Highlights:

1. Model development on the lifetime energy prediction and annual energy assessment.
2. Expression of domestic PV generation potential in various climatic conditions.
3. Demonstration of the importance of the reliability and maintenance of PV systems.
4. Demonstration of the energy prediction risks regarding PV systems' economic viability.

A combined model for PV system lifetime energy prediction and annual energy assessment

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Abstract

This paper presents a generic model for the prediction of the lifetime energy production of photovoltaic (PV) systems and the assessment of their annual energy yield in different time periods of operation. As case studies, it considers domestic PV system generation potentials in the UK and India to demonstrate the model results across a range of contrasting climatic and operating conditions. The model combines long term averages of solar data, a commercial PV system simulation package and a probability density function to express the range of the annual energy prediction in different time periods of system operation. Moreover, a sensitivity analysis based on degradation rates and energy output uncertainties is embedded in the lifetime energy calculations. The importance of the reliability and maintenance of the PV systems and the energy prediction risks, especially regarding economic viability, are demonstrated through the PV lifetime energy potentials in these two countries. It is shown that, even for countries that are significantly different in respect to their solar resource, PV systems may produce similar amounts of energy during their lifetime for reasonable assumptions of degradation rates and uncertainty levels.

Keywords: PV System, Lifetime Energy, PV Potential, Annual Energy Yield

1. Introduction

A key aspect for high photovoltaic (PV) system penetration is financial viability, the assessment of which is dependent on a reliable prediction of the lifetime energy output of the system. For installation in a particular location, the lifetime energy prediction depends on a range of parameters, including system design, system technology and the prevailing climatic conditions. It is also important to consider how the system losses vary with time and any degradation of system components.

A variety of aspects can influence PV system performance including the PV module technology used and the location where the system is installed. Other main influencing parameters are solar irradiation levels, temperature, PV system conversion efficiency, degradation factors during the lifetime, reliability and operational issues (e.g. shading) (Huld et al., 2011). In addition, there is also the uncertainty of how these parameters have been measured or estimated. The Canada Centre for Mineral and Energy Technology found that the combined uncertainty over a PV system's lifetime could be up to 7.9% for an average modelled energy yield (Thevenard and Pelland, 2013). Hence, the uncertainty value cannot be neglected in PV system performance predictions as it can play a key role in the judgement of the system's economic viability.

It is well documented in the literature that uncertainties in the lifetime energy generation and solar output degradation can lead to significant investment risk (Drury et al., 2014; Kumar and Kumar, 2017; Moser et al., 2017; Tomosk et al., 2017). However, a methodology to evaluate photovoltaic generation potentials according to climate and a chosen PV technology considering degradation and lifetime energy generation uncertainties have not been presented yet. The research presented in this manuscript addresses this knowledge gap.

This study uses solar data (irradiation and temperature; PVGIS CM-SAF solar database) for the UK and India provided by the European Joint Research Centre (European Commission, 2001-2008; Huld et al., 2012). The annual energy output of a domestic, optimally designed grid-connected PV system has been calculated using the PVsyst software (University of Geneva, 2010). The default horizon was used and near shading has not been included. Variations in either of these assumptions would be likely to reduce the annual energy output. The size of the PV system was 3kW, since the average installed capacity of residential PV systems in the UK is close to this value (Ofgem, 2015). Although India's PV market deployment is currently mainly based on large-scale PV systems, the same system size (3 kW) and technology was assumed for the Indian example system, for comparison purposes.

Optimum lifetime energy values, based on maximizing the simulated annual energy output, have been calculated for 20 cities across the UK and 36 cities in India. An example of the annual energy yield in different time periods is presented by comparing the capital cities of these countries. However, two representative cities (Cardiff in the UK and Patna (Bihar) in India) were chosen for the detailed comparison of the lifetime energy production because they are close to both the mean and median values of the results. The study assesses the domestic PV system generation potentials for the two countries. However, the model presented in this paper could also be applied to larger systems.

The rest of the paper is organised as follows: Section 2 of the paper presents the methodology used in order to develop the prediction model, which is presented in Section 3. The results from the case studies where the model was applied are discussed in Section 4 while Section 5 presents the conclusions of this work.

2. Methodology

A way to define the long-term energy yield of a PV system is to identify the degradation rate throughout the years of operation. This could be achieved by making indoor or outdoor experiments, by analysing field data from already installed PV systems or by using a degradation model to predict behaviour. All the aforementioned methods for identifying the PV degradation rate, and for ultimately predicting the lifetime energy, have their limitations. More specifically, for the indoor experiments, it is considered difficult to simulate in detail the outdoor operating conditions, as it is difficult to reproduce the synergy between different environmental stresses.

On the other hand, the outdoor experiments require a consistent long-term study and their results cannot be easily generalised since they are location specific. For reported field data, there is an uncertainty included in the validity of these data and sometimes the information provided about these data is limited. Finally, the PV degradation models have constraints due to the assumptions used in the model or factors/parameters determined by a specific experiment and then used in the prediction model, as analysed in Ndiaye et al. (2013).Moreover, for the case of the degradation rate prediction, Phinikarides et al. (2014) have shown that the degradation rate is not only technology and location dependent but methodology dependent as well, as there is the risk of overestimating or underestimating the true degradation rate according to the prediction method used. In this research, the energy prediction model uses reported degradation rates from long-term outdoor studies. However, an assumption is made for the linear correlation between the annual degradation rate and the annual energy output based on the degradation rate analysis of Jordan et al. (2016).

The basic approach to the lifetime energy yield prediction in this study is presented in the block diagram below (Figure 1). PV performance is dependent on the PV system design, module technology and climate. The main parameters regarding the “PV system design” can be accounted for in the simulated annual energy output. For the main parameters of “Climate and module material”, only the irradiation and the temperature are routinely included in the simulations and sometimes, if there are available data, wind speed and direction. However comprehensive the inclusion of parameters in the simulation, the performance result is expressed only for the first year of the PV system operation and the lifetime energy production must extend this by considering the operation of the system thereafter. Hence, the developed methodology presented here takes into account the degradation rates and uncertainties included in the annual energy yield in order to predict the lifetime energy.

