

Citation for published version:

Kong, W, Ma, K & Li, F 2022, 'Probabilistic impact assessment of phase power imbalance in the LV networks with increasing penetrations of low carbon technologies', Electric Power Systems Research, vol. 202, 107607. <https://doi.org/10.1016/j.epsr.2021.107607>

DOI: [10.1016/j.epsr.2021.107607](https://doi.org/10.1016/j.epsr.2021.107607)

Publication date: 2022

Document Version Peer reviewed version

[Link to publication](https://researchportal.bath.ac.uk/en/publications/4bce8e9b-5aba-4b6a-a580-48a07fb076a0)

Publisher Rights CC BY-NC-ND

**University of Bath**

# **Alternative formats**

If you require this document in an alternative format, please contact: openaccess@bath.ac.uk

**General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

**Take down policy**

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

# Electric Power Systems Research

# Probabilistic Impact Assessment of Phase Power Imbalance in the LV networks with Increasing Penetrations of Low Carbon Technologies

--Manuscript Draft--



# **Declaration of interests**

 $\boxtimes$  The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

# Dear Editor,

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

We understand that the Corresponding Author is the sole contact for the Editorial process (including Editorial Manager and direct communications with the office). He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs. We confirm that we have provided a current, correct email address which is accessible by the Corresponding Author and which has been configured to accept email from [k.ma@bath.ac.uk.](mailto:k.ma@bath.ac.uk)

Kind regards, Dr Kang Ma

#### **Probabilistic Impact Assessment of Phase Power Imbalance in the LV networks with**

#### **Increasing Penetrations of Low Carbon Technologies**

Wangwei Kong<sup>1</sup>, Kang Ma<sup>1\*</sup>, and Furong Li<sup>1</sup>

<sup>1</sup> Electronic & Electrical Engineering Department, University of Bath, Bath, UK

\* K.Ma@bath.ac.uk

*Abstract:* **Phase imbalances cause a range of network issue, from day-to-day energy losses to long-run capacity wastes that increase investment costs. The impact on low voltage (LV) network from phase imbalance has been investigated independently for losses and investment. However, no research was carried out on the total imbalance-induced cost (TIC) that includes both day-to-day energy losses and long-run capacity wastes, and how the relationship between the two may change with the increasing penetrations of single-phase low carbon technologies (LCTs). Analysing the TIC is important for distribution network operators (DNOs) as the day-to-day energy loss cost cannot be ignored as it may exceed the long-run network investment cost. This paper develops a new probabilistic framework to investigate the impact of increasing LCT penetration on TIC in the UK's LV distribution networks. Monte Carlo simulations are performed to account for the uncertainties in LCT sizes, connection locations and connection time. Case studies show that the additional energy loss cost exceeds the additional reinforcement cost in urban networks when the LCT penetration level reaches 70%. The key findings will help the DNOs understand the range of TIC and the relationship between imbalance-induced energy losses and capacity wastes under increasing LCT penetrations.**

### **1. Nomenclature**



# **2. Introduction**

Phase imbalance means either the magnitudes of the three phases are not the same, or their phase angles are not 120° apart from each other. Phase imbalance is a widespread problem in the UK. More than 70% of LV networks [1] suffer severe phase power imbalances, mainly caused by uneven load allocation [2], [3] and random load behaviours [3], [4]. Phase imbalance causes two consequences to distribution networks: energy losses [2], [3] and capacity wastes (that are translated into additional investment costs [4], [5]). The phase imbalance problem is further complicated by growing uptake of low carbon technologies (LCTs), including photovoltaic (PV) systems and electric vehicles (EVs) in the distribution system [6], [7]. The National Grid estimates that the UK's number of EVs on the road could reach 36m by 2040 and the capacity of PV units could reach 38GW by 2050 [8]. The increasing LCTs cause phase power imbalance to change randomly and therefore change the relationship between the above two imbalance-induced consequences. As a result, it is important to quantify the consequences of phase power imbalance under increasing penetration of LCTs. This is the focus of the paper.

Much effort is made to analyse the voltage imbalance caused by LCT penetrations, such as uncoordinated EV charging [9-14], PV inverters [14-20] and heat pumps (HPs) [11, 21] in the distribution networks. However, none of the research discussed the impacts of increasing LCT penetration on the phase power imbalance. The phase power imbalance is a direct consequence of voltage and current imbalances [22]. It incurs additional longrun network investment and day-to-day energy loss costs to the distribution networks. These imbalance-induced costs had also been investigated previously in [23], [24]. Reference [23] presented a way to estimate the additional reinforcement cost (ARC) for both LV transformers and main feeders using the degree of power imbalance. Our previous work [24] proposed a method to estimate the ARC and the additional energy loss cost (AELC) for data-scarce LV networks. The AELC includes the transformer copper loss cost and the costs caused by the phase residual current [24]. Nonetheless, these research works only focus on the LV networks with traditional passive loads, rather considering the increasing penetrations of LCTs.

Therefore, there is a gap in assessing the total imbalance-induced cost (TIC), which includes both day-to-day energy loss cost and long-run network investment cost (the latter is caused by imbalance-induced capacity wastes), under increasing penetrations of LCTs.

