

An Evaluation Strategy for Microgrid Reliability Considering the Effects of Protection System

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Abstract— Incorrect responses from protective devices weaken the reliability of microgrids. This paper investigates the effects of the protection system on the reliability performance of a microgrid integrated with weather-dependent microsources. It relies on a stochastic model to simulate the challenges existing in current protection schemes designed for microgrids. Abnormal operating conditions including overcurrent, overvoltage and undervoltage, which are detected by a deficient protection scheme, are analyzed by a defined fuzzy virtual setting value. Their contributions along with conventional random failure rate achieved by statistical results are jointly used to evaluate the short-term outage rate of a feeder. A series of fuzzy reliability indices are further proposed for the short-term and periodical reliability of both microgrid system and customers. Subsequently, an evaluation strategy combined with fuzzy simulation and load restoration is presented as a solution tool. Simulations on a test system are provided to support the necessity of considering the effects of protection operation in evaluating microgrid reliability.

Index Terms—fuzzy number, microgrid, protection system, reliability evaluation, uncertain modeling, virtual setting value

I. INTRODUCTION

RELIABILITY improvement in the power supply is a potential avenue for attracting investments from customers and utilities on microgrid. According to the analysis in [1], the failure rate and the outage duration of internal customers can be mitigated, as well as the outage duration of external customers in some situations. This improvement depends on the operating condition of the microgrid. Thus, it addresses a common concern on the exact amount of reliability benefits that can be expected by the investor or other customers.

The evaluation strategies for microgrid reliability are significantly different from the ones designed for conventional distribution systems. Although the microgrid is regarded as a special type of distribution system with embedded microsources (μ Ss) by some researchers [2], [3], it has several unique features impacting the reliability. The published approaches developed for microgrid reliability evaluation primarily focus on the characteristics of microgrids, as follows,

1) *Weather-dependent μ Ss characterized by intermittent,*

fluctuating and unpredictable behavior. There are two basic approaches to model the uncertainty involved in μ Ss. Some researchers utilized probability density function (pdf) to simulate the randomness related to weather condition, such as the clearness index pdf for solar irradiance [4], [5] and Weibull pdf for wind speed [4]-[6]. Since it is difficult to reflect the seasonal variation of meteorological parameters using pdf, historical data is adopted in [7]-[10] for the μ S modeling.

2) *Grid-connected mode and islanded mode.* Microgrid is flexible in the operation mode: it can operate as an integrated distribution system with μ Ss [5]-[7] or an islanded network [10], [11]. In the islanded mode, energy storage is typically regarded as an essential component to address the accompanying uncertainty in the μ Ss. The energy storage also has the potential to promote system reliability with appropriate installation [12], [13].

3) *Operational strategies including control strategy, load restoration and protection strategy.* Multiple operational strategies in the microgrid affect the reliability performance as well. Since μ Ss are integrated into the microgrid in conjunction with power electronic converters, the contributions of their control strategies are investigated in [14], [15]. Moreover, the restoration sequence in emergencies is prioritized due to a variety of factors, such as the electrical distance [8] and the ownership of the μ Ss [11]. While the protection strategy for microgrids is far from perfect, their impacts on the reliability are discussed in the outage probability [8] and the time of repair [9].

Previous studies have focused on uncertain μ Ss, operation modes and load restoration in the evaluation process. However, few have explored the relationship between the protection scheme and the reliability evaluation in the microgrid. The research reported here investigates a method for evaluating the reliability performance given the current state of microgrid protection. Not merely random failures but abnormal operating conditions, which are analyzed based on the uncertain modeling, are included in evaluating the short-term outage rates of feeders.

The rest of this paper is organized as follows: Section II develops an uncertain model for investigating the influences of microgrid protection on the feeder's outage probability by introducing a fuzzy virtual setting value; a series of short-term and periodical fuzzy reliability indices are defined in Section III to measure the reliability of feeders, customers and the system; a fuzzy simulation embedded enumerative analysis is developed in Section IV as a solution tool; in Section V, the proposed model and approach are evaluated in a microgrid system; finally, Section VI offers conclusions.

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II. UNCERTAIN MODELING OF PROTECTIVE ACTIONS

A. Challenges of Microgrid Protection

Microgrid protection is capable of isolating faulted sections from the rest of the system so as to limit outage influence. As a customer-oriented network, microgrid is suffering random failures and various abnormal operating conditions. Protective devices, such as relays and fuses, are expected to restrict the faulted area and decrease the outage time of customers.

Nowadays, multiple protection schemes initially developed for the distribution system are applied in the microgrid, such as overcurrent protection [16], voltage based protection [17], adaptive protection [18] and differential protection [19]. However, each of them may only be effective in a certain application or encounter some technical difficulties, as analyzed in [20]. The difficulties can be caused by the operation modes of the microgrid, bi-directional flow in the feeders, complex fault current paths and/or the limitation of fault current through the inverter [18], [21]. The incorrect actions of the protective devices caused by deficient protection schemes will negatively affect the reliability benefits of a microgrid.

Essentially, the technical challenges existing in most microgrid protection schemes are results of the fact that the setting value is difficult to be ascertained for a particular protective device. A constant setting value is not recommended in the microgrid due to two operation modes and the unpredictable dynamic behavior of μ Ss [18]. Furthermore, the setting value can be approximated by a linear combination of the fault contributions from the grid and the μ Ss [21]. Considering the varying characteristics of μ Ss, it could further be assumed to follow a normal distribution.

