Disaggregation of Reported Reliability Performance Metrics in Power Distribution Networks

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***Abstract*—This paper introduces the critical need to report reliability performance metrics by distinguishing between different customer-groups, load demand and network types, within very large service areas managed by distribution network operators. Based on various factors, power distribution systems supplying residential demand are categorised in this study into rural, suburban and urban networks. An enhanced time-sequential Monte Carlo simulation procedure is used to carry out reliability assessment for each subsector, enabling disaggregation of reliability indices typically reported for the whole supplied system. Realistic distribution network modelling is achieved by the addition of smart grid technologies such as photovoltaic energy, demand side response and energy storage, to assess their impacts in different networks. Finally, both system and customer-oriented indices, measuring the frequency and duration of interruptions, as well as energy not supplied, are evaluated for a comprehensive analysis.**

Keywords—energy not supplied, disaggregation, monte carlo simulation, reliability indices, smart grid technologies.

I. INTRODUCTION

Energy regulatory bodies ensure that consumers receive a reasonable quality of power supply at fair prices by monitoring and supervising the operation of distribution network operators (DNOs) [1] while protecting customers from potential abuse of monopoly power from DNOs. Accordingly, in the UK, DNOs invest in their networks to deliver an improved system performance for customers and thus earn rewards or avoid penalties under the Interruptions Incentive Scheme (IIS). Various financial and reputational incentives such as public reporting on power delivery encourage a strong output performance by UK DNOs. This is evidenced by the 11% decrease in the number of customer interruptions (CI) and customer minutes lost (CML) in 2017, from 2015, when the RIIO-ED1 price control was started [2].

Within a UK context, the current reliability-performance reporting structure only requires each DNO to provide the average CI and CML for their serviced areas. However, since each of the 14 UK DNOs deliver electricity to millions of customers spread across at least 10,000 km^2 in varying types of networks, i.e. rural areas to cities and towns, a single average value aggregating reliability performance over this spatial extent is insufficient to adequately describe the variation in network reliability performance [3]. While there might be some evidence to support the view that cities have fewer CI and CML than rural areas, it is necessary to quantify not only the extent of such variations but also identify the cases in which rural areas might have better performance [4]. When all DNOs exceed the regulator-imposed performance targets e.g. in 2016-17 (UK), the willingness-to-pay (WTP) by especially the worst-served customers (WSC) is usually under-evaluated because of the 'normalising' effect due to the other highly-reliable areas served. Fig. 1 shows DNO-group financial performance against cost allowances for the first and second years of the RIIO-ED1 price control period where a number of DNOs reached the cap on the rewards that can be earned under the IIS, based on their performance against targets [2]. Although only Western Power Distribution overspent on its allowances, the total expenditure of all the six DNO groups can substantially be reduced if such expenses, as mandatory payments to customers when DNOs fail to meet the guaranteed standards of performance (GSoP), can be reduced. Table I shows UK regulator-imposed requirements for the duration of customer interruptions under the GSoP, so as to protect residential and non-domestic customers from excessive long interruption events [5]. It illustrates the corresponding penalties that DNOs must pay directly to the customers if supply is not restored within a specified period.

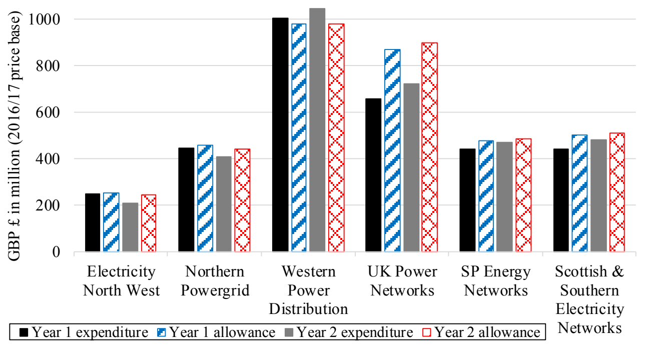


Fig. 1. DNO financial performance against cost allowances for 2015-17 [2].

Accordingly, the contribution of this paper is to demonstrate the need to disaggregate both system and customer-oriented performance indices into contributions from different types of modelled networks in the DNO serviced areas. These are practical considerations given that DNOs report fault events in their systems by distinguishing them based on types of components, network types, load sectors, voltage levels i.e. medium (MV) and low voltage (LV), etc. Moreover, this paper presents a comprehensive reliability assessment by using a combination of averages, probability (PDF) and cumulative (CDF) distribution functions to illustrate the range of index variation. This allows for a rigorous characterisation of varying customer-groups.