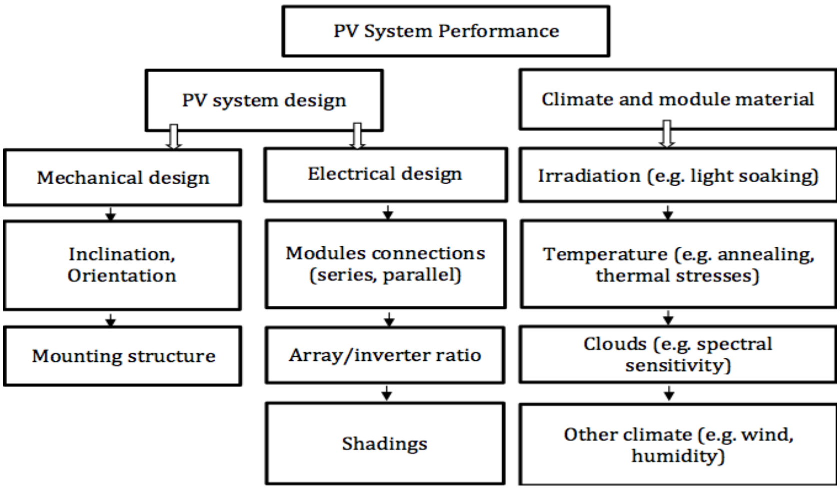

Figure 1: System performance influencing parameters

Furthermore, as it was stated in the introduction, the degradation rates and uncertainties considered in this study concern a 3 kW optimally designed grid-connected PV system (i.e. orientation due south, optimum tilt angle in respect to each location, no shadings, default horizon, optimum inverter/array ratio) analysed in 20 cities across the UK and 36 cities in India. In order to optimise the design according to inverter/array ratio of the system, a 2.5 kW inverter was used for the simulations in the UK cities while a 3kW inverter was used for the simulations in the Indian cities. The technical specifications of the PV module and inverters used in the PV system design are presented in Table 1.

Table 1: PV system technical specifications

Multi-crystalline PV module	**Value**	**PV inverter**	**UK Value**	**India Value**
Number of cells	60	**For the DC side**		
Maximum power rating (P_{max})	250 W	Maximum DC power	2600W	3150W
Open circuit voltage (V_{OC})	37.6 V	Operating MPPT input voltage range	175 – 560V	210 – 560V
Maximum power voltage (V_{MPP})	30.9 V	DC nominal voltage	530 V	530 V
Short circuit current	8.68 A	Maximum input	700 V	700 V

(I_{SC})		voltage		
Maximum power current (I_{MPP})	8.1 A	No. of independent MPP trackers	1	1
Nominal operating cell temperature (NOCT)	47.5 C	Maximum DC current at each MPPT	15 A	15 A
Temperature coefficient of I_{SC}	0.038%/C	**For the AC side**		
Temperature coefficient of V_{OC}	-0.329%/C	AC Nominal Power	2500 W	3000 W
Temperature coefficient of P_{max}	-0.44%/C	Maximum AC Voltage range	180 – 280V	180 – 280V
Bypass diodes	3	Nominal AC frequency range	50 ± 4.5 Hz	50 ± 4.5 Hz
Module efficiency (η)	15.2%	Efficiency: Maximum/Euro-eta	96.3%/95.3%	96.3%/95.3%

2.1 Degradation Rates

One of the most important issues is to establish representative degradation rates but the literature in this regard is diverse and not straightforward to interpret, requiring a careful and thorough analysis. An analytical review on the reported degradation rates for different PV technologies states an average degradation rate for the crystalline silicon technology of 0.7% per year and a median value of 0.5% per year. By considering the reported rates only for the crystalline silicon systems, it can be observed that their median degradation rate does not exceed 1% per year (Jordan and Kurtz, 2013). However, for India, which has diverse and harsh climates, the Solar Energy Centre (now the National Institute of Solar Energy (NISE)) reported a degradation rate up to 2.8% per year for a 10-year old crystalline silicon PV system installation (Sastry et al., 2010).

In this study, 0.5% and 1% degradation rates per year are considered for the sensitivity analysis of the lifetime energy prediction in the UK. However, for the case of India, 1% and 3% degradation rates are included in order to demonstrate the influence of a harsh environment to the lifetime energy yield.

Field studies, which were conducted in harsh environments, have reported annual degradation rates of around 1.1% (Kahoul et al., 2014) and up to 2.96% (Ndiaye et al., 2014). For example, Kahoul et al. (2014) discusses a study conducted in the Sahara region over a period of 11 years for mono-Si modules. The region is characterised by high ambient temperatures while the monthly maximum ambient temperature was more than 40°C during 10 out of the 12 months of the year. Ndiaye et al. (2014) discusses a study conducted at Dakar in Senegal, which has a tropical environment. Two mono-Si and two multi-Si modules were examined for the first few years of their operation. Three out of four modules had an annual degradation rate of more than 1.5% for the examined period. Hence, by considering the 1% and 3% annual degradation rates for India, it can be said that it is a realistic assumption and can actually express the PV potentials of a harsh environment (Dubey et al., 2014; Ying Ye et al., 2014; Sharma and Chandel, 2016).

2.2 Uncertainties

According to a study by Thevenard and Pelland (2013) on the uncertainties in long-term photovoltaic yield predictions, these can be divided into three categories. The first category includes the uncertainties of the irradiation computation at a specific location and the year-to-year variability of the annual irradiation. The year-to-year variability uncertainty is not included in this paper, as the study considers long-term averaged solar data. Hence, the uncertainty value considered for the irradiance computation is 5% according to the PVGIS

CM-SAF database (European Commission, 2001-2008). The second category refers to the uncertainty concerning the transposition model. The transposition model calculates the incident irradiance on a tilted plane from the horizontal irradiance. It has been found that, when the global irradiance is known, the mean bias error of the transposition model is between 0% and -6% for a south oriented array with optimum tilt angle. Based on this, Thevenard and Pelland (2013) concluded that a realistic assumption for this uncertainty is 3%. Hence, this study uses a 3% uncertainty for the transposition model as the energy predictions are for optimally designed systems. The third category includes the uncertainties regarding the PV system performance i.e. module power tolerance, dirt and soiling losses etc. Regarding these uncertainties, PVsyst software accounts for the following factors in the simulations made for this study: losses due to temperature, losses due to irradiance level, wiring ohmic loss (loss fraction 1.5% at standard test conditions (STC)), array soiling losses (loss fraction 3%), module quality loss (loss fraction 1.5%), module mismatch loss (loss fraction 2% at maximum power point (MPP)), incident effect loss (ASHRAE parameterization, parameter b_0=0.05), and inverter losses.