B. A Probabilistic Model for Protection Operation

Rather than focusing on the design of those protection schemes mentioned above, this paper investigates their implementation on each feeder. A trigger value, represented by x_{op} , is hypothetically assigned to each feeder as an operation condition to reflect the overall protection scheme. Similar to the setting value, x_{op} is also assumed to follow a normal distribution with a deviation δ and a probability density function as

$$g(x_{op}) = \frac{1}{\sqrt{2\pi}\delta} \cdot \exp\left[-\frac{(x_{op} - x_{set})^2}{2\delta^2}\right]. \quad (1)$$

The expected value of x_{op} is defined as a virtual setting value x_{set} . In a proper and efficient protection scheme, x_{set} should be consistent with the operating limits of the feeder, which is fundamentally determined by the feeder properties. Thus, the defined x_{set} could be used to judge whether the protective device should operate or not. Given a state variable x , the conditional probabilities of correct action, malfunction and rejection are calculated by (2), (3) and (4), respectively.

$$P_{cor}(x) = \Pr(x \geq x_{op} | x \geq x_{set}) \quad (2)$$

$$P_{mal}(x) = \Pr(x \geq x_{op} | x < x_{set}) \quad (3)$$

$$P_{rej}(x) = \Pr(x < x_{op} | x \geq x_{set}). \quad (4)$$

Since the rejection probability is negligible if the back-up protection is considered [8], this paper only focuses on the probability of protection operations including malfunction and correct action. This probability $P(x)$ is calculated by (5) or alternatively by (6) after applying the law of total probability.

$$P(x) = P_{mal}(x) \cdot \Pr(x < x_{set}) + P_{cor}(x) \cdot \Pr(x \geq x_{set}) \quad (5)$$

$$P(x) = \Pr(x \geq x_{op}) = \int_0^x g(x_{op}) dx_{op}. \quad (6)$$

$P(x)$ is a monotonically increasing function of x as shown by the blue curve in Fig. 1. Specifically, the protective device has a half probability to operate if x equals x_{set} .

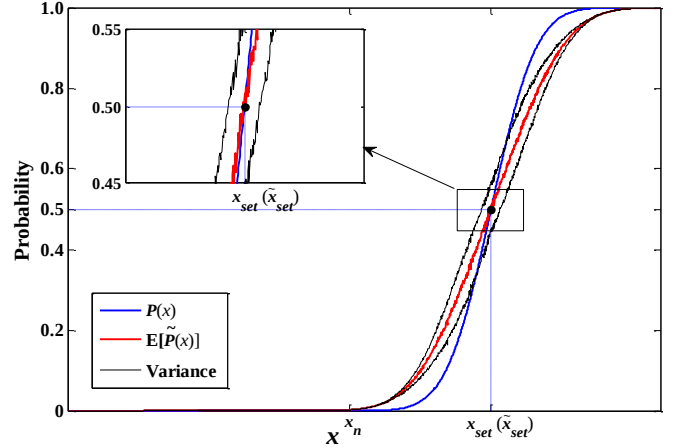


Fig. 1. Operation probabilities of state variable.

C. Fuzzy Virtual Setting Value

As it is illustrated above, the virtual setting value can be applied on the quantitative analysis of protection operation. Besides this, it can also be used as a reference in field protection setting for engineers. Therefore, x_{set} is able to reveal the subjective decision making process for the setting value considering various factors, such as all possible fault analyses, microgrid operating standards and specific load demands. In addition, the feeder operating limit determined by x_{set} allows a certain level of violation, or mathematically, $x < x_{set}$ is a soft constraint. Given these two applications, a fuzzy number $\tilde{x}_{set}$ rather than a certain value x_{set} is deployed to each feeder as its virtual setting value.

Abnormal operating conditions, including overcurrent, over-voltage and undervoltage, are analyzed based on the defined $\tilde{x}_{set}$. Microgrid protection should operate when $I \geq \tilde{I}_{set}$ is satisfied, and its operation probability is measured by $\tilde{P}(I)$ as shown in (7). Due to the maximum allowable variance of voltage, two fuzzy setting values, symbolized by $\tilde{U}_{set}^H$ and $\tilde{U}_{set}^L$, bounds the upper and lower limits. The protection system is expected to engage only if $U \geq \tilde{U}_{set}^H$ or $U \leq \tilde{U}_{set}^L$. Its operation probability is calculated by (8).

$$\tilde{P}(I) = \int_0^I \frac{1}{\sqrt{2\pi}\delta} \cdot \exp\left[-\frac{(I_{op} - \tilde{I}_{set})^2}{2\delta^2}\right] dI_{op} \quad (7)$$

$$\tilde{P}(U) = \max \left\{ \int_0^U g(U_{op}^H) dU_{op}^H, \int_U^{+\infty} g(U_{op}^L) dU_{op}^L \right\}. \quad (8)$$

Two new fuzzy factors $\tilde{\rho}$ and $\tilde{\eta}$ are introduced here as replacements so as to unify the fuzzy virtual setting values of feeders by individual rated value x_n .

$$\tilde{\rho} = \tilde{I}_{set} / I_n \quad (9)$$

$$\tilde{\eta} = |\tilde{U}_{set} - U_n| / U_n. \quad (10)$$

Let $\tilde{\rho}$ be a triangular fuzzy factor (ρ_1, ρ_2, ρ_3) with $\rho_1 < \rho_2 < \rho_3$. Its membership function $\mu_{\tilde{\rho}}(c)$ is shown in (11). Similarly, $\tilde{\eta}$ is fully determined by (η_1, η_2, η_3).