TABLE I. REQUIREMENTS FOR SUPPLY RESTORATION TIMES [5]

No. of Interrupted Customers	Maximum Duration to Restore Supply	Penalty paid to each (£)	
		Domestic Customer	*Non-domestic*
Less than 5,000	12 h	75	150
	After each succeeding 12 h	35	35
5,000 or more	24 h	75	150
	After each succeeding 12 h	35	35

II. METHODOLOGY

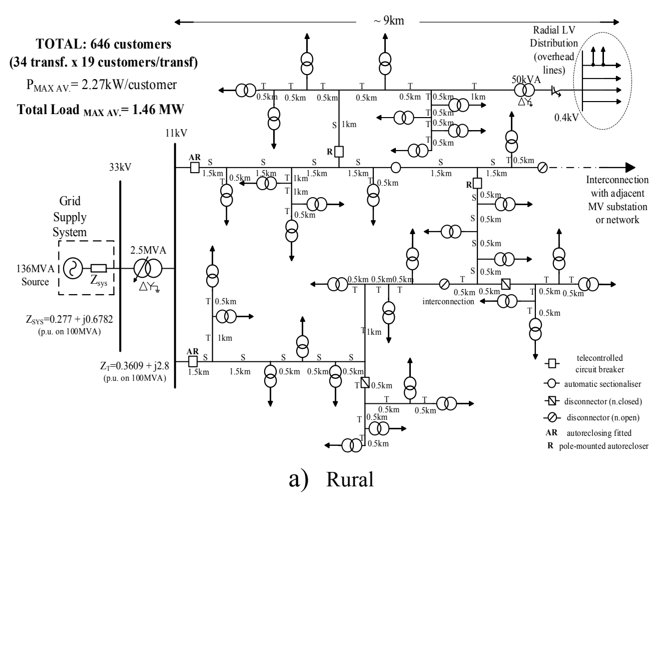
Residential type customer-groups can be categorised based on their load demand into rural (RU), suburban (SU) and urban (U) load subsectors [6]. While these subsectors differ depending on the country [4], they mainly focus on number, location, size and type of demand. Table II shows the MV-line network data used to build the generic models using PSS®E for each subsector in Fig.2. Each cable or overhead line is allocated an ID letter to ease model classification. Full documentation of the 33/11 kV transformers used for each subsector can be found in [7]. These 3 subsectors generally represent the varying topographical layouts, demand densities, and network parameters. Thus, the RU subsector is modelled to represent remote areas with low power density, while the SU subsector represents suburban areas and towns near big cities, i.e. U subsector. The network modelling also utilises aggregation techniques which generate both electrical and reliability equivalents to reduce the complexity of these networks and lower the computational time and cost. Notably, load points (LPs) in each network are 34, 44 and 48, while components are 404, 520 and 592 for RU, SU and U networks.

A. Time Sequential Monte Carlo Simulation

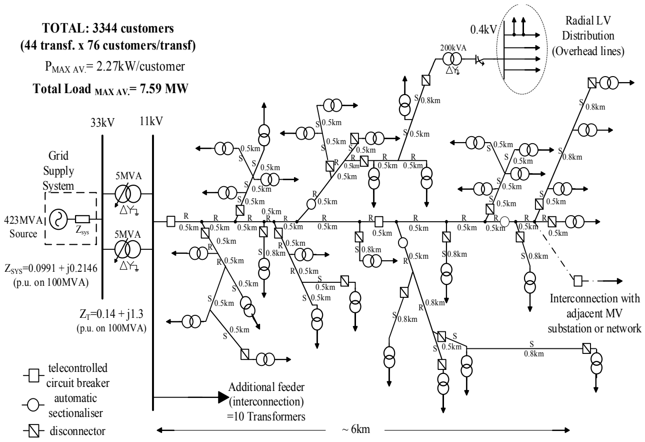
In conventional time-sequential Monte Carlo Simulation (MCS), each power component (PC) is assigned two characteristic parameters - failure rates and repair times, based on historical data, which are converted into time-to-fail and time-to-repair system states respectively, using the inverse-transform method to create a time-discretised network model [8]. This study uses an enhanced MCS where both the failure rates and load demand are modelled to be time-varying for a more accurate reproduction of network behaviour. Moreover, system interruptions are differentiated into long (LI) and short (SI) interruptions to reproduce the variability of faults suffered at the distribution network level. For this study, 54% of faults are modelled as SI while the rest are LI [9]. Using a convergence criterion of 1000 years, the enhanced MCS

