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The short-term intermittency evaluation of distributed photovoltaic power

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ABSTRACT

Uncertainty of distributed photovoltaic(PV) power brings great challenges to the safe and stable operation of power system, in which the intermittency problem is more challenging than the fluctuation. This paper focuses on the intermittency problem of distributed PV power, firstly, an intermittency evaluation method based on generalized extreme value(GEV) theory is proposed to solve the problem of the lack of "small-sample big-gap" events. Secondly, focusing on high risk events such as high-frequency and warning mutation events, probabilistic evaluation indexes were established, including T-hour-period mutation intensity and T-hour-period mutation frequency. Finally, a two-dimensional joint probability distribution of intermittency elements is established, and the concepts of return period and return level are introduced into the photovoltaic field to provide data support for the configuration of energy storage capacity and duration, and to provide auxiliary decision-making for the execution time and development cycle of interactive projects. The proposed method provides a solution for intermittency evaluation in small sample status quo with strong data compatibility and engineering replicability.

1. Introduction

In the background of low-carbon energy transition, photovoltaic [1,2], as an important hand in realizing the "30–60" dual-carbon target [3–5], is developing rapidly. The development of distributed photovoltaic(PV) power plants has also entered an accelerated stage [6], and with the gradual increase in the access rate of distributed PV power plants in medium and low-voltage distribution networks, distribution network operation and scheduling is facing a huge challenge [7]. Some scholars have noted the importance of intermittency for wind and solar power, even describing it as a deterrent drawback [8]. In the opinion of some scholars, the solution to the problem of solar intermittency is more challenging than volatility compared to other new energy sources [9]. The inherent intermittency of new energy sources has brought many unfavorable effects on the overall regulation and control of energy systems, and some scholars have even proposed a new term "intermittent new energy sources" [10]. Some scholars believe that without an effective solution for intermittency, solar energy cannot become a substitute for traditional fossil energy [11]. Therefore, recognizing the intermittency and realizing the effective assessment of intermittency has become a worthwhile research topic, and the refinement study of intraday distributed PV power intermittency is particularly important under the background of normalized source-network-load-storage synergistic optimization.

The intermittency of distributed PV power is one of the intrinsic properties of uncertainty, which cannot be neglected due to its

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strong contribution to the phenomenon of sudden variations in distributed PV power, especially in the presence of severe cloud phenomena [12]. Focusing on intermittency, in terms of qualitative analysis, Daniel Suchet argues that energy can be described as either stable or intermittent and analyzes in detail the difference between intermittency and predictability, variability, and dispatchability [13]; Some scholars ignored the difference between intermittency and uncertainty, using methods such as probability distribution function or wavelet decomposition to analyze power variation characteristics [14,15]; For quantitative analysis, Prasad argued that solar intermittency is essentially the same as wind intermittency and used the same intermittency metric as wind intermittency to study the intermittency of solar energy in Australia [16], however, the limitation of this approach is that the definition of wind intermittency is related to a specific physical source (wind turbulence), and its direct generalization to other energy sources is somewhat controversial [13]. Considering the causes of intermittency, M. Echim states that intermittency is associated with sudden "extreme events" in space or time, or large amplitude changes in plasma variables [17]. Current

Project supported by “the Fundamental Research Funds for the Central Universities”. (B240205007) approaches to the study of intermittency in renewable energy have largely placed a demand on the acquisition of long-term and highly accurate power data [18–21], and, paradoxically, Ted Trainer has argued that the lack of records of rare "big gap" events in renewable energy sources is one of the reasons why the intermittency problem has not been adequately investigated [22]. This also puts forward a specific requirement for the choice of intermittency research methodology, i.e., how to realize an effective assessment of distributed PV intermittency based on a small sample size of mutation events has become a problem worth thinking about.

To address problems posed by solar intermittency, Cong Wu focuses on the fundamental scientific question of how intermittency is affected by aggregation, and proposes that intermittency significantly reduces the cost of balancing the electricity market when solar power is distributed over large geographic areas with significant time differences [9]. However, some studies have shown that the problem caused by short-term intermittency cannot be effectively smoothed by the method of balancing multiple stations in a large geographical area [23]. Viet T. Tran proposed to utilize an energy buffer unit to smooth out voltage and frequency fluctuations at high ramp rates due to intermittency during cloud passage [24]. Quentin Paletta proposed a spatio-temporal neural network architecture for reliable analysis of intermittency using sky images and satellite cloud maps for future state prediction of clouds [25]. However, due to the large number of distributed PV power plants, dispersed location, and small capacity, the method used in the above study is of low feasibility and poor economy, therefore, a more targeted method has to be proposed to realize a comprehensive analysis of the intermittency of distributed PV power generation on the one hand, and on the other hand, it can provide a solution for smoothing out the sudden change of the events due to the intermittency.

In summary, this paper proposes a short-term intermittency assessment method for distributed PV power generation based on the probability distribution theory, and verifies the effectiveness and feasibility of the method by using the historical data of a rooftop distributed PV power plant, which can provide data support for the station reserve storage configuration of distributed PV power plants, provide auxiliary decision-making for the regulation capacity and duration of participation in power supply and demand interaction projects, and provide a solution for the suppression of the sudden-change events caused by intermittency. The method has the following advantages.

1) Considering The current situation of small sample number for power mutation events caused by intermittency, based on the Generalized Extreme Value (GEV) theory to obtain the tail features for the extreme value samples of intermittent indicators, which is conducive to focusing on the high-risk and small probability events, such as mutation warning events and high-frequency mutation events, caused by the changes of intermittency indicators.
2) The concepts of return period and return level are introduced into the field of photovoltaic characteristics analysis, and probabilistic evaluation indexes such as T-hour-period mutation intensity and T-hour-period mutation frequency are established to probabilistically analyze distributed PV power intermittency from the perspective of value and frequency, respectively.
3) Copula function is utilized to construct a two-dimensional joint probability distribution, which reveals the integrated characteristics of intermittency in the setting of joint elements by analyzing the changes in the joint and co-occurring return periods. Furthermore, intermittency solutions such as configuration of energy storage and execution cycle of ource-grid-load-storage interaction project are proposed.

2. Intermittency evaluation based on generalized extreme value theory

The intermittency of PV power is understood to describe the mutability and universality of change [11]. This paper believes that intermittency should be compared with continuity to characterize the mutation phenomenon of distributed PV power data, which refers to the situation of unexpected changes in distributed PV power that cannot be accurately predicted, including positive mutations and negative mutations. In this paper, the single mutation case is regarded as a mutation event, and the evaluation of intermittency is supported by the analysis of mutation events. The paper believes that the intermittency itself should have numeric-value attributes and frequency-rate attributes. The T-hour-period mutation intensity is used to evaluate the probability of the change amplitude of the mutation phenomenon, and the T-hour-period mutation frequency is used to evaluate the probability of the change frequency of the mutation phenomenon.

