A New Approach to Design Reliability Analysis Problems of Solar Panels: A Case Study of the City of Dammam, Saudi Arabia

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Abstract: - Climate change has become a global problem in the last couple of years. That is why many national and international organizations are currently working on renewable energy systems (RESs), like wind turbines and solar panels, to tackle climate change issues. Moving towards the RESs, needs designing efficient models for these systems. A new constrained optimization problem is proposed in this paper to evaluate the performance of solar panels. This problem, which is a reliability analysis problem, aims at finding a point where the system is expected to have the minimum performance. The reliability analysis problem is designed based on a new system performance function that employs the photocurrent equation. Stability and efficiency of the proposed model are first analyzed by a simulation which is based on the Monte Carlo simulation. Then, an experiment is carried out to run the analysis again with real data. For this purpose, the irradiance and temperature data of the City of Dammam, Saudi Arabia, are collected to run the analysis, and then the result is compared with the simulation results. The conjugate gradient direction-based (CGDB) and the conjugate gradient analysis (CGA) methods are employed to solve the optimization problems.

Key-Words: - Optimization, Performance Function, Reliability Analysis, Non-deterministic Optimization, Climate Change, Solar Panels.

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1 Introduction

In recent years, climate change has become a global problem. Research shows that by the middle of this century, the temperature of the planet Earth will most likely increase by 2°C. However, there is no sign that fossil fuel consumptions will be reduced significantly. Sadly, it has been estimated that oil and gas consumption will be doubled, [1], [2].

As a result, many projects, either research or industrial, are now dedicated to developing new renewable energy systems, particularly in fields like solar panels and wind turbines. Governments and City Councils around the world try to motivate companies and individuals to move towards green energy on both industrial and residential scales by providing financial support and incentives, [3], [4], [5].

Given all these efforts, there are still big hurdles to overcome in order to make energy resources greener. Availability of natural resources, such as solar irradiance or wind, is an effective factor in generating renewable energies. But these resources have random, and in some cases unreliable, behavior. For instance, the fact that solar panel stations can be installed where enough irradiance is available can limit the potential of this type of installation.

Research findings show that the accuracy of data collected in real-time can help to improve solar power generation systems. The Internet of Things (IoT) and machine learning algorithms have been used to analyze RESs, [6], [7].

Furthermore, it has been reported that the RESs' power generation costs have been reduced. Optimization techniques like the particle swarm optimization (PSO) have been considered to improve the design and configuration of these systems and resulted in 75% cost reduction between 2010 and 2017, [8], [9].

Formulating an equation to study power generation by solar cells has always been a challenge to figure out how the power generation can be improved, [10]. There are several mathematical models for this purpose based on different characteristics of solar cells.

The very first step to set up each model is to determine its variables. One of the frequently used models for this purpose is the photocurrent equation, which is defined with respect to two widely-used variables: the irradiance G and the temperature T.

These variables would then shape characteristic curves of the system, [11], [12].

Given a solar cell's power generation is calculated by $P = I_{PV}V_{PV}$. It is required to go through the details of the PV's current I_{PV} and voltage V_{PV} among which the current I_{PV} depends on the irradiance and the temperature. On the other hand, the voltage of a solar cell V_{PV} is ideally equal to its diode voltage V_d.

A solar cell's current I_{PV} is often found by the equation $I_{PV} = I_{Ph} - I_d$. In this equation, two components, such as the photocurrent I_{Ph} and the diode's current I_d, are employed to find the current of a solar cell, [13], [14], [15]. Both variables G and T, as the irradiance and temperature, respectively, are present in this equation. In this case, the photocurrent equation is formulated as [16]:

$$I_{Ph}(G,T) = [I_{scn} + K_i(T - T_n)]\frac{G}{G_n} \quad (1)$$

As can be seen, the photocurrent equation depends on two (random) variables G and T, as well as three nominal values I_{scn} nominal short-circuit current, T_n nominal temperature and G_n nominal irradiance, and a current temperature coefficient K_i.

