grid is positive. The financial analysis for BTM projects is based on the savings to the customer obtained from the reduction in their electricity bill. The financial analysis of off-grid projects is based on the cost of electricity generation and will be dealt with in Section 3.

The financial analysis of BTM projects can be based on NPV for which we need to know the discount rate. Alternatively, it can be based on IRR which is the discount rate at which NPV = 0. Each customer has their own discount rate, resulting in different NPVs, and therefore our analysis uses IRR so as to be generally applicable.

We consider the case of a commercial customer subject to (i) electricity charges per kWh of electricity consumed and (ii) demand charges based on the usage (in kWh) during the peak hour each month. The annual savings from using BTM solar in year zero is:

$$S_0 = S_0^E + S_0^D \tag{1}$$

where S_0^E are the savings from reduced electricity charges and S_0^D are the savings from reduced demand charges. These savings are obtained by running an optimization model to determine the optimal battery size and the optimum schedule of power flow into and out of the battery, e.g. Ref. [18,19].

In year t, the savings are:

$$S_t = S_0(1+e)^t\,(1-d)^t \tag{2}$$

where e is the rate of increase of future electricity prices and d is the degradation rate of the solar modules. A major source of risk in solar projects is assumptions about future electricity prices. Although these can be estimated by extrapolating past trends, they are subject to considerable uncertainty due to both political and business factors. The degradation rate of solar modules is also uncertain, as recent estimates [20,21], differ from each other and are based on field measurements over periods of time shorter than the warranted life of today's solar modules of 32 years.

The outgoing cash flows consist of capital and operating costs. The capital costs are incurred in year zero and include the cost of the battery and solar installation $O_0 = C$. The operating costs O_t in year t are composed of the annual maintenance of the system (O^M each year), inverter and battery cell replacement (O^I in year 15) and end of life recycling costs (O^R in the final year, T, of the project). The capital and operating costs in year t are:

$$O_t = O_0 + O^M + O^I + O^R \tag{3}$$

In equation (3), O^M is present for all years, t, and O_0, O^I and O^R are only present when $t = 0$, 15 and T respectively. A more precise, but notationally more complex way of representing (3) is:

$$O_t = O_0\delta_{0,t} + O^M + O^I\delta_{15,t} + O^R\delta_{T,t} \tag{3'}$$

where. $\delta_{i,j} = 1$ when $i = j$, and $\delta_{i,j} = 0$ when $i \neq j$.

The IRR for the project can then be calculated as the discount rate at which the Net Present Value is equal to zero:

$$NPV = \sum_{t=0}^{T} \frac{S_t - O_t}{(1+IRR)^t} = 0 \tag{4}$$

In this paper, we quantify the risk of a BTM solar project as the change in the IRR resulting from a change in the input parameters. Instead of rerunning the model repeatedly for a range of parameter values, we estimate changes in IRR from the derivative of IRR with respect to each parameter, $x_i \in \{e, d, S_0^E, S_0^D, O_0, O^M, O^I, O^R\}$ as given in Table 1. These results are obtained by implicit differentiation of (4) using (1-3).

The change in IRR as a result of a change in a parameter x_i is estimated using the first order approximation:

Table 1
Derivatives of IRR with respect to each of its eight parameters.

i	x_i	$\frac{\partial IRR}{\partial x_i}$
1	e	$\frac{\sum_{t=0}^{T} t(S_0^E+S_0^D)(1+e)^{t-1}(1-d)^t(1+IRR)^{-t}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
2	d	$\frac{\sum_{t=0}^{T} t(S_0^E+S_0^D)(1+e)^{t}(1-d)^{t-1}(1+IRR)^{-t}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
3	S_0^E	$\frac{\sum_{t=0}^{T} (1+e)^{t}(1-d)^{t}(1+IRR)^{-t}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
4	S_0^D	$\frac{\sum_{t=0}^{T} (1+e)^{t}(1-d)^{t}(1+IRR)^{-t}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
5	O^I	$\frac{-(1+IRR)^{-15}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
6	O^R	$\frac{-(1+IRR)^{-32}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
7	O^M	$\frac{\sum_{t=0}^{T} (1+IRR)^{-t}}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$
8	O_0	$\frac{-1}{\sum_{t=0}^{T} t(S_t-O_t)[1+IRR]^{-t-1}}$

$$\delta_{IRR} = \frac{\partial IRR}{\partial x_i}\ \delta_{x_i} \tag{5}$$

where δ represents an incremental change in IRR or in one of the variables x_i, $i = 1, \ldots, 8$ given in Table 1. The change in IRR, δ_{IRR}, as a result of a change in a parameter, δ_{x_i}, is a measure of the risk associated with the uncertainty in the estimation of that parameter, x_i.