2.1. Generalized extreme value theory

The extreme value type definition was first proposed by R. A. Fisher and L. H. C. Tippet in 1928 for the study of seldom-occurring but potentially significant extreme events [26], and has since gained widespread attention and application in a wide range of disciplines, such as finance, hydrology, transportation, and many others [27]. Marco Bee used extreme value theory to estimate and predict conditional risk measures [25], Baorui Dai proposed a generalized extreme value mixture model (GEVMM) for the study of traffic load effects on bridges [28], and Joana Cavadas used extreme value theory under the background of probability study of collision accidents during overtaking travel [29]. However, there are still fewer studies applying GEVs to power systems, especially renewable energy intermittency studies. The studies that have been conducted basically focus on the areas of large outage losses, power market prices, and extreme loads on turbines [30–32]. Similar to hydrological engineering affected by peak flood levels, peak rainfall, and meteorological extremes, the sudden intensity peaks and sudden frequency peaks generated intermittently by distributed PV power generation have a significant impact on distribution network scheduling and operation. Due to the GEV distribution's specificity to the tails of the variable distribution and its low data volume requirements, it offers significant advantages in the current state of intermittent studies where sudden change events are poorly documented.

According to the Fisher-Tippett extreme value type theorem [33], assuming that { $x_1, x_2, \ldots, x_n$ }is a set of independent and identically distributed variables with a sample maximum $M_n = max\,(x_1, x_2, \ldots, x_n)$, if there exist constant columns { $a_n > 0$ } and { b_n } that satisfy Eq. (1), then $H(x)$ is a non-degenerate distribution function called the extreme value distribution. $H(x)$ must belong to one of the three basic distribution function types in Table 1.

$$\lim_{n\to\infty}\Pr\left(\frac{M_n - b_n}{a_n} \le x\right) = H(x), x \in R \tag{1}$$

The location parameter μ, scale parameter σ and shape parameter ξ are introduced to describe $H(x)$. The location parameter μ is mainly used as a measure of the concentration trend of the variable; the scale parameter σ is used to describe the dispersion of the overall distribution of the variable; and the shape parameter ξ determines the shape of the tails of the variable's distribution curve of the extremes, and it can reflect the type of the distribution of the extremes. The formula for the $H(x)$ distribution function is given in Eq. (2).

$$\begin{aligned} &H(x;\mu,\sigma,\varepsilon) = \exp\left\{ -\left(1+\varepsilon\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\varepsilon}} \right\}, \\ &\qquad 1+\varepsilon\frac{x-\mu}{\sigma} > 0 \end{aligned} \tag{2}$$

where $H(x)$ denotes the Generalized Extreme Value distribution; μ represents the "center" of the distribution; σ is used to control the size of the deviation from the center; and ξ determines the type of extreme value distribution to which $H(x)$ belongs, as shown in Table 1.

The probability density distribution (PDF) of the sample extreme value x can be obtained according to the GEV distribution as in Eq. (3).

$$f(x) = \begin{cases} \left(\left(\frac{\varepsilon(x-\mu)}{\sigma}+1\right)\right)^{-\frac{\varepsilon+1}{\varepsilon}} e^{-\left(\frac{\varepsilon(x-\mu)}{\sigma}+1\right)^{-\frac{1}{\varepsilon}}}, \frac{\varepsilon(x-\mu)}{\sigma}+1>0 \\ 0, \frac{\varepsilon(x-\mu)}{\sigma}+1 \le 0 \end{cases} \tag{3}$$

Iqbal Hossain found that the parameter estimation technique has negligible effect on the size of the parameters of the generalized extreme value distribution [34], and considering the excellent properties of unbiased and asymptotic normality of the great likelihood estimation method [35], in this paper, we use the great likelihood estimation method for parameter estimation.

2.2. T-hour-period mutation intensity

Distributed PV power intermittent characteristics and cloud irregular flow and other sudden meteorological changes are strongly correlated, accurate grasp of distributed PV power intermittent characteristics of distributed PV power station for distributed PV power plant large-scale deployment of the setting of the grid security and stable operation of the particularly important.

In this paper, the concepts of return period and return level are introduced into the field of distributed PV power, and the concept of T-hour-period mutation intensity is proposed. Assuming that the distribution of mutation intensity extremes of distributed PV power satisfies the GEV distribution, the return level of power mutation intensity is denoted as MII_T, and the corresponding return period is denoted as T. Defining the return level of T-hour-period power mutation intensity, that is, MII_T as the maximum value of the power

Table 1
Common distribution of extreme value distribution.

Extremal distribution	Basic type	The shape parameter ξ takes the value	Rear or tail section
Extreme type I distribution	Gumbel	$\xi = 0$	slimmer tail
Extreme type II distribution	Fréchet	$\xi > 0$	plump
Extreme type III distribution	Weibull	$\xi < 0$	trim

mutation intensity of the distributed PV power station that occurs during T, it is believed that the probability of the power mutation intensity exceeding the MII_T during the T- -hour-period is $p= 1/T$.

Firstly, the Mutation intensity index (MII) is proposed as an index to characterize the mutation level of power mutation events in distributed PV power generation, where mutation events include both positive and negative mutations (i.e., sudden rise and fall of power). The mutation class is divided into zones based on the absolute difference of power data over a defined time interval, and the absolute power difference is defined as Eq. (4).

$$\Delta P_k = |P_{k+m} - P_k| \tag{4}$$

where P_k is the PV power value of k sampling points, P_{k+m} is the PV power value of $(k+m)$ sampling points.

In order to ensure the effectiveness and rationality of the mutation class classification, this paper proposes a method for determining the numerical range of the mutation class based on iterative self-organized clustering algorithm. Iterative Self Organizing Data Analysis Techniques Algorithm (ISODATA) is a dynamic clustering algorithm in which the number of clusters and cluster centers can be changed automatically and iteratively with the computing process [35,36]. In this paper, mutation classes are determined based on the optimal clustering scheme and further mutation intensity values are obtained. In this paper, considering a single day PV can be effective power generation time 04:00 to 19:00, hourly data as a single interval, the single day power data is divided into 16 intervals, the minimum precision of the sample for the 5 min, the number of hourly power samples is 12, and thus the day of the nth hour of the mutation intensity of the extreme value of the MII_n^{max} can be expressed as in Eq. (5), initialized to obtain the power of the distributed PV power plant mutation intensity extreme value sample sequence.

$$\begin{cases} MII_n^{\max} = \max(MII_k) \\ k \in \{12(n-1), 12(n-1)+1, \ldots 12n-1 \end{cases} \tag{5}$$

where $MIIk$ is the power magnitude at the kth ($k = 1, 2, \ldots, 12$) 5min in a single hourly cycle.

In order to characterize the tolerance of practical engineering to extreme small probability events caused by fluctuations in the extreme values of the variable MII, quantile regression was used to estimate the level of mutation intensity of the sample extremes, MII_p, in terms of $p(0<p<1)$ quantiles of $H(MII: \mu, \sigma, \xi)$, as in Eq. (6).

$$MII_p = \inf\{MII : H(MII) \geq P\} \tag{6}$$

Combined with Eq. (2), the mutation intensity return level MII_p defined as a quantile function can be calculated using Eq. (7).

$$MII_p = H^{-1}(p) = \begin{cases} \mu - \sigma \ln[-\ln(1-p)], \varepsilon = 0 \\ \mu + \dfrac{\sigma\{-1 + [\ln(1-p)]^{-\varepsilon}\}, \varepsilon \neq 0}{\varepsilon} \end{cases} \tag{7}$$

where the return level of the PV power mutation extreme event is defined as the corresponding MII_p value at the p extreme quartile; $T = 1/p$ is the return period, which is defined as the occurrence of an extreme event with a sample size of MII_p once every T-hour intervals, and there is a one-to-one correspondence with the return level.