TABLE II. CONFIGURATIONS OF MV LINES AND PARAMETERS [7]

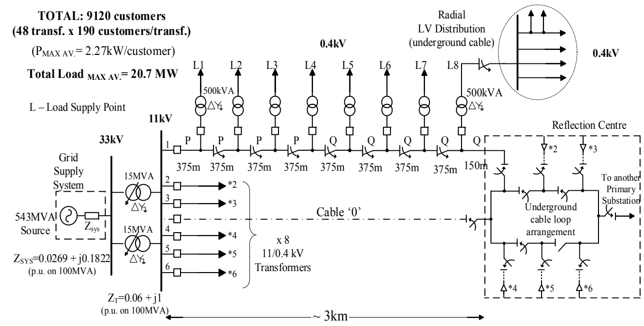
ID	11 kV Line Type Configuration	Cross Sectional Area (mm^2)	Positive seq. Z_{ph}/km R_{ph}/km	Positive seq. Z_{ph}/km X_{ph}/km	Zero-phase seq. Z_0/km R_0/km	Zero-phase seq. Z_0/km X_0/km	Suscept. B/km	Max. current I_{Zph} (Amps)
			(p.u. on 100 MVA base)					
O	Underground Line (Cable)	300	0.0992	0.0632	0.6942	0.2213	0.00027	525
P	- (3-core PICAS cable (screened, stranded Al)	185	0.1227	0.0658	0.8590	0.2301	0.00024	415
Q	- (3-core XLPE stranded/solid Al with 95mm2)	95	0.1440	0.0666	1.0082	0.2332	0.00018	355
R	Overhead Line	150	0.1126	0.1836	0.3925	0.8370	0.00008	490
S	- (AAAC (75 C) 150 or 100 mm2 Oak AL4)	100	0.1466	0.2619	0.3017	1.3133	0.00001	395
T	- (ACSR 54/9 mm2 11kV)	50	0.2163	0.2069	0.7417	0.9986	0.00005	290



a) Rural



b) Suburban



c) Urban

Fig. 2. Generic MV distribution network models [7].

procedure is used to model the stochastic behaviour of the 3 modelled networks [10]. MCS results exemplify the variation arising from the fact that the different networks are made up of a different mix of PCs, demand supplied, and network configuration. This variation is central to the contribution of the paper as it emphasises the requirement to disaggregate network reliability performance based on network type. To complete the base case performance for each subsector network, there is the inclusion of security and quality of supply regulations which stipulate maximum durations of supply restoration based on supplied group demand [11]. Having obtained the network behaviour using MCS, PSS®E (automated using Python scripting) is used to simulate network performance and enable calculation of average values, PDFs and CDFs of all relevant reliability indices.

B. Smart Grid Technologies for Reliability Improvement

This section details the application of 2 combinations (hence network scenarios) of the 3 smart grid technologies proposed in this study – 1) an uncontrolled photovoltaic (PV) system combined with a technique for demand side response (DSR) designed for reliability improvement, and 2) local energy storage (ES) controlled by an energy management system (EMS), also combined with DSR [9, 12].

1) PV+DSR: While PV does not directly reduce the peak demand, it shortens the duration of the load peak, which is useful for current-carrying PCs [13]. Additionally, unpredictable cloud movements lead to power and voltage fluctuations at PV installations that often require altering settings of associated protection systems. For more accurate reproduction of the unpredictability of PV, this study models the most probable PV power output, i.e. considering the same output for each dwelling, which avoids overestimation of the possible benefits by accounting for the clouding effects. Given the expected high levels of PV penetration in future networks [14], this scenario illustrates the effect of uncontrolled PV with a 50% penetration. PV is combined with a DSR application, where 10% of the demand is reduced when the probability of fault occurrence is highest, to ensure upstream faults do not interrupt as much load.

2) ES+DSR: ES is designed to improve reliability performance by providing a backup capacity per customer, per fault, with the intention of reducing the ENS, duration and frequency of sustained interruptions. The designed backup capacity is 3.67 kWh, guided by [15]. ES operation is controlled by an EMS to provide seamless power switching capabilities and continuous supply to consumers. For realistic ES system modelling, the energy is stored from microgeneration operating in islanded mode, and temporally varying state of charge (SOC) characteristics for the ES devices are modelled into the EMS-controlled ES operation. The SOC behaviour is modelled based on electricity tariffs during grid supply, PV generation and load demand. Lastly, the SOC limits are set to 40% and 100% to prevent overheating and ensure long battery life [10]. ES is combined with DSR for reliability improvement and this combination of smart interventions - both corrective (i.e. ES) and preventive (i.e. DSR), is expected to result in the most benefits for network reliability performance. Further details on the development of both scenarios are available in [10].