In addition, there is an uncertainty regarding the accuracy of the PV system simulation. According to PVsyst software, this uncertainty is around 3% (University of Geneva, 2010). However, the simulation accuracy uncertainty in this study is assumed to be 6%, since, according to a survey by PHOTON magazine in 2011, comparing 20 PV simulation programs regarding their yield prediction at three different sites, the maximum difference of the PVsyst yield prediction to the measured yield was 6% (Mermoud, 2011). Hence, the uncertainties considered for the calculation of the PV energy output are the following:

- Irradiance computation 5%,
- Transposition model 3%,
- Extra module power tolerance 3%,
- Simulation accuracy 6%,
- Extra soiling uncertainty only for the case of India 4%.

Although PVsyst software already accounts for losses due to module power tolerance (module quality loss), an additional allowance has been made to account for a change in tolerance over the system lifetime (Vázquez and Rey-Stolle, 2008). In general, tolerances are not considered as uncertainties. They are acceptable limits used to define a process or a product (Bell, 2001). However, in the case of PVsyst software the module power tolerance is used to calculate the module quality loss while the “extra module power tolerance”, which is used in this study, is used to account for the uncertainty of these limits over the system lifetime.

In addition, many areas in India experience dusty environmental conditions, either due to their climatic characteristics (India Meteorological Department, 2010) or to environmental pollution. Numerous studies have examined the effect of dust on the PV energy production and, unsurprisingly, they reveal higher percentages of power loss in dusty environments and/or during dry seasons (Makrides et al., 2012; Sayyah et al., 2014; Weber et al., 2014). Hence, an extra soiling uncertainty is considered only for the case of India since the UK climate does not experience severe soiling effects in the general case (Ghazi and Ip, 2014). The standard equation that is used for the calculation of the combined uncertainties values is shown below:

$$\text{Combined Uncertainty: CU (\%)} = \sqrt{x_1^2 + x_2^2 \ldots + x_n^2}\ , \qquad (1)$$

where x is the uncertainty value in per cent and the indicator n is the number of the values considered for each calculation. The sum in quadrature of the uncertainties is according to the definition of the combined uncertainty where uncertainties of different parameters are combined (Taylor and Kuyatt, 1994; Birch, 2003).

Therefore, the combined uncertainty values that are considered in the sensitivity analysis are: 7.81%, 8.37%, 8.89%, and 9.75%. The value of 7.81% is the minimum combined uncertainty, where only the two main uncertainties are included (irradiance computation and simulation accuracy), and is used only for the UK calculations. The 8.37% uncertainty includes the transposition model uncertainty, the simulation accuracy uncertainty and the irradiance computation uncertainty. The other two uncertainty values also include the extra module power tolerance uncertainty (combined uncertainty: 8.89%) and the extra soiling loss uncertainty (combined uncertainty: 9.75%). The first three are considered for the case of the UK while the last three are considered for India.

3. Model Development

The model developed in this study is based on the reliability model for a photovoltaic module from Vázquez and Rey-Stolle (2008). Generally, the operation period of a PV system is assumed to be at least 25 years since the PV module warranties, provided by the PV manufacturers, are usually around 20-25 years. However, the performance of a system decreases over time due to various degradation mechanisms. The developed model for the lifetime energy prediction is based on statistical formulas and takes into account a range of different degradation rates, taken from installed PV systems and uncertainties reported in the literature. Even though this model is generic, it can provide climate and technology specific results since the degradation rates and the uncertainties considered can be changed according to the location and the PV system technology.

PV system annual energy output is the reference parameter to evaluate the system performance. A simple calculation approach of the minimum annual energy for a certain year of system operation can be defined in relation to its first year energy output as follows:

$$E_{n,min} = E_0 \times U \times (1 - D_{CUM}), \tag{2}$$

where $E_0$is the first year energy output, U is the uncertainty factor for modelled average energy yield over the PV system lifetime (U=1-CU), and D_{CUM} the cumulative annual degradation factor.

If, for example, the PV system lifetime is taken to be 25 years with an annual degradation rate of 1% and a combined uncertainty of 9%, the minimum energy in the 25th year of the system operation would be:

$$E_{n,min} = E_0 \times 0.91 \times 0.75. \tag{3}$$

This study, presents a probabilistic approach in order to predict the annual and lifetime energy yield. Hence, by correlating the value of $E_{n,min}$ to a normal distribution, it is observed that it is equal to the energy value at the point of –σ (on the x-axis) of the normal distribution graph. In a normal distribution 68% of the values are in the range of +σ to –σ. About 95% are within two standard deviations (+2σ to –2σ) while 99.7% of the values are in the range of +3σ to –3σ. The analysis, in this paper, provides examples with all three deviations in order to demonstrate the difference in the energy range prediction according to the considered probability. The PV system energy output, including the uncertainties described above, is assumed to follow a normal distribution. Generally, the normal distribution is considered when the values are expected to be near the average value (Bell, 2001). In this model, the average value is the annual energy in year n. Hence, it can be expected that the prediction of the annual energy in year n has the same possibilities to be higher with the ones to be lower from the average annual energy prediction. The same stands for the lifetime energy prediction, which is the cumulative average annual energy for every year of the system's operation.