When the threshold value u is given, the number of times the distributed PV power mutation intensity exceeds u in T time can be expressed as Eq. (8).

$$U = \sum_{t \leq T} I|MII_t \geq u| \tag{8}$$

where MII_t denotes the peak power of the PV plant at the t th hour; $I_{|MIIt \geq u|}$ is the indicative function, which is 1 when $MII_t \geq u$ and 0 otherwise.

Then, the T-hour-period mutation intensity can represent that during the observation time at T-hour-period, the average number of times that the peak value of distributed PV power mutation intensity exceeds the threshold value u during the observation time at T is 1, that is, $E(U) = 1$. In this case, only one observation per hour is required, and similarly, other time scales such as monthly, quarterly, yearly, etc. can be defined for the study of short-term, medium-term, and long-term intermittency.

An event with a power mutation intensity level not exceeding MII_r per T_r time interval is a weak mutation event; an event with a power mutation intensity level greater than MII_{yj} per T_{yj} time interval is regarded as a warning mutation event. Accordingly, T_r and T_{yj} are the minimum return periods for the occurrence of weak mutation events and warning mutation events in distributed PV power plants, which are calculated as in Eq. (9).

$$\begin{cases} T_r = \dfrac{1}{f^{-1}(MII_r)} = \dfrac{1}{P_r} \\ T_{yi} = \dfrac{1}{f^{-1}(MII_{yi})} = \dfrac{1}{P_{yi}} \end{cases} \tag{9}$$

where f^{-1} denotes the inverse function of f in Eq. (3), and P_r and P_{yj} are the probabilities of weak mutation events and warning mutation events, respectively, for the generation power of distributed PV power plants.

2.3. T-hour-period mutation frequency

During critical power preservation periods such as peak summer and winter, demand response, orderly power consumption and other source-load interaction programs usually need to be implemented continuously in a short period of time, or even multiple times in one day. As the increasingly normalized source-grid-load-storage cooperative optimization, the probabilistic study of the frequency of intraday sudden changes in distributed PV generation power is of guiding significance in frequency and period of participation in power supply and demand interaction projects.

Similar to T-hour-period mutation intensity, the concept of T-hour-period mutation frequency is introduced in this paper. Firstly, the Mutation frequency index (MFI) is proposed as an index to characterize the frequency of power mutation events in distributed PV power generation. The MFI is characterized by the ratio of the number of valid mutation events to the total number of rated statistics at the measured time scale, which is mathematically described as shown in Eq. (10).

$$MFI = \frac{N_{eme}}{N_s} * 100\% \tag{10}$$

where Neme stands for the number of legitimate mutation events and NS for all nominal statistics throughout the measurement period.

Similar to the mutation intensity return level, this paper introduces the concept of mutation frequency return level, which first defines the effective mutation event level NexeT as the maximum value of the number of effective mutation events occurring in distributed PV power plants during T-hour-period, and the corresponding effective mutation period is noted as T. The same quantile regression method was used to estimate the effective mutation event level Nexep for the sample extremes in terms of p(0<p < 1) quantiles of $H(N_{exe}$: μ, σ, ξ), as in Eq. (11).

$$N_{exep} = H^{-1}(p) = \begin{cases} \mu - \sigma \ln[-\ln(1-p)], \varepsilon = 0 \\ \mu + \dfrac{\sigma\{-1 + [\ln(1-p)]^{-\varepsilon}\}, \varepsilon \neq 0}{\varepsilon} \end{cases} \tag{11}$$

On the basis of the concept of effective mutation event level, this paper defines T-hour-period power station power mutation frequency return level MFI_p as the peak of power station distributed PV power mutation frequency in the future T-hour-period. p extreme value quartile point at the corresponding MFIp value as the mutation frequency return level, and T = 1/p for the return period. The expression is as in Eq. (12):

$$MFI_p = \frac{N_{exep}}{N_s} \times 100\% \tag{12}$$

where the effective mutation level Nexep is calculated as in equation (11) and $T=1/p$; NS denotes the total number of nominal statistics in the measured time scale.

Events with a power mutation frequency level not exceeding MFI_d at one power mutation per T_d time interval are low-frequency mutation events; Events with a power mutation frequency level greater than MIIg occurring once per T_g time interval are considered high-frequency mutation events. Accordingly, T_d and T_g are the minimum return periods for low-frequency mutation events and high-frequency mutation events occurring in the distributed PV power plant. Combining Eq. (12) yields the minimum return period for low-frequency mutation events and high-frequency mutation events as in Eq. (13).

$$\begin{cases} T_d = \dfrac{1}{f^{-1}(MFI_d)} = \dfrac{1}{P_d} \\ T_g = \dfrac{1}{f^{-1}(MFI_g)} = \dfrac{1}{P_g} \end{cases} \tag{13}$$

where f^{-1} denotes the inverse function of f in Eq. (3), and Pd and Pg are the probabilities of low-frequency mutation events and high-frequency mutation events for the generation power of distributed PV power plants, respectively.

3. COMPREHENSIVE assessment of distributed PV power intermittency based on Copula function

The research on the power intermittenity of distributed PV power in the previous section focuses on the analysis of a single factor. The traditional single variable has limitations in providing a comprehensive description. The reason of using binary variable is that this paper believes that the dual attributes of intermittency, such as numeric-value and frequency-rate attributes, are indispensable, especially when it comes to practical engineering applications such as energy storage configuration. The T-hour-period mutation intensity is used to evaluate the probability of the change amplitude of the mutation phenomenon, and the T-hour-period mutation frequency is used to evaluate the probability of the change frequency of the mutation phenomenon. Therefore, it is necessary to establish a joint probability model to reflect the dependence between the two dimensions of numeric-value and frequency-rate, so as to effectively analyze the comprehensive characteristics of intermittency.

3.1. Two-dimensional joint probability distribution

According to Sklar's theorem, the joint distribution function can consist of arbitrary marginal distributions and proper Copula functions [37]. Copula function is an effective method for constructing multidimensional non-normal joint distributions, first proposed by Sklar in 1959, which can provide a powerful measure of correlation of nonlinearly correlated variables [38] and can calculate joint probability distributions reflecting the extreme risk of the tails, and it has been widely used in the fields of insurance and finance [39]. In recent years, it has been introduced into multivariate studies such as hydrology, drought, dust storms and other fields [40], and its application in the field of renewable energy is mainly focused on conducting wind power and PV power correlation studies [41]. In this paper, the Copula function is used to establish a two-dimensional joint probability distribution of mutation intensity and mutation frequency to support the comprehensive characteristic analysis of distributed PV power intermittenity.

