

Predictive Analysis of Microgrid Reliability Using a Probabilistic Model of Protection System Operation

Xufeng Xu, *Member, IEEE*, Tingting Wang, Longhua Mu and Joydeep Mitra, *Senior Member, IEEE*

Abstract—Protection continues to be an important factor in the development of microgrids. In this paper, an evaluation strategy is proposed to quantify the effects of deficient protection scheme on reliability indices in a microgrid. In particular, the evaluation strategy takes into account the trigger probability of protective actions under abnormal operating conditions, such as warranted trips, rejections and malfunctions. This trigger probability in per unit time is defined as dynamic outage rate to distinguish static outage rate (i.e., random outage rate). A probabilistic model is constructed by simulating system operating conditions to determine the trigger probability. The model can be characterized by the previously proposed virtual setting value, which can be determined by a predictive analysis to minimize the probability of incorrect protective actions under different operating conditions. With the proposed evaluation strategy, the significance of the impacts of the protection system, in terms of dynamic outage rate and static outage rate, on the operational reliability are demonstrated with a 400 V microgrid system.

Index Terms— Dynamic outage rate, microgrid, operating condition, operational reliability, protection system, virtual setting value

I. INTRODUCTION

MICROGRID reliability reflects the ability of a microgrid system, including microsources (μ Ss), main feeders and lateral distributors, to deliver power to customers at required amount and power quality. Reliability enhancement is a fundamental and essential objective in planning microgrids. On the other hand, benefits of reliability improvement may potentially attract microgrid investments from customers and utilities. How to achieve accurate reliability indices of a microgrid has drawn increasing attentions from researchers.

Existing publications on the topic of microgrid reliability evaluation primarily focus on the analysis of a microgrid's characteristics, such as operation modes [1]–[4], weather-dependent μ Ss [2]–[6], and operational strategies [7], [8]. However, the fundamental data used in the evaluation process is still random failure rates or random outage rates of electrical elements, which are generally calculated from statistical data of

all accidental and unanticipated outages. Thus, it is usually a constant value derived from average failure frequency and duration over a study period such as a year.

In recent years, some researchers investigated the effects of abnormal conditions, such as extreme weather [9], [10], overloading [11] and mechanical aging [12], on the reliability indices in transmission/distribution systems. The results reported from these studies show that extreme conditions significantly deteriorate system reliability performance. Microgrids also experience abnormal operating conditions, in the form of overcurrent, over-voltage, under-voltage and abnormal frequency. They potentially threaten microgrid safety or even cause power outages, which are expected to be eliminated or limited by protection systems. Nowadays, although multiple protection schemes have been developed for microgrids, such as overcurrent protection [13], voltage based protection [14], adaptive protection [15] and differential protection [16], it is still a big challenge to design an integrated protection scheme that can be used in multiple applications or adaptive to different operating conditions. Thus, it is necessary to consider the behavior of protective devices in reliability evaluation.

In prior research [17]–[18], the authors conducted a preliminary investigation on the relationship between deficient protection schemes and microgrid reliability. This paper extends our prior work through the following: 1) Implementation of protection schemes is analyzed from the probabilistic perspective. Specifically, it is applied in each feeder by evaluating the probabilities of protective actions under different operating conditions. 2) Virtual setting value associated with each feeder is set according to minimization of the probability of incorrect protective actions. Moreover, this paper utilizes the concept of operational reliability, which is used in power systems [11], to evaluate microgrid reliability considering operating conditions.

The rest of this paper is organized as follows: in Section II, system operating conditions are simulated based on Latin Hypercube Sampling (LHS) to identify abnormal operating conditions. In Section III, a probabilistic model characterized by the virtual setting value is proposed and deployed to each feeder. A predictive analysis is then used to set virtual setting value and forecast the trigger probability under diverse operating conditions. Section IV proposes an approach to evaluate the operational reliability indices utilizing both dynamic and static outage rates. In Section V, a microgrid test system is employed to demonstrate the feasibility of the proposed approach. Finally, Section VI provides some concluding remarks.

Manuscript received May**, 2016. This work is supported by National Natural Science Foundation of China (51407128).

X. Xu is with California Independent System Operator (CAISO), Folsom, CA 95630 USA (e-mail: xxu@caiso.com)

T. Wang is with American Electric Power (AEP), Columbus, OH 43215 USA (e-mail: twang@aep.com)

L. Mu is with Tongji University, Shanghai, 201804 China (e-mail: lhmu@tongji.edu.cn)

J. Mitra is with Michigan State University, East Lansing, MI, USA (e-mail: mitraj@msu.edu)

II. ANALYSIS OF SHORT-TERM OPERATING CONDITION

To forecast operating conditions of a microgrid, a stochastic model is established in a predetermined short-term Δt (hour) based on limited valid data.

A. Uncertainty Modeling of μ Ss

μ Ss are widely adopted for the capacity of balancing local load demand and providing post-outage power sources. However, many μ Ss are characterized by intermittent, fluctuating and unpredictable power output. Photovoltaic arrays (PV) and wind generators are studied as typical representative of μ Ss. As for PV, the available power represented by G_s can be estimated through a function of solar irradiation S (W/m^2) and its ambient temperature E ($^\circ\text{C}$) [19], as shown in (1). Similarly, a piecewise function $G_w(V)$ is used to estimate the wind generator output under certain values of wind speed V [20], as shown in (2).

$$G_s(S, E) = S \cdot \eta(E) \cdot G_{\text{rate}} / S_{\text{rate}} \quad (1)$$

$$G_w(V) = \begin{cases} G_{\text{rate}}, & V_{\text{rate}} \leq V < V_{\text{co}} \\ \frac{G_{\text{rate}}(V - V_{\text{ci}})}{V_{\text{rate}} - V_{\text{ci}}}, & V_{\text{ci}} \leq V < V_{\text{rate}} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where G_{rate} represents the rated power of each μ S, S_{rate} is the rated value of solar irradiation (W/m^2) and $\eta(E)$ is an array efficiency factor to indicate the impact of ambient temperature E ; V_{ci} , V_{co} and V_{rate} are the cut-in value, the cut-out value and the rated value, respectively.

S can be regarded as a random variable in a period of Δt and it is assumed to follow a Beta distribution [21]. Similarly, a Weibull distribution is assumed for the value of V [22]. The probability density functions are given as follows,

$$f_1(S) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \cdot (S / S_{\text{max}})^{\alpha-1} \cdot (1 - S / S_{\text{max}})^{\beta-1} \quad (3)$$

$$f_2(V) = k / c \cdot (V / c)^{k-1} \cdot \exp[-(V / c)^k] \quad (4)$$

where α and β are two positive shape parameters, S_{max} is the maximum solar irradiation, $\Gamma(\cdot)$ is the Gamma function; k is the shape parameter ($k > 0$) and c is the scale parameter ($c > 0$).