The probability density function is the following:

$$p(E) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{E-\mu}{\sigma}\right)^2\right], \quad (4)$$

where E denotes the system energy output (in kWh), μ is the average annual energy (in kWh) and σ is the standard deviation of the annual energy (in kWh). Both the average annual energy and the standard deviation of the annual energy are time dependent variables. The average annual energy decreases over the years of the PV system operation while the standard deviation of the energy increases as the variability of the module power rating increases due to non-uniform degradation patterns. A linear correlation has been chosen for these two parameters with respect to time (t). The equations are given below:

$$\mu(t) = E_0 - (DE_0 t) \quad (5)$$

$$\sigma(t) = \sigma_0 + (bE_0 t), \quad (6)$$

where E_0 is the first year energy (in kWh), obtained from the system simulation, D is the annual degradation rate, σ_0 is the first year standard deviation and b is the annual variability rate of the standard deviation. Following the normal distribution, the relationship between the combined uncertainty, E_0 and σ_0 is given below

$$E_0 - 3\sigma_0 = E_0(1 - CU). \quad (7)$$

Since the standard deviation of the system output energy is not known, the annual variability rate (b) is determined in accordance with Vázquez and Rey-Stolle's (2008) study for the standard deviation of the module output power, which was found to double after 10 years of field operation. Hence, b is assumed to be equal to:

$$b = \frac{\sigma_0}{E_0} \times \frac{1}{10} \Rightarrow \frac{CU}{3} \times \frac{1}{10}. \quad (8)$$

Below is presented a flowchart of the energy prediction model.

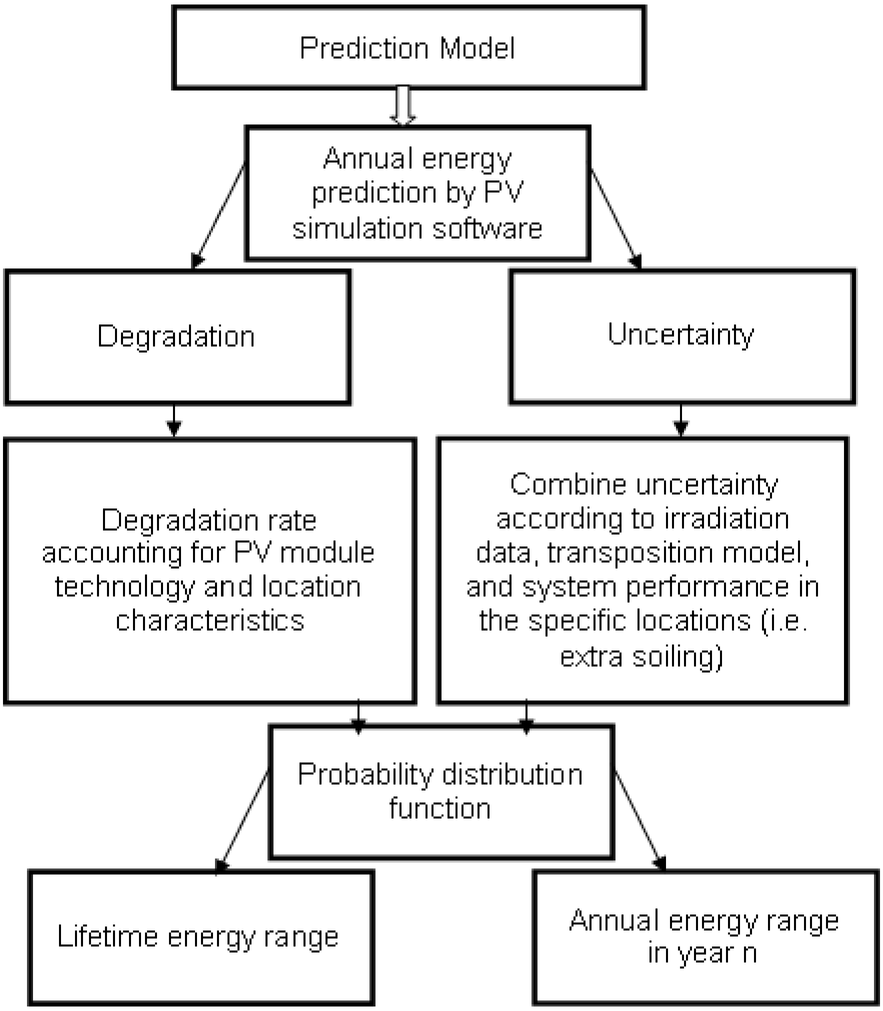

Figure 2: Energy prediction model

It can be seen that the first step is to acquire the first year's annual energy estimation from the PV system simulation. Then, the degradation of the system is included by considering the degradation rates according to the PV module technology and location characteristics. Further, the uncertainties are also included by considering the input data used to obtain the annual energy estimation (i.e. simulation, solar data, transposition model, etc.) and the location characteristics (i.e. extra soiling uncertainty). Finally, the degradation rate and the combined uncertainty are applied in the probability distribution function in order to predict either the lifetime energy prediction range or the annual energy prediction range in year n.

4. Results and Discussion

This section presents and discusses the results of the energy assessment model and the sensitivity analysis, which is embedded in the model. Two annual degradation rates (D) and three combined uncertainty values (CU) were considered for each country. Hence, there are 6 ranges of lifetime energy predictions (scenarios) for each country. Table 2 summarises the degradation and uncertainty values for each scenario.

Table 2: Degradation and uncertainty values for the UK and India

Scenario	UK	India
1	D=0.5%, CU=8.89%	D=1%, CU=9.75%

2	D=0.5%, CU=8.37%	D=1%, CU=8.89%
3	D=0.5%, CU=7.81%	D=1%, CU=8.37%
4	D=1%, CU=8.89%	D=3%, CU=9.75%
5	D=1%, CU=8.37%	D=3%, CU=8.89%
6	D=1%, CU=7.81%	D=3%, CU=8.37%

Figures 3-5 are presented as an example of this model. They demonstrate the distributions for the annual and lifetime energy production of 3kW PV systems in London and in New Delhi. It is observed that the lifetime energy prediction for a residential PV system in London is between 47,800kWh (–3σ) and 77,200kWh (+3σ) while in New Delhi is between 80,700kWh and 130,300kWh, for the case of 1% annual degradation rate and 8.89% combined uncertainty (UK scenario 4, India scenario 2) (Figure 3). Note that the whole range of the output probability is being considered here. Since both distributions have been calculated based on the same uncertainty and degradation values, the percentage difference of their distribution range is the same as the percentage difference of their first year energy (E_0). Hence, the normal distribution of the lifetime energy prediction for New Delhi is 40% wider than the normal distribution for London.

