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Research paper

Global sensitivity analysis of photovoltaic cell parameters based on credibility variance

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ABSTRACT

Photovoltaic cells can directly convert solar energy into electrical energy, which is environmentally friendly and has a wide range of applications. In practical engineering, the uncertainty of photovoltaic cell parameters has an important impact on cell performance. In order to study the influence of parameter uncertainty on the output performance of photovoltaic cells, a photovoltaic cell model is established and five parameters are selected: irradiation intensity, photovoltaic cell surface temperature, temperature coefficient, equivalent series resistance and equivalent parallel resistance. The influence of these parameters on the output power and conversion efficiency of photovoltaic cells is studied by using the global sensitivity analysis method based on fuzzy theory. The principal and total global sensitivity indexes describing the influence of each parameter on the output performance were therefore calculated and ranked. The key parameters influencing the performance of photovoltaic cells were determined to be related to cell surface temperature and equivalent parallel resistance. In actual production and life, the output performance of photovoltaic cells can be improved by controlling these two factors. The results of this study can help to guide the performance analysis and parameter optimization of photovoltaic cells, accelerating the development and improving the adoption of photovoltaic systems.

1. Introduction

With the aggravation of the global energy crisis and increasing environmental pollution, the development of solar energy occupies a critical position in the energy structure (Wang et al., 2021b; Xiong et al., 2022). As photovoltaic (PV) cells directly convert solar energy into electric energy, they represent an increasingly popular source of renewable energy. The number of deployed PV power generation systems has significantly increased worldwide (Wang et al., 2021a; Wu et al., 2022), and many countries have introduced grid pricing policies to accelerate investment in PV power generation. Therefore, research into the performance of PV cells is of great significance for ensuring their continued adoption (Sharma et al., 2021; Sadan and Dwivedi, 2020). To date, many experts and scholars have studied the parameters of PV cells (Chehreh Ghadikolaei, 2021; Chen et al., 2020; Chandran et al., 2021; Ganesh Pardhu and Kota, 2021; Ji et al., 2021). For example, Chen et al. (2020) used variables reduction and improved shark optimization technique to extract photovoltaic cells parameters, Chandran et al. (2021) proposed an improved distribution estimation algorithm to estimate the optimal parameters of fuel cells and solar cells, and Ganesh Pardhu and Kota (2021) proposed a new random radial shift optimization algorithm based on a group algorithm to extract the unknown parameters of solar PV cells. The confirmation and extraction of parameters of photovoltaic cells and their components is of great significance for evaluating the performance of photovoltaic cell systems and preventing aging and failure of systems and components. However, these studies were performed under the assumption that the parameters of PV cells are deterministic, ignoring their uncertainty in the process of design, manufacture, and application. Research has shown that in engineering practice, small fluctuations in key design parameters will lead to significant changes in the output performance of a system (Zhang et al., 2021, 2020b). Therefore, the study of the influence of PV cell parameter uncertainty on output performance is vital for the optimization, development, and adoption of PV cell technology (Sarić and Stanković, 2005).

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Parameter uncertainty consists of objective and subjective uncertainty factors (Cooper et al., 1996). Compared with objective uncertainty, subjective uncertainty cannot be described by probability theory because of inadequate information or deep cognition. Many non-probability theories have accordingly been established to quantitatively describe subjective uncertainty, including fuzzy theory (Zhang et al., 2022), evidence theory (Yu et al., 2021), and cloud theory (Koç and Koç, 2020). Among these, fuzzy theory uses the membership degree to describe the likelihood of events, and is considered to be the most effective theory for describing subjective uncertainty. Therefore, it has become an important theoretical basis for dealing with subjective uncertainty in engineering practice.