The second component of a solar cell's current equation is the current of its diode. I_d is a function of T (the temperature) and the diode's voltage V_d.

$$I_d(T,V_d) = I_S(T)\left(e^{\frac{V_d}{nV_t(T)}} - 1\right) \quad (2)$$

In this paper, a reliability analysis problem is proposed to improve the system design of solar panels. Therefore, the two above-mentioned random variables, the irradiance G and the temperature T, are used in the new problem. This problem is first solved by simulation and then by real-data collected about the City of Dammam, Kingdom of Saudi Arabia, in order to show the effectiveness of the reliability analysis problem.

2 Reliability Analysis Problems, Constrained Optimization

Reliability-related issues of a system are often investigated by solving a reliability analysis problem. Although first-order and second-order models are available to set up these problems, a first-order reliability analysis problem is often employed, as the second-order problems are highly non-linear. The first-order reliability analysis problems are classified as direct and inverse problems, [16].

Both direct and inverse problems are formulated as constrained minimization problems, which in both cases use a system performance function $G(x_1, x_2, \dots, x_n)$. However, these problems are not solved in the original random space, as it could result in high non-linearity of the problem. To overcome this challenge, these problems are always transformed into a standard normal random space using the first-order reliability method (FORM), [14]. It has been reported in the available literature that the second-order reliability method (SORM) and higher orders may add some challenges to the problem due to a high nonlinearity of the relevant transformation, [16]. That is why the FORM is applied to solve the reliability analysis problems in this paper.

In the direct problem, the standard normalized performance function of the system is set equal to zero to create the failure surface. That is, $G_U(u_1, u_2, \dots, u_n) = 0$ is the failure surface (or limit-state function) which divides the space into two sub-spaces, as the safety region and the failure region.

Then, the nearest point on this failure surface to the origin of the standard normalized random space would be found by solving the first-order direct reliability analysis problem. This problem is set up as follows:

$$\min\|(u_1, u_2, \dots, u_n)\|\mathrm{d}$$
$$s.t.\, G_U(u_1, u_2, \dots, u_n) = 0 \quad (3)$$

In the literature, it is reported that this problem can be solved stably and efficiently by the conjugate gradient direction-based (CGDB) method to find the most probable failure point (MPFP) as the optimum point of the problem, [15]. The obtained MPFP is often used to find a target reliability index. This index is defined as the Euclidean norm of the MPFP, which is the same as the distance from the MPFP to the origin of the standard normalized random space.

However, the first-order inverse reliability analysis problem is designed in a reverse way. In this case, the standard normalized system performance function. i.e. $G_U(u_1, u_2, \dots, u_n)$, is minimized in a constrained optimization problem. The constraint of this problem is defined by making the Euclidean norm of the random point $(u_1, u_2, \dots, u_n)$ equal to a (target) reliability index β. It has been reported that the system reaches its minimum performance at this optimum point, namely the minimum performance target point (MPTP).

The inverse reliability analysis problem is set up as follows:

$$\min\ G_U(u_1, u_2, \dots, u_n)\mathrm{d}\quad s.t.\, \|(u_1, u_2, \dots, u_n)\| = \beta \quad (4)$$

The most stable and efficient existing method to solve the above first-order inverse reliability analysis problem is the conjugate gradient analysis (CGA) method, [16].

There are, however, some reliability analysis models available for electricity power networks. In these models, a performance function is often defined for the system, which is then used to set up a probabilistic constraint and then to introduce a reliability-based design optimization (RBDO) model where the cost is minimized while considering the system reliability, [14], [15].

3 New Reliability Analysis Models for Solar Cells

Although many optimization models exist for solar cells, no reliability analysis problem has yet been introduced for these systems. This paper employs the photocurrent equation to introduce a reliability analysis problem for solar panels.

So, the main contributors to the equation of a solar cell's current are the variables G and T, which both have a random nature, and that is why they can be considered as two random variables. However, this equation does not consider reliability-related issues.

Based on the available models in the literature, two random variables, the irradiation G and the temperature T, are used to set up the new reliability analysis problem. Both variables show random behaviors and are considered as random variables in this paper, which follow the Normal distribution, [17].

In general, a solar panel's power generated is formulated as a function of its current I_{PV} and its voltage V_{PV}. However, I_{PV} is a function of two variables, namely the photocurrent I_{Ph} and the current of the diode I_d while V_{PV} equals the voltage of the diode V_d in an ideal situation.