C. Development of an Aggregate Network

Given that DNOs usually report aggregated values of the reliability indices describing the performance of their networks, this research presents reliability indices for a network (termed AGG) which is the equivalent of aggregating the 3 networks presented in this paper (RU, SU and U). This network, therefore, has 13110 customers served by 126 main LPs. To calculate what would be the equivalent reliability indices for this AGG network, a weighted mean of each index is calculated using the 3 subnetworks. Given the results presented later in this paper, (1) and (2) illustrate how a system and customer-oriented index of the AGG network is obtained from the 3 subnetworks. This serves to provide a basis upon which to compare the performance of what would be an entire network area served by a DNO, with the performance of its subnetworks that have varying characteristics, network configuration and customers served.

$$Index\_Sys_{AGG} = \frac{\sum_{i\in\Omega_L}^{N} LP_i Index_i}{\sum_{i\in\Omega_L}^{N} LP_i} \tag{1}$$

$$Index\_Cus_{AGG} = \frac{\sum_{i\in\Omega_L}^{N} LP_i Index_i}{\sum_{k\in\Omega_A}^{N} LP_k} \tag{2}$$

where $Index\_Sys_{AGG}$ and $Index\_Cus_{AGG}$ are the system and customer-oriented indices respectively, Index is the reliability index under consideration, i and k represent each subnetwork, set Ω_L contains all subnetworks, LP is the number of load points, and set Ω_A contains only the LPs affected by either LI or SI depending on the index considered for each network. The next section presents a multifaceted analysis of the results for all networks, all scenarios and all indices describing reliability performance, to emphasise the necessity and benefits of disaggregating reliability metrics when DNOs report on their network performances.

III. Comprehensive Reliability Assessment

There exists an overarching requirement for DNOs to report a more detailed evaluation of network performance due to the high variability in supplied networks. This is motivated by the recent drive in various countries to report disaggregated indices according to network type (RU/SU/U), as it provides essential information for decision-making on measures for continuity of supply improvements [16]. This research goes a step further by not only assessing the different reliability performance of 3 distinct networks but also assessing the impact of the integration of smart grid technologies into these networks, as well as quantifying the benefits they offer to network reliability performance.

A. Base Case Network Performance

Table III presents the reliability indices obtained for each network for the base case performance (i.e. without smart grid technologies). The indices provided are all standard indices aside from CAMIFI, which is defined in [12] and represents a measure of the frequency of SI to only affected customers. Indices for the AGG network are also presented in Table III, which effectively represent a weighted mean of the indices from all 3 networks (as usually presented by DNOs when reporting on their network reliability performance).

TABLE III. Base Case Performance for all Networks

Parameter	Index	Definition	Units*	Performance RU	SU	U	AGG
Energy not supplied	***ENS***	Energy Not Supplied	kWh/cust./y	17.85	150.70	146.37	113.20
	ACCI	Average Customer Curtailment Index	kWh/aff. cust./y	135.38	653.95	1090.41	687.76
Duration of LI	***SAIDI***	System Average Interruption Duration Index	hours/cust./y	0.629	1.351	0.550	0.851
	CAIDI	Customer Average Interruption Duration Index	hours/aff. cust./y	4.337	5.078	3.678	4.490
Frequency of LI	***SAIFI***	System Average Interruption Frequency Index	ints/cust./y	0.139	0.296	0.157	0.201
	CAIFI	Customer Average Interruption Frequency Index	ints/aff. cust./y	0.719	0.966	0.720	0.839
	CIII	Customers Interrupted per Interruption index	aff. cust./int./y	0.657	0.797	0.654	0.728
Frequency of SI	***MAIFI***	Momentary Average Interruption Frequency Index	ints/cust./y	0.188	0.368	0.208	0.259
	CAMIFI	Customer Average Momentary Interruption Frequency Index	ints/aff. cust./y	0.804	1.023	0.797	0.906

*Unit abbreviations are defined as: aff. = affected; cust. = customer; ints = interruptions; y =year