This paper addresses a different problem from [11]: Reference [11] analysed the impacts of four type of LCTs on customer voltage violations and feeder loading levels to help DNOs estimate the LCT hosting capacities for LV distribution feeders. However, this paper focuses on the impacts of LCTs on phase power imbalance and the corresponding TIC. Furthermore, this paper helps DNO find the balance between the dayto-day and long-run costs under increasing penetrations LCTs. The LCTs considered in this paper are EV and PV units because they are expected to rapidly increase in the near future [8]. However, this framework can also be extended to other LCTs.

This paper develops a new framework to quantify the impacts of LCTs on phase power imbalance, including how LCTs affect the TIC, considering both the day-to-day energy losses and long-term investment costs induced by phase imbalance. Monte-Carlo simulation is widely adopted in the existing literature. The reason is that it is a powerful technique in capturing uncertainties associated with LCTs in the power systems. Besides, the Monte-Carlo simulation technique is intuitive and straight forward. Therefore, in this framework, Monte-Carlo simulations are adopted to account for the LCT uncertainties within sizes, connection locations and connection time.

Analysing the TIC helps distribution network operators (DNOs) understand how the relationship between the two consequences may change with the increasing penetrations of single-phase LCTs. The methodology considers three scenarios: EV only scenario, PV only scenario and both EV and PV scenario, given the fact that both PV and EV grow rapidly in the foreseeable future.

The developed framework has practical values: 1) the probabilistic impact assessment helps the DNOs understand the possible impacts of LCTs on power imbalances in the LV distribution networks; 2) the estimated TIC help DNOs understand the relationship between imbalance-induced energy losses and capacity wastes as well as when the TIC reaches the minimum, under increasing LCT penetrations.

The remainder of this paper is organized as follows: Section II presents the overview of the developed methodology; Section III shows the network, LCTs profiles and the calculation of the imbalance-induced costs; Section IV performs the case studies of the probabilistic impact assessment, Section V discuss the results, and Section VI concludes the paper.

#### **3. Overview of methodology**

To perform an accurate impact assessment, full time-series of phase voltage and current data and LCT generation/ consumption data are required as the input data. However, the majority of UK's LV networks are unmonitored and there are significant uncertainties of the LCT's consumption or generation. Full data from 800 representative LV networks throughout a year are used in this paper. Details of the LV networks are explained in Section III-A.

Fig 1 shows the developed approach. The key to this approach is using Monte Carlo simulations to represent the uncertainties of LCTs and calculate the imbalance-induced costs (including ARC and AELC) for all the LV networks with changing LCT penetrations. The approach consists of three stages:



*Fig. 1. Overview of the methodology*

Stage I: Applying k-means clustering method to group the 800 data-rich networks into three clusters, i.e., urban, suburban and rural.

Stage II: A pool of 1000 EV charging profiles and 1000 PV generating profiles are generated. For each penetration level, the LCT profiles are randomly selected from the pool and randomly allocated to the three phases using Monte Carlo simulation. Finally, the imbalance-induced costs are calculated for each LV network under every LCT penetration level. This process iterates for 100 times to perform Monte Carlo analysis.

Stage III: The output from Stage II are ARC and AELC for each network. They work as input for Stage III. The TIC is calculated for each network and the probabilities of being beneficial from LCT penetration are analyzed. If one network benefits from LCT penetration, it means that this network has lower TIC with LCT penetration compared to that without LCT penetration. The TICs under each LCT penetration level are compared and the conclusions of which LCT penetration level has higher probabilities of being beneficial can be drawn.

#### **4. LV networks and LCT profiles**

### *4.1. LV networks*

In this paper, 800 representative data-rich LV networks from the "Low Voltage Network Templates" project [25] are used. These networks are located within the business area of a UK DNO (Western Power Distribution) and cover various geographical areas with different customer types, i.e., domestic, commercial and industrial customers. For example, Cardiff is representative of urban areas that contain large amounts of commercial load; Monmouthshire is a representative for the rural area [25]. These 800 networks cover various customer types and geographical areas (urban, suburban, and rural areas) [24].

#### *4.2. LCT profiles*

A pool of 1000 slow charging residential EV profiles is created considering the battery and the probability distributions of connection times and energy requirements [26]. The highest probability of connecting time happens at 6.30 p.m. and 10.30 p.m. [26]. The highest probability of energy requirement is 8-9 kWh [26]. Slow charging (3kW) is a popular type of charging for UK residential customers. According to [27], 75% of total annual EV demand is charged at the residential side. Therefore, all the EV batteries are assumed to be a common type, i.e., Nissan Leaf (3kW and 24kWh) [11].

A pool of 1000 residential PV generating profiles is generated considering various installation sizes of PV systems and the sun irradiances. It is assumed that all the PV systems receive the same sun irradiances. According to [28], the residential PV systems have seven different sizes and the size of 4 kW is the most popular choice (37% of the total installation). Therefore, the probabilities of PV system sizes for the pool are shown in Table 1.