The sensitivity analysis is a method for studying and analyzing the sensitivity of the state or output changes of a system (or model) to changes in system parameters or surrounding conditions (Choi et al., 2018; Ma et al., 2014). Generally, it can be divided into factor screening methods, local sensitivity analysis methods, or global sensitivity analysis methods (Shi and Chen, 2019; Antoniadis et al., 2021; Laoun et al., 2016). The factor screening method is a qualitative analysis method that can only rank the importance of input variables on the uncertainty of the model output response (Woods and Lewis, 2016). The local sensitivity analysis method is based on the change rate (slope) of the statistical characteristics of the output response at the nominal point according to the distribution parameters of the input variables, reflecting the local influence of the input variables (Saltelli et al., 2000b). The calculation of local sensitivity is efficient, but as it is limited by the selection of nominal points, it cannot directly reflect the contribution of a single input variable or of the interaction of multiple input variables to the statistical characteristics of output performance, and it lacks global and computational stability (Lee et al., 2019; Hamby, 1994). The global sensitivity analysis method can measure the influence of input variables on the output performance of a system when they change within their entire distribution ranges from a global perspective, then rank their importance according to their degree of influence (Sun et al., 2021; Zhang et al., 2020a). This importance ranking has particular guiding significance for the analysis and design of structural systems, as well as probabilistic safety assessment (Qian and Dong, 2022; Wang et al., 2021c). At present, a great deal of research has been conducted yielding specific achievements in the application of global sensitivity analyses, and various global sensitivity indicators have been established accordingly. Generally, these global sensitivity indexes are based on the non-parametric method (correlation coefficient index) (Helton and Davis, 2003), variance (Zhang et al., 2020c), or moment independence (Derennes et al., 2021). Among these approaches, the global sensitivity index based on variance is straightforward and comprehensible, able to quantify the interaction between input variables, and applicable to any input–output model; thus, it has been widely applied (Zhang, 2018).

The output performance of PV cells is affected by the material parameters of the PV components as well as the working environment parameters. Although previous research has discussed the influence of these parameters on the output power of PV cells, the specific influence degree and ranking of these parameters remains unknown. To address this gap, this study used global sensitivity theory to determine the influence of the subjective uncertainty of PV cell parameters on the output power and conversion efficiency of PV cells. The remainder of this paper is organized as follows: in Section 2, the PV cell model is established and the design parameters are extracted; Section 3 discusses the membership functions of the parameters; in Section 4, fuzzy theory is applied to conduct a global sensitivity analysis of the PV cell parameters based on credibility variance; in Section 5, the principal and total global sensitivity index values are analyzed and discussed; finally, Section 6 summarizes the influence of each parameter on the output performance of PV cells and concludes the paper.

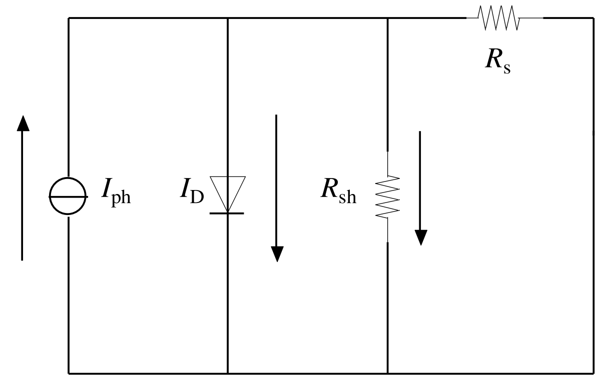

Fig. 1. Photovoltaic cell model equivalent circuit diagram.

2. PV cell model and design parameters

The equivalent circuit of a PV cell is composed of a constant photo-generated current I_{ph}, diode current I_D, and a series of resistors with an equivalent internal parallel resistance R_{sh} and an effective series resistance R_s, as shown in the PV cell model in Fig. 1.

From the equivalent circuit diagram in Fig. 1, the output current of the PV cell can be expressed as follows:

$$I = I_{ph} - I_D - I_{sh} \tag{1}$$

where I_{sh} is the current flowing through the equivalent parallel resistance of the PV cell.

According to the diode principle:

$$I_D = I_o(\exp\frac{q(V + IR_s)}{nKT} - 1) \tag{2}$$

where I_o is the reverse saturation current in the diode, V is the output voltage of the PV cell, q is the electric charge, n is the diode ideality factor, K is the Boltzmann constant, and T is the surface temperature of the PV cell.

Thus, according to Kirchhoff's principle:

$$I_{sh} = \frac{V + IR_s}{R_{sh}} \tag{3}$$

By combining Eqs. (1), (2), and (3), the following expression is obtained:

$$I = I_{ph} - I_o(\exp\frac{q(V + IR_s)}{nKT} - 1) - \frac{V + IR_s}{R_{sh}} \tag{4}$$

where I_{ph} and I_o are functions of temperature and light intensity, respectively, and can be expressed as follows:

$$I_{ph} = \frac{G}{G_{ref}}[I_{ph,ref} + \alpha_{I,sc}(T - T_{ref})] \tag{5}$$

$$\frac{I_o}{I_{o,ref}} = (\frac{T}{T_{ref}})^3 \exp(\frac{q}{nK}(\frac{E_{g,ref}}{T_{ref}} - \frac{E_g}{T})) \tag{6}$$

where G is the irradiation intensity, $\alpha_{I,sc}$ is the temperature coefficient of the short-circuit current, and E_g is the energy bandwidth of the material, which has a temperature characteristic given by $E_g/E_{g,ref} = 1 - 1.0002677(T - T_{ref})$. Here, the subscript *ref* indicates the value under standard test conditions.

