Reliability Assessment for Smart Grid and Future Power Distribution Systems

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***Abstract*— Smart grid incorporates communication and control technologies to provide more efficient and reliable electricity to customers. The infrastructure of such power system will allow the customers to generate and store electricity, and use that in case of an outage or disconnection from the utility. Therefore, the outage of power from the utility side does not necessarily result in loss of electricity. This paper presents a new process for reliability assessment of future power distribution systems affected by the customers' distributed energy resources (DER). The method to calculate the reliability indices, such as SAIFI and SAIDI, based on a Monte Carlo simulation is explained; and results are provided for case studies with residential, commercial, and industrial customers, renewable generation, and battery systems.**

***Keywords*—Battery; distributed generation; future distribution systems; reliability analysis ; smart grid.**

I. Introduction

Reliability has always been of utmost importance during design, operation, and planning of electric power systems. In the recent decades, reliability of power systems has become more critical as the daily lives of people highly depend on electricity. According to the U.S. Energy Information Administration (EIA), over the past three decades, the consumption electricity by appliances and electronic device of U.S. residential customers has almost doubled [1]. The outburst of smart phones, growth of electric vehicles, and introduction of new appliances are now accelerating the need for reliable and available electricity. Nowadays, electricity is being taken for granted by the customers, meaning that long power outages may not be tolerated anymore. On the other hand, the statistics on the reliability of power systems are not promising as the number of outages affecting customers is increasing, and the reliability of the U.S. grid is decreasing by roughly 2% each year [2, 3]. What makes providing reliable electricity to customers even more challenging are the aging infrastructure of power systems, demand that is growing faster than system capacity is expanding, and rising integration of intermittent generation, such as wind turbines and photovoltaic (PV) panels, into the grid [4].

Moving toward smarter grids seems to be an indispensable approach to confronting the challenges of future power systems. Smart grids incorporate information and communications technology (ICT) into the power system infrastructure and aim to provide more reliable, efficient, and secure electric grids [5]. The reliability of an electric grid can be improved as a result of smart grid technologies, such as situational awareness, automated and fast controls, and bidirectional communications. On the other hand, an efficient use of assets may push a power system operating close to the edge, where it will be exposed to higher volatility, and its reliability may adversely be affected [6]. Therefore, it is essential to assess the reliability of smart grids considering the impact of various factors such as customers' DER and customer demand management.

Electricity outages are caused by failures in generation, transmission, or distribution systems. However, outages in the electrical distribution system are responsible for most of the hours that electricity is unavailable to customers [7]. This paper addresses a notable challenge in reliability assessment of the future power distribution systems attributed to availability of distributed generation and storage system. In fact, reliability of conventional power distribution systems is evaluated using commonly accepted indices, such as System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI) [8]. In such systems, which are supplied with a radial network configuration, the direction of power flow is from the utility side to the customers. Hence, there is always a power interruption in a conventional distribution system when an outage occurs disconnecting an upstream feeder directly supplying a load, if that load cannot be transferred to another operating feeder. However, in future power distribution systems, customers using their own distributed generation and previously stored power from their batteries may not even become aware of such outage. Therefore, in this paper, we propose an improved calculation of SAIFI and SAIDI considering the actual outage frequency and duration experienced by the customers. The calculation technique for reliability assessment is based on the Monte Carlo simulation (MCS) approach. This study accounts for the stochastic nature of renewable generation as well as random failure and repair duration in the system. In addition, a number of reliability assessment indices, such as Value of Lost Load ($VOLL_s$), Energy Not Supplied (ENS_s), and Customer Interruption Cost (CIC_s), are proposed from the perspective of each customer sector "s". The customer-side reliability indices are defined to account for the smart grid features and aim to capture the influence of customers' distributed energy resources (DER) on the reliability of future power systems. The reliability assessment approach is explained using simulation case studies, and results are discussed.