B. Latin Hypercube Sampling

To generate the sample space of the meteorological parameters in (1) and (2), a stratified sampling method is used, known as Latin Hypercube Sampling [23]. Compared with the random sampling, this method shows better robustness and improved coverage of probabilistic distribution under a fixed sample size. Main steps of this method are given as follows,

Step 1) Estimate the parameters of the Beta distribution and the Weibull distribution.

Let μ_B and ζ_B be the mean value and the standard deviation of the Beta distribution during Δt , respectively,

$$\begin{cases} \alpha = \mu_B [\mu_B - \mu_B^2 - \zeta_B^2] / \zeta_B^2 \\ \beta = (1 - \mu_B) [\mu_B - \mu_B^2 - \zeta_B^2] / \zeta_B^2 \end{cases} \quad (5)$$

Similarly, given the mean value μ_W and the standard

deviation ζ_W of the Weibull distribution, k and c can be approximated by (6), as deduced in [22].

$$\begin{cases} k = (\zeta_W / \mu_W)^{-1.086} \\ c = \frac{\mu_W}{\Gamma(1 + 1/k)} \end{cases} \quad (6)$$

Step 2) According to the cumulative distribution functions of the two distributions represented by (7) and (8), individual codomains are equally divided into N non-overlapping intervals.

$$F_1(S / S_{\text{max}}) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \int_0^{S / S_{\text{max}}} x^{\alpha-1} \cdot (1 - x)^{\beta-1} dx \quad (7)$$

$$F_2(V) = 1 - \exp[-(V / c)^k]. \quad (8)$$

Step 3) Generate a random value p_i from the uniform distribution in the interval $[(i-1)/N, i/N]$, ($1 \leq i \leq N$).

Step 4) Calculate the i th sampling values of S_i or V_i by the inverse function of F_1 or F_2 .

$$S_i = F_1^{-1}(p_i) \cdot S_{\text{max}} \quad (9)$$

$$V_i = F_2^{-1}(p_i). \quad (10)$$

Step 5) Repeat steps 3 and 4 for N times and assemble two matrices $\mathbf{S} = [S_1, S_2, \dots, S_N]^T$ and $\mathbf{V} = [V_1, V_2, \dots, V_N]^T$.

Step 6) Perform random permutations to reduce the correlation between $\mathbf{S}$ and $\mathbf{V}$.

C. Power Flow Distribution

Power flow distribution in microgrids is subject to the randomness caused by uncertain μ Ss and varying load demands that are difficult to be predicted accurately. A microgrid system as shown in Fig. 1, with the basic data reported in [17] is chosen as an example for power flow calculation during one hour (8:00 AM ~ 9:00 AM).

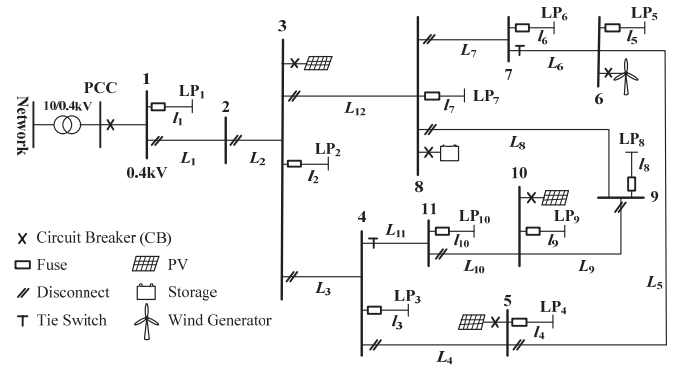


Fig. 1. A microgrid test system.

In this period, the parameters of the two distributions above are generated with the following approach. If the mean value of S represented by μ_S is $100 \text{ W}/\text{m}^2$ and its standard deviation ζ_S is set to 0.4 times μ_S . S_{max} is firstly approximated based on the Chebyshev inequality: $\Pr(|S - \mu_S| \geq \varepsilon) \leq \zeta_S^2 / \varepsilon^2$. If an acceptable threshold of 5% is assumed, ε should be no less than $4.47\zeta_S$.

to satisfy $\Pr(|S - \mu_S| \geq \varepsilon) < 5\%$. Consequently, $S_{\max}$ is set to ' $\mu_S + 4.47\zeta_S$ ' in this study. Then, α and β are determined by μ_B and ζ_B as shown in (5): $\alpha=3.65$, $\beta=6.53$. Similarly, if μ_W is 4 m/s and ζ_W is set to 0.2 times mean value, parameters related to the Weibull distribution are calculated according to (6): $k=5.74$ and $c=4.32$.

Given $N=50000$, stochastic power flows through feeders are simulated using LHS. For instance, the distribution of branch current through L_3 is shown by Fig. 2, where histograms are drawn with an interval of 3/8 A. This distribution can be outlined by a fitting curve which follows a normal distribution, as indicated in the blue curve in Fig. 2. Thus, the feeder current I could be assumed to follow a normal distribution $N(I_{\text{mean}}, \sigma)$ with a probability density function of

$$f(I) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left[-\frac{(I - I_{\text{mean}})^2}{2\sigma^2}\right], I \in [0, +\infty). \quad (11)$$

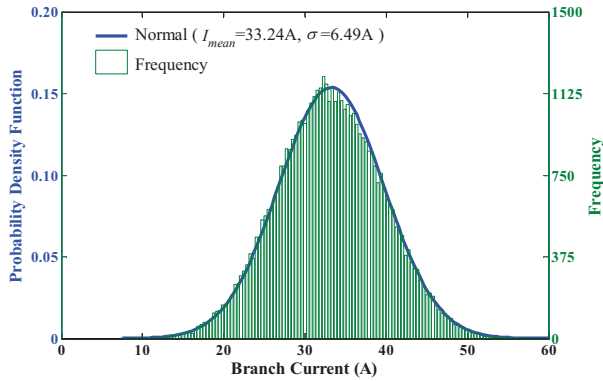


Fig. 2. Branch current distribution at the feeder L_3 .

III. PREDICTIVE ANALYSIS OF PROTECTIVE RESPONSES TO ABNORMAL OPERATING CONDITIONS

For a microgrid, there are a variety of factors resulting in abnormal conditions, such as extreme weather, overloading, major outage clearance in centralized grid and network reconfiguration. The occurrences of abnormal operating conditions exemplified by overcurrent incidents in feeders tend to be more frequent than random outages, such as short or open circuit events. For instance, $I > 50A$ in Fig. 2 indicates an overcurrent through the feeder L_3 given a normal rating of 50 A. Improper reactions to those conditions decrease the microgrid reliability, as investigated in this section based on a model proposed to analyze protective actions. Particularly, the investigation focuses on overcurrent protection, which is widely used in low-voltage networks.