2.1. Validation

In the early stages of planning a solar project there is considerable uncertainty in the parameter values and this uncertainty declines as planning progresses. We therefore validate the analytical approach using ±20% changes in the parameter values as being representative of an intermediate stage in this process. Taking an actual BTM solar project [18], as an example, we now compare the change in IRR calculated from (5) with the change in IRR obtained from rerunning the model. The numerical values of the parameters and the impact of a 20% change in value on the IRR are given in Table 2. The derivatives of IRR given by the equations in Table 1 and the parameters in Table 2 are:

$$\frac{\partial IRR}{\partial O_0} = -4.635e-07;\ \frac{\partial IRR}{\partial O^M} = -6.668e-06;\ \frac{\partial IRR}{\partial O^I} = -1.812e-07;\ \frac{\partial IRR}{\partial O^R} = -6.248e-08$$

$$\frac{\partial IRR}{\partial e} = 1.1989;\ \frac{\partial IRR}{\partial d} = -1.2384;\ \frac{\partial IRR}{\partial S^E} = 8.639e-06;\ \frac{\partial IRR}{\partial S^D} = 8.639e-06$$

The largest discrepancy between the analytical approach and rerunning the model is for the capital cost, O_0. However, this applies only at the early stages of project planning. Once contracts are signed for equipment and installation, the capital cost is known and no longer contributes to risk. For the other parameters in Table 2, we first calculate the proportional differences between the analytical approach and rerunning the model (e.g. for the parameter *e*: 0.006664/0.006721 – 1) for the first 7 parameters. The average absolute value of these proportional differences is 0.875%. It can be seen that there is very good agreement between (5) and rerunning the model, thus validating the analytical approach consisting of (5) and the derivatives in Table 1.

2.2. Differential importance measure

The estimation of risk from (5) is the first application of differentiating IRR with respect to the parameters determining the economic viability of a solar project. We refer to the second application as the differential importance measure (DIM), which was introduced in Ref. [22] and applied to discounted cash flow analysis in Ref. [23]. In terms of our example in Section 2.1, DIM measures the risk, in terms of a change in IRR, due to a change in one of the parameters listed in Table 1 compared to the change in IRR due to a simultaneous change in all parameters. It can be used to rank parameters from those causing more risk to those causing less risk.

To define DIM in general, consider a function $f(\mathbf{x})$ differentiable at $\mathbf{x}^0 = (x_1^0, x_2^0, \ldots, x_n^0)$. The DIM for the parameter x_i is defined as:

$$DIM_i(\mathbf{x}^0,\ \delta\mathbf{x}) = \frac{f_i(\mathbf{x}^0)\ \ \delta_{x_i}}{\sum_{j=1}^n f_j(\mathbf{x}^0)\ \ \delta_{x_j}} \tag{6}$$

where $f_i(\mathbf{x}^0)$ is the partial derivative of f with respect to x_i at its base value $\mathbf{x}^0$, and δ_{x_i} represents a change in x_i, similar to that in (5). $DIM_i(\mathbf{x}^0,\ \delta\mathbf{x})$ measures the importance of each individual parameter x_i as the change in f due to a change of magnitude δ_{x_i} in x_i as a proportion of the change in f due to simultaneous changes δ_{x_j} in all the parameters x_j.

From this definition, it can be seen that DIM is additive, [22]. The risk due to changes in a subset of parameters is obtained by adding the DIMs for the individual parameters.