II. Modeling

This section provides a brief description of different components of the smart grid model. The following figure shows the available resources of an electricity customer. The smart grid customers may utilize these resources to reliably meet their electricity demand.

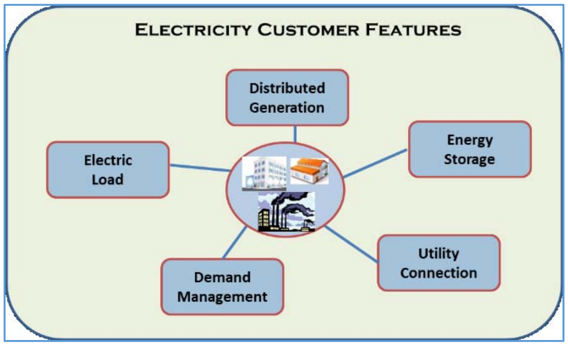

Fig. 1. The features of an electricity customer in a smart grid environment.

Fig. 2 shows a schematic of the model for reliability evaluation, including electric utility, different types of customers, and instances of the areas impacted by different contingencies. The customers may have their own renewable generation and energy storage resources.

The power network is assumed to have a mesh configuration. Therefore, in case of a contingency in the system, only part of the system will be disconnected form the utility. This paper uses a graph theoretic representation of a power distribution system; and instead of simulating individual contingencies, the consequences of these contingencies are modeled as impacted areas. An impacted area is modeled by disconnection of part of the grid including all of the customers within that area around the center of the contingency. These areas are realized using exponential outage rates and normally distributed restoration durations. During the simulation, the contingencies are originated at random points in the network and are surrounded by an impacted area with a radius R_{out}, determined using a uniform distribution between 0 (i.e., no impact) and up to total system interruption. The model is designed to be general; and, in case the capacity of distributed energy resources (DER) is high enough to satisfy the load in an isolated mode from the utility, the overall power network can be a representative of a micro-grid.

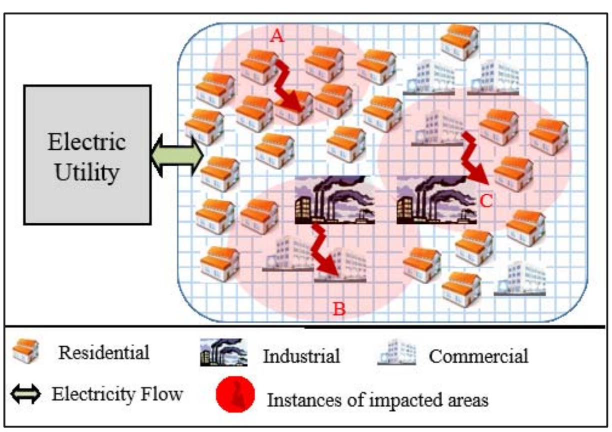

Fig. 2. Main entities of the distribution system model for reliability evaluation, and instances of impacted areas A, B, and C by different contingencies.

The electric utility is simply responsible for providing power to the customers and buying back the extra power. Here, we don't perform load flow analysis and assume that the power flow is within the capacity limits of the equipment. The electric grid is subject to contingencies which may lead to isolated (outage) areas in the system.

Three customer sectors have been considered in the studies: residential, industrial, and commercial. Each sector is realized through an individual load profile. The hourly load of each customer is then calculated using normal distribution with the average value coming from the load profile, depending on the type of the customer.

The hourly output power of two renewable generation systems (wind and PV) are modeled using probability distributions. Hourly wind speed can be adequately represented by the Weibull distribution [9]. A simple power curve formula is then used to calculate the hourly wind power generation, $g_W(t_j)$, as described by (1) [10].

$$g_W(t_j) = \begin{cases} Cap_{\mathrm{W}}\left(\dfrac{V_W(\mathrm{t_j}) - V_{ci}}{V_r - V_{ci}}\right) & V_{ci} \le V_W(\mathrm{t_j}) \le V_r \\ Cap_{\mathrm{W}} & V_r \le V_W(\mathrm{t_j}) \le V_{co} \\ 0 & otherwise \end{cases} \quad (1)$$

Where, Cap_{W} is the rated capacity of the wind turbine, and $V_W(\mathrm{t_j})$ is the wind speed in m/s at time $\mathrm{t_j}$. V_{ci}, V_r, and V_{co} represent cut-in, rated, and cut-out wind speeds of the wind turbine in m/s, respectively.