To facilitate the subsequent calculation of the output power, it is necessary to obtain an explicit current equation in which the

$$\begin{aligned}
P &= IV \\
&= \left[\frac{R_{sh}(I_{ph}+I_o)-V}{R_s+R_{sh}} - \frac{nV_{th}}{R_s}W(X)\right]\cdot V \\
&= \left[\frac{R_{sh}(I_{ph}+I_o)-V}{R_s+R_{sh}} - \frac{n\frac{nKT}{q}}{R_s}W\left(\frac{I_0R_{sh}R_s}{nV_{th}(R_s+R_{sh})}\exp\left(\frac{R_{sh}(R_sI_{ph}+R_sI_o+V)}{nV_{th}(R_s+R_{sh})}\right)\right)\right]\cdot V \\
&= \frac{\left\{R_{sh}\left\{\left\{G\left[I_{ph,ref}+\alpha_{1,sc}\left(T-T_{ref}\right)\right]\right\}/G_{ref}+\left\{I_{o,ref}T^3\exp\left[-\left(E_g/T-E_{g,ref}/T_{ref}\right)/K\right]\right\}/{T_{ref}}^3\right\}-V\right\}}{(R_s+R_{sh})} \\
&\quad - \frac{\left\{TKn * lambertw\left(0,\left\{I_{o,ref}R_sR_{sh}T^2q\exp\left\{\frac{\left\{R_{sh}q\left\{\begin{array}{l}\left\{R_sG\left[I_{ph,ref}+\alpha_{1,sc}\left(T-T_{ref}\right)\right]\right\}/G_{ref}+\\ \left\{I_{o,ref}R_sT^3\exp\left[-\left(E_g/T-E_{g,ref}/T_{ref}\right)/K\right]\right\}/{T_{ref}}^3\end{array}\right\}\right\}}{Tkn\left(R_s+R_{sh}\right)} + \left[\frac{-\left(E_g/T-E_{g,ref}/T_{ref}\right)}{K}\right]\right\}\right\} / \left[{T_{ref}}^3kn\left(R_s+R_{sh}\right)\right]\right)\right\}}{R_sq}
\end{aligned} \tag{9}$$

Box I.

right side does not contain the current term. The explicit current equation is given by the Lambert W function as:

$$I = \frac{R_{sh}(I_{ph}+I_o)-V}{R_s+R_{sh}} - \frac{nV_{th}}{R_s}W(X) \tag{7}$$

for which

$$V_{th} = \frac{nKT}{q},\quad X = \frac{I_0R_{sh}R_s}{nV_{th}(R_s+R_{sh})}\exp\left(\frac{R_{sh}(R_sI_{ph}+R_sI_o+V)}{nV_{th}(R_s+R_{sh})}\right) \tag{8}$$

The output power P can then be expressed as Eq. (9) given in Box I

The conversion efficiency η of a photovoltaic cell is given by:

$$\eta = \frac{I_mV_m}{AG} \tag{10}$$

where V_m is the maximum power point voltage, I_m is the maximum power point current, and A is the PV cell area.

3. Fuzzy Distribution of PV cell parameters

The design parameters of the PV cell model presented in Section 2 include the irradiation intensity G, PV cell temperature T, temperature coefficient of the short-circuit current $\alpha_{1,sc}$, equivalent series resistance R_s, and equivalent parallel resistance R_{sh}. Owing to the uncertainty of the PV cell model itself and the lack of a large amount of performance data during design, each of these parameters has a degree of uncertainty. This study therefore investigated the influence of the uncertainty of the five basic variables G, T, $\alpha_{1,sc}$, R_s, and R_{sh} on the uncertainty of PV cell output power P and conversion efficiency η.

Combining existing data and engineering experience, the five basic PV cell variables were defined as Gaussian fuzzy variables with a membership function $\mu(x_i) = \exp\left[-(x_i-a)^2/2\sigma^2\right]$. Table 1 lists the parameters of this membership function for each variable.

Table 1
Parameters of each Gaussian fuzzy variable.