A. A Probabilistic Model for Microgrid Protection

Conventional protection schemes need to be improved in order to meet the special requirements of microgrids. A constant setting value of protective device may not be appropriate for a microgrid in the presence of two operation modes and integrated μ Ss. To better explain this, two assumptions are made:

- (i) The terminal voltage of each μ S is stable for different operating scenarios.
- (ii) The same power tracking strategy is applied for each μ S after the outage.

Then, the fault current flowing through the protective device, represented by I_R , can be approximated by the fault contributions of the grid I_{Grid} and each μ S $I_{\mu S, i}$ [24], as shown in (12).

$$I_R = I_{\text{Grid}} \times \zeta_{\text{Grid}} + \sum_{i=1}^m I_{\mu S, i} \quad (12)$$

where m is the number of μ Ss inside the microgrid; ζ_{Grid} equals to '1' in the grid-connected mode and '0' in the islanded mode.

(1) The first item relies on the electrical distance between the grid and the outage point, and it is zero in the islanded mode.

(2) In majority scenarios, PVs and wind generators are operating in derated states, as shown in Fig. 3. The fault current contribution from each inverter interfaced μ S is supposed to be proportional to actual power output until it reaches the current limitation. Therefore, the second item can be assumed to follow a truncated normal distribution referred to the stochastic power flow distribution in the normal condition.

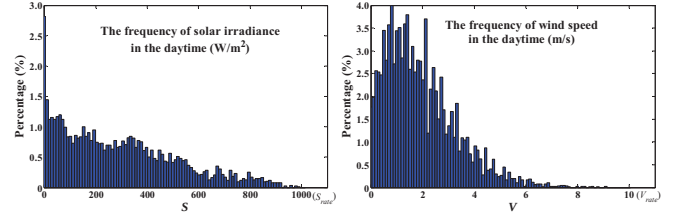


Fig. 3. Annual distributions of meteorological parameters.

Since I_R follows a truncated normal distribution with an upper limit value, the setting value of protective device must be configured accordingly. If this operation requirement is applied to each feeder in a virtual environment, its tripper value I_{op} should also follow a truncated normal distribution $N(I_{\text{set}}, \delta)$. The probability density function $g(I_{op})$ is shown as (13), where I_S is the short-term rated value of the feeder.

$$g(I_{op}) = \frac{1}{\sqrt{2\pi}K\delta} \cdot \exp\left[-\frac{(I_{op} - I_{\text{set}})^2}{2\delta^2}\right], I_{op} \in (0, I_S] \quad (13)$$

$$K = \frac{1}{\sqrt{2\pi}\delta} \cdot \int_0^{I_S} \exp\left[-\frac{(x - I_{\text{set}})^2}{2\delta^2}\right] dx. \quad (14)$$

The mean value of I_{op} is defined as the virtual setting value I_{set} in order to be distinguished from the practical parameter used in protection setting. I_{set} and δ were used to simulate the selectivity and sensitivity of the microgrid protection by the authors in [17]. δ is only dependent on the operational accuracy of the protective device and the effectiveness of the protection strategy, and its ideal value is zero. In the following sections, the parameter configuration of I_{set} will be analyzed from the perspective of reliability improvement.

B. Optimal Virtual Setting Value

For each feeder, its abnormal operating conditions are analyzed by a parameter related to its inherent property, which is defined as expected operational current and represented by I_{exp} . In engineering practice, I_{exp} is normally assumed 1.2 times the rated value of I_N . Given a current distribution $f(I)$, the scenario of abnormal operating conditions is restricted by $I \geq I_{\text{exp}}$,

as the shaded area in Fig. 4. Microgrid protection is required to operate in this scenario.

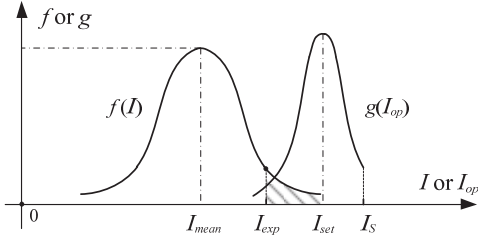


Fig. 4. Probability density functions of I and I_{op} .

However, incorrect actions including rejection and malfunction possibly occur. Specially, considering two events: $\mathbf{A}=\{I \mid I \geq I_{exp}\}$ and $\mathbf{B}=\{I \mid I \geq I_{op}\}$, two parameters are introduced to measure the incorrect actions,

Definition 1: Rejection probability P_{rej} is defined as the probability of $\mathbf{A}$ intersected with the complement of $\mathbf{B}$, or $\Pr\{\mathbf{A} \cap \bar{\mathbf{B}}\}$; Malfunction probability is the probability of $\mathbf{B}$ intersected with the complement of $\mathbf{A}$, or $\Pr\{\bar{\mathbf{A}} \cap \mathbf{B}\}$.

Mathematically, P_{rej} and P_{mal} are calculated by,

$$P_{rej} = \int_{I_{exp}}^{I_S} \int_{I_{op}}^{I_S} f(I)g(I_{op})dIdI_{op} \quad (15)$$

$$P_{mal} = \int_0^{I_{exp}} \int_{I_{op}}^{I_S} f(I)g(I_{op})dIdI_{op} \quad (16)$$

Assuming σ is proportional to I_{mean} with a coefficient $1/n_\sigma$ and δ is proportional to $I_S - I_N$ with a coefficient $1/n_\delta$, P_{rej} or P_{mal} is simplified to be a function of I_{set} and I_{mean} , represented by $P_{rej}(I_{set}, I_{mean})$ or $P_{mal}(I_{set}, I_{mean})$. They could be further expressed by $P_{rej}(\xi, \eta)$ and $P_{mal}(\xi, \eta)$ after defining two new parameters of selectivity factor ξ and mean load rate η , shown as follows,

Definition 2: Selectivity factor ξ is defined to characterize the ratio relationship between the expected operation current and the rated current of a feeder.

$$\xi = I_{set} / I_N \quad (17)$$

Definition 3: Mean load rate η is defined as a measurement of the rating level of a feeder through a period.

$$\eta = I_{mean} / I_N \quad (18)$$

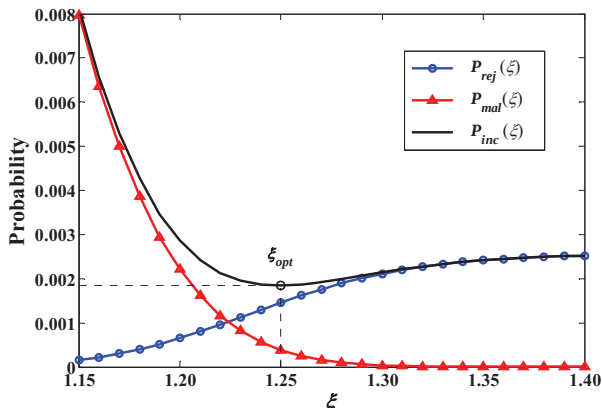


Fig. 5. P_{rej} , P_{mal} , and P_{inc} plotted versus ξ .