Let two random variables X、Y, for an n-dimensional random vector $\boldsymbol{X} = (x_1, \ldots, x_n)$, whose probability density function is $f_X(x_1, \ldots, x_n)$, and the probability distribution function is $F_X(x_1, \ldots, x_n)$; For an n-dimensional random vector $\boldsymbol{Y} = (y_1, \ldots, y_n)$, its probability density function is $f_Y(y_1, \ldots, y_n)$ and the probability distribution function is $F_Y(y_1, \ldots, y_n)$. Denote u=$F_X(x)$, v=$F_Y(y)$, and $C(u, v)$ is the Copula joint distribution function of X、Y. The common Copula functions are divided into two families: the Archimedean Copula function family and the Elliptical Copula function family. Different Copula functions have their own advantages in describing different dependency structures. Archimedean Copulas has a strong track record in modeling tail-dependent and asymmetric dependent structures. The Clayton-Copula function is more sensitive to changes in variables distributed in the lower tails, and is able to characterize the dependence between random variables with lower-tailed dependence and asymmetry, while the Gumbel-Copula function is just the opposite, with a better fit to upper-tailed correlations, and the Frank-Copula function focuses on characterizing the correlation of random variables as a whole. The Gaussian-Copula function in Elliptical Copulas applies to random variables without tail correlation, while the t-Copula function applies to random variables containing symmetric tail correlation. In this paper, the commonly used five types of Copula function as an alternative to construct a two-dimensional joint probability distribution of distributed PV power intermittency assessment elements, the specific expression is shown in Table 2.

In the Table 2, θ is the Copula function parameter, $T_v^{-1}(\cdot)$ is the inverse function of the student t-distribution, $T_{\sum,v}[T_v^{-1}(u), T_v^{-1}(v)]$ is the binary student t-distribution function, $\Phi^{-1}(\cdot)$ is the inverse function of the standard normal distribution, and $\Phi_{\sum}[\Phi^{-1}(u), \Phi^{-1}(v)]$ is the binary normal distribution.

Great likelihood estimation was used for parameter estimation. Combined with the Ordinary Least Squares (OLS) minimization principle for model testing, the optimal joint distribution function was finally selected, where the smaller the value of OLS is, the higher the fitting accuracy, as in Eq. (14).

$$OLS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i' - p_i)^2} \tag{14}$$

where P_i' and P denote the empirical and fitted values, respectively, and n denotes the number of samples of random variables involved in the fit.

3.2. Intermittent element return period

In a statistical sense, the return period refers to the average time interval between two consecutive occurrences of an event, determined by a combination of engineering importance and event hazard. The return periods for two-dimensional variables include joint return periods and homoscedastic return periods [42], and the difference between these two types of homoscedastic periods lies in the definition of the region of occurrence of mutation events, with the former taking into account the probability of a concatenated mutation event, and the latter taking into account the probability of an intersecting mutation event. In this paper, the intermittent elemental return period is defined as the average time interval between the occurrence of some mutation event scenario in distributed PV power.

Let $C(u, v)$ be the Copula joint distribution function of mutation intensity and mutation frequency, u be the marginal distribution function of mutation intensity, and v be the marginal distribution function of mutation frequency. The non-identical present probability is denoted as $H_{or}(u, v)$ and the identical present probability is denoted as $H_{and}(u, v)$, which are calculated as Eqs. (15) and (16),

Table 2
Funtion expressions of typical copulas.

Copulas	Funtion expressions
Gumbel-Copula	$C(u,v) = \exp\left\{-\left[(-\ln u)^{\theta} + (-\ln v)^{\theta}\right]^{\frac{1}{\theta}}\right\}$
Clayton-Copula	$C(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$
Frank-Copula	$C(u,v) = -\frac{1}{\theta}\ln\left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta V} - 1)}{e^{-\theta} - 1}\right]$
t-Copula	$C(u,v;\sum,\gamma) = T_{\sum,\gamma}\left[T_{\gamma}^{-1}(u), T_{\gamma}^{-1}(v)\right]$
Gaussian-Copula	$C(u,v;\sum) = \Phi_{\sum}\left[\Phi^{-1}(u), \Phi^{-1}(v)\right]$

respectively. T_{or} (u, v) is the non-identical return period, which denotes the return period in which at least 1 variable has a non-desired event, and the expression is as in Eq. (17). T_{and} (u, v) is the same-occurrence return period, which denotes the return period of two non-variables with simultaneous non-desired events, with the expression as in equation (18).

$$H_{or}(u, v) = P[U > u \text{ or } V > v] = 1 - C(u, v) \tag{15}$$

$$T_{or}(u, v) = \frac{1}{P[U > u \text{ or } V > v]} = \frac{1}{1 - C(u, v)} \tag{16}$$

$$H_{and}(u, v) = P[U > u \text{ and } V > v] = 1 - u - v + C(u, v) \tag{17}$$

$$T_{and}(u, v) = \frac{1}{P[U > u \text{ and } V > v]} = \frac{1}{1 - u - v + C(u, v)} \tag{18}$$

where P is the probability of occurrence of the mutation event.

The return period of a mutant event is associated with a joint distribution function, where a larger C indicates that the mutant event is less likely to occur and the corresponding return period is larger.

4. Case study

For a rooftop distributed PV power plant with a rated capacity of 5.3 MW in Suzhou City, Jiangsu Province, China, the historical PV power data of the power plant in 2018 are selected, in which the sample data collection interval is 5 min, and this paper focuses on the assessment of intraday distributed PV power intermittency, considering a total of 16 h of daily sampling data from 04:00 to 20:00, and the number of single hourly power samples is 12, and the number of single-day power samples is 192. Four typical meteorological day power data of this weather station were selected, and the distributed PV power curve under typical days was plotted, as shown in Fig. 1.

4.1. Calculated analysis of T-hour-period mutation intensity

The absolute difference in power at the 5min sampling scale was calculated and clustered using ISODATA. Combined with the clustering results, comprehensive consideration of the number of clusters, cluster center value, the power interval division method relying on the rated capacity, the upper and lower limits of the intervals are converted into the rated capacity percentage, in order to meet the demand for universality, consistency and popularization of the PV power mutation level determination of the power stations with different capacities, and the value of the specific mutation intensity index is shown in Table 3.

P_r in the table indicates the rated capacity of the PV plant.

According to Table 3 to determine the distributed PV power mutation intensity values of this power station in 2018, four typical meteorological days are selected to draw the mutation intensity de-temporized statistical distribution map, as shown in Fig. 2.

The initialization of mutation intensity data according to Eq. (5) is carried out to obtain the sequence of mutation intensity extremes of distributed PV plant power generation in 2018, which can be approximated as an independent and identically distributed random variable. According to the Fisher-Tippet extreme value type theorem, it can be assumed that the composed sequence satisfies the GEV distribution. The parameters of the mutation intensity GEV distribution function are obtained using the great likelihood estimation method, for see Table 4.