$$\mu_{\tilde{\rho}}(c) = \begin{cases} \frac{c - \rho_1}{\rho_2 - \rho_1}, & \rho_1 < c < \rho_2 \\ \frac{\rho_3 - c}{\rho_3 - \rho_2}, & \rho_2 < c < \rho_3 \end{cases}. \quad (11)$$

To deal with those fuzzy numbers, this research utilizes the credibility theory, which has been applied in many research fields including power systems [22]. A fuzzy expected value is first introduced for an intuitive comparison of fuzzy values,

Definition 1: Let $\tilde{P}(x)$ be a fuzzy reliability index, its expected value being defined by

$$E[\tilde{P}(x)] = \int_0^{+\infty} \text{Cr}\{\tilde{P}(x) \geq \tau\} d\tau \quad (12)$$

where $\text{Cr}\{\cdot\}$ is the credibility measure which can be calculated by possibility measure 'Pos $\{\cdot\}$ ' and necessity measure 'Nec $\{\cdot\}$ ' [23]

$$\text{Cr}\{\tilde{P}(x) \geq \tau\} = \frac{1}{2} [\text{Pos}\{\tilde{P}(x) \geq \tau\} + \text{Nec}\{\tilde{P}(x) \geq \tau\}] \quad (13)$$

In addition, the variance of the fuzzy variable is defined by (14) to measure the spread of the distribution around $E[\tilde{P}(x)]$.

$$V[\tilde{P}(x)] = E[(\tilde{P}(x) - E[\tilde{P}(x)])^2]. \quad (14)$$

Both $E[\tilde{P}(x)]$ and $V[\tilde{P}(x)]$ can be approximated by the fuzzy simulation, which will be presented in Section IV.B. The simulation results are shown as the red and black curves in Fig. 1.

III. EFFECTS OF PROTECTION OPERATION ON THE RELIABILITY EVALUATION

This study includes two kinds of outage events in evaluating microgrid reliability: random failures and abnormal operating conditions. Their effects on microgrid reliability, especially the second kind, are investigated from both short-term and periodical reliability indices.

A. Short-term Fuzzy Reliability Indices

A three-level index system consisting of the feeder, the customer and the system is designed for this research on

microgrid reliability by referring to the reliability indices of a distribution system in [24]. The reliability performance in the short-term interval $[T, T + \Delta T]$ is quantified as follows:

1) *Feeder* — For a feeder L_l running until time T , its short-term fuzzy outage rate $\tilde{\lambda}_l(x)$ is defined by the outage probability in the following interval ΔT (hour), as shown in (17), ($l=1, 2, \dots, M$, M is the feeder number).

$$\tilde{\lambda}_l(x) = \lim_{\Delta T \rightarrow 0} \frac{\Pr(T \leq t \leq T + \Delta T | t > T)}{\Delta T}. \quad (15)$$

The probability of random failures during ΔT , represented by P_0 , could be roughly evaluated by the product of random failure rate and ΔT . Let λ_0 be a statistical result of annual random outage rate, its short-term value is approximated by $\lambda_0 \cdot \Delta T / 8760$ and P_0 is calculated by (16). The outage probability related to the response of the microgrid protection to abnormal operating conditions is measured by $\tilde{P}(x)$, which is analyzed in Section II.

$$P_0 \approx \lambda_0 \cdot \frac{\Delta T^2}{8760}. \quad (16)$$

In addition, since the protective device normally operates instantaneously, the defined outage rate can be regarded as real-time when ΔT is set to the operation time t_{op} of the protective device. Considering the repair process of the feeder after outage, repair time t_r should also be included in ΔT , meaning $\tilde{\lambda}_l(x)$ defines the average fuzzy outage rate in a short-term, which is referred to as short-term fuzzy outage rate in the rest of this paper,

$$\tilde{\lambda}_l(x) \approx \frac{\max\{\tilde{P}(U) + P_0, \tilde{P}(I) + P_0\}}{t_r + t_{op}}. \quad (17)$$

2) *Customer* — The two fuzzy indices of outage time $\tilde{\omega}_i(x)$ and failure rate $\tilde{\xi}_i(x)$ are assigned to each load point LP_i ($i=1, 2, \dots, N$). They can be evaluated by enumerating each failure event ε_j which affects power supply to customers ($j=1, 2, \dots, M$),

$$\begin{bmatrix} \tilde{\omega}_1(x) \\ \tilde{\omega}_2(x) \\ \dots \\ \tilde{\omega}_N(x) \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1M} \\ r_{21} & r_{22} & \dots & r_{2M} \\ \dots & \dots & \dots & \dots \\ r_{N1} & r_{N2} & \dots & r_{NM} \end{bmatrix} \cdot \begin{bmatrix} \tilde{\lambda}_1(x) \\ \tilde{\lambda}_2(x) \\ \dots \\ \tilde{\lambda}_M(x) \end{bmatrix} \quad (18)$$

$$\tilde{\xi}_i(x) = \sum_{j=1}^M \tilde{\lambda}_j(x) \cdot \text{sgn}(r_{ij}) \quad (19)$$

where $\text{sgn}(\cdot)$ is the signum function in mathematics, r_{ij} the outage time of LP_i in ε_j , and N the number of load points. Since only failures caused by the feeder outage are considered in this study, M is also the number of failure events.