Table III presents indices that are categorised by different reliability parameters, providing for each parameter both the system and customer-oriented index. This is to highlight that, on top of the reasons motivating reporting of disaggregated indices, it is also necessary to report all indices calculated in Table III as there is a significant disproportionate gap between each index pair for the same parameter. A good example is that for all networks assessed, ACCI (measuring curtailed energy per customer interrupted only) is at least 5 times greater than the associated ENS. This highlights one of the major drawbacks of system-oriented reliability indices, which is that they include customers who enjoy uninterrupted power supply for substantially long periods, thereby concealing some of the shortcomings of network performance, especially to WSC [12]. Therefore, customer-oriented indices can complement system ones to present a more accurate picture of the customer-view of network performance and thus aid DNOs in managing customer expectations and thus WTP. The information on performance variability presented by these indices is as valuable as that obtained from assessing different network types and therefore merits their inclusion in DNO-reported network performance.

Given the lower number of customers served by the RU network (646) as well as the lower number of PCs (404), it is generally expected that most of the RU system indices calculated will be the lowest of the 3 networks in Table III. However, it is not surprising that the U network outperforms the RU network in indices such as SAIDI, CAIDI, CIII, and CAMIFI. This is due to the evidence suggesting that denser networks (having a higher ratio of customer/km) have fewer minutes lost per customer per year than less dense networks [4]. There is also a strong correlation between the number of supply interruptions and which type of network consumers are connected to [4], not to mention the higher number of backup supply alternatives. While one might expect urban customers to experience higher levels of quality of supply (low number of interruptions for short periods), the results reveal that this is not a straightforward case. This is because of the varying number and type of PCs, stochastic nature of network behaviour, number of, and spatial variability of customers served. It is also important to note that the AGG network is heavily influenced by the SU network which generally exhibits the worst reliability performance because of the high number of PCs (520), customers served (3344) and dominance of overhead lines for power distribution, which are generally more likely to fail than underground cables used in the U network, for example.

B. Impact of Smart Grid Technologies

While Table III presents only the base case results for each network performance, Fig.3 shows the corresponding impact from the designed smart grid technologies. By providing the percentage reductions of each index from its value in the base case it is possible to quantify, from a reliability perspective, the net impact of these technologies on network performance.

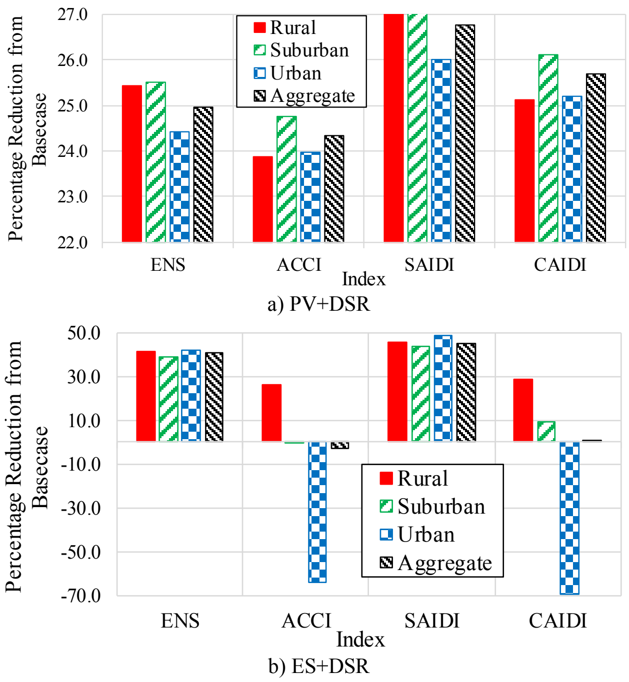


Fig. 3. Impact of smart interventions on ENS and duration of LI indices.

1) Energy not supplied and duration of LI:

Fig. 3 combines two reliability parameters i.e. energy not supplied and duration of LI because of their strong correlation. It is clear from Fig. 3a) that PV+DSR generally has a substantial effect on these two reliability parameters reducing each related index by at least 23% from the base case value. These results thus quantify the capability of this combination of technologies, by applying preventive measures, to enhance reliability. On the other hand, ES+DSR, predominantly a corrective measure, presents a slightly different effect on network reliability performance. As expected, the level of reduction of both system-oriented indices (ENS and SAIDI) is much higher than that in the PV+DSR case, as the EMS-controlled ES technology makes a more intelligent use of energy resources. Reporting disaggregated indices becomes especially incumbent when customer-oriented indices (ACCI and CAIDI) for the same reliability parameters are assessed. ES+DSR has the net effect of increasing (hence 'worsening') ACCI significantly for the U network, less so for the SU network, and offering a reduction in the RU network. For the case of CAIDI, ES+DSR only increases the value of this index in the U network. This is because the symmetric nature of the U network allows for more 'balanced' occurrence of faults that are significantly alleviated by the action of ES+DSR, leading to not only continuous supply but also a significant reduction in the number of LPs affected. This has the net effect of increasing these two customer-oriented indices and presenting the erroneous picture that reliability performance worsens. As a matter of fact, the increase in these indices is a sign that ES+DSR is most effective in the U network.

