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D5.3 Power quality and local network model

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Abstract for dissemination (PU)

This document provides the result of a survey targeting distribution network operators across Europe, with as objective to collect insights on how utility companies are nowadays facing problems regarding power quality. More specifically: overvoltage, undervoltage, voltage unbalance, transformer overload and current congestion have been investigated. Based on the survey results, we were also able to identify multiple gaps between the solutions found in the literature and the in-field implementations of network operators. By addressing these topics, we propose a novel solution to mitigate the power quality deterioration that occurs due to the uptake of low-carbon technologies. The latter is described as a phase-swapping approach. Results show that the proposed solution could be beneficial for network operators due to its low costs.

Contents

List of abbreviations

ADN	Active Distribution Network
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
DERs	Distributed Energy Resources
DOEs	Dynamic Operating Envelopes
DR	Demand Response
DSO	Distribution System Operator
DSSE	Distribution System State Estimation
EMS	Energy Management System
EVs	Electric Vehicles
GIS	Geographic Information System
HC	Hosting Capacity
HPs	Heat Pumps
LCTs	Low-carbon Technologies
LVDNs	Low-voltage Distribution Networks
NRAs	National Regulatory Authorities
NTL	Non-technical Loss
OLTC	On-load Tap Changer
PCC	Point of Common Coupling
PLE	Peak Load Estimation
µPMU	Micro Phasor Measurement Units
PVs	Photovoltaics
RMSE	Root Mean Square Error
SCADA	Supervisory Control and Data Acquisition
SM	Smart Meter

1. Introduction

1.1. Background and motivations

Amidst the growing integration of low-carbon technologies (LCTs), significant complexity has been added to grid management, reshaping the strategies distribution system operators (DSOs) employ for grid observation and planning. This deliverable discusses the evolving role of DSOs, focusing on their challenges and digitalisation strategies, particularly in maintaining power quality and leveraging operational data for control and decision-making.

Historically serving a passive role, low-voltage distribution networks (LVDNs) were catalysts to facilitate unidirectional power flow to end consumers. These predominantly relied on well-established assumptions about the load patterns and consumption behaviour, rather than high power loads, e.g. electric vehicles (EVs) or heat pumps (HPs) or the widespread integration of distributed energy resources (DERs), including rooftop photovoltaic systems (PVs). Owing the predictable nature of peak load patterns and the limited availability of data, models of LVDNs were translated as lumped loads with only the medium voltage segment being considered [1].

Furthermore, they were designed on a `fit-and-forget' policy, therefore incorporating an adequate safety margin to account for the anticipated loading levels and power flows as discussed in deliverable "*D4.3: Digital twin model of DN predicting maximum hosting capacity*" [2]. The proliferation of low-carbon technologies (e.g. PVs, HPs, EVs) has prompted a seismic shift that is reshaping both the physical and operational aspects of how distribution network operators plan and manage LVDNs, expanding their responsibilities. Hence, their role evolved to actively manage and operate increased volumes of low-carbon technologies (LCTs). A concept embodied in the transition to a distribution system operator (DSO), which entails active coordination and real-time management of energy resources to ensure system stability. Projections expect that by 2050, over 70% of LCTs will be connected at distribution level [3].

Such exuberant amounts present unprecedented challenges and could potentially jeopardize grid stability. Subsequently, improving the network visibility becomes paramount since the rate at which end-user customers invest in LCTs is quicker than the typical grid expansion planning and execution processes [4]. Nonetheless, this step encounters two main barriers [5]: the (i) the extensive coverage and the multitude of nodes in distribution networks compared to transmission networks; and (ii) the restricted availability of measurement data, which also necessitates higher resolution. Addressing these barriers is vital for ensuring the long-term resilience and sustainability of the grid. To this end, within this deliverable, we aim to uncover the challenges DSOs face and investigate the current state of the LVDNs.

1.2. Contributions to the state-of-the art

Despite growing academic interest, practical implementation of data-driven methods remain limited. Many DSOs lack accurate digital twin models or smart meter data, while researchers employ non-representative LV networks, emphasising the differing pace of advancement between both. Through a targeted questionnaire-based survey, we aim to uncover the operational challenges DSOs face and propose recommendations to support scalable LCT integration, by seeking to address the following research questions:

RQ1: To which extent are LVDNs currently facing power quality deterioration?