In a scenario with a load rate of η , the total probability of incorrect actions, represented by $P_{inc}(\xi)$, is defined by the sum of $P_{rej}(\xi)$ and $P_{mal}(\xi)$. The value of ξ under the minimum value of P_{inc} is denominated as the optimal selectivity factor ξ_{opt} . Subsequently, an optimal virtual setting value of the feeder is determined by $\xi_{opt} \cdot I_N$. For instance, given $n_\sigma=5$ and $n_\delta=10$, Fig. 5 exhibits the curves of $P_{rej}(\xi)$ and $P_{mal}(\xi)$ under the condition $\eta=0.7$. Despite the monotonicity of P_{rej} and P_{mal} with ξ , as shown in Fig. 5, a minimum in the curve of $P_{inc}(\xi)$ exists.

Similarly, a predictive analysis on ξ_{opt} could be carried out under the different operating conditions of each feeder, which are represented by a series of η . A cluster of curves in Fig. 6 illustrates the impacts of η on P_{inc} and ξ_{opt} . It is evident that P_{inc} increases with the increase of η under a fixed value of ξ , yet ξ_{opt} decreases with the increase of η . These simulation results serve as guidance to engineers for field protection setting: an adaptive parameter is recommended for minimization of rejection and malfunction. In this paper, based on the sampling values of ξ_{opt} under different η , the relationship between ξ_{opt} and η is fitted with a function of $\xi_{opt}(\eta)$. Each feeder is then deployed with an optimal virtual setting value I_{set} , which is adaptively set to $\xi_{opt}(\eta) \cdot I_N$.

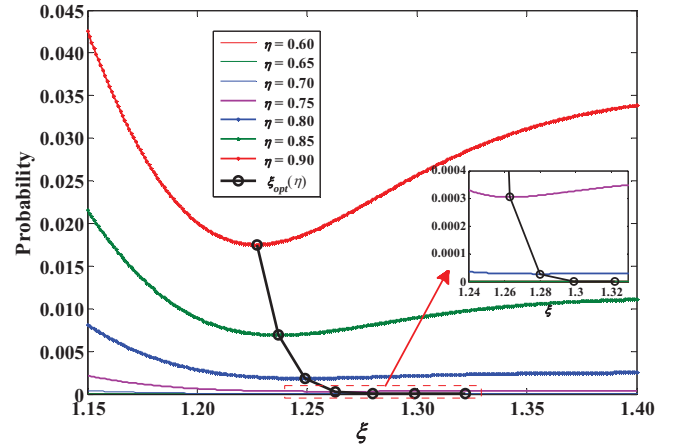


Fig. 6. A cluster of $P_{inc}(\xi)$ with different η .

C. Effects of Incorrect Protective Actions

Two assumptions have been introduced in the above sections: 1) the feeder current follows a normal distribution during Δt ; 2) a probabilistic model is introduced for the simulation of protective operations and I_{set} is determined by means of adaptive setting. Consequently, the probabilities of incorrect protective actions are dependent on I_{mean} or η . $P_{rej}(\eta)$, $P_{mal}(\eta)$ and $P_{inc}(\eta)$ are compared in Fig. 7. This simulation results are applied to evaluate the effects of incorrect protection on reliability indices under different operating conditions.

Since power utilities take the rejection more seriously than the malfunction in low voltage networks such as a microgrid, it is essential to carry out an investigation for the effects of back-up protection. Considering the following four events on the condition of $I > I_{exp}$,

$$\begin{cases} \mathbf{C} : \text{Main protection success} \\ \bar{\mathbf{C}} : \text{Main protection failure} \end{cases}$$

$$\begin{cases} \mathbf{D}: \text{Backup protection success} \\ \bar{\mathbf{D}}: \text{Backup protection failure} \end{cases}$$

The operation probability of the backup protection can be expressed as $\Pr\{\bar{\mathbf{C}} \cap \mathbf{D}\}$. The derivation of (19) is based on the assumption that the backup protection is independent during operations,

$$\begin{aligned} \Pr\{\bar{\mathbf{C}} \cap \mathbf{D}\} &= \Pr\{\bar{\mathbf{C}}\} \cdot \Pr\{\mathbf{D} | \bar{\mathbf{C}}\} \\ &= \Pr\{\bar{\mathbf{C}}\} \cdot \Pr\{\mathbf{D}\}. \end{aligned} \quad (19)$$

The rejection probability after considering the effects of the backup protection is updated by P'_{rej} in (20). Compared with simulation results of P_{rej} and P'_{rej} in Fig. 7, P'_{rej} and its impacts on reliability evaluation is negligible.

$$\begin{aligned} P'_{rej} &= P_{rej} - \Pr\{\bar{\mathbf{C}} \cap \mathbf{D}\} \\ &= \Pr\{\bar{\mathbf{C}}\} \cdot \Pr\{\bar{\mathbf{D}}\}. \end{aligned} \quad (20)$$

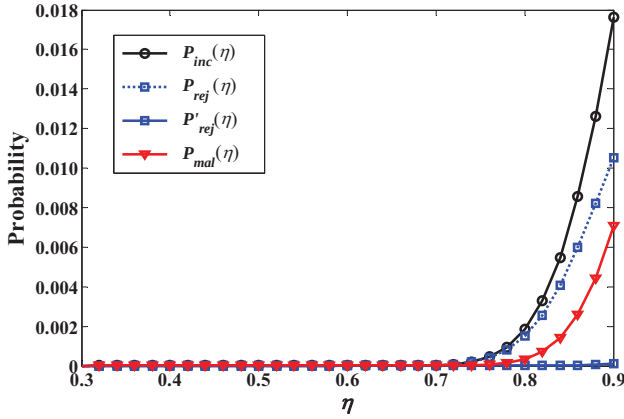


Fig. 7. Probabilities of incorrect actions as functions of η .