3) *System* — The fuzzy average interruption frequency ($\tilde{f}_{AIF}$), fuzzy average interruption duration ($\tilde{f}_{AID}$), and fuzzy energy not supplied ($\tilde{f}_{ENS}$) are defined to evaluate system reliability as

$$\tilde{f}_{\text{AIF}}(x) = \sum_{i=1}^N (\tilde{\xi}_i(x) \cdot m_i) / \sum_{i=1}^N m_i \quad (20)$$

$$\tilde{f}_{\text{AID}}(x) = \sum_{i=1}^N (\tilde{\omega}_i(x) \cdot m_i) / \sum_{i=1}^N m_i \quad (21)$$

$$\tilde{f}_{\text{ENS}}(x) = \sum_{i=1}^N (d_i(x) \cdot \tilde{\omega}_i(x)) / \sum_{i=1}^N m_i \quad (22)$$

where m_i is the number of customers at LP_i , and d_i is the load demand at LP_i .

Assuming $\tilde{f}(x)$ represents one of the fuzzy short-term indices defined in (17) ~ (22), its expected value $E[\tilde{f}(x)]$ has the following characteristic,

Proposition 1: If the outage times of customers are independent on the two outage causes, then $E[\tilde{f}(x)]$ is a linear combination of $E[\tilde{\lambda}_j(x)]$, ($j=1, 2, \dots, M$).

Proof. The hypothesis means that outage influences are identical once an outage happens, regardless of the random failure or the abnormal operating condition. Specifically, r_{ij} is dependent on the state variable x rather than $\tilde{\lambda}_j(x)$. Thus, $\tilde{f}(x)$ would be an expression as follows,

$$\tilde{f}(x) = \sum_{j=1}^M \beta_j \cdot \tilde{\lambda}_j(x) \quad (23)$$

where β_j is a constant determined by the expression of $\tilde{f}(x)$.

Additionally, failure events are independent of each other, meaning $\tilde{\lambda}_1(x)$, $\tilde{\lambda}_2(x)$, ... and $\tilde{\lambda}_M(x)$ are independent fuzzy variables. Then,

$$\begin{aligned} E[\tilde{f}(x)] &= \sum_{j=1}^M E[\beta_j \cdot \tilde{\lambda}_j(x)] \\ &= \sum_{j=1}^M \int_0^{+\infty} \text{Cr}\{\beta_j \cdot \tilde{\lambda}_j(x) \geq \tau\} d\tau \\ &= \sum_{j=1}^M \beta_j \int_0^{+\infty} \text{Cr}\{\tilde{\lambda}_j(x) \geq \frac{\tau}{\beta_j}\} d\frac{\tau}{\beta_j} \\ &= \sum_{j=1}^M \beta_j \cdot E[\tilde{\lambda}_j(x)]. \end{aligned} \quad (24)$$

The proposition is proved.

B. Periodical Fuzzy Reliability Indices

A periodical reliability index $\tilde{F}$ is defined by the sum of short-term indices to measure the microgrid reliability over a period $(0, T]$. The number of short-term indices included is $[T/(t_r+t_{op})]$, where $[\cdot]$ is a mathematical symbol for the nearest integer function. This number will be quite large if an annual period or an even longer period is studied.

An approach based on the scenario technology is applied to relieve the computational load. Since only photovoltaic arrays and wind generation are included in the microgrid test case, a scenario is firstly defined by the combination of solar radiation, ambient temperature and wind speed. Secondly, meteorological data is collected by the interval ΔT . Thirdly, the grid mesh method proposed in [8] is employed to reduce the scenario number. Assuming N_σ is scenario type after the reduction and $n(\sigma_k)$ is the number of scenarios classified in scenario σ_k , $\tilde{F}$ is calculated by

$$\tilde{F} = \sum_{k=1}^{N_\sigma} \tilde{f}(\sigma_k) \cdot n(\sigma_k). \quad (25)$$

Proposition 2: Assuming feeder maintenance can always be accomplished in a period t_r , the expected value of the periodical fuzzy reliability index $E[\tilde{F}]$ is the weighted sum of $E[\tilde{f}(\sigma_k)]$ with a weighing factor of $n(\sigma_k)$ ($k=1, 2, \dots, N_\sigma$).

Proof. If each outage event is accomplished within the repair time t_r , the reliability performance of a feeder will not be affected in the following scenarios, meaning the reliability evaluation processes under different scenarios are independent.

Since $\tilde{f}(\sigma_1)$, $\tilde{f}(\sigma_2)$, ..., $\tilde{f}(\sigma_{N_\sigma})$ are independent fuzzy variables,

$$E[\tilde{F}] = \sum_{k=1}^{N_\sigma} E[\tilde{f}(\sigma_k) \cdot n(\sigma_k)]. \quad (26)$$

Subsequently,

$$\begin{aligned} E[\tilde{f}(\sigma_k) \cdot n(\sigma_k)] &= \int_0^{+\infty} \text{Cr}\{\tilde{f}(\sigma_k) \cdot n(\sigma_k) \geq \tau\} d\tau \\ &= n(\sigma_k) \cdot \int_0^{+\infty} \text{Cr}\{\tilde{f}(\sigma_k) \geq \frac{\tau}{n(\sigma_k)}\} d\frac{\tau}{n(\sigma_k)} \\ &= n(\sigma_k) \cdot E[\tilde{f}(\sigma_k)]. \end{aligned} \quad (27)$$

Thus, $E[\tilde{F}] = n(\sigma_k) \cdot \sum_{k=1}^{N_\sigma} E[\tilde{f}(\sigma_k)]$.