RQ2: What are the challenges and discrepancies between DSOs and academic research regarding the applications of operational data?

As illustrated in Table 1, research on the utilisation of smart meter (SM) data by DSOs seldom covers the challenges of LCTs. Additionally, novel techniques (using artificial intelligence, AI) to evaluate and mitigate power quality problems are subject of extensive research, but a comprehensive assessment of the existing issues network operators are confronted with, is currently missing.

Table 1: Comparison table of the relevant literature.

	Survey-based						**Literature**		**This work**
	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	
No. respondents (EU-27)	7	13	68	20	4	21	–	–	40
No. respondents (Total)	19	19	68	21	4	21	–	–	48
Digitalisation	✓	✓	✓	✓	✓	✓	✓	✓	✓
SM use cases	✓	✓	✓	✓			✓	✓	✓
Applications of AI							✓	✓	✓
Grid performance					✓				✓
Challenges due to LCTs			✓		✓				✓
Technical barriers	✓		✓	✓	✓	✓			✓
Policy recommendations			✓			✓			✓
Academia-DSOs gap				✓					✓

To this end, the main contributions of this study can be summarised as:

- Assessment of the problems encountered during the data gathering process and which DSO-oriented use cases for SM data are applied by grid operators;
- Identifying the primary factors contributing to the discrepancy between academic research and DSO practices;
- In-depth evaluation of the contemporary power quality concerns of DSOs, by means of a questionnaire-based survey (with follow-up interviews) and complemented by a systematic literature review;
- Review of the modelling approaches adopted by network operators in the context of LCTs' uptake and their associated challenges.

The interplay between digitalisation, technical barriers and grid performance requires a multifaceted approach. Therefore, the aforementioned topics in LVDNs have been examined by combining secondary data, interviews, and a questionnaire-based survey (see Figure 1). Moreover, based on expert knowledge, we reviewed the modelling approaches adopted by DSOs.

The data collection was based on three methods: (1) a questionnaire-based survey that was digitally distributed; (2) through reports from network operators, European DSO associations and policy documents from governments; and (3) a review of the relevant existing scientific literature as shown in Figure 1. The questionnaire consisted of seventeen questions which started with general information of the respondents, allowing to categorise them and draw conclusions. These were succeeded with four technical categories: (i) the digitalisation of the LVDN; (ii) the applications of the operational data e.g. smart meter data; (iii) the deployment of LCTs and their impact on the grid; and (iv) open questions regarding the modelling and design rules applied by DSOs, and challenges they encounter. A first screening step consisted of cross-validating or correcting certain fields via annual reports from the DSOs themselves. Next, a literature review was conducted to compare the use cases of operational data as found in literature with the applications considered by DSOs. The systematic approach relied on the PRISMA method.