**Table 1** Probabilities of PV system sizes [28]

Size (kW)					3.5	
Probability 0.01 0.08		0.13	0.14	(0.14)	0.12	0.37

[Fig. 2](#page-11-0) demonstrates the load and generation of substation 3503 with 20% LCT penetration for one day (24 hours). It shows the total traditional load, EV load and PV generation across the three phases. The PV generations are shown as negative.



*Fig. 2. Loads of substation 513503 with 20% LCT penetration*

#### <span id="page-11-0"></span>*4.3. The imbalance-induced costs*

### *3.3.1 The additional reinforcement cost (ARC):*

To measure the severity of phase power imbalances, a common index used among literature is the degree of power imbalances (DPIB). The DPIB index is used as a guidance for phase swapping [22] and it is a vital factor in the estimation of ARC. In [4], a linearised equation for estimation ARC is given as

$$
ARC \approx 3k_fDPIB_f + k_tDPIB_t
$$

where

$$
k_f = Asset_f \cdot (1+d)^{\frac{log U_N}{log(1+r)}} \cdot \frac{log(1+d)}{log(1+r)}
$$
  
\n
$$
k_t = Asset_t \cdot (1+d)^{\frac{log U_N}{log(1+r)}} \cdot \frac{log(1+d)}{log(1+r)}
$$
  
\n
$$
DPIB_f = \frac{max\{P_\emptyset\} - \frac{P_t}{3}}{P_t} \quad \phi \in \{A, B, C\}, \qquad DPIB_t = \frac{P_N}{P_t}
$$

### *3.3.2 The additional energy loss cost (AELC):*

The imbalanced-induced energy loss contains the energy loss caused by the phase residual current [29] and the additional transformer copper loss [30]. The energy loss caused by the phase residual current is calculated considering the TN-S earthing system [31] in this paper. The additional transformer copper loss is the difference between the transformer copper loss under balanced scenario and transformer copper loss under imbalanced scenario.

Therefore, the AELC is given by the sum of these two terms:

$$
AELC = (E_{loss} + E_{t\_i}) \times \pi \tag{2}
$$

where  $E_{loss} = \sum_{t=1}^{N_t} I_{prc}^{2}(t) \cdot R_n \cdot \Delta t$  $t=1$  $E_t$  i =  $E_i - E_{trans}$ 

$$
E_{i} = \sum_{t=1}^{N_{t}} (I_{A}^{2}(t) + I_{B}^{2}(t) + I_{C}^{2}(t)) \cdot R_{w} \cdot \Delta t
$$

$$
E_{trans} = 3 \sum_{t=1}^{N_t} I^2(t) \cdot R_w \cdot \Delta t
$$

 $I_{prc}(t) = [I_A^2(t) + I_B^2(t) + I_C^2(t) - I_A(t)I_B(t) - I_B(t)I_C(t) - I_A(t)I_C(t)]^{1/2}$ 

#### *3.3.3 The total imbalance-induced cost (TIC):*

The TIC is a summation of the ARC and AELC:

$$
TIC = ARC + AELC \tag{3}
$$

where ARC and AELC are explained in (1) and (2), respectively.

The ARC is a present value for the long-term network investment while the AELC is the sum of day-to-day energy loss cost for a year. Considering TIC instead of ARC only helps DNOs avoid excessive energy losses caused by LCTs effectively.

#### **5. Probabilistic impact assessment**

#### *5.1. Methodology*

The developed methodology, as shown in Fig. 3, analyses the probabilistic impacts of LCT penetration on imbalance-induced costs. It considers the uncertainties of EV charging energy requirement, PV system size, connection time and connection location through Monte Carlo simulations under different LCT penetration levels.

It is worthy to note that the substation monitors the total output from the transformer, which is the accumulated load consumption of the whole LV network. The imbalanceinduced costs are calculated from the voltage and current data monitored by the substation. The network topology and load distribution are not necessary for this analysis. Therefore, the LCT penetration for a network is considered as the accumulated generation or consumption patterns of all the LCTs in the network. The main steps are:



*Fig. 3. Overview of the methodology*

- 1) Input data from 800 LV networks and cluster them into three groups, i.e., urban, suburban and rural. K-means clustering is used to group the networks by their annual peak current. This clustering process is done as the same LCT penetration may have different impacts on different clusters. The physical nature of the networks is different. For example, the urban networks have shorter feeders and heavier load compared to rural and suburban networks. As a result, the phase powers in urban networks could change rapidly because of LCT penetrations.
- 2) Generate a pool of 1000 EV charging profiles and 1000 PV generating profiles. The pool of EV charging profiles follows the probability distributions of connection times and energy requirements [26]. The pool of PV generation profiles considers the

installed sized and sun irradiances [28]. The detailed process of generating the pools for LCT profiles is explained in Section IV-B.

