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Original Article

A Resource-Adequacy-Based Reliability Analysis of Solar Panels' Performance in Two Different Environmental Conditions

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Abstract - *Global energy market, which still heavily depends on fossil fuels, is too vulnerable to international tensions, which once again shows the importance of moving towards Renewable Energy Systems (RESs), including solar panels. An important part of this process is to handle reliability issues, which is usually done by using a performance function. These functions often depend on the irradiance and the temperature as two random variables, while the role of each of these variables should be studied further. In this paper, an available resource-adequacy-based reliability analysis problem is used for this purpose. First, a simulation is run to validate the importance of the involved variables in systems' reliability. Then, a comparative study is carried out on resource-adequacy-based reliability analysis of solar panels in two different cities with various environmental conditions (Melbourne, Australia, and Khobar, Saudi Arabia) to check these variables' behavior. This has already resulted in a successful campaign of installing solar panels in a relatively cold-weather city like Melbourne. These case studies have found that Khobar, regardless of its hot summers, has a good irradiance level to generate electricity by solar panels even during the wintertime. As this level of irradiance is better than Melbourne's, it can be concluded that it would be a good idea for Khobar to accelerate moving towards solar panels.*

Keywords - *Performance functions, Resource-adequacy-based reliability analysis, Renewable Energy Systems, Solar panels, Simulation.*

1. Introduction

In the last couple of years, geopolitical conflicts and wars reminded everyone how vulnerable the global economy is when it comes to oil and petrol prices. As an example, Australia is again facing a major jump in unleaded petrol price as a result of the USA - Israel - Iran war; something like (or even worse than) what it experienced when the Russia - Ukraine war began in 2022. In some cases, petrol is being sold at A$3 per litre while there have been reports about petrol stations running out of petrol [25].

In addition, the world has been dealing with the environmental impacts of global warming, resulting in many projects to move away from fossil fuels. However, there have been reports that some of these plans are already shelved in different countries [1]. All this is happening while researchers have reported that the global temperature is about to increase by 2 degrees by mid-century. However, another report has found that the use of fossil fuels (such as oil and natural gas) will be doubled by then [2]. So, it can be seen that more efforts are required to speed up using renewable energy, which cannot be done without improving the design of Renewable Energy Systems (RESs), including solar panels' design [6, 20]. It can then also address concerns about sustainability in future projects, either commercial and industrial projects or residential ones [4].

However, an important consideration of using RESs is to have access to reliable natural resources needed for the system. For example, having a constant irradiation is essential for a solar panel to generate electricity, while wind plays the same role when it comes to the installation of wind turbines. Therefore, taking reliability-related issues into account is an essential part of an RES's design, just like the Internet of Things (IoT), Machine Learning (ML) and Artificial Intelligence (AI) that are employed to enhance these systems [5, 18, 22, 26].

The employed reliability analysis problem in this paper mainly focuses on resource availability and resource adequacy for solar panels. It should be mentioned that degradation, failure mechanisms, component lifetime, and material-dependent factors are beyond the scope of the present analysis. This model was first studied using the Monte Carlo simulation. Then, two case studies of two different locations are applied to validate the results of the employed resource-adequacy-based reliability analysis during the same time period, as there is a lack of this validation in the existing literature.

The cities, which are considered in this paper, are Melbourne, Australia and Khobar, Saudi Arabia. These cities are located in different hemispheres and so do not experience summer and winter at the same time. Therefore, January is selected for this study, which is summer in Melbourne and winter in Khobar.

2. Literature Review

Solar panel is a very popular option for renewable energy adoption, whose design still needs to be improved. The reliability of these panels has been considered for further improvement in the last couple of years. In this process, various mathematical modelling has been employed to enhance system reliability, either in general or as a case study by focusing on a specific location.