If all the δ_{x_i} are equal to each other, (6) simplifies, but in our case, the parameters (listed in Table 1) have different units and are of very different orders of magnitude, so we work in terms of proportional changes. We adapt DIM to measure the parameter importance when the parameters are changed by the same proportion of their nominal value: $\delta_{x_j}/x_j^0 = \delta_{x_i}/x_i^0 \quad \forall j$, in which case DIM becomes:

$$DIM_i(\mathbf{x}^0) = \frac{f_i(\mathbf{x}^0)x_i^0}{\sum_{j=1}^n f_j(\mathbf{x}^0)x_j^0} \tag{7}$$

In this case, $DIM_s(\mathbf{x}^0)$ is directly linked to the elasticity of the function f with respect to x_i:

$$E_i(\mathbf{x}^0) = \frac{f_i(\mathbf{x}^0)x_i^0}{f(\mathbf{x}^0)} \tag{8}$$

with:

$$DIM_i(\mathbf{x}^0) = \frac{E_i(\mathbf{x}^0)}{\sum_{j=1}^n E_j(\mathbf{x}^0)} \tag{9}$$

$DIM_i(\mathbf{x}^0)$ is equivalent to the ratio of the elasticity of f with respect to x_i divided by the sum of the elasticities with respect to all parameters.

We now take $f(\mathbf{x}^0)$ to be $IRR(e, d, S_0^E, S_0^D, O_0, O^M, O^I, O^R)$ given implicitly by (4). We calculate the DIM with respect to its parameters using (7) or (9) with the partial derivatives given in Table 1. The results are given in Table 3, together with a ranking indicating how sensitive IRR is to the same proportional change in each of its parameters. An advantage of using DIM is that, whereas the changes in IRR given in Table 2 were for a specific proportional change in parameter values (20%), the DIM values in Table 3 apply to any proportional change in parameter values, so long as it is the same proportion for each parameter.

The additivity property of DIM noted above allows it to be used to assess the importance of subsets of parameters, e.g. total savings: $S^E + S^D$ or total operating costs: $O^I + O^R + O^M$. The DIM for these combinations of parameters can be obtained by adding the individual DIMs. Thus, the DIM for total savings is 3.65 (higher than the DIM for capital costs) and the DIM for total operating costs is −0.48.

Table 2
Impact on IRR of a ±20% change in parameter base values, giving the results of the analytical approach, re-running the model and the proportional difference between these alternative approaches.

Parameter	Base value	Minus 20%			Plus 20%		
		Analytical Approach	Re-running the model	Proportional Difference	Analytical Approach	Re-running the model	Proportional Difference
e	2.78%	0.006664	0.006721	0.839%	−0.006664	−0.006614	0.758%
d	0.50%	−0.001238	−0.001237	0.144%	0.001238	0.001240	0.147%
S^E	$9,046.69	0.015630	0.016288	4.037%	−0.015630	−0.015150	3.170%
S^D	$2,404.82	0.004155	0.004196	0.978%	−0.004155	−0.004117	0.917%
O^I	$9,406.04	−0.000341	−0.000340	0.151%	0.000341	0.000341	0.151%
O^R	$14,082.00	−0.000176	−0.000175	0.346%	0.000176	0.000177	0.348%
O^M	$1,597.76	−0.002131	−0.002128	0.126%	0.002131	0.002134	0.136%
O_0	$184,884.19	−0.017137	−0.020575	16.707%	0.017137	0.014814	15.687%
IRR	6.46%						

Table 3
Differential importance measure indicating the sensitivity of IRR to the same proportional change in each of its parameters.

Parameters x_i	Base value x_i^0	Differential importance measure $DIM_i^{IRR}(\mathbf{x}^0)$	Rank
e	2.78%	1.23	3
d	0.5%	−0.23	6
S^E	$9,046.69	2.88	2
S^D	$2,404.82	0.77	4
O^I	$9,406.04	−0.06	7
O^R	$14,082.00	−0.03	8
O^M	$1,597.76	−0.39	5
O_0	$184,884.19	−3.16	1

It is important to note that the ranking in Table 3 applies to any proportional change in parameters, but only when the proportional change is the same for all parameters. In practice, the proportional changes in parameters for a solar project may not be the same, and depend on the individual project. For instance the capital cost, O_0 has the highest DIM in Table 3 and is indeed very uncertain at the planning stage. However, once a contract has been signed for the supply and installation of the solar modules and battery, this cost is known and no longer contributes to the risk of the project. Assessing realistic ranges of uncertainty of individual parameters is not straightforward. For instance, operations and maintenance (O&M) costs have been discussed recently in Ref. [24], and we note that much O&M data is dated since it needs to be collected over several years. The conclusion in Ref. [24] is that 0.5% of capital costs is a realistic estimate of annual O&M costs for large systems and 1% is realistic for small systems, similar to our figure of 0.86% $= O^M/O_0$. However [24], does not suggest a range representing the uncertainty in these figures.