IV. EVALUATION APPROACH

A hybrid approach is proposed to evaluate operational reliability in a microgrid with a framework of block diagrams shown in Fig. 8. The evaluation includes operating condition analysis, predictive analysis on protective operation, and reliability evaluation technique. Since the first two issues have already been elaborated in previous sections, this section focuses on the last one.

A. Formulation of Operational Reliability Index

This study classifies the fault causes into random failures and abnormal operating conditions. The outage rate of a feeder in a period $[t, t+\Delta t]$ is composed of two corresponding terms,

1) *Static outage rate or random outage rate* $\lambda_S(t)$. A uniform distribution is assumed for this term, with an annual statistical value of λ_0 .

$$\lambda_S(t) = \lambda_0 \cdot \Delta t / 8760. \quad (21)$$

2) *Dynamic outage rate* $\lambda_D(t)$. Measured by the probability of protective operations per unit time, this term is no longer a constant value. With the deterministic power flow achieved by the mean values of S and V represented as I_{mean} , the operation

probability during $[t, t+\Delta t]$ is a function of I_{mean} or η , as expressed in (22).

$$\begin{aligned} P(I_{mean}) &= \Pr\{I > I_{op} | I > I_{exp}\} \cdot \Pr\{I > I_{exp}\} + P_{mal}(\eta) \\ &= \int_{I_{exp}}^{I_s} \int_0^I f(I) g(I_{op}) dI_{op} dI + P_{mal}(\eta) \\ &= \int_0^{I_s} \int_0^I f(I) g(I_{op}) dI_{op} dI. \end{aligned} \quad (22)$$

If Δt is comparable to the repair time of the feeder, the outage could be fixed within Δt and the possibility of multiple outages is negligible. $\lambda_D(t)$ is approximated by

$$\lambda_D(t) = P(I_{mean}) / \Delta t. \quad (23)$$

According to the above analysis, the feeder outage rate $\lambda(t)$ is dependent of operating conditions, as calculated by

$$\lambda(t) = \lambda_S(t) + \lambda_D(t). \quad (24)$$

Subsequently, average outage time $\omega(t)$ and average failure rate $\zeta(t)$ are selected to measure the short-term reliability on the customer side. Short-term reliability indices of microgrid system include average interruption frequency $f_{AIF}(t)$, average interruption duration $f_{AID}(t)$, and energy not supplied $f_{ENS}(t)$ with more detailed definitions in [17].

In addition, defined by the sum of individual short-term index f_S , the periodical index f_P is used to measure the reliability performance of the feeder, customer or system over a period $(0, T]$.

$$f_P = \sum_{k=1}^{T/\Delta t} f_S(k \cdot \Delta t). \quad (25)$$

B. Evaluation Process

An operating condition analysis embedded strategy is employed to solve this operational reliability evaluation problem. The detailed steps of the procedure shown in Fig. 8 are explained as follows,

- Step 1) Initialization. Hourly meteorological data are collected from historical database or forecasting results.
- Step 2) Sample μ_S and μ_W in $[t, t+\Delta t]$. Subsequently, forecast the power outputs of all PVs and wind generators by formulas (1) and (2), respectively.
- Step 3) Carry out deterministic power flow calculation. The branch power flow achieved is regarded as the mean value during Δt or I_{mean} .
- Step 4) Determine the optimal virtual setting value for each feeder according to $\xi_{opt}(\eta) \cdot I_N$.
- Step 5) Estimate the operation probability of protective actions $P(I_{mean})$ by (22).
- Step 6) Calculate static, dynamic and short-term outage rates of the feeder by (21), (23) and (24), respectively.
- Step 7) Evaluate the short-term reliability indices of customers and system.
- Step 8) Repeat steps 2~7 for $T/\Delta t$ times.
- Step 9) Calculate the periodical value of each reliability index by (25).

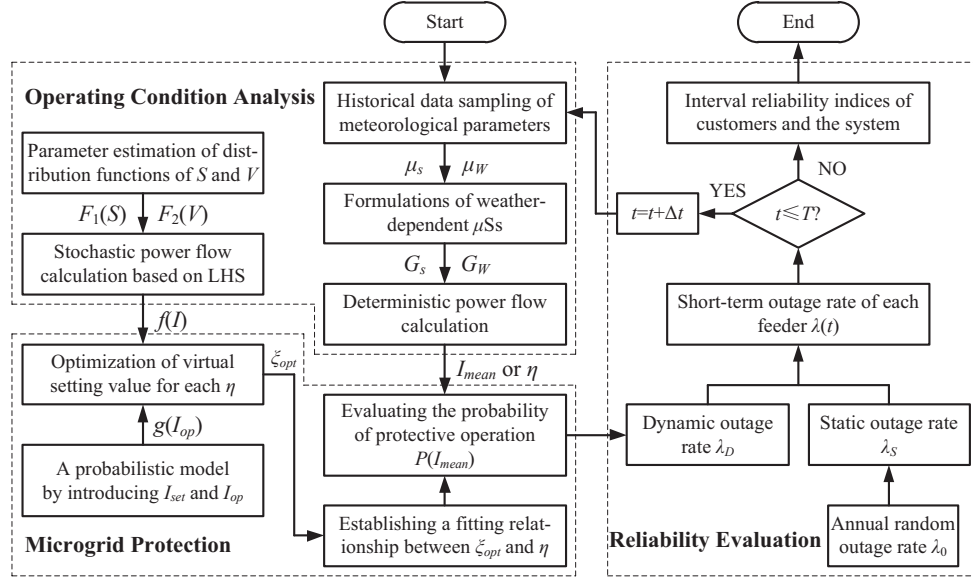


Fig. 8. Proposed operational reliability evaluation procedure.

V. CASE STUDY

A 400 V microgrid system designed in [17], [25] is employed to verify the proposed model and approach. The network structure is composed of 11 nodes and 12 feeders, as given in Fig. 1. Five μ Ss including three PVs, a wind generation and an energy storage system (ESS) are integrated in the microgrid. Their outputs over short-term periods are forecasted according to historical meteorological data at the location of the microgrid. In addition, the profile of average load is shown in Fig. 9. It should be noted that customers are predominantly commercial load and peak consumption seasons are summer and winter.

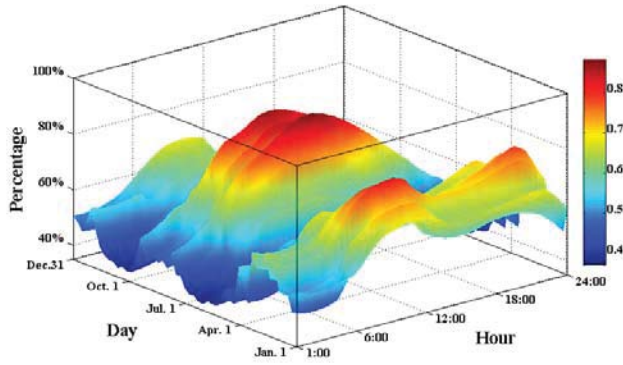


Fig. 9. Annual load profile.