Advantages and disadvantages of solar panels in Ecuador are studied by assessing their reliability [19]. It has been reported that fossil-fuel-dependent countries are not the only ones that may face challenges in generating electricity in the future. As a country that depends on hydroelectric generation, Ecuador needs to move towards solar panels and other renewable energies to achieve an internationally recognised threshold of having access to electricity throughout the year [19].

Moreover, several mathematical models and techniques are studied to enhance solar panels' designs. The Gamma Distribution, with a focus on Erlang Continuous Distribution, has been applied to perform reliability analysis of solar panels. It has been found that when a RES is designed by the sequential stages, the Erlang Continuous Distribution results in optimized outcomes compared with simpler exponential models [23].

The Reliability-based Design Optimization (RBDO) is also employed to improve the system design of solar panels [29]. In this model, sizing optimization of solar panels is combined with reliability analysis, where the installation area is minimized by considering PV installation angle as a design variable, and it has been reported that the proposed RBDO model works more effectively than similar deterministic optimization models in improving system design [27, 29].

Among available mathematical models, one model, which is based on a photocurrent resource and a diode, has become very popular [3]. In this model, the Maximum Power Point (MPP) would be found as $P_{max}(G,T) = \max I_{PV} V_{PV}$, where the solar panel's voltage is ideally equal to its diode's voltage V_d. I_{PV}, which is the solar panel's current, is found by $I_{PV} = I_{Ph} - I_d$, where I_{Ph} and I_d are the photocurrent and the diode's current, respectively.

As can be seen, the irradiance G and the temperature T are considered as two independent random variables in this model [7]. So, the photocurrent equation is set up as:

$$I_{Ph}(G,T) = [I_{scn} + K_i(T - T_n)]\frac{G}{G_n}$$

This model includes three nominal values, such as nominal short-circuit current. I_{scn}, nominal temperature T_n and nominal irradiance G_n. Also, the temperature coefficient is shown by K_i [7].

The second component of the equation of the power generated by a solar panel is the diode's current, which can be found as $I_d(T, V_d) = I_S(T)(e^{\frac{V_d}{n V_t(T)}} - 1)$. This equation depends on the temperature T and the voltage of the diode V_d while V_t represents the thermal voltage [28]. However, this model does not consider a solar panel's reliability, which can be handled by using the system failure rate [6].

Available mathematical models of electricity power networks can be adopted to be used for solar panels. In these models, a probabilistic constraint is often used in the inner loop of an RBDO problem in order to decrease the cost of the system and keep its reliability above a pre-determined level, which is obtained based on the system's failure rate [10].

3. Reliability-based Design Optimization Models

An RBDO problem is indeed a non-deterministic model that considers the reliability of a system during the process of finding the optimum point. For this purpose, a probabilistic constraint is employed in order to make sure safety requirements of the system are met. These requirements often appear as a threshold of the system reliability, which is determined in advance [12].

A reliability analysis problem is solved in the inner loop of a two-level RBDO model in order to meet the above-mentioned requirements. An RBDO problem is generally formulated as [11, 13]:

$$\begin{aligned} &min && \cos(x_1, x_2, \dots, x_n) \\ &s.t. && P_{f_j} \leq \bar{P}_{f_j}, j = 1,2, \dots, n \\ & && X^L \leq X \leq X^U \end{aligned} \tag{1}$$

where x_i is a random variable, bounded between two limits. P_{f_j}, defined as $P[G(X) < g] = F_G(g) = \iint \dots \int_{G(X)<g} f_X(x)\, dx$, represents the failure probability of the system, and $\bar{P}_{f_j}$ is the pre-determined tolerable level of system failure probability.

As part of the RBDO process, a direct reliability analysis problem is solved in the inner loop of this model, aiming at finding a reliability index to be used in the probabilistic constraint. It has been reported that a first-order reliability analysis problem is a preferred way to find this reliability index. Second-order reliability analysis problems are also available but not employed for this purpose, as they often bring high nonlinearity [14].