- 3) Increase the LCT penetration level from 0% to 100% with a step of 10%. The LCT penetration level is defined as the percentage of energy required or generated by LCT over the total traditional passive load consumption. Increasing the LCT penetration level from 0% to 100% aims to cover a wide range of possible situations for the future. Although the 100% LCT penetration is very unlikely for the near future, it can be used as an extreme scenario for DNOs to analyze the impacts on phase power imbalance.
- 4) Select LCT profiles from the pool according to each penetration level and allocate them to the three phases. Both the selection and allocation processes use the Monte Carlo method to embed uncertainties of LCTs.
- 5) Calculate ARC and AELC for each network and store the results. The AELC includes both energy loss cost caused by phase residual current and the energy loss cost caused by transformer copper loss. Note that the ARC is a long-run cost while the AELC is a day-to-day cost. Thus, the calculated ARC is a present value discounted from the future while the AELC represents the total energy loss cost for a year. Besides, the TIC is calculated from ARC and AELC and it is used to evaluate the probability of a network to benefit from LCT penetrations.
- 6) Repeat the steps 100 times to account for uncertainties. Note that 10, 50, 200, 500 and 1000 times of Monte Carlo simulations had been run. However, the 10 and 50 times of simulation cannot cover the whole possible impacts. The rest of the simulation times have a very similar result. Thus, 100 times of simulation is chosen to show better results with shorter programming running time.

#### *5.2. Probabilistic study*

The imbalance-induced costs are calculated for each LV network under different LCT penetration levels. The 800 LV networks consist of urban (11.2%), suburban (44.4%), and rural (44.4%) networks. The average imbalance-induced costs for each group of networks are shown in the case study. A 95% confidence interval is considered while estimating the average costs in this analysis. The probabilistic study considers three scenarios, i.e., EV only, PV only and both EV and PV.

In this paper, the neutral wire resistance  $(R_n)$  is set as 0.244  $\Omega$ /km [29]. The winding resistances  $(R_w)$  are calculated from [32] and presented in Table 2.

<b>Assets</b>	Area	Urhan	Suburban	Rural
Transformer investment cost (k£)		26.4	16 1	5.8
Main feeder investment cost (k£/km)		672	164	15.0
Main feeder length (km)		0 <sub>2</sub>	03	04
No. of feeders connected from transformers 5			35	15
Winding resistance $(\Omega)$		0.0163	0 0 2 6 5	0.0413

**Table 2** Parameters for different areas [32], [33]

To derive the ARC, the investment costs of the feeder and transformer are given in Table II. The discount value (d) is set as 5.0% [23] and [34]. The load growth rate (r) is set as 0.82% [35].

#### *4.2.1 EV only scenario*

[Fig. 4](#page-17-0) shows how the ARC and AELC change with increasing EV penetrations for urban, suburban and rural networks. It can be seen that without EV penetration (i.e., EV penetration level is 0%), the rural networks have the largest ARC but least AELC. The reason is that the ARC is proportional to the DPIB while the AELC is influenced by loading level (as shown in equation (1) and (2)). The rural networks have the largest DPIB but the lowest loading levels compared to suburban and urban networks.

[Fig. 4](#page-17-0) shows that the ARC decreases with EV penetration while the AELC increases with EV penetration. For urban and suburban networks, the ARC decreases gradually. The ARC for rural networks decreases rapidly compared to other networks. It shows that EV penetration reduces the DPIB for all the networks. The DPIB in rural networks has the largest drop compared to suburban and urban networks.



<span id="page-17-0"></span>*Fig. 4. Variation of the average ARC and AELC of urban, suburban and rural networks with EV penetration*

It also shows that the AELC increases with EV penetration. The EV penetration level is defined as the percentage of energy required by EV over the total traditional passive load consumption. Therefore, the loading level is increased proportionally to the EV penetration. As discussed above, the AELC increases with loading level. The urban networks have the largest passive load consumption compared to rural and suburban networks. Thus, the urban networks have the most significant increase in loading level. Consequently, the AELC of urban networks increases dramatically while increasing EV penetration.

When the EV penetration level exceeds 60%, the urban networks' AELC becomes higher than the ARC. When the EV penetration level reaches 100%, the suburban networks' AELC catches up with the ARC and has the trend to keep increasing to exceed the ARC.

[Fig. 5](#page-18-0) shows the average of the TIC for rural, suburban and urban networks. In rural networks, the TIC decreases as the EV penetration level increases. In suburban networks, the TIC reduces as EV penetration level increases up to 50% and stabilizes after 50%. In urban networks, the TIC decreases as EV penetration level increases up to 50% and increases after 50%.



<span id="page-18-0"></span>*Fig. 5. Variation of average TIC of urban, suburban and rural networks with EV penetration*

It indicates that considering the full imbalance-induced cost, i.e., ARC and AELC, 50% of EV penetration brings the maximum benefits for the urban networks. The suburban networks gain more benefit from EV penetration that is larger than 50%. The benefits for rural networks increase with the EV penetration level.

#### *4.2.2 PV only scenario*

[Fig. 6](#page-19-0) shows how the ARC and AELC change with increasing PV penetrations for urban, suburban and rural networks. As discussed above, the rural networks have the largest ARC because they have the largest DPIB compared to other networks. The loading level of rural networks is the lowest, which leads to the lowest AELC. The PV penetration has minor influences on both ARC and AELC as it can be seen that the values of ARC and AELC have only increased slightly with PV penetration.

The reason for this phenomenon is that PV generation mainly changes the DPIB in the noontime because of the nature of the solar system. However, the ARC is decided by the maximum DPIB throughout the whole year. Thus, the impacts of PV penetration on the ARC is insignificant. A detailed discussion of different impacts on DPIB is given in Section V. The increase of PV generation only reduces the loading level in the noontime. However, the AELC is an accumulated value of a whole year. Thus, the impacts of PV penetration on the AELC is insignificant.