Fuzzy variable	Identification	Unit	a	σ
G	x_1	W/m^2	400	8
T	x_2	K	303.15	6.063
$\alpha_{1,sc}$	x_3	mA/C	0.006	1.2×10^{-4}
R_s	x_4	Ω	0.146	2.92×10^{-3}
R_{sh}	x_5	Ω	1182.82	23.6562

4. Global sensitivity analysis of PV cell parameters

4.1. Global sensitivity analysis theory based on credibility variance

The fuzzy structure system model studied in this paper refers to a deterministic model whose input variables are fuzzy and whose output parameters can be expressed as $Y = g(\boldsymbol{x})$. In this study, $\boldsymbol{x} = (x_1,x_2,x_3,x_4,x_5)$ is a five-dimensional fuzzy input variable, and the credibility variance decomposition of the output response is as follows:

$$V(Y) = \sum_{i=1}^{5}V_{x_i} + \sum_{i=1}^{5}\sum_{j=i+1}^{5}V_{x_ix_j} + \cdots + V_{x_1x_2\cdots x_5} \tag{11}$$

in which

$$V_{x_i} = V\left[E\left(Y|x_i\right)\right] \tag{12}$$

$$V_{x_ix_j} = V\left[E\left(Y|x_i,x_j\right)\right] - V_{x_i} - V_{x_j} \tag{13}$$

where V_{x_i} is the first-order variance contribution (principal variance contribution) of the fuzzy input variable x_i to the credibility variance of the output response Y when the fuzzy variable x_i acts alone, and $V_{x_ix_j}$ is the second-order variance contribution of fuzzy input variables x_i and x_j to the credibility variance of the output response Y. The total variance contribution ${V_{x_i}}^T$ of the fuzzy input variable x_i is defined as the sum of all variance contributions related to x_i in Eq. (14), that is,

$${V_{x_i}}^T = V_{x_i} + \sum_{j=1,j\neq i}^{5}V_{x_ix_j} + \sum_{j=1,j\neq i}^{5}\sum_{k=1,k\neq i,k\neq j}^{5}V_{x_ix_jx_k} + \cdots + V_{x_1x_2\cdots x_5} \tag{14}$$

The total variance contribution ${V_{x_i}}^T$ can also be calculated by the following equation:

$${V_{x_i}}^T = V(Y) - V\left[E(Y|x_{-i})\right] \tag{15}$$

where x_{-i} is a four-dimensional variable containing all variables from $\boldsymbol{x}$ except x_i.

For the model $Y = g(\boldsymbol{x})$ with the five-dimensional fuzzy input variable $\boldsymbol{x} = (x_1, x_2, x_3, x_4, x_5)$, the total variance contribution of x_1 is:

$$\begin{aligned} V_{x_1}{}^T &= V_{x_1} + V_{x_1x_2} + V_{x_1x_3} + V_{x_1x_4} + V_{x_1x_5} + \\ &\quad V_{x_1x_2x_3} + V_{x_1x_2x_4} + V_{x_1x_2x_5} + V_{x_1x_3x_4} + V_{x_1x_3x_5} + V_{x_1x_4x_5} + \\ &\quad V_{x_1x_2x_3x_4} + V_{x_1x_2x_3x_5} + V_{x_1x_2x_4x_5} + V_{x_1x_3x_4x_5} + V_{x_1x_2x_3x_4x_5} \end{aligned} \tag{16}$$

According to the variance decomposition Equation (11),

$$\begin{aligned} V(Y) &= V_{x_1} + V_{x_2} + V_{x_3} + V_{x_4} + V_{x_5} \\ &\quad + V_{x_1x_2} + V_{x_1x_3} + V_{x_1x_4} + V_{x_1x_5} + \\ &\quad V_{x_2x_3} + V_{x_2x_4} + V_{x_2x_5} + V_{x_3x_4} + V_{x_3x_5} \\ &\quad + V_{x_4x_5} + V_{x_1x_2x_3} + V_{x_1x_2x_4} + \\ &\quad V_{x_1x_2x_5} + V_{x_1x_3x_4} + V_{x_1x_3x_5} + V_{x_1x_4x_5} + V_{x_2x_3x_4} \\ &\quad + V_{x_2x_3x_5} + V_{x_3x_4x_5} + \\ &\quad V_{x_1x_2x_3x_4} + V_{x_1x_2x_3x_5} + V_{x_1x_2x_4x_5} + V_{x_1x_3x_4x_5} \\ &\quad + V_{x_2x_3x_4x_5} + V_{x_1x_2x_3x_4x_5} \end{aligned} \tag{17}$$