This index is then used in a first-order inverse reliability analysis problem. A standard normalized first-order inverse reliability analysis problem is set up as [14]:

$$\begin{aligned} &min \quad G_U(u_1, u_2, \dots, u_n) \\ &s.t. \quad \|(u_1, u_2, \dots, u_n)\| = \beta \end{aligned} \tag{2}$$

where β is the (target) reliability index, and the variable u_i is the standard normalized random variable.

This problem can be solved by the Conjugate Gradient Analysis (CGA) method or the Unconstrained Polar Reliability Analysis (UPRA) method in order to find the optimum point, which is called the Minimum Performance Target Point (MPTP) [8, 11].

4. Solar Panels' Resource-Adequacy-based Reliability Analysis Problem

Various optimization models are available in the literature, which consider the reliability of an electricity power network in general, or a solar panel, in particular [10]. These models are often set up as a reliability analysis problem, which, in the case of solar panels, a widely used model is designed as a resource-adequacy-based model by using the photocurrent equation that is defined based on two random variables, the irradiance G and temperature T. It has been found that these random variables follow the Normal probability distribution [15, 20].

In a resource-adequacy-based reliability analysis problem introduced for solar panels, the photocurrent equation, shown by I_{Ph}, is used to set up the system performance function. Also, two coefficients are defined that can be found using nominal values of the photocurrent equation, as $\gamma = \frac{I_{scn} - K_i + T_n}{G_n}$ and $\lambda = -\frac{K_i}{G_n}$. The random variables G and T are represented by x_1 and x_2, respectively, with boundaries as $0 \le x_1 < G_n$ and $0 \le x_2 < T_n$. Then, a new system performance function is formulated as:

$$G(x_1, x_2) = \gamma x_1 + \lambda x_1 x_2 \tag{3}$$

It has been reported that the non-linear term of this performance function can be ignored in some cases, as λ could be close to zero as a result of a possible huge gap between the nominal values. After setting up the performance function, a resource-adequacy-based reliability analysis problem is formulated and then standardized. The standard normalized problem, which indeed is a circular minimization problem that employs the previously found reliability index β, is set up as follows:

$$\begin{aligned} &min \quad \gamma(\sigma_1 u_1 + \mu_1) + \lambda(\sigma_1 u_1 + \mu_1)(\sigma_2 u_2 + \mu_2) \\ &s.t. \quad \|(u_1, u_2)\| = \beta \end{aligned} \tag{4}$$

In this problem, u_1 and u_2 These are the standard normalized random variables that are obtained by using the First-Order Reliability Method (FORM). Although general optimization algorithms can be used to solve this problem, it has been found that the Unconstrained Polar Reliability Analysis (UPRA) method and the Conjugate Gradient Analysis (CGA) method are the most stable and efficient methods to find MPTP as the optimum point of the problem [8, 9].

5. Investigating Solar Panels' Performance using the Monte Carlo Simulation

In this Section, the resource-adequacy-based reliability analysis problem (discussed in the previous Section) is analysed by employing the Monte Carlo Simulation (MCS) in order to verify its performance. There are a number of nominal values in this problem whose values are collected from the existing literature. These include nominal short-circuit current. I_{scn}, current temperature coefficient K_i, nominal irradiance G_n and nominal temperature T_n.

Based on the existing literature, $I_{scn} = 4.8$, $K_i = 0.08$, $G_n = 200$ and $T_n = 45$, and so, $\gamma = 0.25$ and $\lambda = -0.0004$. Therefore, the system performance function would be as follows:

$$G(x_1, x_2) = 0.25x_1 - 0.0004x_1x_2$$

In order to simulate the statistical parameters of the random variables, which are normally distributed, and then study the solar panels' performance, the MCS is employed to generate 100 random numbers for each variable. x_1 and x_2. Based on the simulation results, the expected values and standard deviations are found as $[\mu_1, \mu_2] = [7.18, 27.94]$ and $[\sigma_1, \sigma_2] = [1.66, 4.16]$.

