IET Generation, Transmission & Distribution

Research Article

New reward and penalty scheme for electric distribution utilities employing load-based reliability indices

ISSN 1751-8687
Received on 21st November 2017
Revised 15th April 2018
Accepted on 17th May 2018
E-First on 15th June 2018
doi: 10.1049/iet-gtd.2017.1809
www.ietdl.org

Bo Wang[1] ✉, *Jorge Alexis Camacho*[2], *Gary Michael Pulliam*[3], *Amir Hossein Etemadi*[1], *Payman Dehghanian*[1]

[1]*Department of Electrical and Computer Engineering, The George Washington University, Washington, D.C., USA*
[2]*United States Department of Commerce, National Institute of Standards and Technology, Washington, D.C., USA*
[3]*Division of Infrastructure and System Planning, The Public Service Commission of the District of Columbia, Washington, D.C., USA*
✉ *E-mail: wangbo@gwu.edu*

Abstract: Electric distribution utilities are required to continuously deliver reliable electric power to their customers. Regulatory utility commissions often practise reward and penalty schemes to regulate reliability performance of utility companies annually with respect to a desired performance targets. However, the conventional regulation procedures are commonly found based on the customer-based standard reliability indices, which are not able to discern the service characteristics behind the electric meters and, hence, fail to holistically characterise the actual impact of electricity interruption. This study proposes a new method to evaluate the load-based reliability indices in power distribution systems using advanced metering infrastructure data. Furthermore, the authors introduce a reward/penalty regulation scheme for utility regulators to provide a reliability oversight using the proposed load-based reliability metrics. The new load-based reliability metric and the reward/penalty scheme proposed bring about superior advantages as the distribution grids become further complex with a high penetration of distributed energy resources and enabled microgrid flexibilities. Numerical analyses on different settings with and without microgrid considerations reveal the applicability and effectiveness of the proposed approach in real-world scenarios.

Nomenclature

ASIDI′	forecasted value of ASIDI
α	annual severe weather impact factor for a regional distribution system
B_{PF}	benefit of increasing feeder reliability to avoid PF (in $)
B_{RP}	benefit of customer reliability premium (in $)
C_{c}	cost of compensation for long outages
CI	composite index for evaluating feeder reliability
D_i	interruption duration of outage event i
ENS	forecasted value of annual energy not supplied (ENS) to the feeder
ENS′	equivalent ENS to the feeder considering the impacts of microgrid
ENS_{f}	ENS to the electric vehicles caused by failing to charge or swap the batteries
ENS_i	ENS to the feeder during outage event i
E_{l}	effective load control of non-critical loads during outages
G	effective generation supplied to the customer during outages
i	index of an interruption event
IEAR	interrupted energy assessment rate (estimated cost per unserved kWh during outage event i)
IR	incentive rate of utility regulation
L_i	interrupted load in kVA for the outage event i
L_{T}	total connected load served
N	time steps of load forecasting
PF	feeder penalty factor
PF′	forecasted value of PF
S	annual energy supplied to electric vehicles by rescheduling the service
t	index of time intervals (1 to T)
TU_0, TL_0	upper and lower limits of ASIDI′
W_1, W_2, W_3	weight factors for ASIFI, ASIDI, and ASSDI, respectively
x, $\hat{x}$	real and forecasted value of interrupted load

1 Introduction

1.1 Problem description

Electric utilities are continuously seeking solutions to engender a more reliable, cost-effective and interactive power distribution systems through advanced technologies and modernisation efforts supported by the regulatory commissions [1]. Smart grid technologies are deployed to accomplish this modernisation mission and meet the intensified sustainability goals with smart meters, smart appliances, electric vehicles (EVs) and distributed energy resources (DERs), among others [2]. Advanced metering infrastructure (AMI), which consists of smart meters, communication technologies, meter data management system (MDMS), and the associated software/hardware platforms, enables active interactions between the smart grid components. Each end user connected to a node and associated with a smart meter in an AMI system is characterised as a customer regardless of its load scale. Despite the undeniable advantages, smart meters generate data with high velocity and variety resulting in several challenges ranging from tremendous volumes of data to be processed and complicated AMI architectures that are not easy and practical to develop [3].

In a hierarchical AMI architecture, data is automatically collected from customer meters and communicated to the utility MDMS through data access points [4, 5]. AMI implementation enables visualisation of the distribution system assets, operating states, and prevailing conditions including outage events [6]. It also enables more accurate reliability assessments by updating and uploading outage information to the utility database and analytic platforms [7, 8]. Optimal set of maintenance strategies can be adopted based on the outage information corresponding to the utility-controlled territory to improve the system reliability performance requirements [9]. Most utility commissions solely track the system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI) metrics to

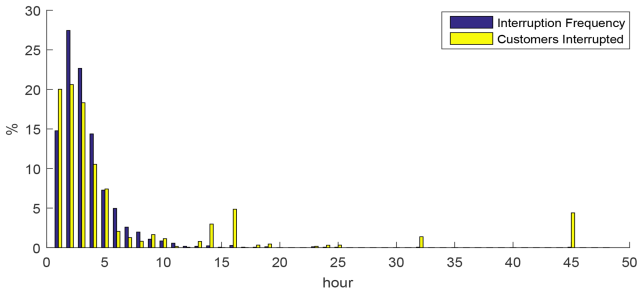

Fig. 1 *Interruption frequency against restoration time (in percentage), and number of customers interrupted against restoration time (in percentage). Daily mean restoration time is utilised and the correlation coefficient is 0.95*