Therefore,

$$V_{x_1}{}^T = V(Y) - V\left[E(Y|x_2, x_3, x_4, x_5)\right] \tag{18}$$

The global sensitivity index, $S_{x_{i_1}x_{i_2}\cdots x_{i_s}}$, is based on the credibility variance and is defined as the ratio of the corresponding input variable variance contribution $V_{x_{i_1}x_{i_2}\cdots x_{i_s}}$ to the output response variance $V(Y)$ as follows:

$$S_{x_{i_1}x_{i_2}\cdots x_{i_s}} = \frac{V_{x_{i_1}x_{i_2}\cdots x_{i_s}}}{V(Y)} \tag{19}$$

The sensitivity index S_{x_i} corresponding to V_{x_i} is called the first-order sensitivity index (principal sensitivity index) of fuzzy input variable x_i, and reflects the influence of x_i acting alone on the credibility variance of the output response Y. The sensitivity index $S_{x_ix_j}$ corresponding to $V_{x_ix_j}$ is called the second-order sensitivity index of fuzzy input variables x_i and x_j, and reflects the influence of the second-order action of x_i and x_j on the credibility variance of the output response Y. The sensitivity index $S_{x_i}{}^T$ corresponding to $V_{x_i}{}^T$ is called the total sensitivity index of fuzzy input variable x_i, and reflects the total influence of x_i on the credibility variance of the output response Y.

4.2. Analysis process

In this section, a global sensitivity analysis of the PV cell model design parameters is conducted based on credibility variance, and the sensitivity of the output according to each variable is quantified by their principal and total global sensitivity indexes. The specific steps in this process are as follows:

(1) Generate N groups of evenly distributed input samples $\boldsymbol{x}_k (k = 1, 2, \ldots, N)$ using the Monte Carlo method and calculate the corresponding joint membership $\upsilon_k = \mu(\boldsymbol{x}_k)$ of each group, where $\mu(\boldsymbol{x})$ is the joint membership function of the fuzzy input variable $\boldsymbol{x}$ and defined as $\mu(\boldsymbol{x}) = \mu(x_1) \wedge \mu(x_2) \wedge \cdots \wedge \mu(x_5)$. Let $a = g(\boldsymbol{x}_1) \wedge g(\boldsymbol{x}_2) \wedge \cdots \wedge g(\boldsymbol{x}_5)$ and $b = g(\boldsymbol{x}_1) \vee g(\boldsymbol{x}_2) \vee \cdots \vee g(\boldsymbol{x}_5)$. Then, randomly generate the value r within the interval $[a, b]$, repeating this process N times. If $r \geq 0$, then $e = e + Cr\{g(\boldsymbol{x}) \geq r\}$ and $Cr\{g(\boldsymbol{x}) \geq r\} = \frac{1}{2}\left(\max_{1\leq k\leq N}\{\upsilon_k | g(\boldsymbol{x}) \geq r\} + \min_{1\leq k\leq N}\{1 - \upsilon_k | g(\boldsymbol{x}) < r\}\right)$; otherwise, $e = e - Cr\{g(\boldsymbol{x}) \leq r\}$ and $Cr\{g(\boldsymbol{x}) \leq r\} = \frac{1}{2}\left(\max_{1\leq k\leq N}\{\upsilon_k | g(\boldsymbol{x}) \leq r\} + \min_{1\leq k\leq N}\{1 - \upsilon_k | g(\boldsymbol{x}) > r\}\right)$. The expectation is given as $E[g(\boldsymbol{x})] = a \vee 0 + b \wedge 0 + e \cdot (b - a)/N$.

(2) Let $g^* = \{g(\boldsymbol{x}) - E[g(\boldsymbol{x})]\}^2$, and use step (1) to calculate the expectation $E[g^*]$ of the fuzzy variable function g^*, then $V[g(\boldsymbol{x})] = E\{g(\boldsymbol{x}) - E[g(\boldsymbol{x})]\}^2 = E[g^*]$.

(3) Generate N groups of evenly distributed input samples $\boldsymbol{x}_k = (x_{1k}, x_{2k}, \ldots, x_{5k})(k = 1, 2, \ldots, N)$ using the Monte Carlo method. For a sample x_{ik^*} of one-dimensional fuzzy input variables x_i, construct N groups of condition samples of the remaining four-dimensional fuzzy variables. Because the input variables are independent of each other, N groups of condition samples corresponding to x_{ik^*} can be constructed as $x_k{}' = (x_{1k}, \ldots, x_{ik^*}, \ldots, x_{5k})(k = 1, 2, \ldots, N)$. Then, calculate the conditional expected value $E[g(\boldsymbol{x})|x_i = x_{ik^*}](k^* = 1, 2, \ldots, N)$ using step (1) and sample $x_k{}'$ under the condition x_{ik^*} established above. Obtain the expected value $E\{E[g(\boldsymbol{x})|x_i]\}$ and variance value $V\{E[g(\boldsymbol{x})|x_i]\}$ of the conditional expectation (i.e., the primary variance contribution V_{x_i} of fuzzy input variable x_i) according to steps (1) and (2), then calculate the principal sensitivity index S_{x_i} according to its definition in Eq. (19).