On the other hand, the function I_{Ph} depend on the variables G and T. Also, I_d is a function of V_d and T. That being said, it can be concluded that the generated power by a solar panel is a three-variable function (G, T, and V_d). As the diode voltage is not a random variable, the other two, i.e., the irradiance G and temperature T, seem to be appropriate to be considered as random variables of the new model. These variables are going to be used to set up a performance function for the solar cells that will ultimately be employed to model the reliability analysis problem.

Two constants will then be defined to use in the introduced system performance function for solar panels. These constants are found based on the nominal values and coefficients of the original photocurrent equation. These coefficients are defined as:

$$\alpha = \frac{I_{scn} - K_i T_n}{G_n} \tag{5}$$

and

$$\gamma = \frac{K_i}{G_n} \tag{6}$$

To set up the new system performance function, the random variables G and T, are shown by ω and φ, respectively. The performance function for solar cells, which is defined based on the photocurrent function, is formulated as:

$$G(\omega, \varphi) = \alpha\omega + \gamma\omega\varphi \tag{7}$$

This function depends on the random variables ω and φ, which represent the irradiance and the temperature. Also, α and γ are the coefficients obtained based on the nominal values and coefficients of the photocurrent function. It should be noted that ω and φ are non-negative real variables. This can be shown as:

$$0 \le \omega \le G_n \quad \& \quad 0 \le \varphi \le T_n \tag{8}$$

If the second coefficient γ was too close to zero, then the second term, which includes both random variables ω and φ, becomes ineffective, and so the system performance function would lose its non-linear behavior. In this case, conventional search optimization algorithms (in addition to reliability analysis methods) could also be employed to solve the problem.

Based on the discussion in the previous Section, random variables of a reliability analysis problem (ω and φ) first need to be standard normalized. As part of this transformation, the performance function $G(\omega, \varphi)$ would also be standard normalized and converted to $G(u_1, u_2)$.

The first-order reliability method (FORM) is often used to perform the transfer in order to reduce the nonlinearity of the problem. Once the transformations are complete, the proposed performance function (7) would be employed to formulate the following reliability analysis problems. As both random variables follow the Normal distribution, these transformations are defined as $\omega = \sigma_1 u_1 + \mu_1$ and $\varphi = \sigma_2 u_2 + \mu_2$.

Therefore, a first-order direct reliability analysis problem is written as follows. Note that this is the standard normalized problem, and that is why the variables are shown by u_1 and u_2.

$$\min \|(u_1, u_2)\| \tag{9}$$
$$s.t.\, c_1(\sigma_1 u_1 + \mu_1) + c_2(\sigma_1 u_1 + \mu_1)(\sigma_2 u_2 + \mu_2) = 0$$

where u_1 and u_2 are two random variables in the U-space. That is, random variables ω and φ are converted to standard normal random variables u_1 and u_2. Also, the proposed system performance function $G(\omega, \varphi)$ is employed to introduce the equality constraint in this reliability analysis problem.

The other problem, i.e., the inverse problem, is also set up in the new random space as follows:

$$\min c_1(\sigma_1 u_1 + \mu_1) + c_2(\sigma_1 u_1 + \mu_1)(\sigma_2 u_2 + \mu_2)$$
$$s.t. \|(u_1, u_2)\| = \beta \tag{10}$$

In this problem, β represents the target reliability index. It can be seen that the system performance function $G(\omega, \varphi)$ is not used in the constraint. Instead, it makes the objective function of the inverse reliability analysis problem. Also, the constraint is based on the Euclidean Norm of new random variables u_1 and u_2.

It has been reported in the literature that the CGDB and CGA methods are the most stable and efficient methods to solve the direct and inverse problems, respectively. The first problem is solved to find the MPFP. This point shows where a solar cell probably stops working and so fails to generate electricity. Also, the main aim of solving the second problem is to find where the MPTP is. This optimum point is where the system would most likely show its minimum performance.

A numerical simulation and a case study will be used in the next Section to illustrate more details about the introduced model.