evaluate system reliability and reward/penalise the electric utilities accordingly depending on their performance with regard to the desired targets and requirements. Reward and penalty schemes (RPSs) are, hence, designed to regulate the performance of the electric distribution companies based on the reported reliability performance metrics [10–13]. However, the aforementioned two customer-based reliability indices are dominated by residential customers [14]. For instance, based on the data provided by the local utility, the US District of Columbia features 99% penetration of AMI, residential customers in this area consume 17% of total load but accounting for 90% of the AMI customers. Some utilities have started migrating to a new decision paradigm by including the momentary average interruption frequency index (MAIFI) as part of their reliability performance evaluations but load-based reliability indices such as average system interruption frequency index (ASIFI) and average system interruption duration index (ASIDI) are still not widely used. The challenge to wide adoption of such load-based reliability metrics is acquiring information on the quantity of the interrupted load, which could be more challenging than the number of interrupted customers [14]. With the increasing trend in penetration of distributed renewable ERs (DERs), local storage units, and demand response programmes and load control mechanisms, real-time assessment of interrupted loads becomes more and more challenging than ever before. As a result, reliability regulatory policies should also go through a transformation to meet such emerging challenges in future.

1.2 Literature survey

In exploring the existing literature, an automated reliability assessment mechanism is designed in [15] to calculate both customer-based and load-based key reliability indices, where pre-outage kVA is utilised to quantitatively assess the ASIFI and ASIDI metrics. In [16], the annual average number of connected loads is utilised to calculate the ASIDI metric and to design the RPS for electric utilities. However, the ASIDI metrics calculated in [15, 16] are unable to reflect load profile variations and DER spatio-temporal impacts. The SAIFI and SAIDI indices of reliability are modified in [17] to incorporate the priority and corresponding penalty factor (PF) for interrupted load of each customer when direct load controls of all consumers are enabled. However, the energy not supplied (ENS) during an outage event still needs to be assessed to account for the amount and duration of load interruptions. New metrics have been proposed to assess the reliability of microgrids in [18] and to optimise the DER allocation in [19], through value-based reliability planning approaches. The simulation results based on load point average failure rate and average outage duration in [20] are different from the true values captured during interruptions. Several techniques for analysing utility long-term investment plans are suggested in [21, 22], where the reliability indices and utility regulations are overlooked. A multi-agent system architecture for virtual power plants has been introduced to manage smart grids and forecast energy demand in [23], where a detailed model for low-level management of virtual power plants is introduced. With a lower load forecast error, virtual power plants are shown to achieve a decentralised intelligent management and communication with other agents through negotiation. Load forecasting (LF) at the feeder level and even the consumer level through AMI data is also approached in [24–28], where numerical results indicated acceptable short-term LF (STLF) performance with appropriate load aggregation levels. Note that the aforementioned references neither evaluated the predictability of load-based reliability indices nor calculated the load-based reliability metrics considering high penetration of DERs. Currently, public literature available specifically on studying the RPS for distribution utilities considering the impacts of microgrids is scarce and research efforts must be focused to address this emerging topic of interest from the perspective of a utility regulator.

1.3 Contributions

The contributions of this paper are three-fold: (i) to explore the applicability of the load-based reliability metrics and calculate such reliability indices of ASIDI using the AMI-captured load data and LF techniques; (ii) to introduce a new reliability index and an AMI-assisted reliability assessment architecture to incorporate the impacts of microgrids; (iii) to propose a novel RPS to regulate the reliability performance of distribution utilities based on specific feeder characteristics and via employing the proposed load-based reliability metrics.

This paper is organised as follows. In Section 2, we present the proposed AMI-assisted architecture for assessing the suggested load-based reliability metrics in power distribution systems. A new reliability regulation mechanism from the utility regulator perspective using the proposed load-based reliability metrics is introduced in Section 3. Numerical case studies based on both traditional and the proposed RPS schemes are conducted in Section 4, where the impacts of microgrids and DER penetrations are extensively explored. Moreover, finally comes the conclusions in Section 5 that summarises this paper contributions.

2 AMI-assisted reliability assessment

Hourly customer load profiles for several years are usually uploaded and stored to MDMS by utilities through an AMI platform. Hence, we regard the mean total aggregated load as the average load, L_T, in contrast with the transformer rated kVA, which has been the common practise in the past. In this section, hourly load data from smart meters is used to calculate the ASIDI. The missing data of smart meters is treated as 0 kW.

2.1 Calculation of ASIDI using AMI data

Different outage events are characterised with different interruption durations and impose different system-wide impacts. Fig. 1 illustrates the distribution of interruption frequency and number of interrupted customers for the District of Columbia distribution system from 2011 to 2015. As one can see from Fig. 1, interruption duration and number of interrupted customers are highly correlated: 91.5% of the average outage durations are <6 h and affect 79.0% of the total interrupted customers. Hence, majority of the outage events can be forecasted through an STLF mechanism with the lead time of 1 h to 1 day ahead. The main uncorrelated observations are related to the long interruption duration outages with a large number of customers affected but with lower frequency. Medium-term LF (MTLF) can be applied for outage events that last more than 24 h with relatively large number of affected customers.

Algorithm 1: Algorithm for calculating ENS

1: Import the hourly customer load profiles of the feeder for 5 years as well as the yearly outage report. Calculate the average load L_T.

2: Calculate the outage duration D_i for each outage event i.

3: For each outage event i, if $D_i \leq 1$, consider the pre-outage load as the interrupted load; otherwise, aggregate the load profiles of interrupted customers, forecast N-step ahead interrupted load.

4: Calculate ENS_i for the outage event i.

5: Sum ENS_i to get the ENS.