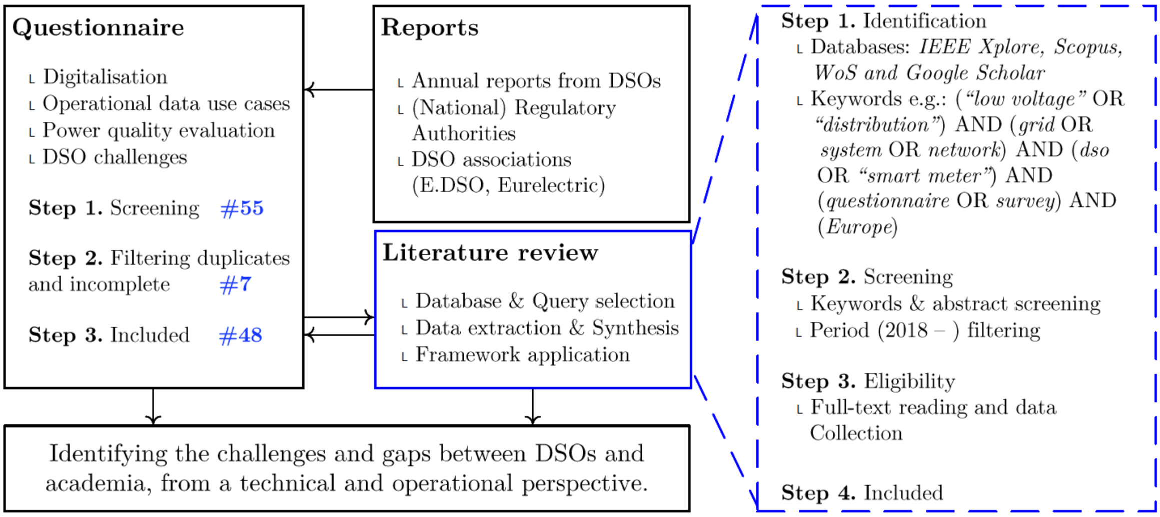


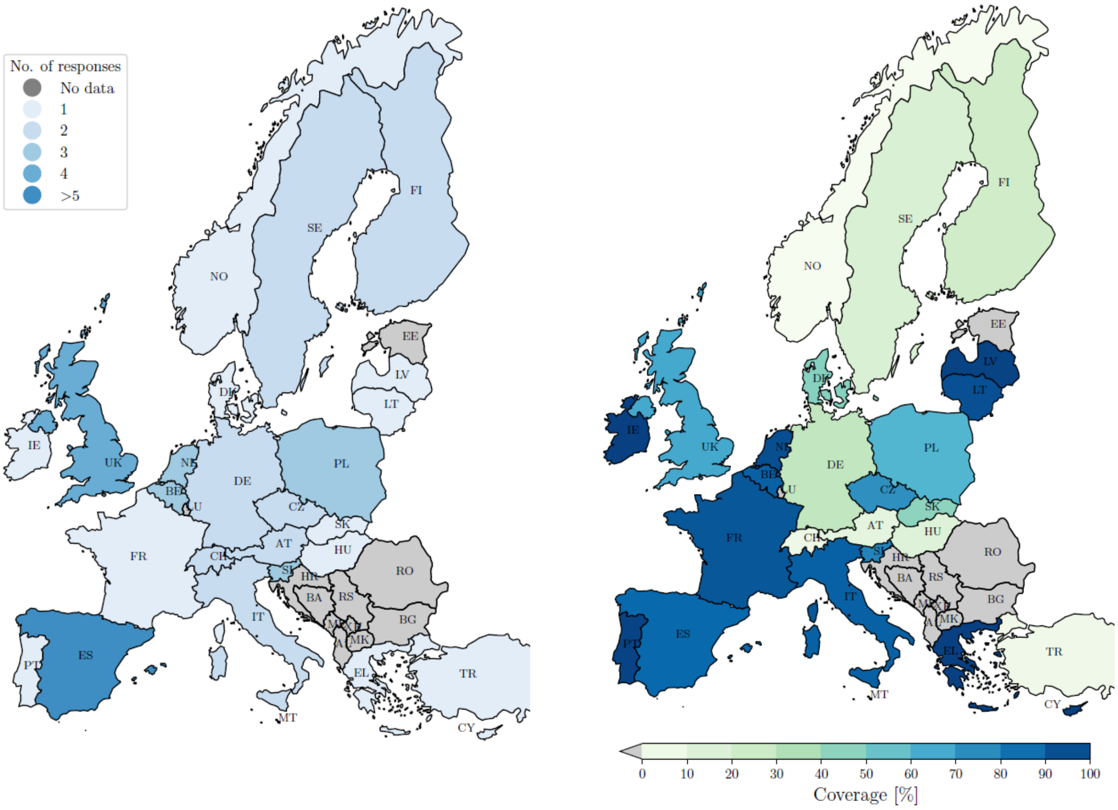
Figure 1: Overview of the systematic review methodology and the literature process.

1.3. About the respondents

Following the data filtering procedure (see Figure 1), data were collected from 48 DSOs based in 25 countries, collectively serving approximately 193.1 million customers. As some of the respondents are from non-EU Member States, some questions were less applicable, but demonstrate how other countries perform. Specific information about the DSOs cannot be disclosed for anonymity and confidentiality reasons.