<span id="page-19-0"></span>*Fig. 6. Variation of the average ARC and AELC of urban, suburban and rural networks with PV penetration*

Because of the minor changes in both ARC and AELC, there are insignificant increases of TIC for all the networks (as shown in Fig. 7). However, such an increase of TIC is negligible comparing to other network operations.



*Fig. 7. Variation of average TIC of urban, suburban and rural networks with PV penetration*

*4.2.3 Both EV and PV scenario*

The third scenario considers both EV and PV penetrations at the same time. In the following content, 'EV and PV' are referred to as 'LCT' for simplicity. For this scenario, EV and PV are considering to have the same penetration level, i.e., if the LCT penetration level is 10%, it means that both the EV and PV have a penetration level of 10%. The LCTs are randomly selected from the pool using Monte Carlo and randomly allocated to the three phases using norm distribution.

[Fig. 8](#page-20-0) shows that the ARC decreases with LCT penetration while the AELC increases with LCT penetration. For urban and suburban networks, the ARC decreases gradually. The ARC for rural networks decreases rapidly compared to other networks. It shows that EV penetration reduces the DPIB for all the networks. The DPIB in rural networks has the largest drop compared to suburban and urban networks.

It also shows that the AELC increases with LCT penetration. Though the total amount of EV consumption equals the PV generation, PV generation mainly reduces the loading level in the noontime. In contrast, EV consumption has possibilities to increase the loading level at any time of the day. Therefore, the AELC has raised because of the increasing of LCT connections. Among all the networks, the urban networks have the largest increase in loading level. Consequently, the AELC of urban networks increases with increasing LCT penetration.



<span id="page-20-0"></span>*Fig. 8. Variation of the average ARC and AELC of urban, suburban and rural networks with LCT penetration*

When the EV penetration level exceeds 65%, the urban networks' AELC becomes higher than the ARC. When the LCT penetration level reaches 100%, the suburban networks' AELC catches up with the ARC and has the trend to keep increasing to exceed the ARC.

[Fig. 9](#page-21-0) shows that, in urban networks, the TIC decreases as the LCT penetration level increases up to 50% and decreases after 60%. In suburban networks, the TIC reduces as LCT penetration level increases up to 60% and stabilizes after 60%. In rural networks, the TIC decreases as the LCT penetration level increases.



<span id="page-21-0"></span>*Fig. 9. Variation of average TIC of urban, suburban and rural networks with LCT penetration*

Therefore, to balance the long-run investment cost and day-to-day energy loss cost, 50% - 60% of LCT penetration brings the maximum benefits for the urban networks. The suburban networks will gain more benefits from LCT penetration that is larger than 50%. The rural networks will always benefit from LCT penetration.

To further understand the possible influences of LCT penetration. The probability (with 95% confidence) of networks to have reduced TIC with LCT penetration is calculated for each penetration level. This demonstrates the benefits from LCT penetration.

[Fig. 10,](#page-22-0) [Fig. 11](#page-22-1) and [Fig. 12](#page-22-2) show the probabilities of having reduced TIC with EV penetration in rural, suburban and urban networks, respectively. The colour map indicates the ratio of networks applicable to each scenario. For example, with 20% LCT penetration, 40% of rural networks, 43% of suburban networks and 40% of urban networks have more than 0.5 probability (50% chance) to benefit from EV penetration. It is also shown that 60% of LCT penetrations have higher probabilities of bringing benefits for the majority of LV networks compared to that of 50% of LCT penetration.



<span id="page-22-0"></span>*Fig. 10. The probability of being beneficial from LCT penetration for rural networks*



<span id="page-22-1"></span>Probability of being beneficial *Fig. 11. The probability of being beneficial from LCT penetration for suburban networks*



Probability of being beneficial

<span id="page-22-2"></span>*Fig. 12. The probability of being beneficial from LCT penetration for urban networks*

#### **6. Discussion**

Fig 13 shows the changes of DPIB in different penetration scenarios for all the networks i.e., no LCT scenario, EV only scenario, PV only scenario and both EV and PV scenario. The penetration level is 100% for all the scenarios. Rural networks have the largest DPIB while urban networks have the smallest DPIB. Compared to the scenario of no LCT penetration, the EV penetration scenario and LCT penetration scenario both reduce DPIB significantly. In contrast, the PV penetration scenario has very insignificant changes to the DPIB. The DPIB in LCT penetration scenario is slightly smaller than that of the EV penetration scenario.



*Fig. 13. DPIB in different penetration scenarios*

The reason is that DPIB is defined as the ratio of the deviation of the maximum power  $(max{P_{\emptyset}})$  from the average power  $(\frac{P_t}{3})$  to the total power  $(P_t)$  along the whole year (as shown in (1)). In LV distribution networks, the maximum load demand mainly occurs in the evening time around 6:30 p.m., as shown in Fig 2. This is also the time that majority EVs are connected to the grid to begin charging. Consequently, the EV connections have great possibilities of increasing the  $\frac{P_t}{3}$  and as a result, reduce the DPIB. Oppositely, PV generations mainly generate energy during the noontime. As a result, the PV penetration has low possibilities of reducing the DPIB.