A. Comparison of Reliability Indices

The proposed approach is compared with two traditional evaluation strategies, as designed for the following cases,

Case 1: the proposed approach.

Case 2: without considering the dynamic outage rate, i.e. $P(I_{mean})=0$.

Case 3: I_{op} is set to a constant value of I_{exp} . In this case, $P(I_{mean})$ is forecasted through $\int_{I_{exp}}^{+\infty} f(I)dI$, and $\lambda(t)$ is calculated by (24).

The evaluation results are compared in TABLE I. Case 2 and

Case 3 are two extreme scenarios considering microgrid protection. Since only random failures are accounted in Case 2, the reliability indices are underestimated. On the other hand, an over-sensitive protection also weakens the system reliability performance. As analyzed in Section III.B, malfunction probability in Case 3 is larger than that obtained by utilizing the optimal value of I_{set} (i.e. Case 1).

TABLE I
COMPARISON OF ANNUAL SYSTEM RELIABILITY INDICES

Cases \ Indices	Case 1	Case 2		Case 3	
	Standard	Value	Error (%)	Value	Error (%)
f_{AIF} (int/cus-yr)	0.1936	0.1684	13.02	0.2343	21.02
f_{AID} (hr/cus-yr)	0.1892	0.1731	8.51	0.2149	13.58
f_{ENS} (kWh/yr)	5.9868	5.2255	12.72	7.1793	19.92

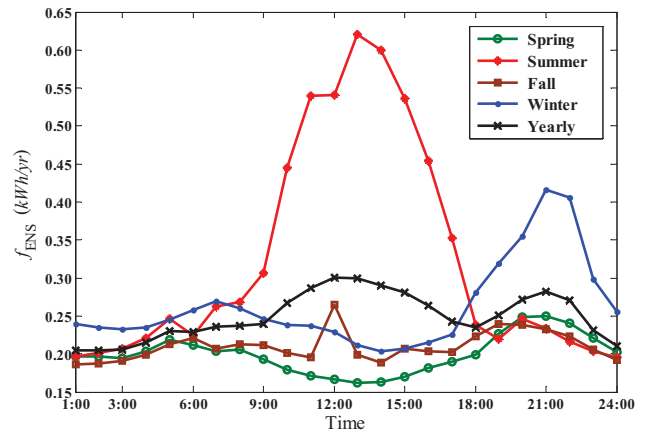


Fig. 10. Comparison of seasonal indices in f_{ENS} .

Average daily reliability profiles in four seasons are compared in Fig. 10. The following conclusions could be drawn

from this contrastive study,

(1) f_{ENS} is no longer a constant value throughout the year, as the one achieved in Case 2. Its value is closely related to the operating conditions at different time periods. For this microgrid, it has a relatively high reliability level in spring but a low level in summer.

(2) There are two obvious peaks occurring in the daytime of summer and in the nighttime of winter. Those peaks are consistent with load peak shown in Fig. 9. It is difficult to control and forecast the load demand inside a microgrid. However, some strategies like graduated power tariff can be applied for peak load shifting in order to improve reliability.

B. Optimal Virtual Setting Value

In the previous analysis, an adaptive virtual setting value or $\xi_{opt}(\eta)$ is set in order to accommodate operating conditions of a feeder. A new case, Case 4, is designed to investigate the effects of virtual setting value on the reliability: ξ is set to $\xi_{opt}(\bar{\eta})$ for each feeder, where $\bar{\eta}$ is the average load rate of a feeder in the studied period. The system reliability indices are compared in TABLE II and the annual outage time of customers in Fig. 11.

TABLE II
COMPARISON OF CASE 1 AND CASE 4

Indices	f_{AIF} (int/cus-yr)	f_{AID} (hr/cus-yr)	f_{ENS} (kWh/yr)
Case 1	0.1936	0.1892	5.9868
Case 4	0.1694	0.1738	5.2569
Error (%)	12.50	8.14	12.19

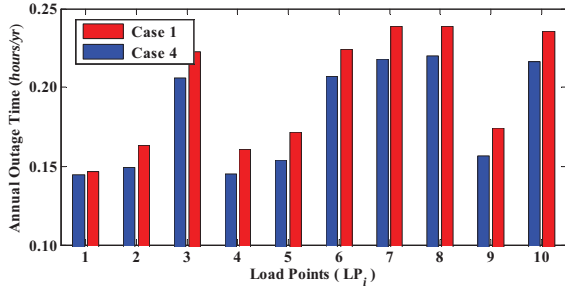


Fig. 11. Comparison of annual outage times.

According to the above comparisons, the reliability indices in Case 4 are overestimated as smaller indices are achieved. The simulation in Fig. 6 indicate that $\xi_{opt}(\eta)$ decreases as η increases.

(1) $\eta \geq \bar{\eta}$: $\xi_{opt}(\eta) \leq \xi_{opt}(\bar{\eta})$ or $I_{set}(\bar{\eta}) \geq I_{set}(\eta)$. Since the virtual setting value is set to a larger value, the malfunction probability is underestimated. It can be noticed from Fig. 5 that $P_{mal}[\xi_{opt}(\bar{\eta})] \leq P_{mal}[\xi_{opt}(\eta)]$.

(2) $\eta < \bar{\eta}$: $\xi_{opt}(\eta) > \xi_{opt}(\bar{\eta})$. Although P_{mal} is overestimated, its contributions to reliability indices are much lower compared to the scenario of $\eta \geq \bar{\eta}$, as evidenced by Fig. 6. For a feeder, the probability of the event $\{I > I_{op}\}$ is negligible if its loading keeps at a low level.

From a reliability perspective, each protective operation

deteriorates reliability indices, regardless of whether the operation is caused by correct actions or malfunctions. In addition, P'_{rej} shown in Fig. 7 has also been neglected considering the function of the backup protection. However, more serious damages to the microgrid may be caused by rejections than by malfunctions. Full trust of backup protection for rejection reductions should essentially be avoided. In this research, ξ_{opt} is optimized according to the minimum of P_{inc} rather than P_{mal} .

C. Operating Condition

In this microgrid, the ESS with a rated power of 10 kW is connected to Bus No. 8 and its capacity is limited to a continuous power supply during the repair process of a feeder (the repair time is set to 1 hour). In Cases 1-4, the operational model used in this work assumes that the ESS is charged during normal operation (or grid connected mode) and discharges only in the islanded mode resulting from predicted outages. In Case 5, the ESS is required to generate power whenever the maximum load rate among all feeders is over 0.8.