The survey was conducted over a six-month period, from March 2024 to August 2024. The geographic distribution of the respondents is illustrated in Figure 2. Certain countries exhibit a disproportionate ratio of respondents relative to the total number of DSOs, e.g. for Italy 2 responses were collected, while the country accounts for 123 DSOs. This can be attributed to the respondent(s) being an inter-municipal company that represent several DSOs, owned by a municipality or regional authority.

The surveyed network operators exhibit considerable variation in terms of operating voltages, number of connected customers and coverage of their service area. In this respect, the DSOs were categorised in accordance with the methodology outlined in [14]. For analytical purposes, DSOs operating within an area comprising less than 1500 km² are categorised as urban grid operators. Conversely, for larger areas, the DSO classification is based on the number of customers it serves. Accordingly, the term *small* is used to delineate entities with less than 1 million customers, *medium* for those serving between 1-10 million and finally those exceeding 10 million are categorised as *big*. In alignment with the aforementioned classification, this study encompasses 12 small, 22 medium, 5 big and 9 urban DSOs as shown in Figure 3.



(a) Number of respondents per country *(b) Coverage of connected customers*

Figure 2: Spatial distribution of the respondents.

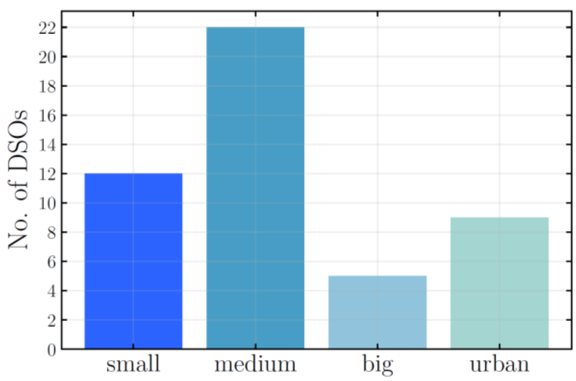


Figure 3: Categorisation of the responding DSOs.

2. Survey findings

In accordance with the Third Energy Package, Member States were required to commence the implementation of SMs. Participating DSOs were asked to self-evaluate the SM roll-out within their perimeter, the results are compared to the latest findings from ACER[1] and CEER[2] 2024 retail market study. Accordingly, our findings revealed a comparatively higher penetration level in Poland and a lower level in the UK. This is attributable to the sample of responding DSOs, which does not cover the whole area. Another interesting aspect to consider, is the granularity of the time intervals, which significantly affects the applicability of operational data [13]. Consistent with the European Commission's recommendation 2012/148/EU, a general consensus to adopt a 15-minute update frequency was reached for SM readings. The latter allows the information to be used to achieve energy savings via e.g. demand response (DR) schemes. In practice, while the reading intervals are not uniformly mandated at a 15-minute resolution, the majority of the countries have adopted this interval. Nonetheless, notable deviations emerged. For instance, one urban Czech DSO reported 15min, a small Finnish DSO indicated 5min; and big DSOs in Spain and Germany reported 15min. The latter were mainly privately owned by international investment firms, active in other countries. Table 2 summarises the SM deployment and the sampling intervals adopted by each country.

Table 2: Smart meter roll-out and sampling intervals. *Italicised are non-EU-27 members.*

Country	Deployment	Granularity
Austria	94%	15min
Belgium	37%	15min
Cyprus	1%	30min
Czechia	4%	60min
Denmark	100%	60min
Finland	100%	15min
France	100%	15min
Germany	1%	60min
United Kingdom	*53%*	*30min*
Greece	4%	15min
Hungary	10%	15min
Ireland, Republic of	73%	15min
Italy	100%	15min
Latvia	100%	15min
Lithuania	48%	15min
Netherlands, the	92%	15min
Norway	*100%*	*60min*
Poland	34%	15min
Portugal	92%	15min
Slovakia	19%	15min
Slovenia	92%	15min
Spain	99%	60min
Sweden	100%	15min
Switzerland	*29%*	*15min*
Turkey	*2%*	*60min*