These statistical parameters are used to transform both random variables and the performance function into the standard normal random space. Therefore, the standard normalized performance function would be:

$$G(u_1, u_2) = 0.4u_1 - 0.01u_2 - 0.003u_1u_2 + 1.71$$

So, the first-order inverse problem can now be set up in the standard normal space as below:

$$\begin{array}{ll} min & 0.4u_1 - 0.01u_2 - 0.003u_1u_2 + 1.71 \\ s.t. & \|(u_1, u_2)\| = 2 \end{array}$$

where the reliability index β is 2.

This problem is solved using the CGA method, which can find the optimum point (MPTP) as $(x_1^*, x_2^*) = (3.8601, 28.0174)$ where $G(x_1^*, x_2^*) = 0.9164$. Also, the MPTP satisfies all the boundary conditions of both random variables, the irradiance and temperature, as $0 \leq x_1 < G_n = 200$ and $0 \leq x_2 < T_n = 45$.

By comparing the MPTP with the initial design point, it can be seen that even though values of both variables have been updated by the CGA method, the main adjustment has occurred in the first random variable, the irradiance G. This variable needs to be equal to 3.8601 to guarantee the minimum performance of the system, while its initial value was 7.18, and that means almost half of the available irradiance is sufficient to get the minimum system performance. This finding complies with the non-linearity characteristic of the performance function discussed in the previous Section, and so the simulation result is verified.

6. An Applied Case-Study Validation using a Comparative Analysis of Solar Panels' Performance

Solar panels' resource-adequacy-based reliability analysis problem is used in this Section in order to validate the results of two case studies in two different environmental conditions. The locations selected for this study are Melbourne, Australia and Khobar, Saudi Arabia, for which data has been collected for January 2025.

Melbourne is selected as a successful city to attract more and more people to install solar panels every year, even though it is considered a relatively cold and rainy city in Australia [24]. On the other hand, Khobar is a city with very hot summers and ample sunshine. It should also be mentioned that these cities are located in two different hemispheres, and so while January is one of the coldest months of winter in Khobar, as it is in the northern hemisphere, it is always a hot summer month in Melbourne, which is located in the southern hemisphere.

Temperature is recorded and reported in Australia and Saudi Arabia in terms of Celsius. Therefore, the same scale is used in this paper to show the temperature data, which indeed represents the maximum temperature of the day.

On the other hand, the unit of irradiance, which measures the rate of energy received from the sunshine per unit area, is kilowatt-hours per square meter, and so the irradiance data shown in this paper has the units of $\frac{kWh}{m^2}$.

All the collected data are publicly available on the Internet. For the data collection process, the Australian Bureau of Statistics (ABS) is used for Melbourne's temperature, while the irradiance data of Melbourne is collected from the Bureau of Meteorology (BoM) website. On the other hand, the Weather Underground's website is used to collect the temperature data for Khobar, and NASA's website is used to collect Khobar's irradiance data.

Table 1 in the appendix shows the collected data for both locations in detail. It can be seen that Melbourne's irradiance is greater than Khobar's irradiance in 25 days (out of 31 days of January) while Melbourne's temperature is warmer than Khobar's only in 14 days during the same period. Therefore, it can be concluded that there is no relationship between these variables. For instance, the first day of January 2025 was warmer in Khobar, while the irradiance of Melbourne was much higher than Khobar's irradiance on the same day.

6.1. Case Study of Melbourne, Australia, January 2025

Both random variables follow the Normal distribution, and so to find their statistical parameters, the mean value and the standard deviation of the data collected for each variable should be found. Based on the recorded data for Melbourne, these parameters are found as $[\mu_1, \mu_2] = [6.2355, 25.3194]$ and $[\sigma_1, \sigma_2] = [2.1780, 3.9512]$. The following figure represents the data as a bar chart.