Accordingly, the fitted GEV distribution plot of *MII* and the P–P plot utilized for assessing the goodness-of-fit of the GEV distribution

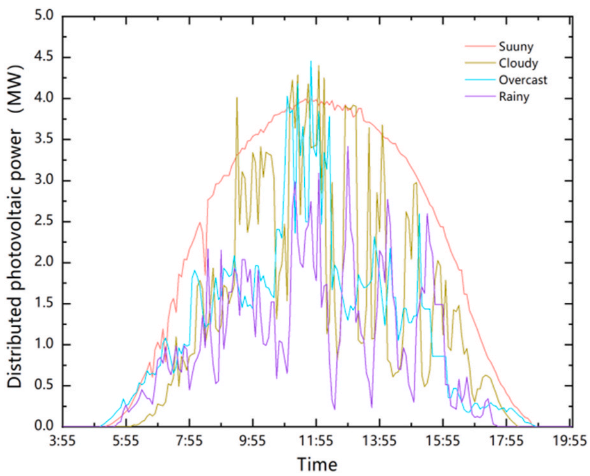

Fig. 1. Distributed PV power profiles in a typical day.

Table 3
Value of mutation intensity index.

Category	Cluster center(MW)	Power interval	MII
1	0.026	$\Delta P < 1\%P_r$	1
2	0.100	$1\%P_r \leq \Delta P < 3\%P_r$	2
3	0.258	$3\%P_r \leq \Delta P < 6\%P_r$	3
4	0.453	$6\%P_r \leq \Delta P < 10\%P_r$	4
5	0.712	$10\%P_r \leq \Delta P < 15\%P_r$	5
6	1.027	$15\%P_r \leq \Delta P < 21\%P_r$	6
7	2.677	$21\%P_r \leq \Delta P < 100\%P_r$	7

are presented in Fig. 3. The shape parameter ξ is negative, showing a truncated tail characteristic. The MII extreme value data obeys a type III extreme value distribution over the time scale, i.e., it corresponds to a bounded Weibull distribution, which is due to the fact that the intensity of the sudden change in the power of distributed PV power is unlikely to exceed its relative base value (i.e., corresponding to the rated capacity of the power plant), in line with its upper bounded nature. As shown in Fig. 3, when the probability distribution function of *MII* is denoted as $H(MII\text{: } \mu, \sigma, \xi)$, its corresponding P–P plot should exhibit a close approximation to a linear relationship.

According to Eq. (7), the variation curve of the return level of mutation intensity of distributed PV power is obtained, as shown in Fig. 4.

Fluctuation includes intensity and rate attributes. For further analysis, DRI is calculated by Eq. (9) rely on historical data of rooftop PV stations (see Fig. 7).

It can be seen intuitively in Fig. 4 that the mutation intensity has a higher return level when the P-value is small, that is, the return period is long. The setting is based on the occurrence of one event with a power mutation intensity level not exceeding 2 (i.e., $MII \leq 2$) as a weak mutation event; The occurrence of a single event with a power mutation intensity level of not less than 6 (i.e., $MII \geq 6$) is considered a warning mutation event. As can be seen in Fig. 4, the corresponding mutation intensity at the 0.12 extreme quantile is 6, which means that the probability of a warning mutation event occurring during the corresponding return period is 0.12

The corresponding mutation strength at the 0.64 extreme quantile is 2, i.e., the probability of a weak mutation event occurring during the corresponding return period is 0.64.

In addition, the corresponding mutation intensity at the 0.80 extreme quantile is 1, which numerically indicates the prevalence of the presence of distributed PV power intermittency. To further investigate the change of mutation intensity in T-hour-period, the curve of mutation intensity change in T-hour-period was plotted as shown in Fig. 5.

According to the survey, the power supply and demand interaction projects implemented in various provinces in China are usually issued 2 h before the starting moment of implementation, and the duration of a single implementation is about (2–6) hours. As can be seen in Fig. 5, the minimum return period for a weak mutation event in distributed PV power is 1.56 h, and the minimum return period for a mutation event with a mutation intensity of 4 is 3.22 h. Therefore, considering the intermittent smoothing demand of distributed PV power and the economics of energy storage allocation, the station reserve storage capacity should be able to achieve at least the smoothing target for weakly abrupt events (i.e., $MII \leq 2$), i.e., the distributed PV-side distribution storage capacity should be at least 3 % of the rated capacity of the station. At the same time, oriented to the normalized source network load and storage management needs, from the economic point of view, the base capacity of the station reserve energy storage can be set to meet the 4-h-period of the sudden change in the intensity of the smoothing of the demand for the goal, that is, set at 10 % of the rated capacity of the power station. This conclusion coincides with the policy requirements of many provinces in China, for instance, Fujian, Jiangxi, Gansu, Shaanxi, Liaoning and other provinces require that the energy storage configuration capacity of PV power stations is not less than 10 %. In addition, it can be seen from Fig. 5 that the minimum return period for a warning mutation event (i.e., $MII \geq 6$) for distributed PV

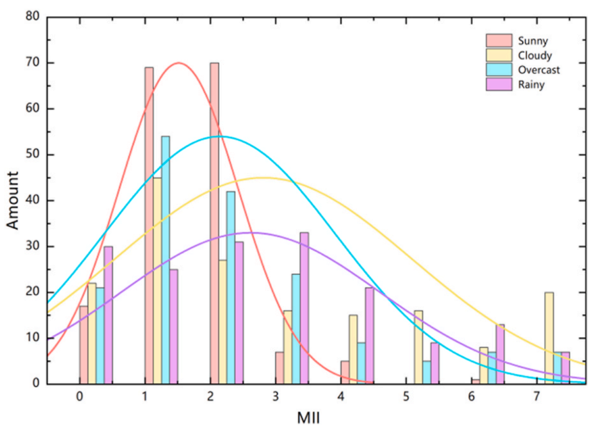

Fig. 2. Statistical analysis of MII for four typical days.

Table 4
GEV distribution parameters of MII.

Index	ξ	σ	μ
MII	−0.1367	2.0159	2.0471

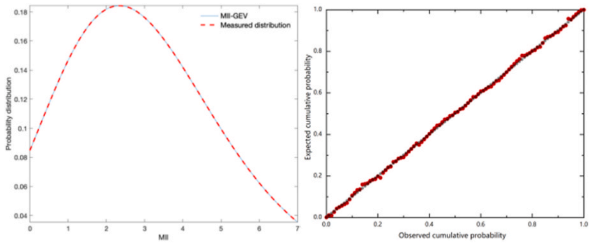

Fig. 3. Fitting graph and P–P plot of GEV distribution for MII.

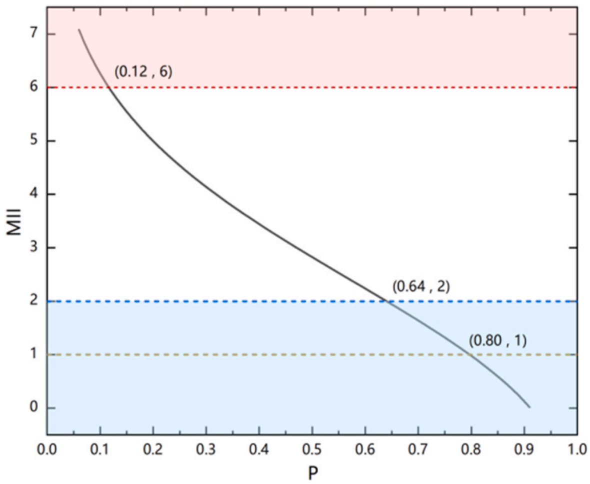

Fig. 4. Return level duration curve of MII.