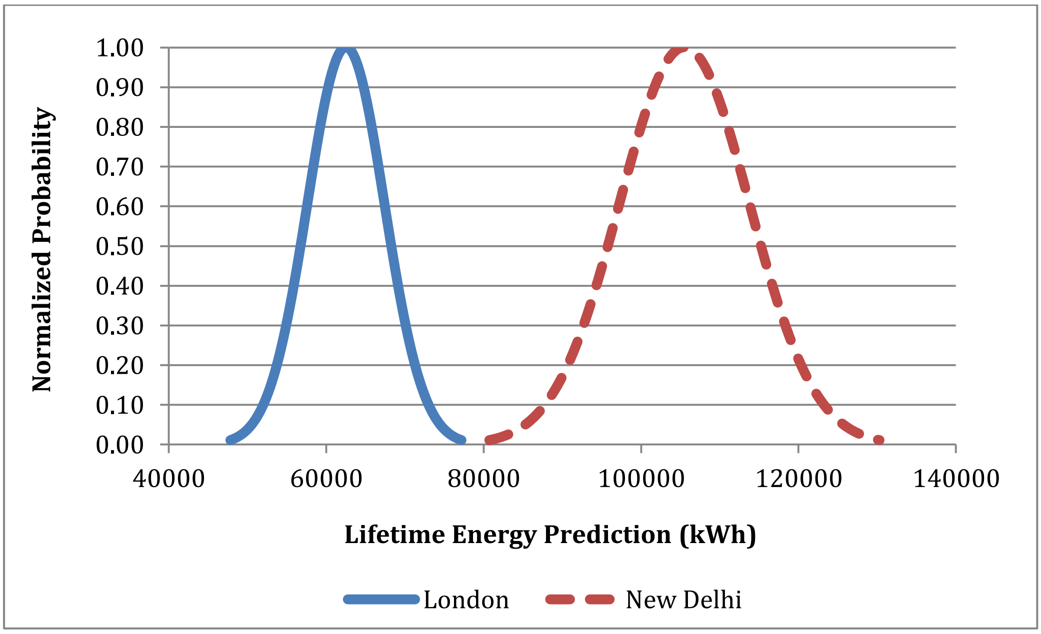

Figure 3: Normal distribution for the lifetime energy prediction of a 3kW PV systems in London and in New Delhi (annual degradation rate 1%, combined uncertainty 8.89%, project lifetime 25 years)

Figures 4 and 5 show the variations in the annual energy output through different times of the system operation. It can be seen that, as the range of the annual energy output increases over time, it becomes more difficult to assess the annual energy production of the system. Moreover, the figures have been designed on the same x-axis scale in order to show the comparison of the annual energy output between these two cities over time.

The deviation of the normal distribution of this model is dependent on the combined uncertainty value while the energy values are dependent on the annual degradation rate. Hence, Figures 3-5 offer a comparison between the capital cities of the two countries under the same conditions and consequently of the difference in their solar resource (i.e. theoretical energy potentials).

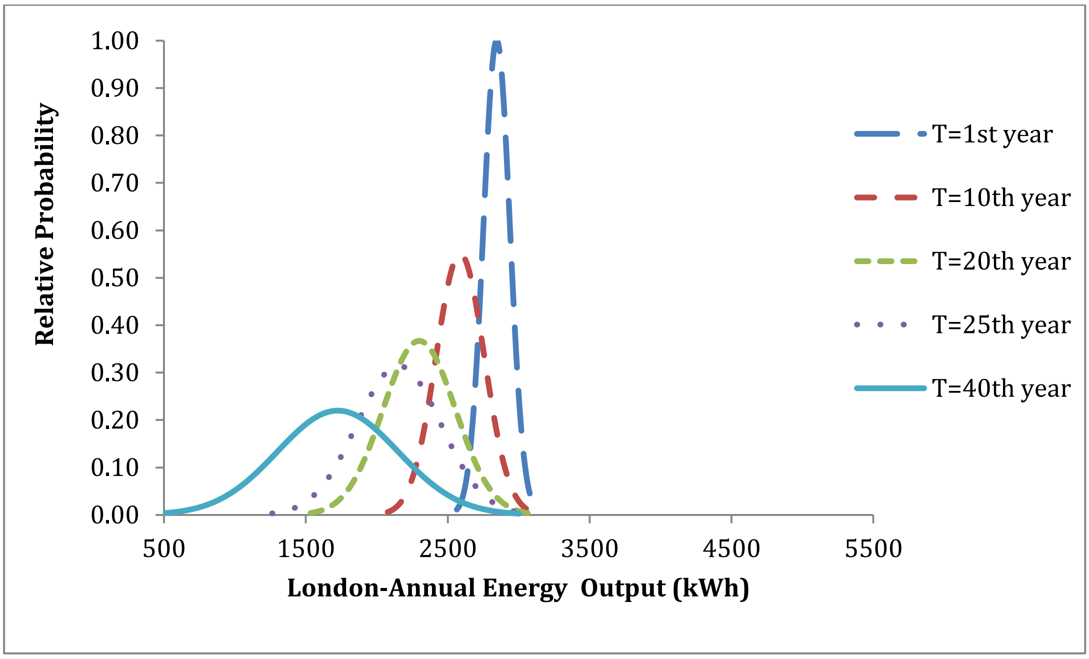

Figure 4: Normal distribution for the annual energy prediction of a 3kW PV system in London for different years of the system operation (annual degradation rate 1%, combined uncertainty 8.89%)