[1] ACER: Agency for the Cooperation of Energy Regulators
[2] CEER: Council of European Energy Regulators

Regarding the issues pertaining to the SM data gathering process, we discerned four categories:

- Power line communication or telecom congestion takes the crown with the majority of the DSOs (47%) identifying it as the primary issue they encounter. One of the reasons is the excessive amount of data being transferred, while originally the wired network was not intended for.
- Limited coverage of the (cellular) communication network was the second in line (30%), which mainly occurs in rural and remote areas while roaming possibilities are restricted for border regions. In addition to the communication network (principally the responsibility of a third-party provider), respondents occasionally mentioned a weak Narrowband Internet of Things (NB-IoT) signal due to the SMs being installed indoors (mainly in the UK). Another reason is the phasing out of the GPRS services.
- To a lesser extent, complications related to the SMs themselves were delineated, including both, invalid or missing meter readings and hardware failures, which to some extent required a reactivation of the SM by the network operator.
- Data privacy concerns were mainly identified by British DSOs, due to the implementation of the UK Data Protection Act and the Data Access and Privacy Framework. However, individual interviews revealed that privacy often hindered use cases of operational data.

Remarkably, 19% of the respondents indicated they do not encounter issues. This group predominantly comprised DSOs with a limited operating area or modest customer base (i.e. urban and small DSOs respectively). By contrast, big DSOs within this subset had a relatively marginal SM roll-out (< 15%), or were already engaged in the deployment of second generation SMs. Article 59(1) of the EU Directive 2019/944, stipulates national regulatory authorities (NRAs) to submit periodic reports on the performance of DSOs concerning smart grid developments and founded on a series of indicators.

3. Operational data applications

3.1. Different types of measurement devices

The range of potential applications for advanced metering infrastructure (AMI), including smart meters is extensive and diverse. These applications are well documented in the literature, addressing a variety of topics pertinent to a diverse set of stakeholders, ranging from end-users to aggregators, flexibility providers, and DSOs [15]. However, developing and operating distribution grid energy services requires massive amounts of heterogeneous data which is not solely provided by AMI, but also from supervisory control and data acquisition (SCADA) systems, or micro phasor measurement units (µPMU). Aforementioned advanced sensor devices are being classified as operational data sources, referring to information extracted from the distribution grid measurement devices [12]. On the question whether they had a SCADA system, µPMUs, AMI or similar measurement devices in place to control and monitor their assets, participating DSOs responded as follows:

- Approximatively 90% of the respondents utilise SCADA systems;
- 17% have µPMUs in place, aligned with the 21% observed by the JRC (2020, [16]);
- 70% indicate to use AMI as control and monitoring device;
- 30% mentioned additional devices (e.g. power quality meters).

A comparative overview of the three types of measuring devices is presented in Table 3.

Table 3: Comparison of the measurement devices.

Category	Metering level	Sample rate	Parameters	Application
SCADA	Substation level	Every 2~5sec	Voltage magnitudes; Active and reactive power	Measurement and control (e.g. send control command to switching devices such as circuit breakers), fault detection, and communication.
μPMU	Substation & Feeder level	> 512 per sec	(Phase) Phasor voltage and current; Active and reactive power	Achieve a better visibility (in real-time) of the distribution network. DSOs can use the data from μPMUs as input for the SCADA system.
AMI	Customer-side	Every 15min - 1h	Energy; (Phase) voltage and currents; Active and reactive power; Power factor	Besides its main purpose (i.e. billing), AMI can be used for near-real time control through DR schemes.

3.2. State-of-the-art applications for operation data

Through a meticulous literature review, several distribution network-oriented topics using operational data have been identified [12, 13, 17, 18], embracing: (i) power system operation & monitoring, (ii) investment planning & asset management, (iii) distribution system state estimation (DSSE), (iv) forecasting, and (v) flexibility management. Each of these categories are characterised by specific services that necessitates different measurement units from the operational data. While some topics may overlap, distinctions between subcategories are maintained to ensure clarity, even if the boundaries are sometimes fine or nuanced. Figure 4 visualises the taxonomy of the dominating distribution network-oriented topics.