Fig 14 shows the changes of the phase residual current  $(I_{prc})$  in different penetration scenarios for all the networks. The penetration level is 100% for all the scenarios. Urban networks have the largest  $I_{prc}$  while rural networks have the smallest  $I_{prc}$ . The EV penetration scenario increases  $I_{prc}$  relatively significantly compared to the PV and LCT penetration scenarios. The  $I_{prc}$  in EV penetration scenario is the largest among all the scenarios.



*Fig. 14. Phase residual current () in different penetration scenarios*

Consequently, the EV penetration scenario has larger impacts on the AELC compared to other scenarios. Oppositely, PV and LCT penetration scenarios have minor impacts on the AELC.

#### **7. Conclusions**

A probabilistic impact assessment framework is developed to analyse the total imbalance-induced cost (TIC) in the low voltage (LV) networks with increasing penetrations of low carbon technologies (LCTs). The TIC includes both day-to-day energy loss cost and long-run network investment cost. The framework uses Monte Carlo simulations to account for the uncertainties associated with the LCTs. Full time-series data from 800 LV substations are used for the case studies.

The results show that the energy loss cost may exceed the network investment with penetration of single-phase LCTs. To balance the long-run investment cost and day-today energy loss cost, the urban networks achieve the maximum benefits when the LCT penetration level is 50% - 60%. The suburban networks gain more benefits from LCT penetration that is larger than 50%. The rural networks will always benefit from the increase of LCT penetration. To further understand the impacts of LCT penetration on networks. A probability analysis is performed to identify the probability, with 95% confidence, of networks to have reduced TIC with LCT penetrations. Results indicate that 60% of LCT penetration has the highest probability to bring the maximum benefits for the majority of the LV networks.

The developed impact assessment framework help DNOs understand the potential of benefits that LV networks can obtain from LCTs penetrations. Moreover, the developed framework can be used as a tool to perform a cost-benefit analysis for phase balancing solutions. Therefore, it guides the DNOs in investing phase balancing solutions to cope with the increasing LCT penetrations.