The output power of a PV system depends on many parameters, including environmental factors (e.g., temperature, cloud cover, dust, etc. [11]) and solar panel related (e.g., technology, type of installation, etc. [12]).

We use the daily mean hourly solar irradiance data and assume the irradiance for different hours follow normal distributions. Next, the PV generation at each hour, $g_{PV}(t_j)$, is calculated using (2) [13].

$$g_{PV}(t_j) = \begin{cases} Cap_{\mathrm{PV}}\left(\dfrac{IR(\mathrm{t_j})^2}{IR_{std} \times IR_C}\right) & IR(\mathrm{t_j}) \le IR_C \\ Cap_{\mathrm{PV}}\left(\dfrac{IR(\mathrm{t_j})}{IR_{std}}\right) & IR_C \le IR(\mathrm{t_j}) \le IR_{std} \\ Cap_{\mathrm{PV}} & IR(\mathrm{t_j}) \ge IR_{std} \end{cases} \quad (2)$$

Where, Cap_{PV} is the rated capacity of the PV system, and $V_W(\mathrm{t_j})$ is the solar irradiance at time step t_j in W/m^2. IR_C and IR_{std} represent specific solar irradiance close to 150 W/m^2 and solar irradiance in the standard environment in W/m^2, respectively.

III. PROPOSED RELIABILITY EVALUATION METHOD

The reliability of the system is assessed using a sequential MCS approach. In this method, the time to the next failure and the duration of failure in the system are determined by sampling the associated failure and repair probability distributions, respectively. The load and generation of each customer are also determined using their provided probability distributions as discussed.

In a smart grid, the demand side management (DSM) affects the way power is supplied and being used by the customers. Therefore, the DSM can impact the reliability of the system. The proposed reliability evaluation method considers the impacts of random outages and the customer demand management on the reliability. In order to model the impact of the DSM, the total demand, total local generation, and available battery charge of customer x at time step t_j are denoted by $d_x(t_j)$, $g_x(t_j)$, and $b_x(t_j)$, respectively.

In case of a contingency, the impact of a customer's demand management can be simply modeled by the following process:

1- If $d_x(t_j) > 0$, then try to supply the load from the generation ($g_x(t_j)$)
2- If the residual demand ($d'_x(t_j)$) is not zero, then use the battery storage up to ($\min\{b_x(t_j), DR_x\}$) to supply the load.
3- If the $d'_x(t_j)$ is nil, then there is no loss of load ($LOL_x(t_j) = 0$); otherwise $LOL_x(t_j) = d'_x(t_j)$

In the above process, DR_x is the maximum allowable battery discharge rate for customer x in % of battery capacity per t_j. We define $LOL_x(t_j)$ to represent the amount of customer x's loss of load power at time step t_j. We further define the index of interruption, $IOI_x(t_j)$, as:

$$IOI_x(t_j) = \begin{cases} 1 & LOL_x(t_j) > 0 \\ 0 & Otherwise \end{cases} \tag{3}$$

Subsequently, we define the index of interruption frequency, $IOIF_{x,k}$, by taking the union of IOI for each customer x affected by the outage k, as expressed by (4), where T_k is the set of all time steps during outage k.

$$IOIF_{x,k} = \bigcup_{t_j \in T_k} IOI_x(t_j) \tag{4}$$

Equation 4 indicates that if a customer cannot meet the load for one or more time steps during an outage, then the customer is counted as interrupted due to that outage (i.e., $IOIF_{x,k} = 1$).