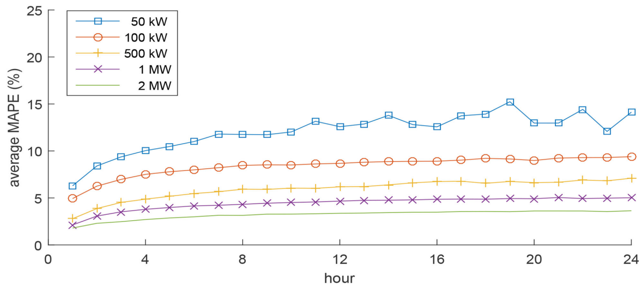

Fig. 2 *Average MAPE on the STLF results against the forecast lead time of 1, 2, ..., 24 h ahead. Each line represents the aggregated load scale*

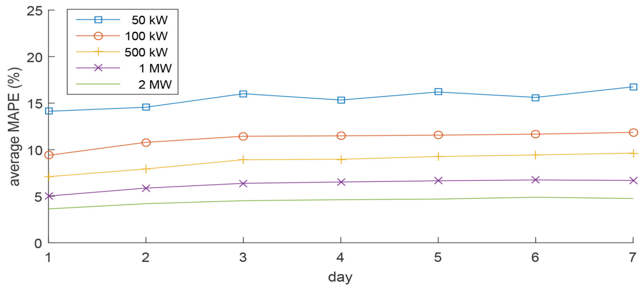

Fig. 3 *Average MAPE on the MTLF results against the forecast lead time of 1, 2, ..., 7 days ahead. Each line represents the aggregated load scale*

We propose Algorithm 1 to calculate the annual ENS of the feeders. Historical customer load profiles are aggregated to predict the hourly interrupted load during each outage event considering different chronological and weather conditions. Then, ENS metrics during outage events (ENS_i) are calculated considering outage start and end times, and then added up to evaluate ENS. In step 3, if outage duration is ≤1 h, we use pre-outage load profile as the load does not change much in an hour and load forecast with resolution of <1 h is hard to achieve in this model. In case where the interruption duration is longer than 1 h, we modified the neural networks (NNs) in [29] to forecast the interrupted load. LF time horizons vary from 1 h to 1 week and we forecast N as EndHour–StartHour + 1 h-ahead load. When N is ≤24 h, we use STLF; otherwise, MTLF is applied. The interrupted load profiles are aggregated utilising the AMI data. Then, the Levenberg–Marquardt approach with 22 hidden neurons are used to train the model. The ASIDI index of reliability is calculated as in the equation below:

$$\mathrm{ASIDI} = \frac{\mathrm{ENS}}{L_{\mathrm{T}}} \tag{1}$$

We use mean absolute percentage error (MAPE) to measure the forecast performance [25]. The MAPE is defined as the ratio of the absolute forecast errors and the actual observed values

$$\mathrm{MAPE}(x, \hat{x}) = \frac{100}{T} \sum_{t=1}^{T} \left| \frac{x(t) - \hat{x}(t)}{x(t)} \right| \tag{2}$$

where $x = \{x(1), \ldots, x(T)\}$ are actual values, $\hat{x} = \{\hat{x}(1), \ldots, \hat{x}(T)\}$ are corresponding forecast values, and $x(t)$ is time series.

Two feeders in the US District of Columbia are used here to demonstrate the effectiveness of the proposed algorithm. The anonymous load profile data and historical outage reports of the two feeders are provided by the Potomac Electric Power Company. Both feeders are overhead lines feeding residential loads and a few commercial customers. Feeder 1 supplies 549 customers with an average load demand of 1.47 MW, whereas Feeder 2 supplies 1476 customers with the average load demand of 2.46 MW. We used 3 years historical load data from June 2013 to May 2016, where the first 2 years of the data were used for training and estimating the model parameters, and observations from the past year were utilised for model evaluation and performance verification. We also employed historical temperature data of the Ronald Reagan Washington National Airport (DCA) from the National Oceanic and Atmospheric Administration [30].

We randomly select subsets of customers with different load scales from the two feeders, aggregate their load profiles, and sample ten times for each load scale to estimate the LF error of the interrupted load. The average MAPE for the forecasted interrupted load by STLF and MTLF techniques are demonstrated in Figs. 2 and 3, respectively. The MAPE corresponding to the forecasted interrupted load increases when the aggregated load decreases and interruption duration increases. According to Fig. 2, the average MAPE for a load scale of 50 kW is higher than 10% and even unstable when interruption lasts more than 4 h. However, the average MAPE of interrupted load with the load scale of more than 500 kW is relatively low and does not increase much even when the interruption lasts for several days as shown in Fig. 3. The MAPE of the forecasted load decreases through load aggregation, which is commonly expected in the industry practise. However, we demonstrate here the performance of the proposed Algorithm 1 in this application: the MAPE associated with the ASIDI metric is small when the feeder has medium or low reliability level. The reason lies in the facts that (i) the MAPE associated with a large amount of interrupted loads is low and less sensitive to interruption duration and (ii) the contributions of the severe outage events dominate the reliability index of ASIDI. The MAPE associated with the ASIDI further decreases as LF error is approximated by a normal probability distribution with mean value of 0. When the feeder is more reliable, less load will be interrupted and, hence, the ASIDI metric becomes smaller while the corresponding MAPE is relatively large.