### **8. References**

- [1] K. Ma, R. Li, and F. Li, "Utility-Scale Estimation of Additional Reinforcement Cost from 3-Phase Imbalance Considering Thermal Constraints," *IEEE Transactions on Power Systems,* vol. PP, no. 99, pp. 1-1, 2016.
- [2] "Electricity distribution units and loss percentages summary," [https://www.ofgem.gov.uk/sites/default/files/docs/2010/08/distribution-units-and-loss-percentages](https://www.ofgem.gov.uk/sites/default/files/docs/2010/08/distribution-units-and-loss-percentages-summary.pdf)[summary.pdf.](https://www.ofgem.gov.uk/sites/default/files/docs/2010/08/distribution-units-and-loss-percentages-summary.pdf)
- [3] "Electricity Distribution Price Control Review Final Proposals Incentives and Obligations," [https://www.ofgem.gov.uk/ofgem-publications/46748/fp2incentives-and-obligations-final.pdf.](https://www.ofgem.gov.uk/ofgem-publications/46748/fp2incentives-and-obligations-final.pdf)
- [4] K. Ma, R. Li, and F. Li, "Quantification of Additional Asset Reinforcement Cost From 3-Phase Imbalance," *IEEE Transactions on Power Systems,* vol. 31, no. 4, pp. 2885-2891, 2016.
- [5] J. Zhu, M. Y. Chow, and F. Zhang, "Phase balancing using mixed-integer programming," *IEEE Transactions on Power Systems,* vol. 13, no. 4, pp. 1487-1492, 1998.
- [6] *Future Power System Architecture*, Institution of Engineering and Technology, 2016.
- [7] *Open Networks Future Worlds*, Energy Networks Association, 2018.
- [8] "Future Energy Scenarios," 2019; [http://fes.nationalgrid.com/media/1363/fes-interactive-version](http://fes.nationalgrid.com/media/1363/fes-interactive-version-final.pdf)[final.pdf.](http://fes.nationalgrid.com/media/1363/fes-interactive-version-final.pdf)
- [9] A. Ul-Haq, C. Cecati, K. Strunz, and E. Abbasi, "Impact of Electric Vehicle Charging on Voltage Unbalance in an Urban Distribution Network," *Intelligent Industrial Systems,* vol. 1, no. 1, pp. 51-60, 2015.
- [10] K. Clement-Nyns, E. Haesen, and J. Driesen, "The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid," *IEEE Transactions on Power Systems,* vol. 25, no. 1, pp. 371-380, 2010.
- [11] A. Navarro-Espinosa, and L. F. Ochoa, "Probabilistic Impact Assessment of Low Carbon Technologies in LV Distribution Systems," *IEEE Transactions on Power Systems,* vol. 31, no. 3, pp. 2192-2203, 2016.
- [12] E. Vega-Fuentes, and M. Denai, "Enhanced Electric Vehicle Integration in the UK Low-Voltage Networks With Distributed Phase Shifting Control," *IEEE Access,* vol. 7, pp. 46796-46807, 2019.
- [13] J. Quirós-Tortós, L. F. Ochoa, S. W. Alnaser, and T. Butler, "Control of EV Charging Points for Thermal and Voltage Management of LV Networks," *IEEE Transactions on Power Systems,* vol. 31, no. 4, pp. 3028-3039, 2016.
- [14] J. F. Franco, A. T. Procopiou, J. Quirós-Tortós, and L. F. Ochoa, "Advanced control of OLTC-enabled LV networks with PV systems and EVs," IET Generation, Transmission & Distribution, vol. 13, no. 14, pp. 2967-2975, 2019.
- [15] T. R. Ricciardi, K. Petrou, J. F. Franco, and L. F. Ochoa, "Defining Customer Export Limits in PV-Rich Low Voltage Networks," IEEE Transactions on Power Systems, vol. 34, no. 1, pp. 87-97, 2019.
- [16] J. D. Watson, N. R. Watson, D. Santos-Martin, A. R. Wood, S. Lemon, and A. J. V. Miller, "Impact of solar photovoltaics on the low-voltage distribution network in New Zealand," IET Generation, Transmission & Distribution, vol. 10, no. 1, pp. 1-9, 2016.
- [17] S. Hashemi, and J. Østergaard, "Methods and strategies for overvoltage prevention in low voltage distribution systems with PV," IET Renewable Power Generation, vol. 11, no. 2, pp. 205-214, 2017.
- [18] D. Schwanz, F. Möller, S. K. Rönnberg, J. Meyer, and M. H. J. Bollen, "Stochastic Assessment of Voltage Unbalance Due to Single-Phase-Connected Solar Power," IEEE Transactions on Power Delivery, vol. 32, no. 2, pp. 852-861, 2017.
- [19] R. Torquato, D. Salles, C. O. Pereira, P. C. Meira, and W. Freitas, "A Comprehensive Assessment of PV Hosting Capacity on Low-Voltage Distribution Systems," IEEE Transactions on Power Delivery, vol. 33, no. 2, pp. 1002-1012, 2018.
- [20] A. Dubey, and S. Santoso, "On Estimation and Sensitivity Analysis of Distribution Circuit's Photovoltaic Hosting Capacity," IEEE Transactions on Power Systems, vol. 32, no. 4, pp. 2779-2789, 2017.
- [21] A. Navarro-Espinosa, and P. Mancarella, "Probabilistic modeling and assessment of the impact of electric heat pumps on low voltage distribution networks," Applied Energy, vol. 127, pp. 249-266, 2014.
- [22] W. Kong, K. Ma, and Q. Wu, "Three-Phase Power Imbalance Decomposition Into Systematic Imbalance and Random Imbalance," IEEE Transactions on Power Systems, vol. 33, no. 3, pp. 3001- 3012, 2018.
- [23] K. Ma, R. Li, and F. Li, "Utility-Scale Estimation of Additional Reinforcement Cost From Three-Phase Imbalance Considering Thermal Constraints," IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3912-3923, 2017.
- [24] W. Kong, K. Ma, L. Fang, R. Wei, and F. Li, "Cost-Benefit Analysis of Phase Balancing Solution for Data-scarce LV Networks by Cluster-Wise Gaussian Process Regression," IEEE Transactions on Power Systems, pp. 1-1, 2020.
- [25] R. Li, C. Gu, F. Li, G. Shaddick, and M. Dale, "Development of Low Voltage Network Templates Part I: Substation Clustering and Classification," Power Systems, IEEE Transactions on, vol. 30, no. 6, pp. 3036-3044, 2015.
- [26] P. Richardson, M. Moran, J. Taylor, A. Maitra, and A. Keane, Impact of electric vehicle charging on residential distribution networks: An Irish demonstration initiative, 2013.
- [27] T. Dodson, and S. Slater, Electric vehicle charging behaviour study, National Grid ESO, 2019.
- [28] A. Navarro, L. F. Ochoa, and D. Randles, "Monte Carlo-based assessment of PV impacts on real UK low voltage networks," in 2013 IEEE Power & Energy Society General Meeting, 2013, pp. 1-5.
- [29] L. Fang, K. Ma, R. Li, Z. Wang, and H. Shi, "A Statistical Approach to Estimate Imbalance-Induced Energy Losses for Data-Scarce Low Voltage Networks," IEEE Transactions on Power Systems, pp. 1- 1, 2019.
- [30] E. O, O. O, and I. A;, "Evaluation Of Distribution System Losses Due To Unbalanced Load In Transformers A Case Study Of Guinness 15MVA, 33/11KV, Injection Substation And Its Associated 11/0.415kv Transformers In Benin City, Nigeria," International Journal of Engineering Research & Technology, vol. 2, no. 3, March, 2013.
- [31] G. Cronshaw, EARTHING: YOUR QUESTIONS ANSWERED, IEE Wiring Matters, 2005.
- [32] S. Electric. "HV/LV distribution transformers," [http://mt.schneider](http://mt.schneider-electric.be/main/tfo/catalogue/an_iec.pdf)[electric.be/main/tfo/catalogue/an\\_iec.pdf.](http://mt.schneider-electric.be/main/tfo/catalogue/an_iec.pdf)
- [33] Y. Zhang, F. Li, Z. Hu, and G. Shaddick, "Quantification of low voltage network reinforcement costs: A statistical approach," IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 810-818, 2013.
- [34] A. S. Sidhu, M. G. Pollitt, and K. L. Anaya, "A social cost benefit analysis of grid-scale electrical energy storage projects: A case study," Applied Energy, vol. 212, pp. 881-894, 2018/02/15/, 2018.
- [35] "Pathways for the GB Electricity Sector to 2030," [https://www.energy](https://www.energy-uk.org.uk/publication.html?task=file.download&id=5722)[uk.org.uk/publication.html?task=file.download&id=5722](https://www.energy-uk.org.uk/publication.html?task=file.download&id=5722)