The main reason for this is because the number of affected LPs is significantly reduced, thus presenting a higher ACCI or duration of LI for only the affected customers. Table IV illustrates this property where the percentage number of LPs affected by LI reduces from 14% of the 48 LPs in the base case to only 3% when ES+DSR is applied, for the U network. Conversely, the reductions to the number of affected LPs are not as large when ES+DSR is deployed in the RU and SU networks. The impact of ES+DSR on the U network is also communicated by the fact that corresponding ENS and SAIDI percentage reductions from the base case are marginally highest in this network than in the RU and SU networks.

TABLE IV. NUMBER OF LPS AFFECTED BY SUPPLY INTERRUPTIONS

Network Scenario		Base case			PV+DSR			ES+DSR		
MV Network		RU	SU	U	RU	SU	U	RU	SU	U
Number of LPs Affected by:	LI	4.22	10.26	6.64	4.22	10.26	6.64	2.56	4.81	1.64
	SI	5.58	12.63	8.39	5.58	12.63	8.39	5.76	12.82	8.60
Percentage number of LPs affected by:	LI	12%	23%	14%	12%	23%	14%	8%	11%	3%
	SI	16%	29%	17%	16%	29%	17%	17%	29%	18%

The probability distributions of the indices from these two reliability parameters can be used to further illustrate the capability of ES+DSR. While ENS is further analysed in the next subsection, Fig. 4 presents the CDF analysis of SAIDI when ES+DSR has been deployed. This graph shows better reliability performance improvement in the U network through the effective use of ES+DSR.

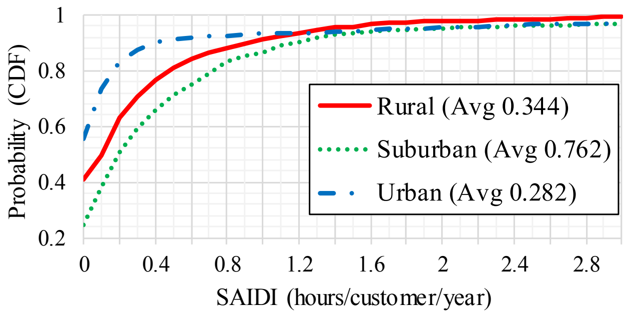


Fig. 4. Impact of ES+DSR on SAIDI for all MV networks.

Moreover, Fig. 4 shows that there is a higher probability (0.833) of customers experiencing an interruption of 0.2 hours or 12 minutes in the U network, than the probability in the RU network (0.629) and the SU network (0.508). This result is significant as it highlights key planning and operational decisions for the focus and deployment of such technologies to these various types of distribution networks.

2) Frequency of Interruptions:

Fig. 5 presents a similar analysis with a focus on the frequency of interruptions. However, in this case the effect of PV+DSR is not considered as its amount of penetration is not enough to influence the frequency of interruptions. The deployment of PV+DSR, at a 50% PV penetration and 10% load demand for DSR, essentially lowers the period for which a customer experiences an interruption, thereby reducing the ENS only. Table IV also emphasises why PV+DSR does not have a similar impact on the same indices for each network as ES+DSR does, since the number of LPs affected by LI does not change from the base case. However, Fig. 5 shows that the predominantly corrective application of ES+DSR enables for it to affect the frequency of both LI and SI to the extent that it reduces SAIFI by 75% in the U network and by over 35% in the RU one. The impact of ES+DSR is less significant on CAIFI and CIII indices, which basically represent supply interruptions to affected customers and the number of affected customers per interruption respectively. For all indices measuring frequency of LI, it is clear that the U network benefits most from the application of ES+DSR. Additionally, the higher reduction in CAIFI shows that impact of LI to affected customers is actually more reduced for the RU customers than the SU ones, with the application of ES+DSR. Notably, both indices measuring frequency of SI experience an increase from the base case when ES+DSR is deployed. This is mainly due to those occasions when ES lowers the length of LI to such an extent that they last for only short periods, i.e. long enough to be classified as SI as per [1]. Therefore, while ES+DSR does not directly affect frequency of SI, it does convert some LI to SI. However, this increase in the frequency of SI indices should not be interpreted as a negative impact on the network transient behaviour but rather as an improvement in network capability to alleviate faults. Thus, it will not have a tangible effect on network protection settings or related solutions which aim to reduce the SI in the system which, if not alleviated, can lead directly to power quality issues cascading in equipment failure [17].