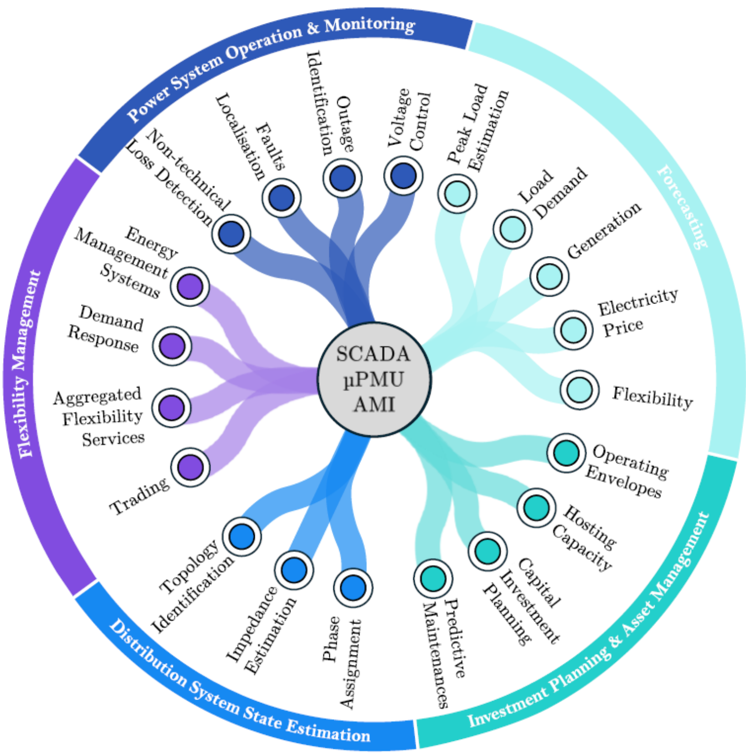


Figure 4: Taxonomy of the various applications of operational data.

3.2.1. Power system operation & Monitoring

Voltage control in LVDNs traditionally relies on SCADA systems for telemetry and remote switching. However, the integration of LCTs introduces variability that challenges conventional methods like on-load tap changers (OLTCs), voltage regulators, and D-STATCOMs. Modern approaches emphasize active network management using centralized and decentralized autonomous and coordinated strategies [19]. These include network reconfiguration, shunt compensation, and demand-side management, complemented by source-level curtailment and inverter control. Advanced optimization techniques and fairness-based curtailment schemes further enhance voltage stability under dynamic conditions.

Outage detection and localisation in LVDNs is complex due to radial structures, unbalanced loads, and low observability. Solutions range from probabilistic models leveraging AMI data to machine learning and deep learning approaches that adapt to diverse grid characteristics. Enhanced methods, such as sparse tracking using differential phasors, improve accuracy by prioritizing state variables and identifying event zones [20]. These innovations enable faster and more reliable fault identification, supporting resilient network operations.

Non-technical losses (NTLs), primarily electricity theft or unmetered consumption [21], are detected using data-oriented, network-oriented, or hybrid approaches. Data-oriented methods analyse consumer data from smart meters, while network-oriented techniques use power flow and equipment data. Hybrid models combine both, offering improved fraud detection through feature engineering and anomaly analysis. Advanced algorithms using operational data, including correlation-based methods, achieve high accuracy.

3.2.2. Investment Planning & Asset Management

Metering and operational data play a critical role in guiding maintenance strategies and long-term investment decisions. Accurate asset condition monitoring enables preventive maintenance, reducing costs and minimizing outages [22]. SCADA data supports failure probability estimation, while hosting capacity (HC) studies inform planning for integrating low-carbon technologies (LCTs) [23]. These studies compare passive measures like grid reinforcement with active flexibility solutions, using deterministic and stochastic approaches to address uncertainty.

As networks evolve with high LCT penetration, DSOs are shifting from rigid HC limits to dynamic operating envelopes (DOEs). DOEs define time-varying active and reactive power limits at customer or aggregated levels, ensuring safe operation while maximizing flexibility [24]. By forecasting and disseminating these envelopes to aggregators, DSOs can optimize LCT integration and prevent voltage (or thermal) violations, and enable cost-effective grid adaptation.