The expected values of periodical fuzzy indices are used to compare the microgrid reliability in the following sections. In addition, engineers are concerned with the critical value for satisfying a certain fuzzy chance constraint in some situations. A pessimistic value is introduced here for those cases,

Definition 2: Let $\tilde{F}$ be a fuzzy reliability index and γ be a confidence level, $\gamma \in (0, 1]$. $\tilde{F}_{\text{inf}}(\gamma)$ is defined as the γ -pessimistic reliability index of $\tilde{F}$,

$$\tilde{F}_{\text{inf}}(\gamma) = \inf\{\bar{F} \mid \text{Cr}\{\tilde{F} \leq \bar{F}\} \geq \gamma\}. \quad (28)$$

Remark: Of the two fuzzy indices $\tilde{F}$ and $\tilde{F}'$, the former has a higher reliability level if $E[\tilde{F}] < E[\tilde{F}']$ or $\tilde{F}_{\text{inf}}(\gamma) < \tilde{F}'_{\text{inf}}(\gamma)$.

IV. EVALUATION STRATEGIES

A. Solution Process

A fuzzy simulation embedded failure mode and effects analysis is proposed for evaluating fuzzy reliability indices of the microgrid. The flowchart of the solution process is shown in Fig. 2. The fuzzy simulation and load restoration mentioned here will be explained in detail later.

B. Fuzzy Simulation

The fuzzy simulation is chosen to approximate the fuzzy expected value. Using $E[\tilde{P}(I)]$ for example, it is simulated as follows:

- Step 1) Set $e=0$, with B representing the sampling number.
- Step 2) Randomly generate c_b from $[\rho_1, \rho_3]$ and use $v_b = \mu_{\tilde{P}}(c_b)$, ($b=1, 2, \dots, B$).
- Step 3) Calculate the sampling value of $\tilde{I}_{\text{set}}$ by $c_b \cdot I_n$ and $P(I)$

using (7).

Step 4) Generate two boundaries,

$$P_{\min} = P(I, c_1) \cap P(I, c_2) \cdots \cap P(I, c_B) \quad (29)$$

$$P_{\max} = P(I, c_1) \cup P(I, c_2) \cdots \cup P(I, c_B). \quad (30)$$

Step 5) Randomly generate a from $[P_{\min}, P_{\max}]$.

Step 6) $e \leftarrow e + \text{Cr}\{\tilde{P}(I) \geq a\}$. $\text{Cr}\{\tilde{P}(I) \geq a\}$ is estimated by

$$\text{Cr}\{\tilde{P}(I) \geq a\} = \frac{1}{2} \left(\max_{1 \leq b \leq B} \{v_b \mid P(I, c_b) \geq a\} + \min_{1 \leq b \leq B} \{1 - v_b \mid P(I, c_b) > a\} \right). \quad (31)$$

Step 7) Repeat Step 5 and Step 6 B times.

Step 8) Return $E[\tilde{P}(I)]$.

$$E[\tilde{P}(I)] = P_{\min} \cup 0 + P_{\max} \cap 0 + e \cdot (P_{\max} - P_{\min}) / B. \quad (32)$$

Given a state variable x , the impact of fuzzy value $\tilde{x}_{\text{set}}$ on $P(x)$ is evaluated using the above steps. Subsequently, a fitting function describing the relationship between $E[\tilde{P}(x)]$ and x is determined.

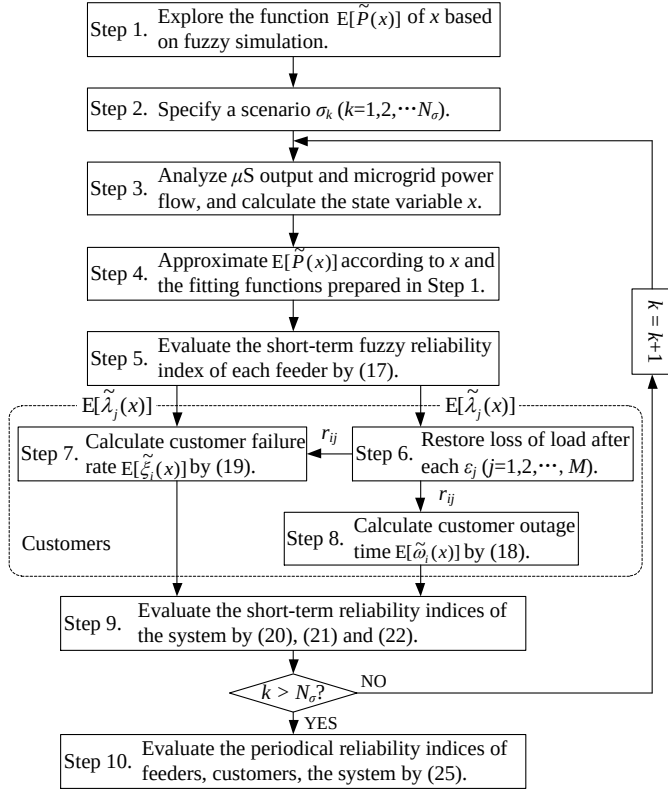


Fig. 2. Flowchart of the evaluation procedure.

The γ -pessimistic reliability index $\tilde{F}_{\text{inf}}(\gamma)$ can also be estimated using the fuzzy simulation. According to the definition of credibility measure, a monotonous function $L(\bar{F})$ defined by (33) is used to approximate the credibility of fuzzy event $\tilde{F}(x) \leq \bar{F}$ or $\text{Cr}\{\tilde{F}(x) \leq \bar{F}\}$; and then, a bisection search is employed to find the maximal value $\bar{F}$ such that $L(\bar{F}) \geq \gamma$ holds; finally, $\bar{F}$ is the estimated value of $\tilde{F}_{\text{inf}}(\gamma)$.

$$L(\bar{F}) = \frac{1}{2} \left(\max_{1 \leq b \leq B} \{v_b \mid F(x, c_b, v_b) \leq \bar{F}\} + \min_{1 \leq b \leq B} \{1 - v_b \mid F(x, c_b, v_b) > \bar{F}\} \right). \quad (33)$$

C. Load Restoration

Load restoration is proposed here for analyzing the electricity supply to load point LP_i ($i=1, 2, \dots, N$) after each fault. As an illustration, the microgrid shown in Fig. 3 is integrated to the grid through the Point of Common Coupling (PCC) and it is also connected to two separate systems through two tie-lines.