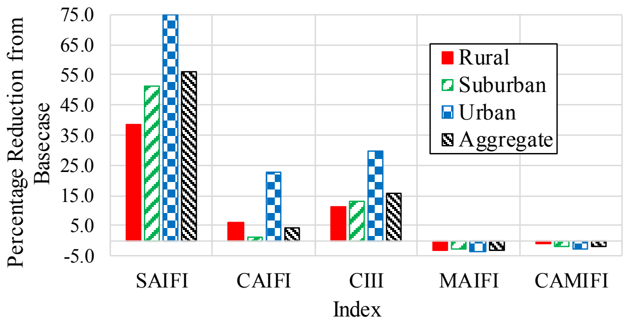


Fig. 5. Impact of ES+DSR on the frequency of LI indices.

Fig. 6 presents the CDF analysis of SAIFI after ES+DSR deployment. As before, ES+DSR exhibits the highest impact on the U network followed by the RU and SU networks. Notably, each customer in any of the 3 networks has a very high probability of experiencing no more than 1 LI per year.

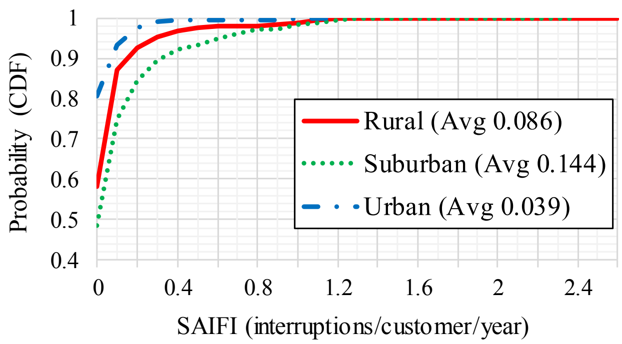


Fig. 6. Impact of ES+DSR on SAIFI for all MV networks.

C. Assessment of Energy not Supplied

One of the most important indices to communicate network reliability performance is ENS. Despite currently not being widely reported by DNOs to regulators [2], this index is central to a very useful understanding of the capability of a network to minimise the net impact of supply interruptions to the customers served. By limiting ENS, it is possible to raise the WTP of customers who are then more tolerant about the occurrence of supply interruptions given their confidence in the ability to have alternative supply during these periods. In this way, upstream faults that affect the continuity of supply are more tolerable given that customers continue to enjoy a high-quality continuous supply. However, even in the event that DNOs reported this index, as they currently do for SAIFI and SAIDI indices, they might do so by aggregating the total ENS in their served area. A PDF of this case might look like the one present in Fig. 7, which shows the PDF for the AGG network earlier described. This once again compels the necessity for disaggregation of this ENS index because as shown in Fig. 7, the net effect of having these networks aggregated, is to significantly lower the collective probability of having no (or 0) ENS to the network. This is because aggregating the networks concentrates possible ENS values to the average value given various contributions from the constituent networks i.e. RU, SU and U. This is also the case when smart grid technologies are applied to the so-called aggregate (AGG) network. Furthermore, ES+DSR has a most significant impact of increasing the probability of ENS values within the range 1-50 kWh per customer per year, given the combined average reduction to the ENS offered by ES+DSR in all constituent networks. Therefore, as part of the recommendation from this research, Fig. 8 illustrates how much information can be extracted from these networks if their reliability performance indices are disaggregated and reported as such. As can be seen in this Fig. 8, the values of ENS around 1-50 kWh mainly occur in the RU and SU networks i.e. have the highest probability of occurrence.