2.2 Proposed load-based reliability metrics considering penetration of DERs and EVs

Microgrids can improve the reliability performance of the power distribution systems. Load interruptions can be reduced through an effective allocation and utilisation of the distributed generation supply and direct load control mechanisms. Despite its advantages, it also brings about difficult-to-manage challenges for public utility commissions (PUCs) to collect the high-resolution AMI data since many microgrids are owned by the customers and/or third parties. The utility may not have access to AMI data from the microgrids as utility commissions only regulate utility assets. In this paper, we introduce *observation point* to reflect the scope of data collection from the feeder. We define a smart meter as observable if the information behind the smart meter can be acquired. Consequently, a utility-owned microgrid is observable as the utility can gather all the information behind the microgrid substation meter. A single meter connected to a node is unobservable as there is no meter behind. If a third party or residential facility owns a microgrid and they are willing to share information behind the meter with the utility company, this smart meter connected to the microgrid is observable too. Hence, the distribution system reliability assessment will terminate on where the utility observation points end, which is in contrast with the traditional view of to the point where the utility assets are covered. The equivalent ENS of each feeder is calculated as follows in the equation below:

$$\mathrm{ENS}' = \mathrm{ENS} - E_{\mathrm{l}} - G \tag{3}$$

where ENS is the forecasted energy demand of the interrupted customers, E_{l} is the effective load control applied to non-critical loads, and G are the loads partially supplied via DERs which are measured via the connected production meter. The procedure to calculate ENS′ is presented in Fig. 4. For each feeder, we first check if each interrupted node is observable. If it is observable, we acquire the load profile, measured generation, and effective load control corresponding to the load being served at that node. If it is unobservable, we only gather the load profile from the connected smart meter. We then aggregate the load profiles of the customers that are interrupted during the same time interval, then forecast the load demand, and eventually calculate ENS as introduced earlier in Section 2.1.

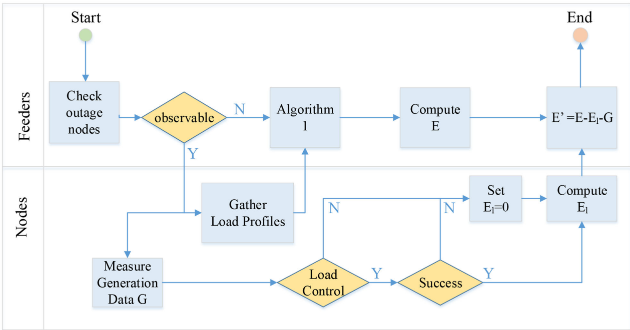

Fig. 4 *Implementation procedure of the proposed offline reliability assessment loop*

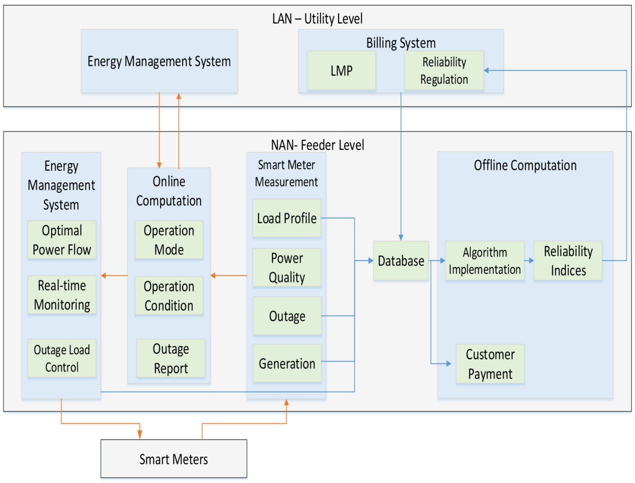

Fig. 5 *Logical view of the proposed advanced meter infrastructure*

We assume EVs are charged under plug-in or battery swapping mode and their daily charging curves are stable. An aggregator is assumed to be responsible for charging the EVs so as to meet the customer demand and also to coordinate the operation of the energy management system under the plug-in mode. When an interruption occurs and is recovered before the EV departure time, the state of charge (SOC) of the EV battery is metered: if it is less than the expected SOC at the EV departure time, the difference between expected SOC and captured SOC actually reflects the ENS to the customer $\mathrm{ENS_f}$ and can be assessed by the aggregator. If the aggregator charges the EV battery to expected SOC after the interruption but before the EV scheduled departure time, we regard the EV load as not interrupted. The extra energy supplied to the load demand during the interval between the restoration time and the EV departure time is the difference between the actual energy supplied to the load and the scheduled energy supplied in that time interval and is actually amounted equal to the shifted load. Under battery swapping mode, EVs can utilise the battery swapping stations (BSSs) connected to adjacent feeders without interruption, if customers are well informed and the batteries are not already depleted (i.e. the BSS connected to the interrupted feeder can supply power to the feeder). We assume the EVs belonged to the interrupted feeder can swap their batteries with a discount; hence, the battery swapping process can be recorded and the increased SOC of their batteries can be regarded as the shifted load. Note that the EV load interruption $\mathrm{ENS_f}$ caused by a failure in battery swapping, leading to a travel delay, can be acquired via post-surveys.

We define the EV service interruption S as the energy interrupted but re-dispatched via aggregators or BSSs. Rather than a direct outage, EV service interruption can lead to an intensified operational cost or customer inconvenience indirectly. With the low penetration of EVs, the utility may jointly forecast the customer and the EV loads, and, hence, the shifted load S can be regarded as the effective generation G during the interruption to calculate ENS'. With the high penetration of EVs, the utility may forecast the load and schedule the controllable loads separately, and therefore the total interrupted energy will be represented as $\mathrm{ENS}' + \mathrm{ENS_f}$. We still use pre-outage served (connected) kVA to calculate the ASIFI index of reliability, as introduced in (4). The concept and its calculation procedure are detailed in [15] and reflect the instantaneous load interruption. ASIDI in [31] is adjusted in order to reflect sustained interruptions and incorporate microgrid impacts as shown in (5). We propose the average system service disruption index (ASSDI) as a new load-based reliability index to reflect service interruption to flexible loads such as EVs, as introduced in the equation below:

$$\mathrm{ASIFI} = \frac{\sum L_i}{L_\mathrm{T}} \tag{4}$$

$$\mathrm{ASIDI} = \frac{\mathrm{ENS}' + \mathrm{ENS_f}}{L_\mathrm{T}} \tag{5}$$

$$\mathrm{ASSDI} = \frac{S}{L_\mathrm{T}} \tag{6}$$

2.3 Proposed AMI architecture

Fig. 5 demonstrates the proposed AMI architecture: a hierarchical system including smart meters, neighbourhood area networks (NANs), and the local area networks (LAN) within the utility domain. In contrast with the conventional AMI structures through which meter data is directly uploaded to MDMS, the proposed architecture contains two inter-connected loops: (i) the *online loop* represented by red lines is mainly focusing on grid monitoring and power flow controls. Since the main concerns for the LAN are system operational states and power flow constraints, this online computational platform can swiftly classify and process the measurements and upload the necessary information. The online loop normally transmits data every 2 s to 5 min; (ii) the *offline loop* represented by blue lines store all data in the NAN-level database. Having evaluated the ENS' index associated with the neighbourhood feeders as shown in Fig. 4, NAN then calculates the three introduced load-based reliability indices using (4)–(6) and upload the results to LAN. The LAN-level billing system then maps different reliability performance levels of system feeders and analyses the overall reliability of the distribution system. The utility can also send the locational marginal prices (LMPs) to the NAN and calculate the electricity pricings at the NAN-level billing system.

This new architecture is suitable for prosumer-oriented smart grids with highly densed penetration of DERs and can be employed even by electric utilities with high-speed data transfer requirements. The primary advantages of the suggested AMI architecture can be summarised as follows:

- It preserves and protects customer privacy in the physical layer of communication network systems. The customer load profiles are actually to be stored in the NAN networks and will not require to be uploaded into a centralised data centre.
- It shrinks the volume of data uploaded into the utility MDMS platform. With the envisioned online and offline computation loops, the measured data is classified and processed before an upload process starts. All the information can be recorded in the NAN and, hence, the communication capacity requirement from NAN to LAN significantly decreases.
- It brings about potentials for more accurate load forecast and feeder health diagnosis with local weather and temperature information as well as feeder-level data analytics.
- It offers opportunities for fast and efficient energy management in distribution systems. With the suggested online computation loop, wide area networks can acquire robust real-time system operational conditions from distribution feeders. Through a system-wide optimal power flow mechanism, the feeder-level energy management signal can be sent to NANs. As NANs gather smart meters data and monitor the feeder in real time,

they can determine the operation points of each DER and load control signals for each connected node.

3 Proposed utility regulation model

A distribution utility owns, monitors, and controls hundreds of feeders, the reliability performance of which is closely dependent on the reliability characteristics of its feeders. We classify feeders of the distribution system based on different reliability requirements, and we propose a mechanism for their regulation via contracts between the distribution utilities and the PUCs. The suggested utility regulation model accommodates the new load-based reliability metrics using the AMI data and captures well the utility requirements under high penetration of DERs and microgrid-enabled flexibilities. Details of the proposed regulation model are presented as follows.

3.1 Feeder PF

For the distribution feeders with AMI infrastructure installed, the ASIFI, ASIDI, and ASSDI metrics can be assessed using AMI data. We propose the PF in (7) that integrates the aforementioned reliability indices and can be utilised to penalise the utilities if they do not meet the reliability performance requirements

$$\mathrm{PF} = \mathrm{IR}(1-\alpha)(\mathrm{CI}-1) \tag{7}$$

where IR is the incentive rate to reflect the penalty and reward characteristics and α is the impact factor driven by the annual severe weather conditions and their impact on the distribution system. We introduce a composite index (CI) to represent the difference between the expected and the realised reliability performance

$$\mathrm{CI} = W_1\left(\frac{\mathrm{ASIFI}}{\mathrm{ASIFI}_0}\right) + W_2\left(\frac{\mathrm{ASIDI}}{\mathrm{ASIDI}_0}\right) + W_3\left(\frac{\mathrm{ASSDI}}{\mathrm{ASSDI}_0}\right) \tag{8}$$

where W_1, W_2, and W_3 are the weight factors for each reliability metric assigned by the distribution utility experts and they add to one. ASIFI_0, ASIDI_0, and ASSDI_0 are expected values set by utility regulators. If $\mathrm{CI}-1<0$, the utility meets the customer requirements and provides extra high-quality reliability services and, hence, it should be rewarded. By improving the grid reliability performance, the CI degrades from CI_1 to CI_2 and the benefit for avoiding the PF could be quantified as follows:

$$B_{\mathrm{PF}} = \mathrm{IR}(\mathrm{CI}_1 - \mathrm{CI}_2) \tag{9}$$

A value-based reliability planning approach together with the Monte Carlo simulation can be employed to locate the minimum-cost solution of a feeder for an improved system reliability. The marginal price (MP) for improving the system reliability can be then found as IR. The reliability indices at this optimal point are set as the expected values in (8). The weights can be set based on the feeder characteristics. For instance, W_1 can be higher if it feeds sensitive and critical loads (e.g. hospital or military services) that can be extensively affected by a momentary interruption.

3.2 Suggested regulation procedure

If ASIDI′ is the estimated ASIDI metric for a feeder using Algorithm 1, we define the lower bound TL_0 as the ASIDI′ value that the PUC will employ for evaluating the ASIDI performance of the feeder with an acceptable MAPE. We use the upper bound TU_0 of ASIDI′ as the minimum reliability requirement of the feeder. Although feeder outage events vary annually depending on the frequency and scale of the events as well as many other factors driven by weather and cyber conditions, the customer outage duration should be limited within a tolerable time period depending on the types of customers (industrial, agricultural, commercials, residential etc.). For instance, we assume 12 h of outage duration for residential customers.