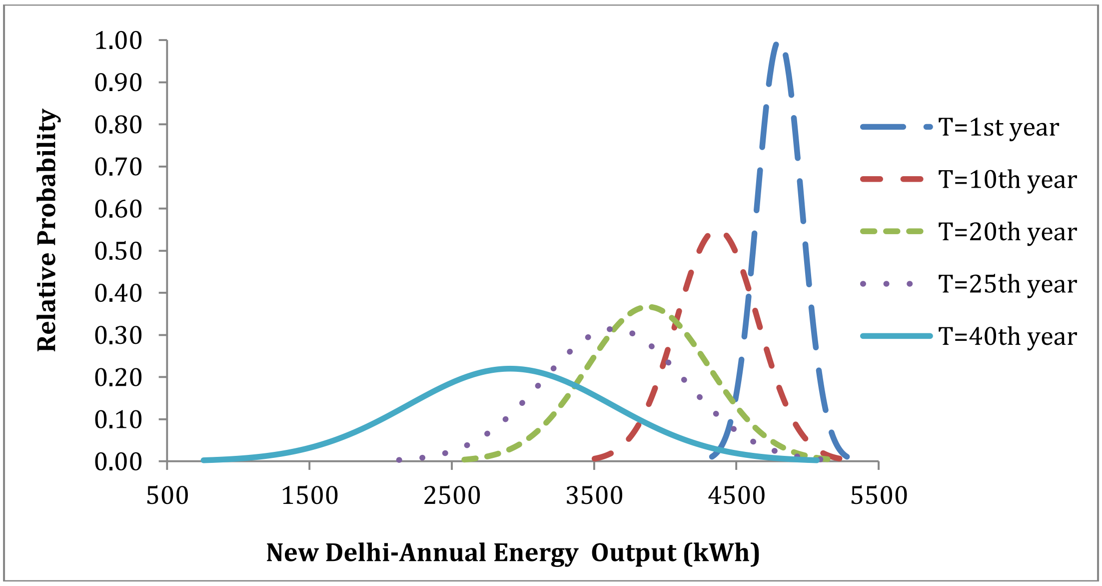

Figure 5: Normal distribution for the annual energy prediction of a 3kW PV system in New Delhi for different years of the system operation (annual degradation rate 1%, combined uncertainty 8.89%)

For the next section of the analysis, the city of Patna in the state of Bihar in India and the city of Cardiff in the UK have been chosen in order to capture the diversity of the conditions between the two countries. These cities have been chosen as representatives for the UK and India because their first year annual energy output is very close to the average and median values of the examined cities around the UK and India.

In Figure 6, the comparison of the lifetime energy ranges for the UK and India is shown. For the case of India, both degradation rates have been considered using the highest uncertainty value (9.75%) (scenarios 1 and 4). Similarly for the UK, the highest uncertainty value (8.89%) is used and the relevant degradation rates (scenarios 1 and 4). It is clear that the deviation of lifetime energy output for Patna is larger as the uncertainty value used is higher than that for Cardiff. Moreover, the lifetime energy ranges do not differ much for Cardiff while they differ greatly for Patna. This illustrates that if the system does not have a good operation and maintenance environment, consequently resulting in producing less energy, the uncertainty of its economic viability increases regardless of the solar resource potential of the location. For example, the perceived economic viability for a system installed in Patna will depend on the chosen value of its lifetime energy prediction. By considering only the degradation rate, the mean value for the 25 years of system operation would be expected to be around 101,000 kWh for 1% annual degradation rate while it would be around 70,800 kWh for 3% annual degradation rate. This alone is a 30% difference in the lifetime energy prediction. If the uncertainty is also included, for a combined uncertainty of 9.75%, the deviation would be ± 17,300 kWh for ± 2σ and ±8,700 kWh for ±σ. Depending on the chosen mean value of the lifetime energy, these deviations could give a difference in lifetime energy prediction of between 9% and 24%. Note that the ±σ and ± 2σ were selected instead of ±3σ for the above example because they offer a narrower lifetime energy range and a sufficient probability percentage, both of which provide a more realistic prediction for an investor.

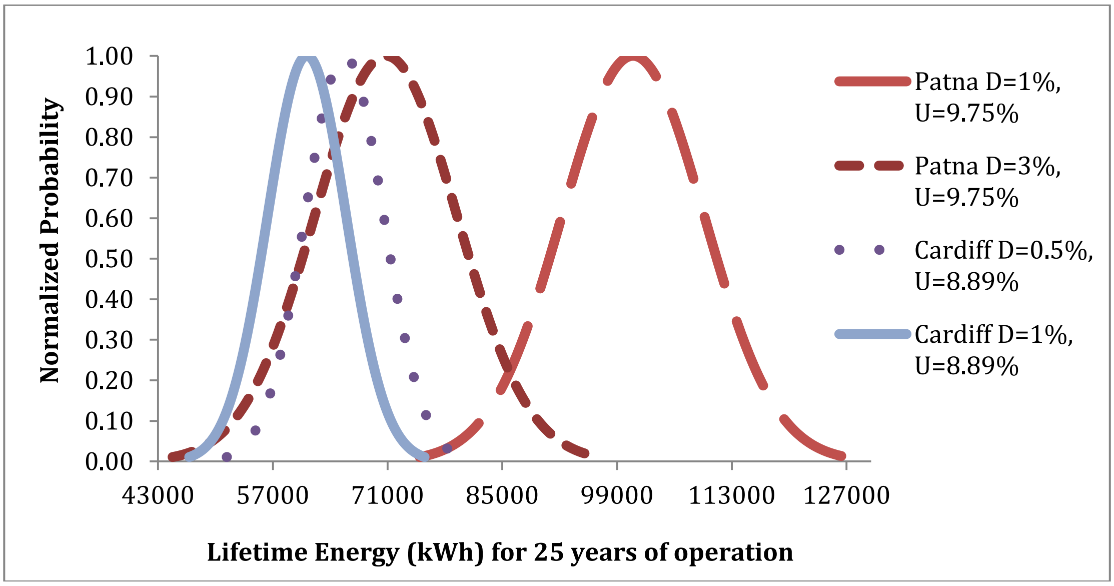

Figure 6: Normal distribution for the lifetime energy prediction of a 3kW PV system in Cardiff (UK) and Patna (Bihar-India)

Table 4 presents the lifetime ranges for ± 2σ deviation for all the scenarios for Cardiff and Patna, as representative ranges for the UK and India.