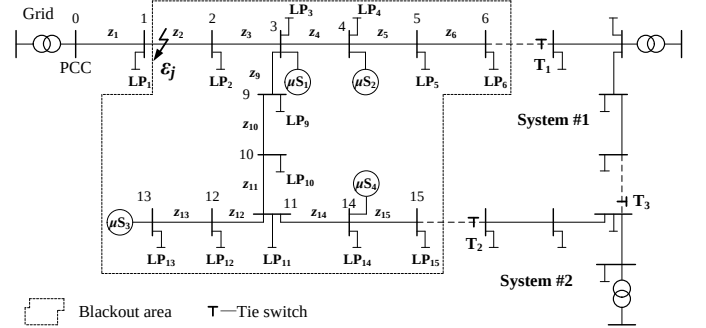


Fig. 3. A sample of microgrid.

The restoration process is explained below:

Step 1) Specify a failure event ϵ_j ($j=1, 2, \dots, M$).

Step 2) Determine the blackout areas represented by dotted lines in Fig. 3. Set the outage times of the load points outside of those areas, such as LP_1 , to zero ($r_{ij}=0$).

Step 3) Find the loss of load set Ω_L and the alternative power source set Ω_G in the blackout area as shown in (34) and (35), with N_L and N_G representing the number of load points in Ω_L and the alternative sources in Ω_G , respectively.

$$\Omega_L = \{LP_2, \dots, LP_6, LP_9, \dots, LP_{15}\} \quad (34)$$

$$\Omega_G = \{\mu S_1, \mu S_2, \mu S_3, \mu S_4, T_1, T_2\}. \quad (35)$$

Step 4) Define the electrical distance Z_{is} as the accumulated value of the series impedances of the feeders between alternative power source G_s and LP_i . For instance, the electrical distance between LP_2 and μS_2 is represented by Z_{12} with the value of $z_3 + z_4$.

$$Z_{is} = \sum_{l \in \Lambda} z_l \quad (36)$$

where Λ is the set of the feeders between them and z_l is the impedance of feeder l .

Then, generate the electrical distance matrix $\mathbf{Z}$.

$$\mathbf{Z} = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1N_G} \\ Z_{21} & Z_{22} & \cdots & Z_{2N_G} \\ \cdots & \cdots & \cdots & \cdots \\ Z_{N_L 1} & Z_{N_L 2} & \cdots & Z_{N_L N_G} \end{bmatrix}. \quad (37)$$

Step 5) Evaluate the available capacities of the μS s or the tie lines based on the power flow analysis.

Step 6) This research uses the following heuristic rule: the restoration begins from the alternative power source

with a maximal value of G_s . Then column matrix $\mathbf{Z}_s$ generated from $\mathbf{Z}$, which is sorted by Z_{is} , is selected as the restoration sequence of G_s .

- Step 7) Recover the load points in Ω_L using G_s according to the restoration sequence, source capacity, load demand and line loss.
- Step 8) Determine if the loss of load can be recovered. If it can be, r_{ij} is the fault isolation time t_d ; subsequently, remove LP_i outside Ω_L . If it cannot be recovered, r_{ij} is the repair time t_r .
- Step 9) End the restoration process, and generate the following matrix $\mathbf{r}$,

$$\mathbf{r} = [r_{ij}]_{N \times M} \quad (38)$$

V. CASE STUDY

The test system used here is the microgrid system proposed by K. Rudion *et al.* [25] and modified by the authors in [8]. This system with the rated voltage 0.4 kV includes 10 load points and 5 μ S points. Two types of customers including residential load and commercial load with a total peak value of 53.22 kW are included. Three photovoltaic arrays, one wind generation and one energy storage (at No.8 bus) with a total capacity of 34 kW are deployed in the system.

Additional parameters related to uncertainty modeling are specified here: $\tilde{\rho}$ is (1.15, 1.20, 1.25), and $\tilde{\eta}$ is (11%, 12%, 13%). The deviation of the trigger value δ_i is set to $I_n/20$ for overcurrent or δ_U is $U_n/55$ for overvoltage and undervoltage.

A. Reliability Indices Comparison

TABLE I displays the three cases designed for the comparison study: only the random failure is considered in Case A, and Case C is different from Case B in the virtual setting value.

TABLE I
THREE CASES WITH DIFFERENT PROTECTION OPTIONS

Conditions	Outage events	Virtual setting value
Case A	Random failure	—
Case B	Random failure and abnormal operating condition	x_{set}
Case C	Random failure and abnormal operating condition	$\tilde{x}_{set}$

1) System

The annual reliability indices of the microgrid system are compared in TABLE II.

TABLE II
RELIABILITY INDICES OF THE MICROGRID SYSTEM

Reliability indices	f_{AIF} (int/cus-yr)	f_{AID} (hr/cus-yr)	f_{ENS} (kWh/yr)
Case A [8]	0.1684	0.0861	2.1009
Case B	0.1957	0.0926	2.3675
Case C*	0.2767	0.1142	3.2268

Note: * are fuzzy expected values.