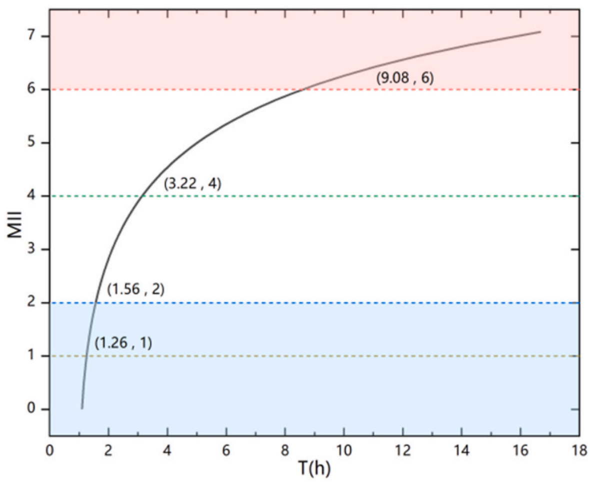

Fig. 5. T-hour-period curve of MII.

power is 9.08 h. Therefore, from the perspective of the short-term time scale, the existence of warning mutation events cannot be ignored, and the energy storage can be configured by no less than 21 % of the installed capacity of the power station to meet the normal independent operation needs. This conclusion is also consistent with the project construction requirements of some provinces in China, such as Hebei, Hubei, Qinghai and so on.

4.2. Calculation and analysis of T-hour-period mutations frequency

Different from the auxiliary decision guidance of T-hour-period mutation intensity for energy storage and power supply and demand interactive project capacity regulation in terms of capacity allocation, the T-hour-period mutation frequency can provide data support in terms of station-reserve energy storage allocation duration and response speed requirements.

In this paper, the event of MII $\geq$2 is set as Effective mutation event (EME), and the distributed PV power mutation frequency value of this power station in 2018 is calculated in accordance with Eq. (10), and four typical meteorological days are selected to draw the mutation frequency time-series analysis diagram, as shown in Fig. 6.

Combined with Eq. (5), the mutation frequency data is initialized to obtain the 2018 distributed PV power plant generation power mutation frequency extreme value sequence. According to the Fisher-Tippet extreme value type theorem, it can be assumed that the composed sequence satisfies the GEV distribution. The parameters of the mutation frequency GEV distribution function were obtained using the great likelihood estimation method, for see Table 5.

Accordingly, the fitted GEV distribution plot of *MFI* and the P–P plot utilized for assessing the goodness-of-fit of the GEV distribution are presented in Fig. 7. The shape parameter ξ is negative, showing a truncated tail characteristic and obeying a type III extreme value distribution, which corresponds to a bounded Weibull distribution, which is due to the fact that the frequency degree of the sudden change in the power of distributed PV power is unlikely to be more than 100 %, which is in line with its upper bounded characteristic. As shown in Fig. 3, when the probability distribution function of *MFI* is denoted as $H(MFI: \mu, \sigma, \xi)$, its corresponding P–P plot should exhibit a close approximation to a linear relationship.

Combining Eq. (11) and Eq. (12) yields the variation curve of the sudden change frequency return level of distributed PV power, as shown in Fig. 8.

It can be seen intuitively in Fig. 8 that the mutation frequency has a higher return level when the P-value is small, that is, the return period is long. The setting is based on the occurrence of one power mutation frequency level not exceeding 20 % (i.e., $MFI \leq 20\%$) as a low-frequency mutation event; An event in which a single power mutation frequency level greater than 80 % (i.e., $MFI \geq 80\%$) occurs is considered a high-frequency mutation event. From Fig. 8, it can be seen that the 0.18 extreme quartile corresponds to a mutation frequency level of 80 % at the 0.18 extreme quartile, and the probability of a high-frequency mutation event occurring during the corresponding return period is considered to be 0.18; The probability of a low-frequency mutation event occurring during the corresponding return period is considered to be 0.80 if the corresponding mutation frequency level at the 0.80 extreme quartile corresponds to 20 %, which also confirms the widespread existence of distributed PV power intermittency from a frequency perspective. To further investigate the change of mutation frequency in T-hour-period, the change curve was plotted as shown in Fig. 9.

As can be seen in Fig. 9, the mutation frequency level is 92.10 % in 16-h-period, which once again confirms the prevalence and extensiveness of distributed PV power intermittency. The minimum return period for low-frequency mutation events in distributed PV power is 1.25 h, and at the same time, the 2-h-period mutation frequency is 52.50 %, the 3-h-period mutation frequency is 67.02 %, the 4-h-period mutation frequency is 73.87 %, the 5-h-period mutation frequency is 78.25 %, and the 6-h-period mutation frequency is 81.29 %. Therefore, when the energy storage configuration of the distributed PV station is targeted at normalized management of intermittency, the storage operation duration can be considered as (2–4) hours. In addition, the minimum return period corresponding to 80 % mutation frequency is 5.5 h, and the duration of a single project can be (4–6) hours when participating in power supply and

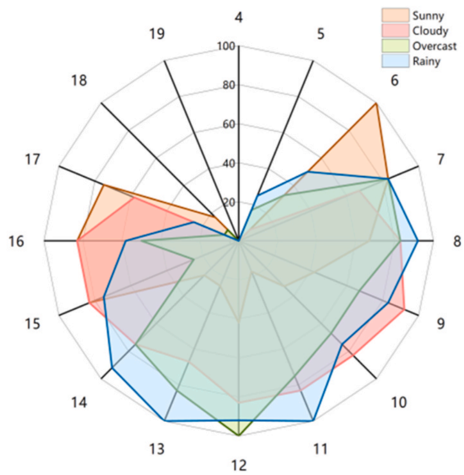

Fig. 6. Radar plot of MFI in time series for four typical days.

Table 5
GEV distribution parameters of MII.

Index	ξ	σ	μ
MII	−0.5864	38.5491	39.7897

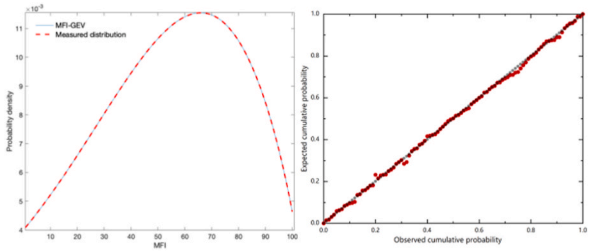

Fig. 7. Fitting graph and P–P plot of GEV distribution for MFI.