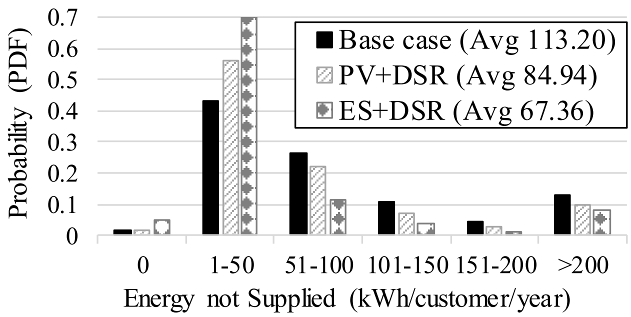


Fig. 7. ENS per scenario for the AGG network.

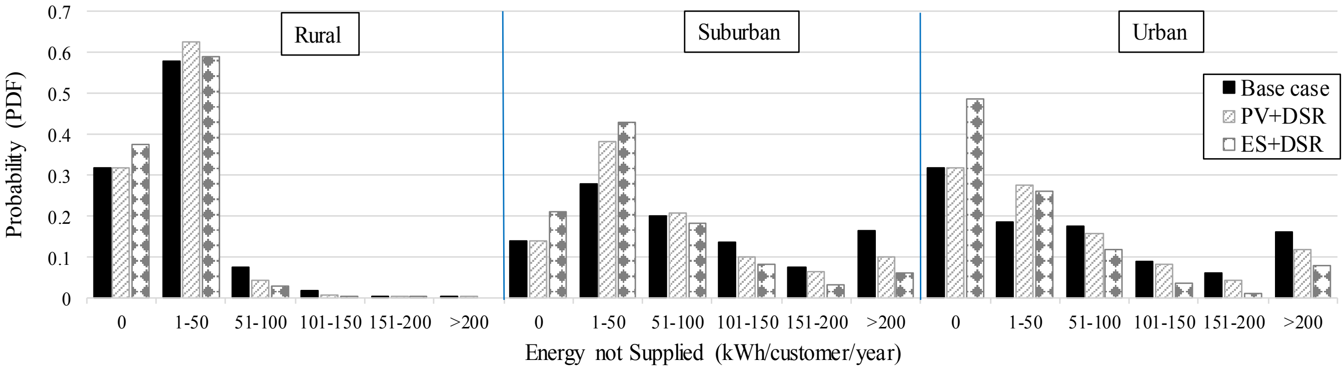


Fig. 8. ENS per network per scenario.

It is also evident that while the RU network will have a very low likelihood of having any of its customers suffer more than 100 kWh of ENS per year, different customers in the SU network will invariably have a much more variable spread of the possible ENS each year. As a direct comparison to the SU network, the U network benefits significantly from ES+DSR, which raises the probability of 0 ENS from the base case. It is also notable that, despite the larger number of customers in the U network (9120) as compared to 3344 customers in the SU network, the probability of ENS values higher than 200 kWh per customer per year are relatively the same regardless of the smart grid technology deployed. This means the U network has got a significantly better overall performance than the SU network. It is thus clear that the possible amount of information lost is significantly higher if ENS index is reported with Fig. 7 as opposed to Fig. 8.

IV. CONCLUSIONS AND FURTHER WORK

This paper addresses the necessity to distinguish between different spatially distributed customer-groups, in different types of distribution networks, when reporting the associated periodic reliability performance. This is important to ensure that the customer WTP is enhanced by their confidence in the continuity of power supply and the DNO-reporting on power delivery. A comprehensive analysis of the reliability assessment of 3 different modelled subsector networks is presented, i.e. RU, SU and U, allowing for an accurate disaggregation of these indices from the typically reported aggregate values. The results are a comprehensive set of average values and probability distributions of reliability indices measuring both the frequency and duration of interruptions and ENS. This allows for suitable identification of opportunities for targeted performance-enhancing solutions given the various strengths and weaknesses of the various networks. It is found that the common use of an aggregate network to present reliability indices masks very useful information about network reliability performance that would otherwise be highly beneficial in decision making when selecting methods to employ to improve quality of supply.

This research goes a step further than just quantifying the reliability performance variation between different networks, by assessing the impact of the integration of smart grid technologies into the various networks. Different combinations of PV, DSR and ES are proposed for deployment and the different impacts of these technologies on each type of network are assessed. This facilitates accurate quantification of where these technologies might be deployed most efficiently and to what effect. All this information serves to inform customers in ways in which they can increase the level of satisfaction with the overall electricity product, DNOs in ways to ensure higher quality and continuous power supply, and finally, regulators in ways to increase the fairness of the trade between consumers and DNOs. Further work will continue to disaggregate the reliability indices into contributions from different power components and this will further enhance the development of targeted solutions given varying network circumstances and prevalent technologies.

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