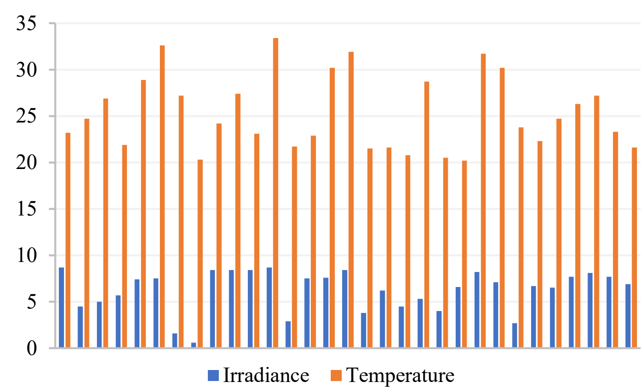

Fig. 1 Melbourne's data for the irradiance and temperature

The same nominal values as the previous Section are used to formulate this problem, and so, the system performance function is $G(x_1, x_2) = 0.25x_1 - 0.0004x_1x_2$. So, a new problem, based on the statistical parameters of Melbourne's data, can then be set up as following:

$$\begin{array}{ll} min & 0.5224u_1 - 0.0098u_2 - 0.0034u_1u_2 + 1.4957 \\ s.t. & \|(u_1, u_2)\| = 2 \end{array}$$

This problem is solved by the CGA method, and the optimum point is found as $(x_1^*, x_2^*) = (1.8796, 25.3732)$ where the performance function value is $G(x_1^*, x_2^*) = 0.4482$.

6.2. Case Study of Khobar, Saudi Arabia, January 2025

A similar approach is applied in this Subsection to figure out the statistical parameters of variables for Khobar. As discussed before, both random variables follow the Normal distribution, and so the mean value and the standard deviation are found as $[\mu_1, \mu_2] = [3.5960, 24.4516]$ and $[\sigma_1, \sigma_2] = [0.6109, 1.7931]$ based on the recorded data for Khobar. The recorded data is displayed by the following bar chart.

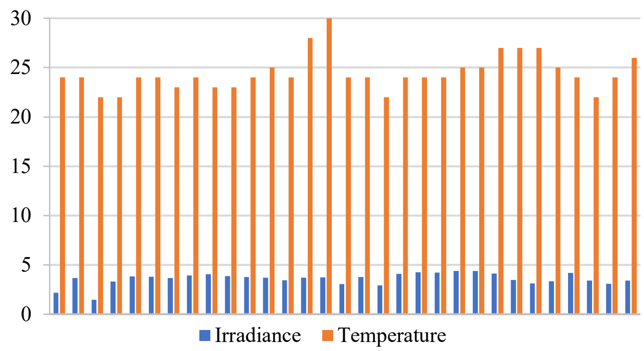

Fig. 2 Khobar's data for the irradiance and temperature

Therefore, a new standard normalized system performance function can be formulated as $G(u_1, u_2) = 0.1467u_1 - 0.0026u_2 - 0.0004u_1u_2 + 0.8638$ based on the same nominal values as before, and also the recorded data for Khobar. Then, the inverse problem would be as follows:

$$\begin{aligned} &min \quad 0.1467u_1 - 0.0026u_2 - 0.0004u_1u_2 + 0.8638 \\ &s.t. \qquad\qquad\qquad \|(u_1, u_2)\| = 2 \end{aligned}$$

The CGA method is employed to solve the problem, which has resulted in $(x_1^*, x_2^*) = (1.7633, 24.4757)$ as the optimum point, while the system performance function value would be $G(x_1^*, x_2^*) = 0.4211$.

7. Discussion and Future Works

An inverse resource-adequacy-based reliability analysis problem is set up for each case study in this paper to investigate the system performance of solar cells in two different environmental conditions. Two cities from two different countries are selected to formulate performance functions based on the recorded data of irradiation and temperature.

The initial design point of each problem is indeed equal to the expected value of both random variables. These design points are updated by the CGA method to eventually find the optimum point (MPTP). By comparing the optimum point of each case study with the relevant initial design point, it can be concluded that the main change happens to the irradiance, not the temperature. Not only does this finding once again confirm the simulation results carried out in this paper, but it also sheds light on a similar fact about the locations selected for the comparative analysis.