Hourly average interruption frequency in Case 5 is compared with that of Case 1 in Fig. 12. Although the peaks of f_{AIF} in Case 5 still correspond to the peaks of feeders' load rates, as exemplified in Fig. 13, a significant decrease of those peak values can be observed for Case 5. Thus, the energy storage has a positive influence on peak load shifting and reliability improvement. In addition, three system reliability indices are listed in the second column of TABLE III.

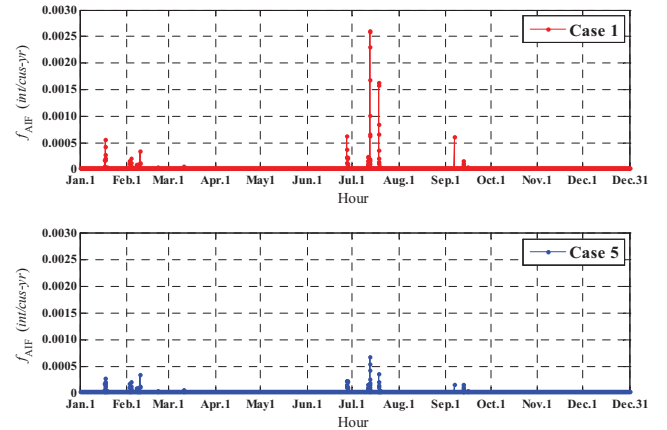


Fig. 12. Comparison of hourly indices in f_{ENS} .

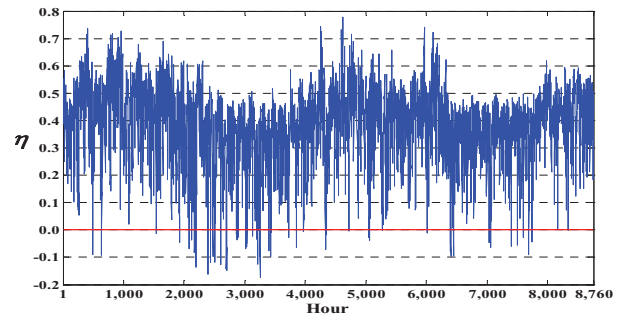


Fig. 13. Load rate of L_3 .

Since power flow in the microgrid fluctuates in a wide range, the utilization rates of most components remain relatively low from the perspective of the load rate. If the load demand is forecasted to increase by 10% in five years and by 20% in ten years, the resultant reliability indices are compared in TABLE III. For this microgrid, an upgrade of network within ten years is recommended.

TABLE III
RELIABILITY PERFORMANCES WITH LOAD INCREASE

Period	Present	After 5 years (+10%)	After 10 years (+20%)
Load demand (kW)	53.22	58.54	63.86
Customer Number	410	451	492
μ S Capacity (kW)	34	34	34
f_{AIF} (int/cus-yr)	0.1779	0.2632	0.8051
f_{AID} (hr/cus-yr)	0.1779	0.2019	0.3389
f_{ENS} (kWh/yr)	5.4342	6.9642	14.3231

Similarly, Fig. 14 investigates the relationship between f_{ENS} and the increase in total μ S capacity. The blue curve represents the scenario where all μ Ss are PVs; conversely, the red curve denotes that all μ Ss are wind based. From the case study, some trends can be observed:

(1) Since the integrated μ Ss are able to relieve the load rates of the feeders connected to the utility, f_{ENS} decreases in three schemes of the μ S deployment. However, a power flow in reversed direction occurs when their generated power is above demand, as shown in Fig. 13 (below the red line). The delivery of the generated power from PV or wind generator is limited by the terminal feeder; therefore, there is a minimum value of reliability improvement by investing in μ Ss.

(2) Loads are higher during the daytime, overlapping with the period of PV production; therefore, the reliability index corresponding to the blue curve is lower than the red one, and even lower than the black curve through the first two simulation points.

(3) If all μ Ss inside the microgrid are of the same type, an identical profile in available power can be expected. Such a scenario is not effective in overcoming local power shortage and line congestion. A diversified combination of μ Ss is helpful in maintaining microgrid reliability.

VI. CONCLUSION

This paper concentrates on the impacts of imperfect protection scheme on microgrid reliability evaluation. A probabilistic model with optimized parameters is developed to simulate protective responses under abnormal operating conditions. All potential operations of microgrid protection are measured in terms of operation probability. Simulation results illustrate the necessity to consider microgrid protection for reliability evaluation under its current status. However, this study focuses on overcurrent protection scheme and follow-up studies on other protection schemes will be carried out in the

future.

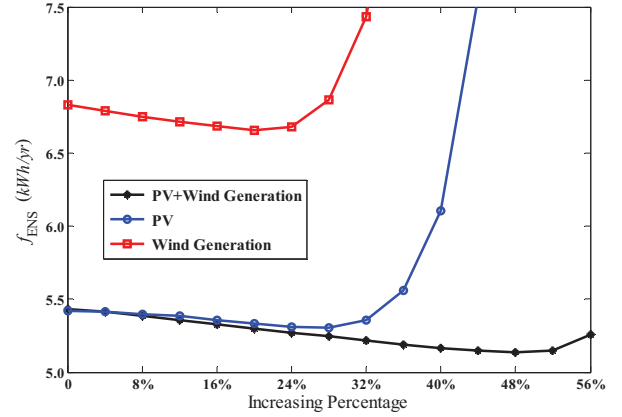


Fig. 14. f_{ENS} with different μ S penetration levels.