(4) Generate N groups of evenly distributed input samples $\boldsymbol{x}_k = (x_{1k}, x_{2k}, \ldots, x_{5k})(k = 1, 2, \ldots, N)$ using the Monte Carlo method. For a sample $x_{-ik^*} = (x_{1k^*}, x_{2k^*}, \ldots, x_{(i-1)k^*}, x_{(i+1)k^*}, \ldots, x_{5k^*})$ of four-dimensional fuzzy input variables x_{-i}, because the input variables are independent of each other, N groups of condition samples corresponding to x_{-ik^*} can be constructed as $x_k{}'' = (x_{1k^*}, \ldots, x_{(i-1)k^*}, x_{ik^*}, x_{(i+1)k^*}, \ldots, x_{5k^*})(k = 1, 2, \ldots, N)$. Next, using step (1) and the sample $x_k{}''$ under the condition x_{-ik^*} constructed above, calculate the conditional expected value $E[g(\boldsymbol{x})|\boldsymbol{x}_{-i} = \boldsymbol{x}_{-ik^*}](k^* = 1, 2, \ldots, N)$. Finally, obtain the expected value $E\{E[g(\boldsymbol{x})|\boldsymbol{x}_{-i}]\}$ and variance value $V\{E[g(\boldsymbol{x})|\boldsymbol{x}_{-i}]\}$ of the conditional expectation (i.e., the total variance contribution $V_{x_i}{}^T = V(g(\boldsymbol{x})) - V[E(g(\boldsymbol{x})|\boldsymbol{x}_{-i})]$ of fuzzy input variable x_i) according to steps (1) and (2), and calculate the total sensitivity index $S_{x_i}{}^T$ according its definition in Eq. (19).

5. Analysis and discussion

5.1. Global sensitivities of output power

Table 2 provides the principal global sensitivity index values describing the influence of each individual PV cell parameter on the output power P; these values are compared in Fig. 2. The principal global sensitivity index values can be ranked in the order of $S_T > S_G > S_{R_{sh}} > S_{R_s} > S_{\alpha_{1,sc}}$, and the comparison indicates that the cell surface temperature T has by far the greatest influence, followed by the irradiation intensity G, equivalent parallel resistance R_{sh}, equivalent series resistance R_s, and finally the short-circuit current temperature coefficient $\alpha_{1,sc}$, each of which has relatively little influence.

According to Table 3, the ranking of the indexes describing the total global sensitivity of the output power P to each of the five PV cell parameters when acting together is $S_T{}^T > S_{R_{sh}}{}^T > S_G{}^T > S_{R_s}{}^T > S_{\alpha_{1,sc}}{}^T$. Furthermore, the comparison of the total global sensitivity indexes in Fig. 3 indicates that the influences of the cell surface temperature T and equivalent parallel resistance R_{sh} on output power P are clearly the greatest, whereas those of the irradiation intensity G, equivalent series resistance R_s, and current temperature coefficient $\alpha_{1,sc}$ are considerably smaller and can therefore be ignored. Among them, the cell surface temperature has the greatest impact on the output performance of photovoltaic cells, which is similar to the existing research results (Rashel et al., 2016).

Table 2
Principal global sensitivity indexes of PV cell parameters according to their influence on output power P.

Parameter	G	T	$\alpha_{\mathrm{I},sc}$	R_s	R_{sh}
S_{x_i}	0.0031	0.2094	1.1748×10^{-4}	1.1921×10^{-4}	3.5855×10^{-4}