Table 4: Lifetime energy ranges for all the scenarios for Cardiff and Patna

Scenario	Cardiff, UK(kWh, ± 2σ)		Patna, Bihar, India(kWh, ± 2σ)	
	Upper limit	Lower Limit	Upper limit	Lower Limit

1	75310	56150	118310	83620
2	74750	56710	116780	85150
3	74150	57310	115850	86080
4	70740	51580	88130	53450
5	70180	52140	86610	54970
6	69580	52740	85680	55900

The average energy yield from already installed PV systems in the UK among five subsequent years (2010-2014) and for an optimum panel orientation was found to be 994 kWh/kW per year (Mason, N., 2016). Hence, for a 3 kW PV system, this energy yield would have been 2982 kWh/year. The first year's average annual energy yield of this model in the UK is 2800 ± 165 kWh (2σ). According to the model, for the five first subsequent years of PV system operation (if the system was installed in 2009, first year's annual energy in 2010), the average annual energy would have been 2774 ± 200 kWh (2σ) for Scenario 1. Hence, it is clearly shown that the model's energy prediction is very close to the actual field data. Similarly, for India two locations were validated against field data: 1) a 10 MW grid connected PV plant at Ramagundam, Telangana, which was monitored for the first year of its operation (Kumar and Sudhakar, 2015), and 2) a 3 MW PV plant at Kolar, Karnataka, which was monitored for two subsequent years during its operation (Gajjar et al., 2015). From the state of Telangana, the model's first year's annual energy of a 3 kW PV system is 4720 ± 280 kWh (2σ) (Scenario 2) while the actual energy yield of a 3kW PV system would have been 4737 kWh. Further, for Karnataka state the average energy yield from the two subsequent years of monitoring is 4255 MWh/year. If a 3 kW system is to be assumed, then the average energy yield would have been 4255 kWh/year. The model gives an average value of 4630 ± 353 kWh (2σ) (Scenario 2). For the comparisons in India, the model locations were chosen according to the locations where the actual PV plants are installed and not as an average value from the 36 cities examined in the model.

Finally, Figures 7 and 8 present the ranges for the lifetime energy prediction for all 6 scenarios for each country. These ranges refer to a 3kW PV system and they have a 95% probability of occurrence as they account for –2σ to +2σ of the probability density function. For the UK cities, it can be observed that most of the lifetime energy prediction ranges lie between 60,000 to 70,000 kWh. In the southern cities of the UK, this range could be raised to 70,000 - 80,000 kWh while in the northern cities it could be decrease to 50,000 - 60,000 kWh (Figure 7).

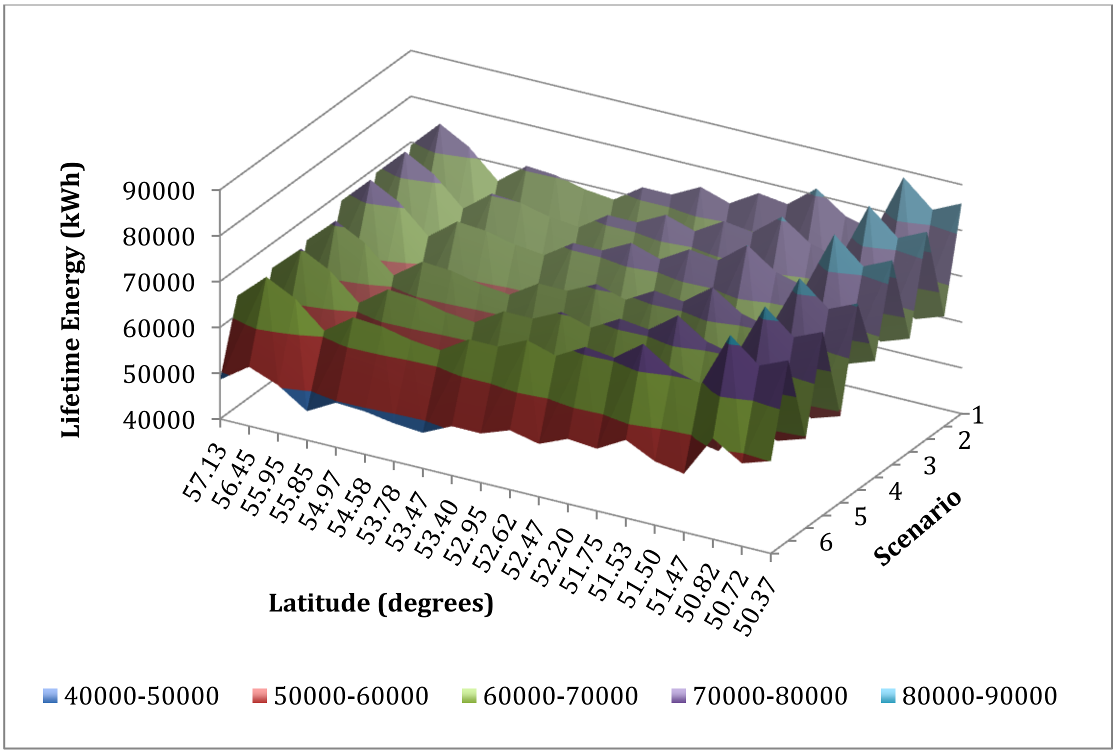

Figure 7: Lifetime energy prediction range of a 3 kW PV system in the UK-small scale PV potentials (The x-axis represents the latitudes of the examined cities in decreasing order and is not a numerical scale)

For India, the variation in the ranges is larger since the degradation rates used have a much greater difference between them. Hence, it can be observed that most of the lifetime energy prediction ranges lie between 70,000 to 100,000 kWh, although in certain scenarios there are areas where the lifetime energy production of a 3 kW system would be less than 70,000 kWh (Figure 8). In addition, because India is a large country and is characterised by various climates, there is not a straightforward correlation between the solar resource and the latitude.