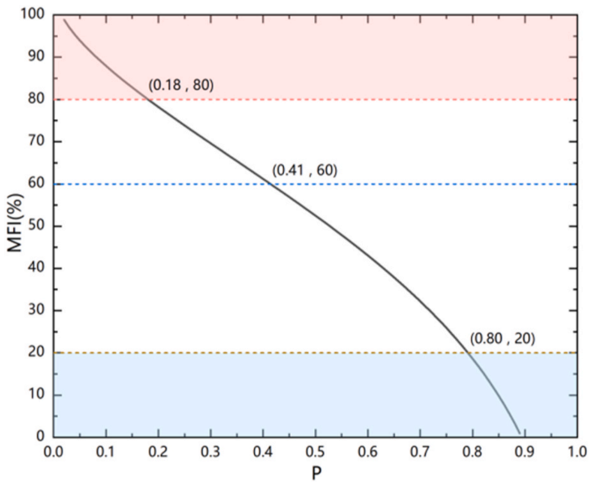

Fig. 8. Return level duration curve of MFI.

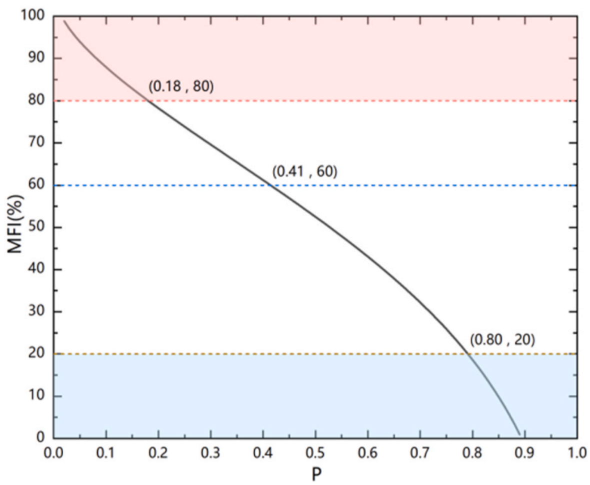

Fig. 9. T-hour-period curve of MFI.

demand projects to suppress high-frequency mutation events from economic considerations. At the same time, for distributed PV power stations, new energy storage such as flywheel energy storage and super capacitor energy storage can be mainly considered to meet the response speed requirements under normal management when medium-frequency and high-frequency mutation events occur.

4.3. Fitting analysis of the joint distribution of intermittency elements

Selecting a suitable Copula model function to portray the interdependent structure of the intermittent elements, so as to establish the Copula model of MII and MFI is an important part of constructing the joint distribution of distributed PV power intermittent characteristics. In this paper, we initially propose to select five common Copula models, and select the optimal function from Clayton-Copula, Gaussian-Copula, Frank-Copula, Gumbel-Copula, and t-Copula for the fitting analysis of two-dimensional joint distribution of intermittent elements.

Considering that mutation intensity and mutation frequency often possess correlation in the process of intermittent events, after the estimation work of the unknown parameters in the Copula model, the correlation analysis between the intermittent elements was carried out by using Spearman's correlation coefficient ρ and Kendall's correlation coefficient τ. Both ρ and τ pass the test of significance at the 0.05 level, and the results of parameter estimation and corresponding correlation coefficient calculations for different Copula functions are given in Table 6, where θ denotes the linear correlation parameter of the Copula model.

Table 6 demonstrates the apparent strong correlation between the intermittent elements, which lends itself to the Copula modeling of the joint probability distribution of MII and MFI. Among them, Clayton-Copula, Frank-Copula, and t-Copula better reflect the rank correlation between MII and MFI compared to the other functions, and the t-Copula model has a degree of freedom of three. To further evaluate the advantages and disadvantages of the three models, empirical Copula is introduced, and the optimal fitting function is selected by OLS principle according to Eq. (11), and the calculation is shown in Table 7.

Table 7 shows that the Clayton-Copula model can better fit the intermittent element mutation intensity and mutation frequency, plotting the Copula density function and distribution function of the intermittent element - mutation intensity and mutation frequency, as in Fig. 10.

From Eqs. (17) and (18), the joint and co-occurring return periods of the intermittent elements are obtained, respectively, and the joint and co-occurring return period contour plots of the mutation intensity and mutation frequency are plotted, as shown in Figs. 11 and 12. Combining Figs. 11 and 12 shows that the maximum joint return period for MII and MFI is 7.74 h, while the maximum co-occurrence return period is 41.8 h, with the overall trend of the two types of return periods being opposite. It is clear that for intermittent elements, the joint return period is smaller than the simultaneous return period for the same combination of intermittent element return levels, i.e., the probability of occurrence of either single-element event is greater than the probability of simultaneous occurrence of a two-element event.

As can be seen from Fig. 11, the joint return period gradually increases as MII or MFI increases. The joint return period for the occurrence of a mutation warning event (i.e., $MII \geq 6$) or a high-frequency mutation event (i.e., $MFI \geq 80\ \%$) is 3.56 h. The joint return period for the occurrence of a weak mutation event (i.e., $MII \leq 2$) or a low-frequency mutation event (i.e., $MFI \leq 20\ \%$) was 1.22 h. In addition, observing Fig. 11, the joint return period for an extreme mutation event in MII or MFI is 7.74 h, which shows that there is a generalized risk of intraday mutation events in distributed PV power. However, allocating energy storage or regulating resource capacity determination based solely on the joint return period suffers from allocation redundancy and low resource utilization. Therefore, further analysis is carried out in conjunction with the recurrence period in Fig. 12.

Further analysis of Fig. 12 shows that the isochronous return period for the occurrence of a low-frequency-weak mutation event (i.e., $MII \leq 2$ and $MFI \leq 20\ \%$) is 1.71 h, which is lower than the 2-h lead time for the source-network-load-storage interaction project. On the one hand, this finding confirms the prevalence of the occurrence of low-frequency weak mutation events, and on the other hand, puts forward a requirement for the minimum operating hours for energy storage configuration, that is, it should be able to satisfy the operating time requirement of at least 1.71 h. This data is consistent with the operating time requirements of some provinces in China for the energy storage configuration of PV projects, such as Shandong, Henan, Gansu and Hainan provinces, which have put forward a minimum operating time requirement of 2 h. According to the survey, Hainan Province has the highest sunshine hours in China, which can reach 8.7 h/day, while the range of sunshine hours in other regions is (2.9–6.6) hours/day. Combined with Fig. 12, the minimum isochronous return period for the occurrence of a high-frequency-warning mutation event (i.e., $MII \geq 6$ and $MFI \geq 80\ \%$) is 10.10 h, which is longer than 8.7 h, so this paper argues that from the economic point of view, operators of distributed PV power stations can consider participating in power supply and demand interaction projects to suppress the impact of high-frequency sudden change warning events under intermittent influence, and the project participation period can be (2–3) days.

In this chapter, focusing on events with low probability and high mutation risk events, the purpose of which is to overcome the uncertainty of distributed photovoltaic power, provides auxiliary decision support for energy storage configuration and the formulation of short-term interactive projects. From the perspective of engineering application, in order to verify the superiority of the method proposed in this paper, taking energy storage configuration as an example, the minimum capacity requirements for photovoltaic project allocation in most provinces of China were investigated, and the research results coincided with the conclusions obtained in this paper. The specific results are shown in Table 8.

From the perspective of configuration methods, at present, most studies on energy storage configuration for new energy (especially solar PV) focus on the optimization of multi-objective configuration, such as light rejection rate and operation economy, or the optimization of mixed energy storage with different attributes, but few studies on the basic response capability configuration of energy storage for uncertainty calming demand. Table 9 shows the comparison results of the energy storage configuration method with the

Table 6
Results of correlation index.