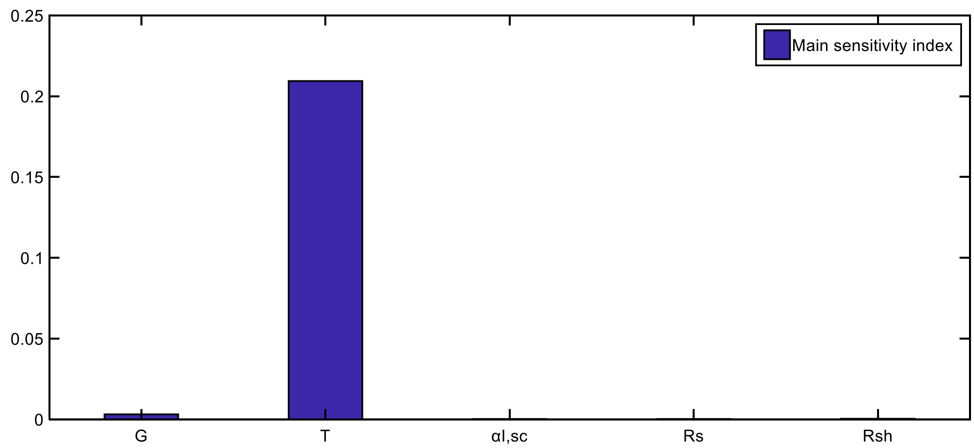

Fig. 2. Principal global sensitivity indexes of PV cell parameters according to their influence on output power.

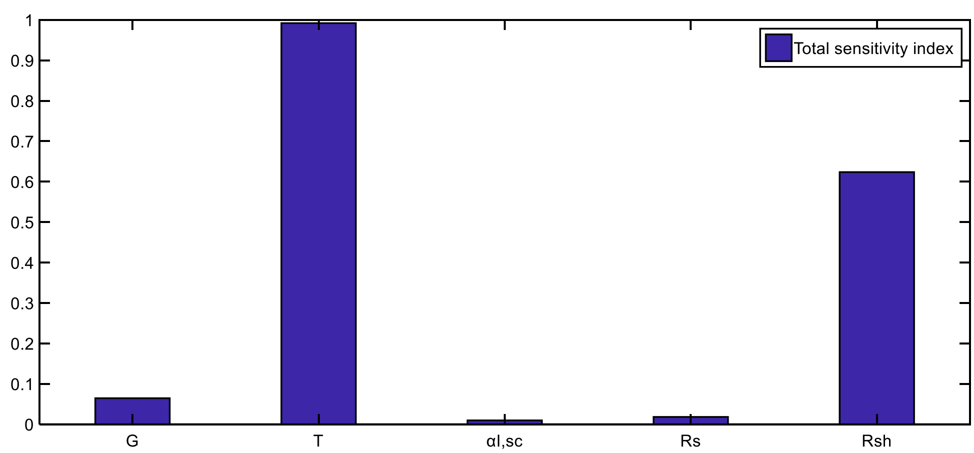

Fig. 3. Total global sensitivity indexes of PV cell parameters according to their influence on output power.

Table 3
Total global sensitivity indexes of PV cell parameters according to their influence on output power P.

Parameter	G	T	$\alpha_{\mathrm{I},sc}$	R_s	R_{sh}
${S_{x_i}}^T$	0.0645	0.9919	0.0096	0.0182	0.6236

5.2. Global sensitivities of conversion efficiency

Table 4 provides the principal global sensitivity index values describing the influence of each individual PV cell parameter on the conversion efficiency η; these values are compared in Fig. 4. The principal global sensitivity index values can be ranked in order of $S_{R_{sh}} > S_{R_s} > S_G > S_{\alpha_{\mathrm{I},sc}} > S_T$. The comparison indicates that the equivalent parallel resistance R_{sh} has the greatest influence on the conversion efficiency η, followed by the equivalent series resistance R_s, irradiation intensity G, current temperature coefficient $\alpha_{\mathrm{I},sc}$, and cell surface temperature T.

According to Table 5, the index values describing the total global sensitivity of the conversion efficiency η to the PV cell parameters when acting together can be ranked in order of ${S_T}^T > {S_{R_{sh}}}^T > {S_{\alpha_{\mathrm{I},sc}}}^T > {S_G}^T > {S_{R_s}}^T$ Furthermore, the comparison in Fig. 5 indicates that the cell surface temperature T and equivalent parallel resistance R_{sh} have by far the greatest influences on the conversion efficiency η, whereas the current temperature coefficient $\alpha_{\mathrm{I},sc}$, irradiation intensity G, and equivalent series resistance R_s have much smaller influences and can therefore be ignored.

6. Conclusion

To address the instability of PV cell output performance according to the inherent fluctuation of design parameters, this study applied the global sensitivity index based on fuzzy theory to measure the influence of inherent design parameter fluctuation on the stability of PV cell output power P and conversion efficiency η. The Monte Carlo method was used to calculate the principal and global sensitivity indexes of the design variables based on the credibility variance. The results show that compared with the cell surface temperature T and equivalent parallel resistance R_{sh}, the total global sensitivity index values of the short-circuit current temperature coefficient $\alpha_{\mathrm{I},sc}$, irradiation intensity G, and equivalent series resistance R_s are minimal for both the output power P and conversion efficiency η, and the effects of their variation can therefore be ignored. Therefore, the key design parameters of PV cells are related to the working environment (T) and material (R_{sh}). In actual production and application, the

Table 4
Principal global sensitivity indexes of PV cell parameters according to their influence on conversion efficiency η.