Table 1 Proposed utility regulation settings

ASIDI′	Reliability level	Reward or penalty
$< \mathrm{TL}_0$	high	fixed PF
$\mathrm{TL}_0 \leq \mathrm{ASIDI}' < \mathrm{TU}_0$	medium	PF
$\geq \mathrm{TU}_0$	low	PF and C_c

The suggested regulation criteria for feeders are tabulated in Table 1. If $\mathrm{ASIDI}' < \mathrm{TL}_0$, we regard the feeder to have a high reliability performance and since the feeder-level CI is difficult to calculate, the utility is not penalised but instead is offered a fixed monetary reward. When the annual $\mathrm{ASIDI}' \geq \mathrm{TL}_0$, CI can be quantified with acceptable MAPE and the PF is utilised to regulate the feeder reliability performance. If $\mathrm{ASIDI}' \geq \mathrm{TU}_0$, the utility is penalised with regard to PF, and customers with interruption duration greater than TU_0 should be compensated accordingly. The compensation C_c to be provided by the utility can be acquired via the post-event customer surveys.

To the best of our knowledge and inquiries from the industry partners, this effort is the first to propose criteria to regulate the reliability performance of the distribution utilities based on the feeder characteristics in contrast with the conventional regulation policies that are based on the annual utility performance over the entire network under control. Through the proposed framework, the decision makers can realise the geographical reliability performance of the feeders by classifying them based on their different structures. The proposed framework can also discern different feeder reliability requirements by setting the regulation parameters in (7) and (8) based on the feeder characteristics. As we propose to employ the load-based reliability indices to regulate the distribution utilities, this new utility regulation paradigm can, in turn, drive utility companies toward value-based reliability improvement now and in future.

It is worth mentioning that sometimes during interruptions, the utility may be willing to swap some loads to the adjacent feeder, especially when there are parallel radial feeders with tie-lines between the feeders [32]. We still count the load swapped to other adjacent feeders as the load of the original feeder. The smart meters will not count the swapped load repetitively and the feeder-level utility regulation method does not change.

3.3 Reliability premium

As the electric utility makes extra effort to avoid power interruptions for specific types of customers in the feeder, we define the customer reliability premium to account for such improvements. The power G supplied to the customers during feeder-level interruptions can be acquired and the customer reliability premium is calculated using the equation below:

$$B_{\mathrm{RP}} = \mathrm{IEAR} \times G \tag{10}$$

where interrupted energy assessment rate (IEAR) is the estimated cost per unserved kWh during each outage event and is typically driven by several factors including the outage time, outage duration, and the load types. IEAR can be assessed using the customer surveys [33].

If the microgrid is a non-utility asset but observable, the customers owning the microgrid should not pay any B_{RP} to the utility and can get benefit B_{PF} by helping the utility avoid the penalties. When the DERs in the microgrid are on the outage, the utility can supply the customers through the available backup generations and charge the customers equal to B_{RP}. Under such circumstances, if the utility fails to supply the customers during DER interruptions, the utility does not have the liability or the liability is limited to the segment of energy already contracted between the utility and the customers. If this microgrid is unobservable, meaning it refuses to share the reliability information and to be regulated by the utility, then the utility only needs to provide the contracted capacity to the customers and evaluate the ENS based on the data from smart meters connected to

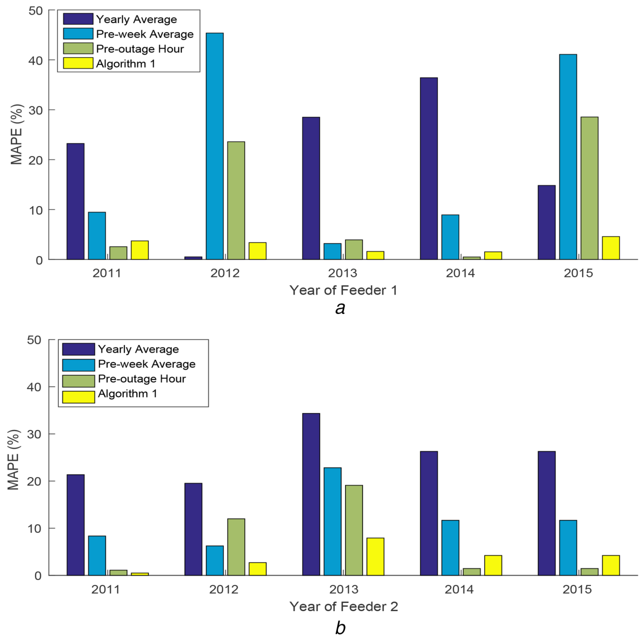

Fig. 6 *Prediction error of the ASIDI index for both feeders*
(a) Simulated ASIDI for Feeder 1 from 2011 to 2015 are 32.63, 16.09, 2.44, 3.64, and 0.31 (h), ***(b)*** Simulated ASIDI for Feeder 2 from 2011 to 2015 are 9.66, 13.62, 2.55, 4.49, and 0.67 (h)

the microgrid. In the case of an outage behind the meter, the third-party company who owns the asset should be responsible for the interruption loss and is not counted as a reliability issue for the utility. In the case of an outage in front of the *observation point*, the utility should be charged for the power that should have supplied to the customers behind the meter, even if the third party has built a microgrid to avoid the outage. In such scenarios, customers or the third party will not get the benefit B_{PF}.

The proposed regulation scheme with *observation points* will encourage distribution utilities to regulate the reliability of all feeders within their jurisdictions regardless of the ownership of the assets. With the extensive deployment of non-utility microgrids in a foreseeable future, the proposed utility regulation approach can still evaluate the geographical reliability performance indices by encouraging the utilities to integrate non-utility assets.