3.2.3. Distribution System State Estimation

Accurate DSSE is essential for reliable network operation and planning but is often challenged by incomplete or erroneous data, such as unreported reconfigurations or incorrect phase connectivity [25]. These inaccuracies can lead to false alarms, voltage issues, and inefficient optimization. To mitigate this, DSSE workflows incorporate anomaly detection and data pre-processing, alongside geographic information system (GIS) corrections. Applications fall into three main clusters: topology identification, impedance estimation, and phase assignment.

Topology Identification**:** Methods range from static GIS-based reconstruction to data-driven approaches using SM and µPMU measurements. Techniques include regression models, recursive grouping, and algorithms leveraging voltage-current relationships to infer switch states and connectivity, even under limited observability [26].

Impedance Estimation: Accurate line impedance estimation improves protection settings and operational performance. Approaches include linear approximations using historical data, two-step admittance-based methods [27] with iterative corrections, and advanced regression models capable of estimating neutral line impedances in three-phase systems.

Phase Assignment: Correct phase connectivity is critical for load balancing and capacity estimation. Modern solutions replace manual verification with clustering, regression, and correlation-based algorithms using SM voltage and consumption data [28]. Advanced methods address multi-substation scenarios and achieve high accuracy even with sparse measurements.

3.2.4. Forecasting

Forecasting in distribution systems spans multiple applications, including peak load estimation (PLE), demand, generation, electricity prices, and flexibility. Each application requires different time horizons, i.e. short, medium, or long term, depending on operational or planning needs [29]. Smart meters enable more accurate peak load prediction and transformer ampacity estimation, improving asset life management. Advanced models such as neural networks, cross-learning, and dynamic mode decomposition enhance short- and long-term demand forecasting, supporting DSOs in managing large asset portfolios [30].

Generation forecasting leverages weather data and hybrid models combining convolutional neural networks, long-short term memory and autoregression algorithms to capture spatial and temporal correlations for renewable energy sources [31]. Flexibility forecasting uses index-based methods to inform DSOs about real-time operational manoeuvres, while electricity price forecasting has gained relevance due to LCT's variability (although DSO are merely stakeholders of the solutions that emerge from these), with deep learning outperforming traditional approaches [32]. Overall, forecasting tools are critical for optimizing operations, planning investments, and integrating distributed resources efficiently.

3.2.5. Flexibility Management

The rise of low-carbon technologies (LCTs) has driven the adoption of energy management systems (EMSs) that leverage smart meter data for applications such as self-consumption optimization, peak demand reduction, and cost minimization. Advanced control strategies include metaheuristic algorithms for interpretable decision trees, reinforcement learning, and model predictive control [33], enabling real-world cost optimization and operational efficiency. Note that the later has been developed within the ECOFLEX project and is described in deliverable "*D5.2 Multi-energy community energy management*" [34]. Forecasting-based EMSs balance profitability, complexity, and security by minimizing energy exchange between prosumers and the grid.

DR schemes and hierarchical control strategies allow DSOs to aggregate flexibility from assets like heat pumps and EVs, reducing congestion and enabling participation in energy markets [35]. Data-driven optimal power flow models integrate network parameters and fairness objectives to manage DER curtailment effectively. Beyond DR, peer-to-peer energy trading introduces a decentralized paradigm where prosumers balance surpluses and deficits, with

DSOs ensuring grid integrity during scheduled exchanges [36]. These approaches collectively enhance grid resilience and unlock new flexibility services.