A practitioner, dealing with a specific project, and having their own estimates of ranges of uncertainty for individual parameters, may prefer to use those ranges in (6). Equations (7) and (9) and the ranking in Table 3 are suitable when ranges of uncertainty in individual parameters are not known and when it is reasonable to investigate, instead, the effect of the same proportional change in each parameter.

3. Risk assessment for utility scale and off-grid solar projects

The IRR is a natural measure of the economic viability of behind-the-meter solar projects, since it weighs the capital and operating costs against the financial savings from the project. In the case of utility scale projects and off-grid projects, the utility and the off-grid user are more interested in the lowest cost source for electricity generation, and the issue of savings or revenues to offset those costs does not arise. In these cases, the measure adopted in the industry to evaluate cost is the LCOE[2] given by the sum of discounted costs over the lifetime of the project divided by the sum of the discounted electrical energy produced over the lifetime:

$$LCOE = \frac{\sum_{t=0}^{T} \frac{O_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_t}{(1+r)^t}} = \frac{\sum_{t=0}^{T} \frac{O_t}{(1+r)^t}}{\sum_{t=0}^{T} \frac{E_0(1-d)^t}{(1+r)^t}} = \frac{\sum_{t=0}^{T} \frac{O_t}{(1+r)^t}}{E_0 \sum_{t=0}^{T} k^t} = \frac{1-k}{E_0\left(1-k^{T+1}\right)} \sum_{t=0}^{T} \frac{O_t}{(1+r)^t} \tag{10}$$

where r is the discount rate, d is the degradation rate of the solar modules, O_t is the operation cost equation in (3), E_0 is the electricity produced in year zero and the electricity produced in year t is:

$$E_t = E_0(1-d)^t \tag{11}$$

and

$$k = \frac{1-d}{1+r} \tag{12}$$

Using (3), the derivatives of LCOE with respect to its parameters are given in Table 4:

From (10), LCOE is linear in O_t so that, when its first derivative, (16), is used in (5) we obtain an exact estimate of the sensitivity of LCOE to changes in O_t. However (13), (14) and (15) provide only first order approximations, since LCOE is non-linear in the corresponding parameters. We now assess the accuracy of these approximations.

3.1. Validation

We assess the accuracy of the analytical approach to risk assessment for LCOE, using an example of an off-grid solar project in Yanbu, Saudi Arabia modeled using the commercial software package, HOMER [25], as reported in Ref. [26]. The parameters relevant to the risk analysis are given in Table 5 and a complete parameter listing is given in Refs. [26]. This project has a shorter time horizon (25 years) than the project used in Section 2.1 and the inverter and battery cell replacement is done in year 14.

Using the parameters in Table 5, the derivatives of LCOE given by (13) – (16) are:

[2] The profitability of utility scale solar projects developed by an independent electricity generator and paid by the utility under a Power Purchasing Agreement (PPA) would be evaluated using IRR since, in this case, there is a revenue stream against which to offset the costs, see Section 2.

Table 4
Derivatives of LCOE with respect to each of its seven parameters.

i	x_i	$\frac{\partial LCOE}{\partial x_i}$	Equn #
1	r	$\frac{1-k}{E_0\left(1-k^{T+1}\right)}\sum_{t=0}^{T}\frac{-tO_t}{(1+r)^{t+1}}+\left[\frac{k}{E_0(1+r)\left(1-k^{T+1}\right)}\right]\left[1-\frac{(T+1)(1-k)k^T}{1-k^{T+1}}\right]\sum_{t=0}^{T}\frac{O_t}{(1+r)^t}$	(13)
2	d	$\frac{1}{E_0}\frac{1}{(1+r)\left(1-k^{T+1}\right)}\left[1-\frac{(1-k)(T+1)k^T}{1-k^{T+1}}\right]\sum_{t=0}^{T}\frac{O_t}{(1+r)^t}$	(14)
3	E_0	$-\frac{1-k}{E_0^2\left(1-k^{T+1}\right)}\sum_{t=0}^{T}\frac{O_t}{(1+r)^t}$	(15)
4	O^I	$\frac{1-k}{E_0\left(1-k^{T+1}\right)}\frac{1}{(1+r)^{14}}$	(16a)
5	O^R	$\frac{1-k}{E_0\left(1-k^{T+1}\right)}\frac{1}{(1+r)^{25}}$	(16b)
6	O^M	$\frac{1-k}{E_0\left(1-k^{T+1}\right)}\sum_{t=0}^{T}\frac{1}{(1+r)^t}=\frac{1-k}{E_0\left(1-k^{T+1}\right)}\frac{\left(1-q^{T+1}\right)}{1-q}$ where $q=\frac{1}{1+r}$	(16c)
7	O_0	$\frac{1-k}{E_0\left(1-k^{T+1}\right)}$	(16d)