Parameter	G	T	$\alpha_{I,sc}$	R_s	R_{sh}
S_{x_i}	5.1719×10^{-5}	8.3697×10^{-6}	4.8839×10^{-5}	5.8822×10^{-5}	1.3118×10^{-4}

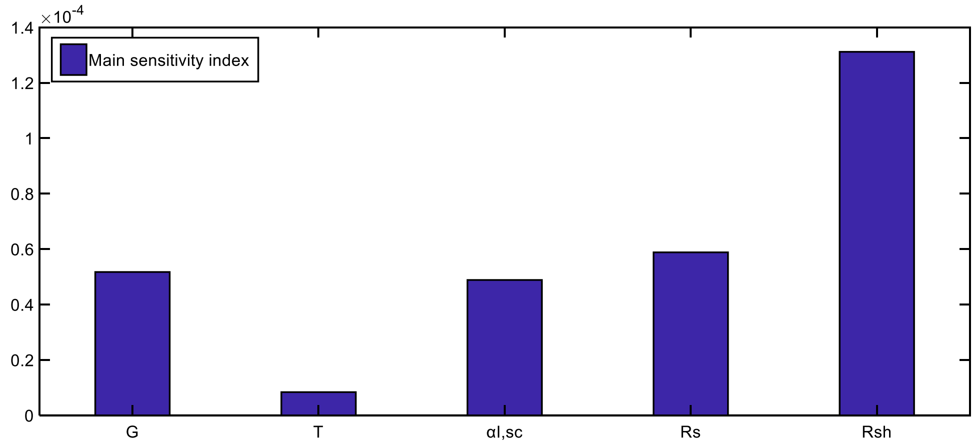

Fig. 4. Principal global sensitivity indexes of PV cell parameters according to their influence on conversion efficiency η.

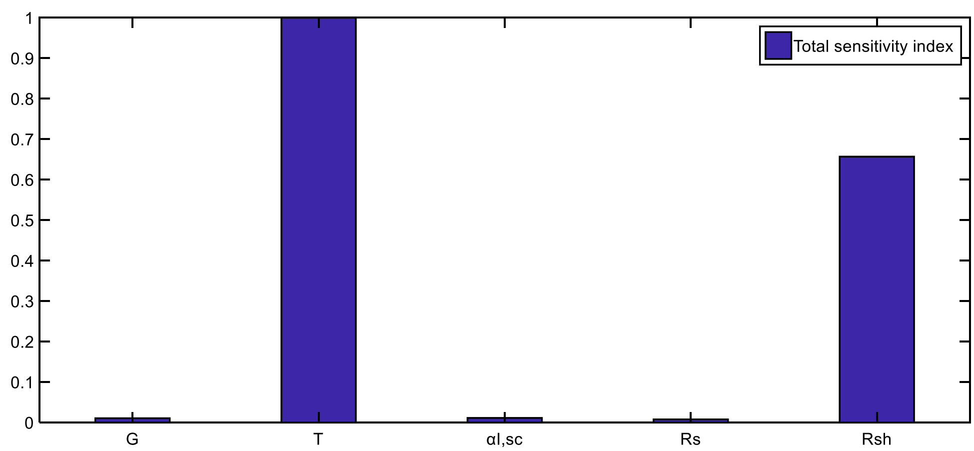

Fig. 5. Total global sensitivity indexes of PV cell parameters according to their influence on conversion efficiency η.

Table 5
Total global sensitivity indexes of PV cell parameters according to their influence on conversion efficiency η.

Parameter	G	T	$\alpha_{I,sc}$	R_s	R_{sh}
$S_{x_i}{}^T$	0.0104	0.9997	0.0112	0.0076	0.6566

output performance of PV cells can therefore be improved by controlling material selection(ensure a consistent equivalent parallel resistance R_{sh}) and expected working environment temperature T. The results of this study can provide guidance for the design and optimization of future PV cells, and further improve their application and utility to increase adoption.

CRediT authorship contribution statement

Feng Zhang: Train of thought ,Methodology, Submit. **Cheng Han:** Creation of models, Calculation, Writing – original draft. **Mingying Wu:** Modify. **Xinting Hou:** Verification. **Xinhe Wang:** Data curation. **Bingqiang Li:** Review.

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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