4 Numerical Experiments of Reliability Analysis Problems

Four parameters are involved in the introduced performance function in this paper. These parameters are I_{scn}, K_i, G_n and T_n. Table 1 shows the value of these parameters, which are found by reviewing the existing literature.

Table 1. Nominal values of parameters of the reliability analysis problem –

Parameter	Value
Nominal Short Circuit Current I_{scn}	4 A
Current Temperature Coefficient K_i	0.4 A/K
Nominal Irradiance G_n	100 W/m^2
Nominal Temperature T_n	29.8 K

Source: [12]

The coefficients α and γ are consequently calculated by using the above parameters. So, it can be seen that $\alpha = 0.334$ and $\gamma = -0.004$. These parameters are going to be used in the proposed performance function.

As previously discussed, the random variables ω and φ represent the irradiance G and the temperature T, respectively. Therefore, a system performance function can be defined as below, based on the parameters represented in Table 1:

$$G(\omega, \varphi) = 0.334\ \omega - 0.004\ \omega\varphi \tag{11}$$

The next two Sections are dedicated to analyzing the new reliability analysis problem introduced in this paper.

First, a numerical simulation is performed to check the problem in a simulation process and find out how stably and efficiently the methods can solve the problem. A direct reliability analysis problem and an inverse reliability analysis problem are solved using the best methods available in the literature.

Then, a case study is included in the second Section below, which is based on data collected for the City of Dammam, Kingdom of Saudi Arabia. Both reliability analysis problems are again solved using this real-world data by employing the CGDB and CGA methods, which were also employed to solve the simulation problems.

5 Numerical Simulation

The random variables ω and φ both follow the Normal distribution function with statistical parameters $\omega \sim (8, 1.6)$ and $\varphi \sim (31, 5.4)$. The random variables and the system performance should be standard normalized using these parameters.
So, the random variables are replaced as:

$$\omega = 1.6u_1 + 8 \quad \& \quad \varphi = 5.4u_2 + 31$$

Therefore, a system performance function can be defined as follows:

$$G(u_1, u_2) = 0.34u_1 - 0.18u_2 - 0.05u_1u_2 + 1.67 \tag{12}$$

5.1 Direct Problem

The first-order direct problem (8) is rewritten based on the standard normalized performance function as follows:

$$\min\|(u_1, u_2)\| \tag{13}$$
$$s.t. 0.34u_1 - 0.18u_2 - 0.05u_1u_2 + 1.67 = 0$$

The CGDB method works best to solve this problem. This method needs 18 iterations to solve the problem and find the optimum point, which is shown by MPFP. This is indeed the closest point on the failure surface $G(u_1, u_2) = 0$ to the origin of the U-space.

The optimum point found by this method is $(w^*, \varphi^*) = (0.0023, 31.0723)$. Both conditions of $0 \leq \omega < G_n = 100$ and $0 \leq \varphi < T_n = 298$ are met, which means the optimum point satisfies the optimization constraints.

5.2 Inverse Problem

The first-order inverse problem (9) is used in this Subsection by applying the standard normalized performance function and assuming the target reliability index β to be equal to 3. Therefore, the problem can be formulated as:

$$\min\ 13.892\, u_1 - 1.008\, u_2 - 0.3312\, u_1 u_2 + 42.28 \quad s.t. \|(u_1, u_2)\| = 3 \tag{14}$$

Based on the available literature, the CGA method is the best method to solve this problem, which needs only 13 iterations to converge. The optimum point MPTP found by this method is $(w^*, \varphi^*) = (3.8217, 31.1106)$ where $G(\omega, \varphi) = 9.6599$.

It can be seen that both boundary constraints of the problem, allocated to the random variables, are again met.

6 Case Study of the City of Dammam, Kingdom of Saudi Arabia

This Section includes a case study which is based on data collected about the City of Dammam, Kingdom of Saudi Arabia. For this purpose, a comprehensive search is carried out, and so two databases are selected to collect data about the irradiation and temperature, which are the random variables of the introduced problem. It has already been explained that both of these random variables follow the Normal probability distribution.