$$\frac{\partial LCOE}{\partial O_0}=0.004311;\quad \frac{\partial LCOE}{\partial O^M}=0.05033;\quad \frac{\partial LCOE}{\partial O^I}=0.001468;\quad \frac{\partial LCOE}{\partial O^R}=0.0006295; \tag{17a}$$

$$\frac{\partial LCOE}{\partial d}=0.9764;\quad \frac{\partial LCOE}{\partial r}=0.7595;\quad \frac{\partial LCOE}{\partial E_0}=-0.005664 \tag{17b}$$

A comparison of risk assessment using our analytical approach with the results of re-running the model are given in Table 6 for 20% changes in the corresponding parameters. It can be seen that the results of the analytical approach are almost identical to those obtained by re-running the model. As noted above, the derivatives of LCOE with respect to O_t give exact results when used in (5), since LCOE is linear in O_t.

Table 6 shows a slight discrepancy in $\partial LCOE/\partial E_0$ when it is estimated from (15), since $LCOE$ involves the inverse of E_0. If we use the analytical approach to estimate $1/LCOE$, instead of estimating LCOE itself, then the dependence on E_0 becomes linear so that the analytical approach yields an exact result:

$$\frac{1}{LCOE}=\frac{E_0\left(1-k^{T+1}\right)}{(1-k)\sum_{t=0}^{T}\frac{O_t}{(1+r)^t}}$$
$$\frac{\partial}{\partial E_0}\frac{1}{LCOE}=\frac{\left(1-k^{T+1}\right)}{(1-k)\sum_{t=0}^{T}\frac{O_t}{(1+r)^t}} \tag{18}$$

These results demonstrate that the analytical approach to risk assessment yields exact results for changes in LCOE corresponding to changes in capital costs, operating costs and the electricity generated in the base year. For 20% changes in the degradation rate, d, the analytical approach is 0.01% different from the result of re-running the model. For 20% changes in the discount rate, r, the analytical approach is 0.088%–0.144% different from the result of re-running the model. In summary, the analytical approach based on first derivatives gives very accurate results and avoids the necessity of re-running the model multiple times.

3.2. Differential importance measure

We calculate the DIM for $LCOE(O_0, O^M, O^I, O^R, d, r, E_0)$ with respect to its parameters using (7) or (9) with the partial derivatives given in (17). The results are given in Table 7, together with a ranking indicating how sensitive IRR is to the same proportional change in each of its parameters.

The ranking of parameters for LCOE in Table 7 is similar to that for IRR in Table 3. The only difference is the parameters ranked first and second. The BTM project in Table 3 has two sources of dollar savings: electricity charges and demand charges, which contribute to the IRR, whereas the LCOE analysis in Table 7 is based on the amount of electricity generated, E_0. When the DIMs for the two sources of savings in Table 3 are totaled (using the additivity property of DIM) then the ranking of parameter importance for IRR and LCOE becomes identical.

As with Table 3, we note that the ranking in Table 7 applies to any proportional change in parameters, but only if the proportional change is the same for each parameter. An analyst assessing the risk of a specific solar project may have their own ranges of uncertainty for each

Table 5
Parameters for an off-grid solar/battery project in Yanbu, Saudi Arabia.

Parameter	Units	Value
PV capacity	kW	17075
PV electricity (annual) in year 0, (E_0)	Million kWh per year	21.144
PV capital cost	$m	13.6
Battery capital cost	$m	8.49
Inverter capital cost	$m	2.06
Total capital cost, (O_0)	$m	24.15
Operating costs (annual), (O^M)	$m per year	0.24
Inverter and battery cell replacement in year 14, (O^I)	$m	2.64
Recycling revenue in year 25, (O^R)	$m	0.47
Degradation rate (per year), d	%	0.75
Discount rate, r	%	8.0
Time horizon, T	years	25
LCOE	$/kWh	0.1200

Table 6
Comparison of LCOE from the analytical approach with LCOE from re-running the model, for ±20% changes in model parameters for an off-grid solar/battery project. The base value of LCOE is $0.1200/kWh.