Since the electricity customers with reliability premiums are charged with the electricity price of IEAR instead of the normal price, some customers may be willing to maintain only the critical portion of the loads or they may participate in the utility demand response or load control programmes during outages. In such scenarios, the SAIFI and SAIDI metrics of the feeder cannot be assessed as the customers are partially supplied. However, the customer loads can be classified into different priority levels if they are observable. Instead of supplying power to a specific type of customers, critical loads will be supplied with a high priority during an outage event. Hence, the proposed RPS can best compromise different load types to ensure an acceptable reliability performance of the feeder for all customers.

It is worth noting that electric utilities with AMI facilities store the interruption data in the MDMS, where detailed information about the outage causes is available. The IEEE Std. 1366 (2012) recommends that ‘it may be advantageous to calculate the reliability indices without planned interruptions in order to review performance during unplanned events’. Hence, one can exclude such special circumstances (e.g. scheduled interruptions, outage of customer-owned facilities etc.) when calculating the system reliability indices.

4 Numerical results

This section compares the performance of the traditional regulatory approaches by PUCs and the one proposed in this paper with and without microgrid considerations.

4.1 Utility regulation methods without microgrid

A Californian utility in [21] is regulated via a traditional RPS. When the SAIDI metric of reliability changes from 53 to 65 min, neither a penalty nor a reward is assessed. The utility will be penalised with \$1 million per 1 min SAIDI above 65 min up to \$18 million at 83 min and above. It will be rewarded with \$1 million per 1 min SAIDI below 53 min and up to \$18 million at 35 min and below.

We regulate utilities using AMI data by first evaluating the ASIDI′ for each feeder. To examine the effectiveness of the suggested ASIDI′, we simulate interruptions on two feeders introduced in Section 2.1. The ASIDI′ calculated using the LF approach is compared with the simulated ASIDI. Outage reports from 2011 to 2015 are employed to simulate the interruptions and outages are moved into one certain week beginning with 9 October 2015 when no outage was reported. Other information such as outage start time, outage duration, and total customers affected are kept unchanged. Interrupted customers are randomly selected and no microgrid was assumed for the two feeders. Algorithm 1 is applied on the two feeders, the results of which are illustrated in Figs. 6*a* and *b*. Compared to the cases where annual average load, pre-week average load, and pre-outage hourly load are employed, the MAPEs corresponding to the suggested ASIDI using Algorithm 1 are low and stable. We also simulate the interruptions on the two feeders during other time intervals when outages did not actually happen. The results demonstrate that the MAPEs of the ASIDI metric using Algorithm 1 is ≤5% when the reliability index ASIDI is >3 h. It can be seen that the MAPEs do not decrease much when ASIDI keeps increasing since there are cases where customers with a small load aggregation suffer a long-time interruption during major event days of the year. When no feeder-level outage happens (e.g. in 2015), the MAPE corresponding to the ASIDI can reach 10%.

We also evaluate the reliability of each feeder using the proposed utility regulation policy and settings in Table 1. If $\mathrm{TL}_0 = 3$ h, the calculated error for ASIDI′ of the two feeders will not exceed 5%, while if $\mathrm{TL}_0 = 0.5$ h, it will reach a maximum of 10%. The TL_0 and related MAPE will not significantly change due to the load aggregation effect which is commonly noted. However, in order to estimate an acceptable level of MAPE and TL_0 for specific feeders, the utility can still import the outage reports and simulate the outage events during the time periods that interruptions did not actually happen. If $\mathrm{TL}_0 = 0.5$ and $\mathrm{TU}_0 = 12$ are set for Feeder 1, then the utility will be charged with PF and C_{c} in 2011 and 2012, will pay PF in 2013 and 2014 and will be rewarded a fixed PF in 2015. We assume the fixed PF is \$15,000. One can set $0 < \alpha < 1$ to reduce the penalty imposed to the utility in 2011 and 2012 and set $\alpha = 0$ during other years.

4.2 Impacts of microgrid on the regulation market

The outage events on Feeder 1 in year 2014 are simulated and the regulatory impacts of microgrids are investigated. The microgrid model utilised for the studied feeder is illustrated in Fig. 7, where it includes a 200 kW PV system, a total of 830 EVs in the feeder with EV penetration level of 30%. We assume the BSS has enough capacity and EV batteries will be swapped immediately as the customers arrive. Hourly energy consumption of swapping batteries is derived from [34]. The BSS reserves 20% of the capacity and can be discharged to 5% of its capacity during interruptions. Moreover, the BSS is assumed to have 1 h delay to return to service after discharging to its minimum capacity. Hourly LMP from PJM market [35] is used to calculate the BSS-scheduled charge/discharge curve in a grid-connected mode. The static switch is designed to open when there is a fault between the main supply (utility) and load 1, and therefore the PV, the BSS, and load points 2 and 3 will operate in an islanding mode. The following five scenarios are discussed considering the feeder-level interruptions from 16:31 to 18:20 of the day:

- *Scenario 1*: uses simulated reliability indices in 2014 without microgrid considerations.