In Case A, λ_0 is assigned to each feeder, an approach widely used with acceptable accuracy, especially when the state variables of each feeder have sufficient margins. However, this case ignores the impact of the operating condition in the evaluation process.

The outage possibility caused by abnormal operating conditions is considered in Case B. Its contribution to the reliability indices, such as f_{AIF} , is approximately 13.95% higher than for Case A.

For Case C, all indices listed in TABLE II are fuzzy expected values, all of which are larger than those in the corresponding indices in Case B. That is, the microgrid system exhibits lower reliability performance after considering the fuzzy virtual setting values. The reason for this reduction is that $E[\tilde{P}(x)]$ is no less than $P(x)$ in the normal operating condition ($I \leq I_{set}$ and $U_{set}^L \leq U \leq U_{set}^H$) as shown in Fig. 1 because of two facts: (a) x_{set} is regarded as a fuzzy value; (b) $P(x)$ is a nonlinear function.

2) Feeder

The annual outage rates for the feeders except for the two tie lines, L_6 and L_{11} , are compared in Fig. 4. In Case A, the unit value of the random outage rate is set to 0.1 /yr-km for each feeder, meaning that the feeder random outage rate depends only on its length. In Case B, only the randomness involved in setting values is analyzed in terms of x_{op} . In Case C, the fuzzy factor involved in determining x_{set} is further considered.

The simulation plotted in Fig. 4 illustrates that reliability indices without considering uncertainty factors appear to be unduly optimistic. It also indicates that the risk of protection operation other than feeder length has a significant effect on the feeder outage rate. For example, L_3 has a lower outage rate than L_4 in Cases B and C, in spite of a longer length.

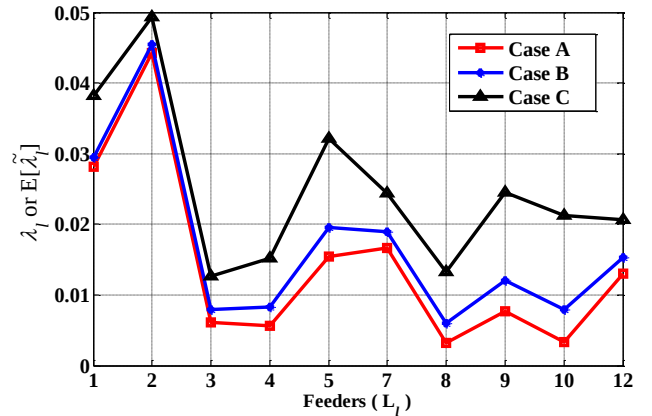


Fig. 4. Annual outage rates of the feeders.

3) Customer

The following two conclusions can be drawn from the comparisons in customer reliability indices shown in Fig. 5:

First, the microgrid has the ability to improve the reliability of the power supply to customers within it. If no μ Ss are included in the network, LP_1 has the highest reliability indices among all load points. However, it is quite different under the microgrid condition. The outage times of the restorable load points depend on the switching time from the grid-connected mode to the islanded mode (0.2h). LP_1 exhibits a low recovery

priority after outage because of its electrical distance from each μS . Its outage time is closely related to both the outage rate and the repair time of the power utility (0.015/yr and 8h). Thus, the reliability of LP_1 will not significantly benefit from microgrid development.

Second, the reliability indices of the load points at the ends of such feeders as LP_5 , LP_6 and LP_{10} are more likely to be affected when the operating condition is considered. Conversely, the load points, for example LP_7 and LP_8 , close to the slack bus in islanded mode (No.8 bus) are more likely to be benefited.

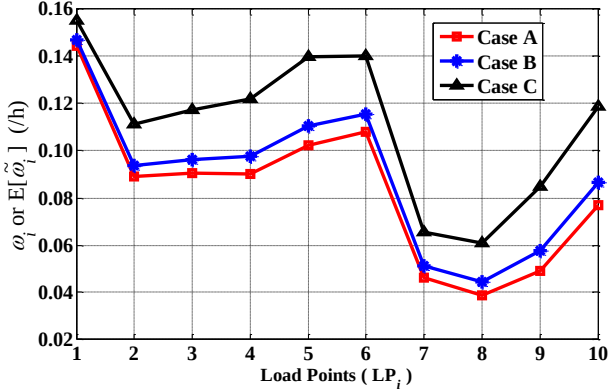


Fig. 5. Average annual outage time for the customers.

B. Impact of the Protection Operation

1) Virtual setting values

The fuzzy expected value of annual index f_{ENS} is the function of $E[\tilde{\eta}]$ and $E[\tilde{\rho}]$, as described in Fig. 6. The contours beneath the surface indicate the ranges of $E[\tilde{\eta}]$ and $E[\tilde{\rho}]$ needed to maintain the index at a certain level. $E[\tilde{f}_{ENS}]$ decreases to 2.1010 when both $E[\tilde{\eta}]$ and $E[\tilde{\rho}]$ are large enough, a value close to the ideal result in Case A (2.1009). Thus, to ensure high reliability, the setting values should encompass a wide range, although this conclusion cannot be used to guide the setting process.

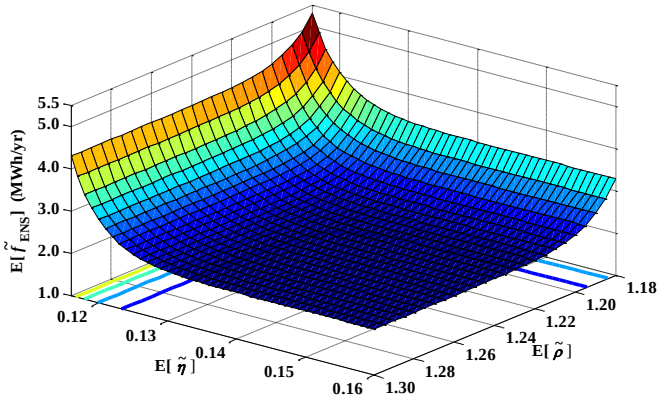


Fig. 6. The relationship between the ENS and the setting values.