Parameter	Base value	Minus 20%			Plus 20%		
		Analytical Approach	Re-running the model	Proportional difference	Analytical Approach	Re-running the model	Proportional difference
O_0	$24.15m	0.09874	0.09874	0%	0.14080	0.14080	0%
O^M	$0.24m/yr	0.11735	0.11735	0%	0.12218	0.12218	0%
O^I	$2.64m	0.11892	0.11892	0%	0.12061	0.12061	0%
O^R	$0.47m	0.11980	0.11980	0%	0.11974	0.11974	0%
d	0.75%	0.11830	0.11831	0.01%	0.12123	0.12124	0.01%
r	8%	0.10762	0.10777	0.14%	0.13192	0.13204	0.09%
E_0 using (15)	21.14 GWh	0.14372	0.14971	4.00%	0.09581	0.09981	4.01%
E_0 using (18)	21.14 GWh	0.14971	0.14971	0%	0.09981	0.09981	0%
LCOE	$0.12/kWh						

Table 7
Differential importance measure indicating the sensitivity of LCOE to the same proportional change in each of its parameters.

Parameters x_i	Base value x_i^0	Differential importance measure $DIM_i^{LCOE}(\mathbf{x}^0)$	Rank
O_0	$24.15m	1.516	2
O^M	$0.24m	0.1759	4
O^I	$2.64m	0.05642	6
O^R	$0.47m	0.00431	7
D	0.75%	0.1066	5
R	8.0%	0.8848	3
E_0	21.144 GWh	−1.744	1

parameter, in which case DIM could be calculated from (6). In other cases, when the range of uncertainty is not known and it is reasonable to assume that the proportional changes are the same for each parameter, then (7), (9) and Table 7 would be appropriate.

4. Discussion

In Sections 2 and 3 of this paper, we have derived and validated an analytical approach to risk assessment for the economics of solar power projects. The impact of various model parameters on IRR is demonstrated in Section 2 for a behind-the-meter project under net-metering. In Section 3, the impact of similar parameters on the LCOE of an off-grid project is demonstrated. Under a feed in tariff or a power purchasing agreement, the approach would be the same as in Section 2, but with fewer parameters since those associated with uncertainty in future electricity prices would not be needed.

The analytical approach is based on a first order approximation using first partial derivatives of IRR and LCOE with respect to their parameters (given in Tables 1 and 4), resulting in a linear relation to changes in those parameters, (5). HOMER [27], also gives an example in which the impact of parameter variations on LCOE is linear. Ignoring second and higher derivatives is validated in Tables 2 and 6, which show that, for some parameters, a first order approximation is exact and the average accuracy for the other parameters is within 0.875% for IRR and 0.0595% for LCOE. The analytical approach proposed in (5) can also evaluate the effect of interactions among multiple parameters.

The benefit of the analytical approach compared to re-running the model is reduced processing requirements, which translates into improved response time for the user. This is particularly useful when a Monte Carlo simulation is required involving many values of a parameter following a given probability distribution. This paper has shown that the linear approximation of IRR and LCOE using first partial derivatives is accurate to within a fraction of a percentage point. The probability distributions of IRR and LCOE can therefore be obtained from linear transformations of the probability distribution of the parameter with minimal processing requirements.

The differential importance measure [22], is calculated from the first derivatives and is used to obtain a ranking of parameters to determine which are more/less important (i.e. have more/less impact on IRR and LCOE) when each parameter is varied by the same proportion. The differential importance measure is additive, which allows us to assess the importance of subsets of parameters. The ranking is very similar for IRR and LCOE, as shown in Tables 3 and 7 This finding supports the methodology based on first derivatives since IRR and LCOE are very different measures of economic viability and the analytical expressions for their first derivatives are also very different, see Tables 1 and 4. The differential importance measure has been applied in the past to discounted cash flow analysis [23], but the present paper presents its first application to the IRR of a solar project. The authors of the present paper have not been able to find any application of the differential importance measure to LCOE so this paper presents its first application in that area.