In this study the time step is assumed to be one hour, and therefore, the duration of interruption can directly be calculated by adding up the multiples of the hours (i.e. IOI). The index of interruption duration, $IOID_{x,k}$, is defined by (5) which represents the duration of interruption per outage k, for each customer x.

$$IOID_{x,k} = \sum_{t_j \in T_k} IOI_x(t_j) \tag{5}$$

Finally, $SAIFI$ and $SAIDI$ are defined as:

$$SAIFI = \frac{\sum_{x=1}^{N} \sum_{k=1}^{N_{con}} IOIF_{x,k}}{N \times T} \tag{6}$$

$$SAIDI = \frac{\sum_{x=1}^{N} \sum_{k=1}^{N_{con}} IOID_{x,k}}{N \times T} \tag{7}$$

where N and N_{con} are the total number of customers and contingencies within duration of T years. SAIFI and SAIDI represent the average frequency and duration of interruptions per customer of the power distribution system for the duration of T years, respectively.

As previously mentioned, we define the customer-side reliability indices to determine the impact of the local electricity generation and storage as well as DSM on the reliability per customer sector. The indices include: Value of Lost Load ($VOLL_s$), Energy Not Supplied (ENS_s), and Customer Interruption Cost (CIC_s), for a customer. ENS_s, $VOLL_s$, and CIC_s, are in $\frac{\boldsymbol{kWh}}{\boldsymbol{customer,year}}$, $\frac{\$}{\boldsymbol{kWh}}$, and $\frac{\$}{\boldsymbol{year}}$ for each customer sector s, respectively. For example, in a case of residential customers, the equations are defined as follows.

$$ENS_R = \frac{\sum_{xr=1}^{N_R} \sum_{j=1}^{J} LOL_{xr}(t_j)}{N_R \times T} \tag{8}$$

$$VOLL_R = \frac{\sum_{xr=1}^{N_R} \sum_{k=1}^{N_{con}} \frac{CDF_R(IOID_{x,k})}{IOID_{x,k}}}{N_R \times N_{con}} \tag{9}$$

$$CIC_R = ENS_R \times VOLL_R \tag{10}$$

where, xr and N_R are the index and total number of the residential customers, respectively. J is the simulation hours in T years; CDF_R represents the residential customer damage function which is a function of interruption duration. Equations (8-10) may be revised for commercial and industrial customer sectors by replacing "xr" with "xc" and "xi", and subscript "R" with "C" and "I" subscripts, respectively.

IV. Case Study

The case studies are provided to perform reliability assessment and determine the impact of customer DER, such as renewable generation and storage systems on the results.

The first system studied includes only the residential customers. In the second case study, the customers are diverse from residential, commercial and industrial sectors. The parameters of the system for these cases are provided in Table I and II, respectively. $\overline{Cap_B}$ and $\overline{Cap_G}$ are average battery and generation capacities of the customers; λ and μ are failure and repair rates for the contingencies in the system used for both case studies. d_{max} represents the maximum demand of a customer which is used along with the load profiles to determine the load value at each hour.

TABLE I. CASE STUDY PARAMETERS WITH RESIDENTIAL CUSTOMERS.

Parameter	N_R	$\overline{Cap_B}$	$\overline{Cap_G}$	λ	μ	d_{max}
Value	*400*	*1.25*	*0.5*	*2*	2×10^{-4}	*1.1*
Unit	-	*kWh*	*kW*	$\frac{1}{Year}$	$\frac{1}{Year}$	*kW*

TABLE II. STUDY PARAMETERS WITH COMMERCIAL & INDUSTRIAL CUSTOMERS.