2) Variances of the trigger values

The f_{ENS} is also related to the sensitivity of the protection operation as shown in Fig. 7. The two axes are defined by the proportion of the deviation in the rated values of the state variables. The resulting surface suggests that the reliability

index is sensitive to the fluctuation in node voltage, partly because no reactive power compensation device is used in the network. Thus, the voltage quality still deserves a special consideration in a microgrid.

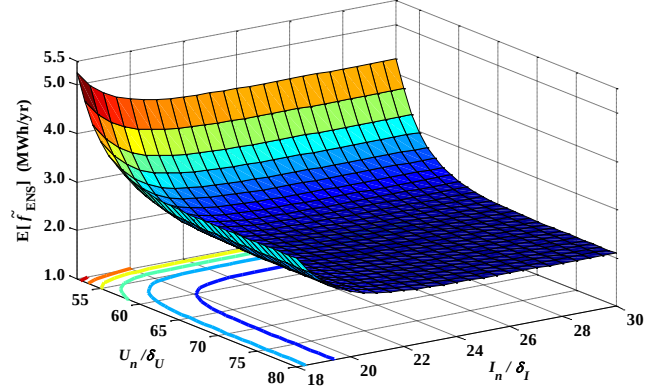


Fig. 7. The relationship between ENS and measurement errors.

C. Daily Reliability Index

If this microgrid is located in a town in eastern China, its daily reliability performance is simulated based on the average values of daily meteorology data in July. Fig. 8 illustrates the fuzzy expected values of the f_{ENS} in conjunction with daily power profiles. The following conclusions can be drawn from this simulation:

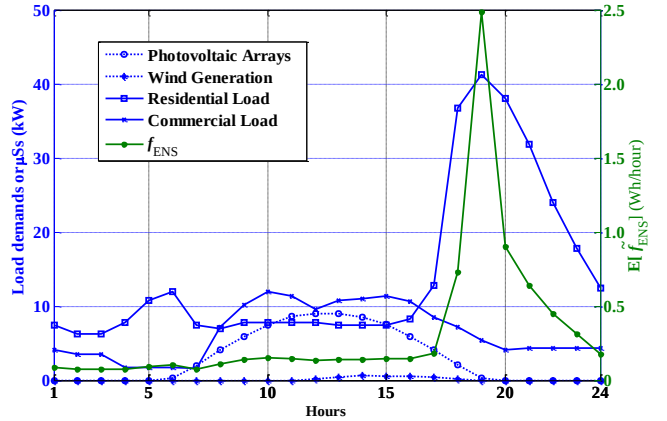


Fig. 8. Fuzzy expected values of ENS for a specified day.

(a) The μS s could not provide enough power to meet the load demands inside the microgrid in July.

(b) The peak values of the load demand, primarily residential load, occur at or near 19:00. At this time, the system reliability deteriorates along with the increase of $E[\tilde{f}_{ENS}]$, evidenced by the tripping accidents that frequently occur on summer evenings, which are the peak load periods in the local residential area.

(c) System reliability remains at a relatively high level during non-peak periods since most outages are caused by the random failure.

(d) Given the similarities between commercial load profile and photovoltaic arrays output profile, this μS can effectively counteract the peak values of the load. The development of

photovoltaic arrays would be beneficial from the perspective of reliability improvement, assuming that the commercial area provides the necessary conditions for it.

Fig. 9 shows the pessimistic values of the system reliability indices under different confidence levels γ on the same day. All three indices are monotonic increasing with a confidence level γ . Thus, a high confidence level γ needs a larger value $\bar{F}$ to satisfy the credibility inequality constraint $\text{Cr}\{\tilde{F} \leq \bar{F}\} \geq \gamma$. A relatively lower reliability can be expected if a higher confidence level is demanded.

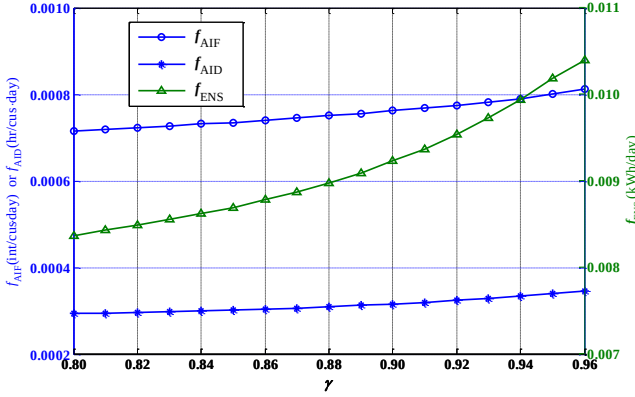


Fig. 9. Daily γ -pessimistic reliability indices $\tilde{F}_{inf}(\gamma)$.

VI. CONCLUSION

This research investigated the potential effects of protective devices on reliability indices in microgrids. The simulations in a test system demonstrated that reliability indices achieved without considering the protection operation in abnormal operating conditions are optimistic. They also confirmed that the uncertainties involved in the trigger values and the decision making process of the virtual setting values have negative effects on reliability indices. Future research will continue to evaluate the probability of malfunctions and rejections of the protective device under various scenarios, resulting in a predictive study on their effects on microgrid reliability.

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