4.1. Commercial implementation of the analytical approach to risk assessment

Many solar project developers use commercial software to assess the economic viability of their project. The method described in the present paper could be implemented in this software. The internal details of such software are often confidential; however, the user guides imply that risk analysis is currently implemented by re-running the model:

- PVSyst [28], uses batch mode to run the model repeatedly with different parameter values.
- System Advisor Model, SAM [29], provides "parametric and stochastic modeling for analyses that investigate the impacts on model results of variations and uncertainty in assumptions" using "multiple simulations."
- HOMER [30], states "HOMER performs a separate optimization procedure for each specified value."
- REOpt [31], states "REopt can be used to run thousands of scenarios to evaluate the effects of varying specific inputs (e.g., technology costs, utility escalation rates, and other assumptions)."

The analytical approach proposed in the present paper could therefore be implemented in commercial software to speed up response time for the user and reduce processing requirements. The extent to which response time is improved depends on the software used and on the specifics of individual projects and is therefore beyond the scope of this paper.

4.2. Limitations and future work

The analytical method of risk assessment developed in this paper has been validated for the economic analysis of solar projects with respect to the parameters involved in that analysis: costs, savings, energy yield, degradation rate and discount rate. It is not proposed to use this method for the engineering analysis involved in optimizing the design of the solar system, e.g. scheduling the power flow into and out of the battery and sizing the battery. Many constraints involved in such optimizations are linear [18,19], resulting in the optimal design potentially being a discontinuous function of its parameters. Such discontinuities are an inherent possibility in optimization over a feasible space that is not strictly convex. An approach based on partial derivatives is not therefore necessarily appropriate for engineering design, and the optimizations may need to be recalculated for a range of parameter values.

Future work could investigate whether there are conditions under which discontinuities would not occur in practice so that an approach based on partial derivatives could be used.

The present paper derives and validates the analytical risk assessment methodology for solar electric power generation. It could also be derived and validated for other forms of renewable energy using parameterizations specific to each energy generation technology.

5. Conclusions

Risk analysis is important both for securing funding for individual solar projects and also for bundling multiple individual solar projects into tradable securities that can attract hundreds of millions of dollars from institutional investors. Commercial software is typically used to model the economic viability of solar projects and includes re-running the model for a range of parameter values in order to assess the risk of uncertainty in the value of those parameters. This paper provides an analytical approach which avoids the necessity of re-running the model, thus reducing processing requirements and improving response time to the user. These advantages are particularly valuable in the case of Monte Carlo simulations involving many values of multiple parameters.

The analytical method derived in this paper is based on first order approximations to two measures of economic viability, Internal Rate of Return (IRR) and Levelized Cost of Electricity (LCOE), using partial derivatives of IRR and LCOE with respect to their parameters. The method is validated for 20% changes in parameter values on case examples for the IRR of a behind-the-meter project under net-metering and for the LCOE of an off-grid project. Compared to re-running the model, the analytical method is least accurate for the capital cost of the projects; however, this is only relevant at an early stage in project planning. Once contracts have been signed with a supplier and installer, the capital cost is known and is no longer a source of risk. The difference between re-running the model and the analytical method for 20% changes in the remaining parameters (degradation rate, rate of increase of future electricity prices, discount rate, energy yield, annual O&M costs, battery cell & inverter replacement costs and end-of-life recycling costs) is on average 0.875% for changes in IRR. For LCOE, the analytical method is exact with respect to changes in capital costs, O&M costs, battery cell and inverter replacement costs, recycling costs and energy yield costs. It is within 0.01% for a 20% change in the degradation rate and 0.14% for a 20% change in the discount rate.

The assessment of risk using this new analytical approach is extended to calculate the Differential Importance Measure (DIM) which can be used when the proportional change is the same in each parameter to provide a ranking of their contribution to risk. The ranking is identical for IRR and for LCOE applied to the case examples used for validation in the present paper.

The contribution of this paper is to provide the partial derivatives of IRR and LCOE with respect to a range of parameters and to use them to provide an analytical method of risk assessment that avoids the necessity of re-running models of solar economics for ranges of parameter values. This paper also presents the first time DIM has been applied to the IRR of a solar project and the first time it has been applied to LCOE.

Author contributions

Audrey-Anne Guindon contributed formal analysis of differential importance measures plus formal analysis and validation of IRR methodology. David Wright contributed conceptualization, funding acquisition and formal analysis and validation of LCOE methodology. Both authors contributed to writing the draft and final version of the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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