Based on the collected data, the irradiance of Melbourne was higher than the irradiance of Khobar in 84% of the days during the time of the study, while Melbourne had warmer weather than Khobar in less than 50% of the same month. However, the fact that the main adjustment by the CGA method is done on the irradiance complies with the collected data, which shows the irradiance plays a more important role than the temperature in this problem.

Further, about half the initial irradiance of Khobar, which was experiencing a cold winter, is enough to seal the minimum system performance, and it is pretty much similar to the findings of the simulation in this paper. However, during the hot summer of Melbourne, only 30% of the initial irradiance could guarantee the target performance of the system.

However, there are other environmental, social, and economic factors, such as dust accumulation, humidity, community support, and government incentives, which can affect solar cells' performance. These factors can be considered in future research to introduce other reliability analysis models for solar cells to improve their performance even further.

8. Conclusion

This paper focuses on solar panels' performance in terms of resource-adequacy-based reliability. For this purpose, an available problem of solar panels is employed, which is based on the photocurrent function. The system performance function depends on two normally distributed random variables, the irradiance G and the temperature T. This model is first analyzed by a Monte Carlo simulation in which 100 simulations are run to solve the problem and find its optimum point. The simulation result confirms an already established result that the irradiance plays the main role in determining solar panels' performance when it comes to resource-adequacy-based analysis.

After the simulation, a comparative analysis is carried out by using two case studies from two different cities during January 2025 to validate the results. A resource-adequacy-based reliability analysis problem is solved based on the data collected for each city in order to compare the system's performance in different geographical conditions. Findings of these case studies verify the result of the simulation carried out in this paper. It is found that the higher importance of irradiance, compared with the temperature, is independent of the location and their weather and environmental conditions in resource-adequacy-based reliability analysis.

The optimum points of these problems show how many days of a month (in each of these cities) the required natural resources were available for solar panels to generate electricity. This can be done by comparing the first component of the optimum point with the recorded daily data of irradiance of the month. In this study, the daily irradiance of Melbourne was less than the irradiance of the relevant optimum point in only two days during January 2025, while Khobar had only one day with insufficient irradiance to generate electricity by solar panels. Given that the data of this study is collected during the summer time of Melbourne and winter time of Khobar, it can be concluded that Khobar (and in general, Saudi Arabia) has a reliable source of irradiance to use solar energy to generate electricity and move away from fossil fuels.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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Appendix

Recorded data during January 2025.

Table 1. Recorded irradiance and temperature data for Melbourne and Khobar during January 2025

	Melbourne		Khobar	
Date	**Irradiance (kWh/m^2)**	**Temp. ($^{\circ}C$)**	**Irradiance (kWh/m^2)**	**Temp. ($^{\circ}C$)**
1	8.7	23	2.2	24
2	4.5	25	3.7	24
3	5	27	1.5	22
4	5.7	22	3.3	22
5	7.4	29	3.8	24
6	7.5	33	3.8	24
7	1.6	27	3.7	23
8	0.6	20	3.9	24
9	8.4	24	4.1	23
10	8.4	27	3.9	23
11	8.4	23	3.8	24
12	8.7	33	3.7	25
13	2.9	22	3.4	24
14	7.5	23	3.7	28
15	7.6	30	3.7	30
16	8.4	32	3.1	24
17	3.8	22	3.8	24
18	6.2	22	2.9	22
19	4.5	21	4.1	24
20	5.3	29	4.3	24
21	4	21	4.2	24
22	6.6	20	4.4	25
23	8.2	32	4.4	25
24	7.1	30	4.1	27
25	2.7	24	3.5	27
26	6.7	22	3.1	27

27	6.5	25	3.3	25
28	7.7	26	4.2	24
29	8.1	27	3.4	22
30	7.7	23	3.1	24
31	6.9	22	3.4	26