Parameter	N	$\overline{Cap_B}$	$\overline{Cap_G}$	d_{max}
Commercial	200	*2.5*	*1*	*1.6*
Industrial	*20*	*15*	*25*	*20*
Unit	-	*kWh*	*kW*	*kW*

Hourly data used for the wind speed, solar radiation, and customer loads are from [14], [15], and [16], respectively, where the average data for three load sectors, wind and PV generation are depicted in Figs. 3 and 4, and used to calculate $d_x(t_j)$ and $g_x(t_j)$ respectively. The customer damage functions used for the loss-of-load cost analysis per customer sector are based on typical data from [17-18].

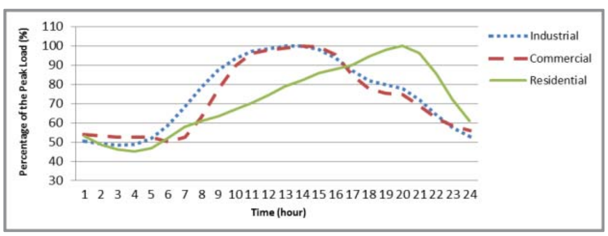

Fig. 3. Average load profiles for residential, commercial, and industrial loads.

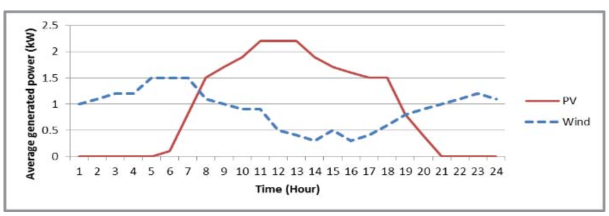

Fig. 4. Average PV and wind generation profiles.

V. RESULTS AND DISCUSSIONS

A. Reliability analysis with residential customers

In this study, the customers are all from the residential sector. The objective is to investigate the impact of renewable generation and storage systems on the reliability from the system and customer points of view.

Table III shows the reliability indices of a case study in this case. As the percentage of customers with generation and battery increases, both the average duration and frequency of the interruption in the system decreases.

TABLE III. RELIABILITY INDEXES WITH DIFFERENT PERCENTAGES OF THE CUSTOMERS OWNING GENERATION-BATTERY SYSTEMS

Customer Type	Percentage with Battery/Gen	SAIFI $(\frac{1}{Customer, year})$	SAIDI $(\frac{hrs}{customer, year})$
Residential	0%	1.35	4.07
	50%	0.86	2.57
	100%	0.66	1.55

Table IV provides the reliability indices from the customer's perspective, for the same study. As a result of using DER, customers' energy not supplied and the interruption costs decrease. According to the results, by having 50% and 100% of customers own distributed generation and battery systems, the customer interruption cost drops by 45% and 79%, respectively.

TABLE IV. CUSTOMER PERSPECTIVE RELIABILITY WITH DIFFERENT PERCENTAGES OF THEM OWNING GENERATION-BATTERY SYSTEMS

Customer Sector	Percentage with Batt/Gen	$VOLL_R$ $(\$/kWh)$	ENS_R $(\frac{kWh}{customer, year})$
Residential	0%	6.67	2.91
	50%	6.65	1.6
	100%	6.5	0.62

B. Reliability analysis with residential, commercial, and industrial customers

In this case, the customers are diversified from residential, commercial, and industrial sectors, with the parameters provided in Tables I and II. These customers have different load profiles during an average day, as shown in Fig. 3. Similar to the previous case, Table V shows how the reliability of the smart grid improves by having higher percentages of the customers own DER. In addition, the diversity of the customers leads to lower SAIFI and SAIDI values, and therefore, an improvement in system reliability.

TABLE V. RELIABILITY INDEXES WITH DIFFERENT PERCENTAGES OF THE CUSTOMERS OWNING GENERATION-BATTERY SYSTEMS

Customer Type	Percentage with Battery/Gen	SAIFI $(\frac{1}{Customer, year})$	SAIDI $(\frac{hrs}{customer, year})$
Residential Commercial Industrial	0%	1.2	3.3
	50%	0.8	2.2
	100%	0.62	1.5

VI. CONCLUSIONS AND FUTURE WORK

A reliability assessment method was proposed based on Monte Carlo simulation technique to capture the impact of active customers and distributed energy resources on system reliability. Reliability was assessed from both the system and customer point of view by applying a number of commonly used and newly defined indices. The results indicate that both frequency and duration of interruptions can be improved with higher DER capacities. In fact, the new reliability calculation suggests that by having additional electricity resources at the customer side, the reliability of the system improves, while by using the conventional method of reliability calculation, the results would not be different in these cases.