Copulas	Kendall	Spearman	θ
Gumbel-Copula	0.8493	0.6672	0.8381
Clayton-Copula	0.8690	0.6936	4.5274
Frank-Copula	0.8846	0.6966	11.2559
t-Copula	0.8728	0.7069	0.8959
Gaussian-Copula	0.8258	0.6327	0.8381

Table 7
Results of ordinary least squares.

Rule	Clayton-Copula	Frank-Copula	t-Copula
OLS	0.0268	0.1036	0.1106

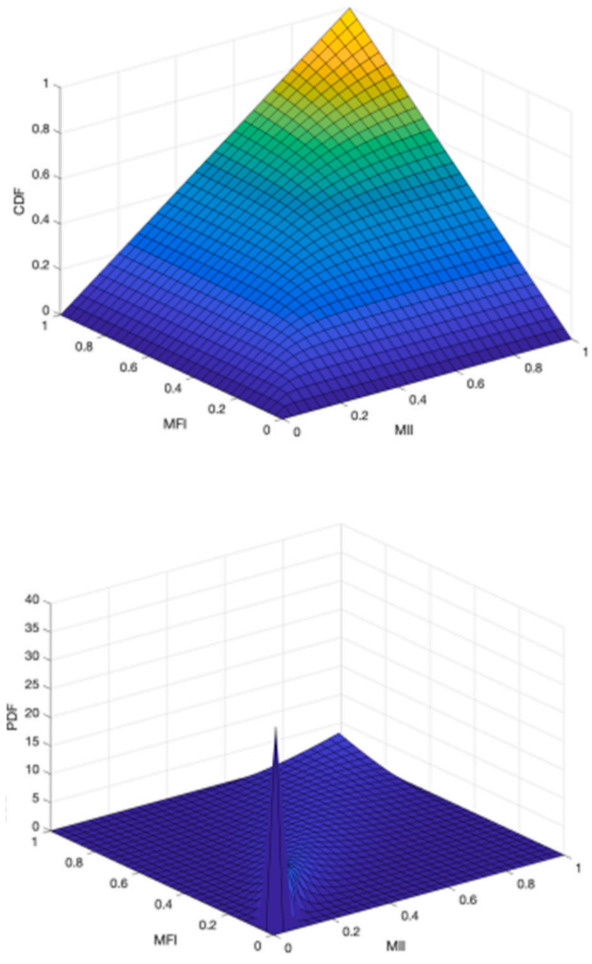

Fig. 10. Clayton-Copula function distribution function plot and density function plot.

method proposed in this paper to compensate the prediction error [43].

5. Conclusions

With the aim of overcoming intermittency, this paper applied generalized extreme value theory to study the mutation extreme events generated by the intermittency of distributed photovoltaic power, and reveals the comprehensive characteristics of intermittency in the context of element correlation through the construction of probability evaluation index. The main conclusions of this

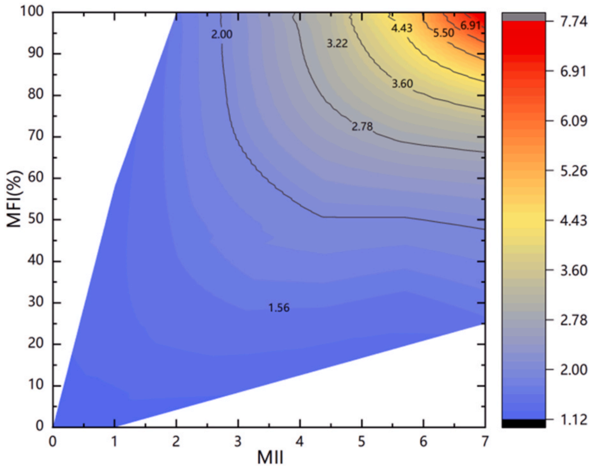

Fig. 11. Joint return period isoline of MII and MFI.

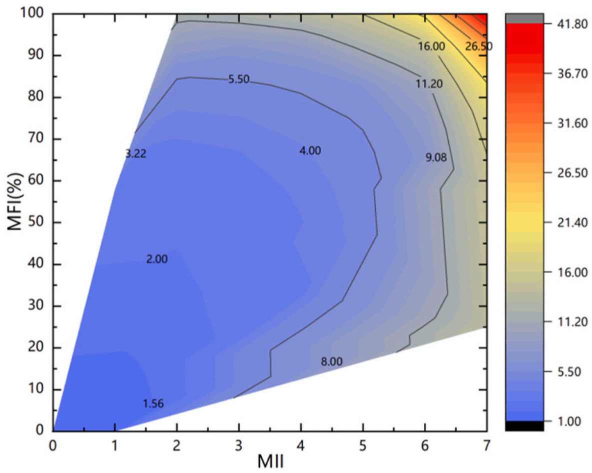

Fig. 12. Co-occurrence return period isoline of MII and MFI.

Table 8
Configuration requirements of energy storage capacity for photovoltaic projects in some cities of China.

Province	Time	City	Minimum capacity ratio	Duration requirement/h
Zhejiang	08/2023	Jinhua	10 %	2
	04/2023	Zhuji	10 %	
	05/2022	Yongkang	10 %	
	12/2021	Hangzhou	10 %	
Guangxi	12/2023	Nanning	10 %	2
Henan	10/2023	/	10 %	2
Guangdong	07/2023	Jiangmen	10 %	1
	01/2023	Zhuhai	10 %	2
Guizhou	05/2023	/	10 %	/
Jiangsu	05/2022	Suzhou	8 %	2
	10/2022	Wuxi	8 %	
Sichuan	12/2022	/	10 %	2

paper are as follows:

1) Based on the generalized extreme value theory, this paper provides a solution to solve the problem of lack of "extreme event" record in intermittency research, and effectively supports the research of "small-sample big-gap" events.

Table 9
Comparison of energy storage configuration methods.

Method	MLPSO	The method proposed
Commonality	Consider the impact of uncertainty	
Goal	Compensated prediction error	Calming intermittency
Core method	t-location-scale distribution	Generalized extreme value distribution
Core elements	Prediction error under the influence of uncertainty	Low probability and high mutation risk events due to strong uncertainty
Configuration	Hybrid storage capacity configuration	Basic capacity and duration
Peculiarity	Strong dependence on prediction model and accuracy	High data compatibility with small sample size Project replicability

2) By introducing the concepts of recurrence period and recurrence level, T-hour-period mutation intensity and T-hour-period mutation frequency proposed can provide an auxiliary decision for the configuration of energy storage capacity and duration.
3) Based on the two-dimensional joint distribution of intermittency elements, the universality and extensiveness of the intermittency of distributed photovoltaic power are verified, which can further clarifies the operation duration demand of energy storage and the development cycle of interactive projects.

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Data availability statement

The data that has been used is confidential.

CRediT authorship contribution statement

Yili Ma: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Yi Huang:** Visualization, Software, Investigation, Data curation. **Yue Yuan:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition.

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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