REFERENCES

- [1] I. S. Bae and J. O. Kim, "Reliability evaluation of customers in a microgrid," *IEEE Trans. Power Syst.*, vol.23, no. 3, pp.1416-1422, Aug. 2008.
- [2] Y. Y. M. Atwa, E. F. El-Saadany, M. M. A. Salama, R. Seethapathy, M. Assam, and S. Conti, "Adequacy evaluation of distribution system including wind/solar DG during different modes of operation," *IEEE Trans. Power Syst.*, vol.26, no.4, pp.1945-1952, Nov. 2011.
- [3] M. A. Muhaini and G. T. Heydt, "Evaluating future power distribution system reliability including distributed generation," *IEEE Trans. Power Del.*, vol.28, no.4, pp.2264-2272, Oct. 2013.
- [4] Y. M. Atwa and E. F. El-Saadany, "Reliability evaluation for distribution system with renewable distributed generation during islanded mode of operation," *IEEE Trans. Power Syst.*, vol.24, no.2, pp.572-582, May 2009.
- [5] C. Chen, W. Wu, B. Zhang, and C. Singh, "An analytical adequacy evaluation method for distribution networks considering protection strategies and distributed generators," *IEEE Trans. Power Del.*, to be published, Dec. 2014.
- [6] S. Wang, Z. Li, L. Wu, M. Shahidepour, and Z. Li, "New metrics for assessing the reliability and economics of microgrids in distribution system," *IEEE Trans. Power Syst.*, vol.28, no.3, pp.2852-2861, Aug. 2013.
- [7] X. Zhan, T. Xiang, H. Chen, B. Zhou, and Z. Yang, "Vulnerability assessment and reconfiguration of microgrid through search vector artificial physics optimization algorithm," *Electr. Power Energy Syst.*, vol.62, pp.679-688, 2014.
- [8] H. E. Farag, M. M. A. Abdelaziz, and E. F. El-Saadany, "Voltage and reactive power impacts on successful operation of islanded microgrids," *IEEE Trans. Power Syst.*, vol.28, no. 2, pp.1716-1727, May 2013.
- [9] K. Alvehag and L. Soder, "A reliability model for distribution systems incorporating seasonal variations in severe weather," *IEEE Trans. Power Del.*, vol. 26, no. 2, pp. 910-919, Apr. 2011.
- [10] R. Rocchetta, Y.F. Li, and E. Zio, "Risk assessment and risk-cost optimization of distributed power generation systems considering extreme weather conditions," *Reliab. Eng. Syst. Saf.*, vol. 136, pp. 47-61, 2015.
- [11] Y. Sun, P. Wang, L. Cheng, and H. Liu, "Operational reliability assessment of power systems considering conditional-dependent failure rate," *IET Gener. Transm. Distrib.*, vol.4, no.1, pp.60-72, Jan. 2010.
- [12] J. He, Y. Sun, P. Wang and L. Cheng, "A hybrid conditions-dependent outage model of a transformer in reliability evaluation," *IEEE Trans. Power Del.*, vol. 24, no. 4, pp. 2025-2033, Oct. 2009.
- [13] A. H. Etemadi and Reza Iravani, "Overcurrent and overload protection of directly voltage-controlled distributed resources in a microgrid," *IEEE Trans. Ind. Electron.*, vol. 60, no. 12, pp.5629-5638, Dec. 2013.
- [14] H. Al-Nasseri, M. A. Redfern, and F. Li, "A voltage based protection for micro-grids containing power electronic converters," presented at the *Power Eng. Soc. Gen. Meeting*, Montreal, QC, Canada, Sep. 2006.

- [15] L. Che, M. E. Khodayar, and M. Shahidehpour, "Adaptive protection system for microgrids: protection practices of a functional microgrid system," *IEEE Electrification Mag.*, vol.2, no.1, pp.66-80, Mar. 2014.
- [16] E. Casagrande, W. L. Woon, H. H. Zeineldin, and D. Svetinovic, "A differential sequence component protection scheme for microgrids with inverter-based distributed generators," *IEEE Trans. Smart Grid*, vol.5, no.1, pp.29-37, Jan. 2014.
- [17] X. Xu, J. Mitra, T. Wang and L. Mu, "Evaluation of operational reliability of a microgrid using a short-term outage model," *IEEE Trans. Power Syst.*, vol.29, no.5, pp.2238-2247, Sep. 2014.
- [18] X. Xu, J. Mitra, T. Wang, and L. Mu, "An evaluation strategy for microgrid reliability considering the effects of protection system," *IEEE Trans. Power Del.*, vol.31, no.5, pp.1989-1997, Oct. 2016.
- [19] E. S. Gavanidou and A. G. Bakirtzis, "Design of a stand alone system with renewable energy sources using trade off methods," *IEEE Trans. Energy Convers.*, vol. 7, no. 1, pp. 42-48, Mar. 1992.
- [20] H. Yu, C. Y. Chung, K. P. Wong, and J. H. Zhang, "A chance constrained transmission network expansion planning method with consideration of load and wind farm uncertainties," *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp.1568-1576, Aug. 2009.
- [21] S. H. Karaki, R. B. Chedid and R. Ramadan, "Probabilistic performance assessment of autonomous solar-wind energy conversion systems," *IEEE Trans. Energy Convers.*, vol.14, No.3, pp.766-772, Sep. 1999.
- [22] C. G. Justus, W. R. Hargraves, A. Mikhail, and D. Graber, "Methods for estimating wind speed frequency distributions," *Journal of Applied Meteorology*, vol.17, no.3, pp. 350-353, March 1978.
- [23] M. D. McKay, R. J. Beckman, and W. J. Conover, "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics*, vol. 21, no.2, pp. 239-245, May 1979.
- [24] T. S. Ustun, C. Ozansoy, and A. Zayegh, "Fault current coefficient and time delay assignment for microgrid protection system with central protection unit," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 598-606, May 2013.
- [25] K. Rudion, A. Orths, Z. A. Styczynski, and K. Strunz, "Design of benchmark of medium voltage distribution network for investigation of DG integration," presented at the *Power Eng. Soc. Gen. Meeting*, Montreal, QC, Canada, Sep. 2006.



Joydeep Mitra (S'94–M'97–SM'02) received the B.Tech. (Hons.) degrees in electrical engineering from Indian Institute of Technology, Kharagpur, India, and the Ph.D. degree in electrical engineering from Texas A&M University, College Station, TX, USA.

He is an Associate Professor of Electrical Engineering at Michigan State University, East Lansing, MI, USA. Prior to this, he was Associate Professor at New Mexico State University, Las Cruces, NM, USA, Assistant Professor at North Dakota State University, Fargo, ND, USA, and Senior Consulting Engineer at LCG Consulting, Los Altos, CA, USA. His research interests include power system reliability, distributed energy resources, and power system planning.



Xufeng Xu (M'11) received the B.E. degree and the Ph.D. degree in electrical engineering from Zhejiang University, Hangzhou, China, in 2004 and 2009 respectively. He is currently working at California Independent System Operator, Folsom, CA, USA.

His research interests include microgrid reliability, power system planning, optimization algorithms and renewable energy integration.



Tingting Wang received the Ph.D. degree in electrical engineering at Clemson University, Clemson, USA, in 2013. She is currently working at American Electric Power, Columbus, OH, USA.

Her research interest focuses on renewable energy integration, power system transient and electricity market.



Longhua Mu received the B.E., M.E. and Ph.D. degrees in electrical engineering from China University of Mining and Technology, Xuzhou, China, in 1986, 1988 and 1998, respectively. He has been a full professor in the department of electrical engineering, Tongji University, Shanghai, China, since 2004.

His current research interests include protective relaying of power system, power quality and microgrid control.