REFERENCES

[1] RESIDENTIAL ENERGY CONSUMPTION SURVEY (RECS), U.S. Energy Information Administration, Mar. 2011.

[2] M. Amin and P. F. Schewe, "Preventing Blackouts," Scientific American, pp. 60 – 67, May 2007.

[3] J. H. Eto, K. H. LaCommare, P. Larsen, A. Todd, and E. Fisher, "An Examination of Temporal Trends in Electricity Reliability Based on Reports from U.S. Electric Utilities," Ernest Orlando Lawrence Berkeley National Laboratory, Jan. 2012.

[4] NERC Special Report, "Accommodating High Levels of Variable Generation," North American Electric Reliability Corporation, Apr. 2009.

[5] T. Kostyk and J. Herkert, "Societal Implications of the Emerging Smart Grid," *Comm. ACM*, vol. 55, no. 11, pp. 34- 36, Nov. 2012.

[6] K. Moslehi, and R. Kumar, "A Reliability Perspective of the Smart Grid," *IEEE Trans. on Smart Grid*, vol.1, no.1, pp. 57- 64, Jun. 2010.

[7] "Reliability of Electric Utility Distribution Systems," EPRI, Oct. 2000.

[8] IEEE Standard 1366, "IEEE Guide for Electric Power Distribution Reliability Indices", 2004.

[9] S. Kahrobaee, S. Asgarpoor, and W. Qiao, "Optimum Sizing of Distributed Generation and Storage Capacity in Smart Households, "*IEEE Trans. on Smart Grid*, vol. 4, pp. 1791 – 1801, Dec. 2013.

[10] W. R. Powell, "An analytical expression for the average output power of a wind machine," *Solar Energy*, vol. 26, no. 1, pp. 77-80, 1981.

[11] V.V. Tyagi, N.A.A. Rahim, A. Jeyraj, L. Selvaraj, "Progress in solar PV technology: Research and achievement," Renewable and Sustainable Energy Reviews, vol. 20, pp. 443- 461, Elsevier, 2013.

[12] B.Parida, S.Iniyan, R.Goic,"A review of solar photovoltaic technologies,"*Renewable & Sustain. Energy Reviews*,vol.15,pp.1625-1636, 2011.

[13] J. Park, W. Liang, J. Choi, A. A. El-Keib, M. Shahidehpour, R. Billinton, "A Probabilistic Reliability Evaluation of A Power System Including Solar/Photovoltaic Cell Generator," IEEE Power & Energy GM, 2009.

[14] Historical data of hourly wind speed measured by Kimball (KIBM) airport weather station [online]. Available: www.wunderground.com.

[15] W.B. Wan, M.Z. Ibrahim, K.B. Samo, A.M. Muzathik, "Monthly mean hourly global solar radiation estimation,"*Solar Energy*,pp.379–387,2012.

[16] Southern California Edison Load Profiles, Regulatory Information [online], Available: www.sce.com/AboutSCE/Regulatory/loadprofiles loadprofiles.htm

[17] M. J. Sullivan, M. Mercurio, and J. Schellenberg, "Estimated Value of Service Reliability for Electric Utility Customers in the United States," Ernest Orlando Lawrence Berkeley National Laboratory, Jun. 2009.

[18] J. Giraldez, S. Booth, K. Anderson, and K. Massey, "Valuing Energy Security: Customer Damage Function Methodology and Case Studies at DoD Installations," Technical report, NREL/TP-7A30-55913, Oct. 2012.