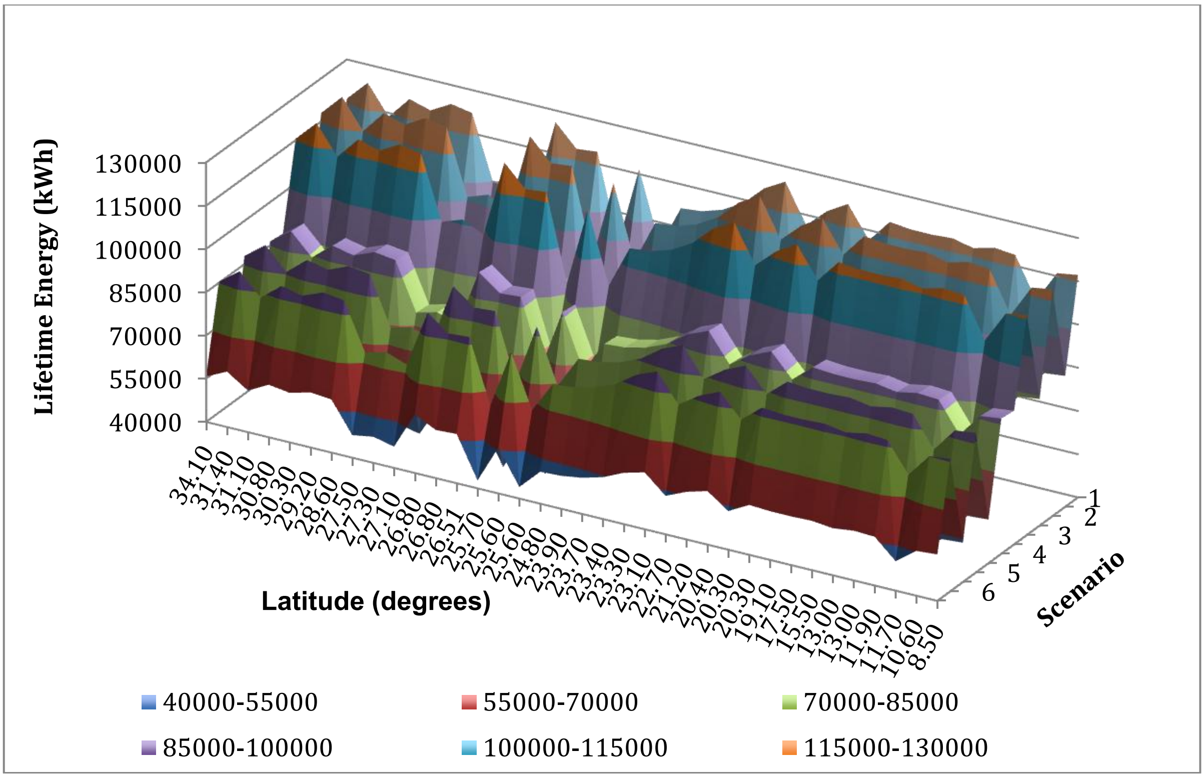

Figure 8: Lifetime energy prediction range of a 3 kW PV system in India-small scale PV potentials (The x-axis represents the latitudes of the examined cities in decreasing order and is not a numerical scale. Note that the colour scheme has a different range to that for Figure 7)

The analysis has shown that, while it is expected that, during its lifetime, a PV system in India will produce higher amounts of energy compared to the UK, due to its greater solar resource, the environmental stresses might reduce this possibility. Thus, further education on array cleaning regimes and operation and maintenance issues is needed in countries such as India for the better exploitation of their solar resource (Mani and Pillai, 2010; Pillai et al.,2014; Lopez-Garcia et al., 2016). A study regarding the potential of PV systems in countries with high solar insolation clearly demonstrated the advantage of installing a PV system in such locations (Makrides et al., 2010). However, the examined location was Nicosia in Cyprus, which has a Mediterranean climate with different characteristics from the Indian climates. Hence, this might not be the case for some locations in India where high solar irradiation is available but the environment is harsh.

The model was validated against the average energy yield of the UK and for two locations in India. The results were accurate by using a –2σ to +2σ deviation and show that the actual data are between these limits. However, in order to calculate the economic yield for a PV system in a certain location, the uncertainties included in the lifetime cost analysis also have to be considered. A common metric to make an economic assessment of a PV system is the Levelised cost of Energy (LCOE), which is defined as the lifetime cost divided by the lifetime energy production of a system. The LCOE formula can take various forms depending on the variables included in the calculations (Georgitsioti et al., 2014). Some of the variables are the ones discussed in this study concerning the lifetime energy prediction while the others concern the lifetime finance of a PV system. Hence, for the economic assessment of a PV system in a specific location the current market policies and prices have to be acquired as well as defining any uncertainties included in the financial variables used for the lifetime cost analysis.

5. Conclusions

This paper demonstrates the importance of the operation and maintenance conditions of a domestic PV system and presents a model for the energy assessment and prediction. It clearly shows that even for these two countries, which are significantly different in respect to their solar resource, PV systems may produce similar amounts of energy during their lifetime for reasonable assumptions of degradation rates and uncertainty levels. The uncertainty in the energy output needs to be considered when assessing the PV system's economic viability. As has been demonstrated for the city of Patna in India, depending on the chosen mean lifetime energy prediction and for a combined uncertainty of 9.75%, the chosen deviations (i.e. ±σ and ±2σ) could give a difference in the lifetime energy prediction between 9% and 24%. Hence, the investor should be aware of the energy prediction risks (i.e. calculation method of the lifetime energy, chosen lifetime energy mean value, combined uncertainty value and deviation), especially in investments where a minimum rate of return is specified. Moreover, the lifetime energy potentials of domestic PV system have been presented, for realistic assumptions and an optimum system design. The results have shown an intermediate lifetime energy range of 60,000-70,000 kWh for the UK while for India it was between 70,000-100,000 kWh, assuming a 25-year lifetime in both cases. Finally, the model presented is a generic model, which can be modified according to the climatic characteristics of each location and the PV system technology.

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