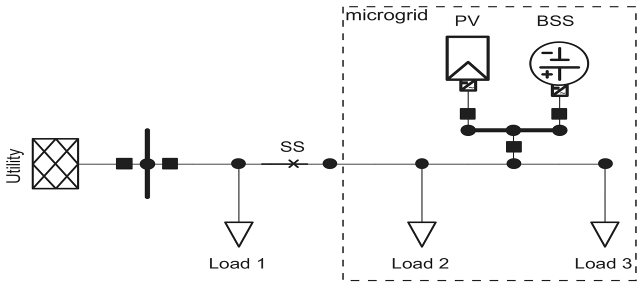

Fig. 7 *Single-line diagram of Feeder 1 with microgrid considerations*

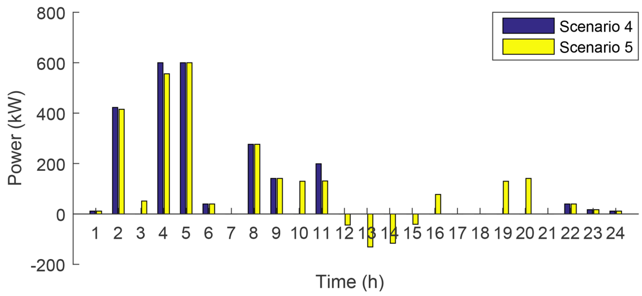

Fig. 8 *Hourly charge/discharge rates of the BSS*

- *Scenario 2*: assumes the BSS has 450 kWh storage capacity and 150 kW charging rate; the BSS continues to serve EVs during the 1.82 h feeder-level interruption until 5% of its capacity is reached.
- *Scenario 3*: assumes the BSS has the same capacity as scenario 2 but supplies energy to the feeder during an interruption; EVs are informed to swap their batteries at other BSSs.
- *Scenario 4*: assumes the BSS has 1.8 MWh storage capacity and 600 kW charging rate; EVs are informed to swap their batteries at other BSSs; demand response and direct load control are employed to recover the 200 kW non-critical load during the sustained interruptions.
- *Scenario 5*: the BSS and load control remain same as scenario 4, except that the transformer connected to the utility has a capacity limit of 2.3 MW.

Table 2 provides the reliability metrics and the regulation results under the five scenarios above, where the parameters are set as $W_1 = 0.3$, $W_2 = 0.6$, $W_3 = 0.1$, $\text{ASIFI}_0 = 1$, $\text{ASIDI}_0 = 2.5$, and $\text{ASSDI}_0 = 2.5$. The IR is assumed to be \$20,000. The reliability indices in scenario 1 are acquired from the simulation results in Fig. 6. Reliability indices in scenarios 2 and 3 are estimated based on those in scenario 1 by considering different operational strategies of the microgrid during the feeder-level interruptions. The PF in scenario 2 is observed higher than that in scenario 1 as some EVs are not served by the BSS and, hence, contribute to the increase in ASIDI. In scenario 3, PF is decreased by supplying the feeder with the BSS energy. Although swapping batteries in other feeders can lead to an inconvenience to some EV customers, the consequence of rearranging the battery swapping is far less than the load interruption. The remaining SOC of the BSS is 272 kWh in both scenarios 2 and 3 when the interruption is initiated.

Scenarios 4 and 5 are investigated to evaluate the reliability performance of the feeder with different BSS and substation capacity levels. The hourly charge and discharge rates of the BSS in its grid-connected mode are demonstrated in Fig. 8. The BSS dispatch signal is scheduled by day-ahead energy market and updated hourly within an hour-ahead schedule. At the time when the interruption happens, the SOC of BSS is 882 and 639 kWh in scenarios 4 and 5, respectively. The SOC of the BSS in scenario 4 is higher than that in scenario 3 due to the increase in the BSS capacity, resulting in a decrease in PF compared with scenario 3. If the microgrid is owned by a third party, the B_{PF} paid by the utility to the third party will increase to \$4776. Fig. 8 illustrates that the BSS discharges to supply the grid from 11:00 to 15:00 in scenario 5 since the substation capacity is less than the feeder summer peak load of 2.57 MW. So the remaining SOC of the BSS in scenario 5 is less than that in scenario 4 at 16:31 when the interruption happens. As a result, the PF in scenario 5 is observed higher than that in scenario 4.

Table 2 Regulation results of feeder 1 in different studied scenarios

	ASIFI	ASIDI (h)	ASSDI (h)	PF (\$)	PF′ (\$)
scenario 1	1.75	3.64	0	7972	7732
scenario 2	1.71	3.74	0	8212	7924
scenario 3	1.61	3.45	0.29	6452	6212
scenario 4	1.31	2.83	0.29	1676	1436
scenario 5	1.31	3.00	0.29	2492	2204

It can be observed that the proposed utility regulation scheme can well reflect the influence of the microgrid control strategy and component capacity on the feeder reliability performance. The difference between the PF and PF′ calculated using ASIDI′ is generally small and can be accepted by the utility. The PF′ values are also calculated based on the pre-outage BSS dispatch schedule and, hence, do not include the error in the forecasted *S* compared with the actual realised *S*. However, this has been shown to have a minimum impact on PF′ as we propose to penalise the service disruption less than load interruption.

5 Conclusions

The smart grid revolutionary paradigm with grid-scale deployment and integration of the AMI and DERs has been and will continue changing the reliability structure of power distribution systems and, hence, new methods and regulatory schemes are yet to be developed to evaluate system reliability performance over time. Different from the traditional customer-oriented reliability indices, this paper first introduced a new load-based reliability metric, so called ASSDI, using AMI data. Through several case studies using real data, we showed in this paper that the calculation of feeder-level ASIDI using AMI data can be quite accurately accomplished with low MAPEs. Second, a new AMI architecture was proposed for distribution utilities to adopt the new reliability metrics in future smart grids. Third, a new utility regulation scheme based on the proposed load-based reliability indices was suggested to facilitate the reliability analysis of the power distribution systems with different feeder reliability requirements and microgrid penetration levels. Numerical case studies demonstrated that the proposed utility reward/penalty scheme can be applied in real-world energy markets to evaluate the feeder reliability performance and integrate microgrids regardless of the different possible ownership structures.

6 Acknowledgment

The authors thank the United States National Association of Regulatory Utility Commissioners (NARUC) for their support of this research.

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