The irradiation data is collected from NASA's website. This data covers the same period of time and the same location as the collected data for temperature to ensure consistency of the data to be used in this paper. The statistical parameters of the irradiance ω are $(6.41, 0.54)$.

The data about temperature is collected from the Weather Underground website. Recorded temperature (with the degree of Celsius) of the City of Dammam, Kingdom of Saudi Arabia, is collected during all 365 days of 2023. The mean value and standard deviation of the random variable are calculated. As the temperature is shown by φ in this paper, statistical parameters of this variable can be found as $\varphi \sim (37.58, 1.27)$.

More information on the data collection process, its resources, and methodologies can be shared by third parties upon request.

So, the performance function can now be standard normalized for this case study by using the above-mentioned information. So,

$$G(u_1, u_2) = 0.09\, u_1 - 0.03\, u_2 - 0.02\, u_1 u_2 + 1.18 \tag{15}$$

6.1 Direct Reliability Analysis Problem

The direct problem of a solar panel can now be set up based on the real-data collected for this case study. So, it is going to be as follows:

$$\min \|(u_1, u_2)\| \tag{16}$$
$$s.t.\ 0.09\, u_1 - 0.03\, u_2 - 0.02\, u_1 u_2 + 1.18 = 0$$

As the CGDB method is the best method to solve the direct reliability analysis problems, this method is applied to solve the reliability analysis problem in this Subsection.

After 23 iterations of the CGDB method, an MPFP is found as $(0.0003, 37.5623)$. It can be seen that both conditions of $0 \leq \omega < G_n = 100$ and $0 \leq \varphi < T_n = 298$ are met, indicating the feasibility of the solution.

6.2 Inverse Reliability Analysis Problem

In this Subsection, the inverse problem is set up for the current case study. The reliability index β is assumed to be 3, and both random variables as well as the performance function of the system are transformed into the U-space.

So, the inverse problem can be written as follows:

$$\min\ 0.09\, u_1 - 0.03\, u_2 - 0.02\, u_1 u_2 + 1.18\, s.t. \|(u_1, u_2)\| = 3 \tag{17}$$

As discussed earlier, the most stable and efficient method to solve this problem is the CGA method, which is employed to find the MPTP. The CGA method converges after 83 iterations and can find the optimum point MPTP as $(w^*, \varphi^*) = (4.7936, 37.5552)$ where $G(\omega, \varphi) = 0.1417$.

Again, both boundary constraints of the irradiation and temperature are satisfied by the obtained optimum point.

It can be seen that the solar cell system is expected to fail at $(0.0003, 37.5623)$, which is the MPFP obtained by solving the direct reliability analysis problem. Also, the minimum performance of the system could happen when the irradiance G is equal to 4.7936, and the temperature T is 37.5552, which are found as the optimum point (MPTP) of the inverse problem.

7 Conclusion and Future Works

Not only cost effectiveness of renewable energy systems needs to be considered when designing these systems, but their reliability cannot be ignored. This is to ensure that a new system meets the minimum criteria to perform reliably.

Two reliability analysis problems for solar panels, which are widely accepted to be used to address reliability concerns, have been introduced in this paper. The photocurrent function is considered to set up relevant performance functions. Both reliability analysis problems are then formulated by using this performance function.

Numerical experiments are performed in this paper to check the performance of these problems. A numerical simulation is carried out first which is based on the data available in the literature. Then, real-data collected for a case study are used to run the performance analysis again.

The case study is conducted by employing data of the City of Dammam in the Kingdom of Saudi Arabia. The data is collected from two trusted online resources, introduced in the paper, on random variables of solar cells' reliability analysis problems. Both reliability analysis problems are solved again using this data.

It is found that the temperature T is not an effective factor to figure out where the optimum point is. This point is the main spot in which the system may fail.

The coefficient of the second term of the performance function became too small (almost zero), which can be a result of selecting the photocurrent equation to set up the system reliability analysis problem. That means it may not be an appropriate choice to set up a new solar panel system performance function using the photocurrent equation.

Therefore, as part of the future works, the next studies could be about finding another equation to replace the photocurrent equation, probably with higher nonlinearity in the performance function of the system, to enhance the problem's design. This would be helpful to investigate the potential effects of all factors involved in the process.

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