# Highlights (mandatory)

- phase imbalance causes both day-to-day energy losses and long-run capacity wastes,
- Analysing the total imbalance-induced cost is important for distribution network operators as the day-to-day energy loss cost may exceed the longrun network investment cost
- Monte Carlo simulation is adopted to account for the uncertainties associated with the low carbon technologies
- 60% penetration of low carbon technologies has the highest probability to bring the maximum benefits for the majority of the LV networks

# **Response to the reviewers' comments**

We would first like to thank the editor and reviewers for their time and efforts on this paper. They have led to significant improvement to the manuscript.

We have treated each and every comment seriously and have provided a thorough response (and associated revisions) to each comment.

We have addressed all comments.

The original comments are in **bold**; our responses are in ordinary font; and our revisions in the manuscript are in red.

# **Reviewer #2:**

# **Comment 1.**

**The entire paper having so many abbreviations. Need to provide nomenclature.**

# **Response**

We fully agree with the reviewer. A nomenclature section is added as the first section of the paper.



# **1. Nomenclature**

# **Comment 2.**

**In page number 4, in section II, "Error! Reference Source Not Found" message will occur. Rectify that problem.**

#### **Response**

We have corrected the format error. The updated contents are shown as:

Fig 1 shows the developed approach.

#### **Comment 3.**

**Monte Carlo simulation technique is very known one. But you are adopted this technique to your framework. So, is there any specific reason to adopt this for your work? Justify.**

#### **Response**

Monte-Carlo simulation is widely adopted in the existing literature. The reason is that it is a powerful technique in capturing uncertainties associated with LCTs in the power systems. Besides, the Monte-Carlo simulation technique is intuitive and straight forward. Therefore, in this framework, Monte-Carlo simulations are adopted to account for the LCT uncertainties within sizes, connection locations and connection time.

### **Reviewer #3:**

### **Comment 1.**

### **In your paper you have to reduce the similarity index below 12%.**

#### **Response**

Firstly, we would like to clarify that the submitted paper is a part of the first author's PhD thesis. This is perfectly legitimate because:

1) When we first submitted the R0 version of this paper, the PhD thesis had not been submitted then. The PhD viva later took place when this paper was under review and the viva turned out to be successful. Later the PhD thesis is publicised and then this paper's review came back, causing some overlap in words.

2) It is perfectly normal for a PhD student to put his/her own work in a paper as well as the thesis.

We have revised the paper according to the reviewers' comments to improve the content and also reduce the similarity index.

# **Comment 2.**

# **The concluding part in your paper is not clear. Response**

We have revised the conclusion of the paper:

A probabilistic impact assessment framework is developed to analyse the total imbalance-induced cost (TIC) in the low voltage (LV) networks with increasing penetrations of low carbon technologies (LCTs). The TIC includes both day-to-day energy loss cost and long-run network investment cost. The framework uses Monte Carlo simulations to account for the uncertainties associated with the LCTs. Full timeseries data from 800 LV substations are used for the case studies.

The results show that the energy loss cost may exceed the network investment with penetration of single-phase LCTs. To balance the long-run investment cost and dayto-day energy loss cost, the urban networks achieve the maximum benefits when the LCT penetration level is 50% - 60%. The suburban networks gain more benefits from LCT penetration that is larger than 50%. The rural networks will always benefit from the increase of LCT penetration. To further understand the impacts of LCT penetration on networks. A probability analysis is performed to identify the probability, with 95% confidence, of networks to have reduced TIC with LCT penetrations. Results indicate that 60% of LCT penetration has the highest probability to bring the maximum benefits for the majority of the LV networks.

The developed impact assessment framework help DNOs understand the potential of benefits that LV networks can obtain from LCTs penetrations. Moreover, the developed framework can be used as a tool to perform a cost-benefit analysis for phase balancing solutions. Therefore, it guides the DNOs in investing phase balancing solutions to cope with the increasing LCT penetrations.

# **Credit Author Statement**

# Paper title: **Probabilistic Impact Assessment of Phase Power Imbalance in the LV networks with Increasing Penetrations of Low Carbon Technologies**

Dr Wangwei Kong contributed to implementing the methodology, performing case studies, validating the results, writing the paper draft and revising.

Dr Kang Ma contributed to conceptualization, revising the paper and supervision of the research.

Prof Furong Li contributed to conceptualization.

Dr Kang Ma on behalf of all authors

22 June 2021