3.3. Gap between research and utility implementation of operation data solutions

3.3.1. Discussions on power system operation & monitoring

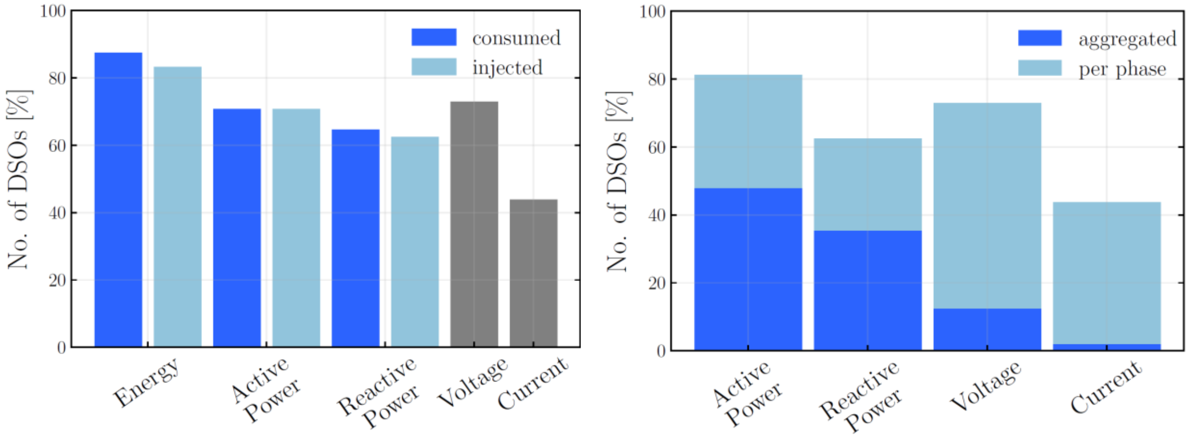
Although advanced AI models for fault localisation, anomaly detection, and voltage control are actively researched, large-scale deployment by DSOs remains limited. Key barriers include a lack of skilled personnel, inadequate infrastructure, fragmented data systems, and regulatory constraints (e.g. reactive power control [37]). DSOs also question the scalability and whether the incremental accuracy gains justify the cost. For example, narrowing fault location from hundreds to tens of metres rarely impacts restoration logistics, as labour and civil works dominate outage costs. Deploying widespread sensors and complex algorithms add operational burdens that DSOs struggle to replicate at scale. Transparency is another concern: NRAs require explainable, auditable methods, yet many academic models are too opaque for regulatory approval. EU interoperability rules further complicate adoption, as DSOs are cautious of sharing granular smart meter data that could erode their informational advantage. Ref. [38] proposes a scalable reconfiguration method, but its reliance on detailed network models may hinder implementation. Despite these challenges, OLTC applications are growing, but high costs remain a barrier for certain DSOs. Encouragingly, DSOs are exploring operational data for NTL detection, with the `last gasp' as a typical example mentioned by respondents.

3.3.2. Discussions on investment planning & asset management

The majority of DSOs continue to rely on rule-based approaches for predictive maintenance and long-term investment planning, creating a persistent gap between industry practice and academic research. Scaling advanced data-driven solutions is hindered by limited access to high-quality training data, alongside concerns over data privacy and cybersecurity. While Ref. [39] includes substantial volumes of SM data, the authors acknowledge representativeness bias, as 15min recordings are self-activated by more engaged households. Furthermore, these dwellings are predominantly newer and equipped with LCTs. DSOs are also reluctant to share granular or synthetic datasets, as it may weaken their role as data stewards. Without clear governance frameworks, synthetic data initiatives risk undermining trust and accountability. In planning, DSOs typically adopt deterministic worst-case snapshots for HC – maximum demand and maximum generation – due to their simplicity and evident justification during regulatory audits. Although academia promotes probabilistic HC and DOEs to enhance DER integration, these methods face scalability and transparency challenges. Oversizing cables and transformers remains common, as infrastructure works dominate costs, rendering hyper-accurate peak forecasts economically irrelevant. Probabilistic models, while technically superior, are harder to justify to regulators, creating approval hurdles. Recent research, however, stress the potential of operational data to support probabilistic approaches and DOEs, offering greater grid flexibility.

3.3.3. Discussions on distribution system state estimation

The survey revealed considerable potential for leveraging SM data in DSSE, and was identified as a priority by many DSOs. To this end, utilities collect multiple meter readings (Figure 5, a), with the majority used for billing (87% of respondents). Active and reactive power readings are also widely reported, with active power frequently used in regression-based DSSE models. To assess data suitability, we examined the ratio of single-phase to aggregated measurements. While energy and power data are typically aggregated, voltage and current records are predominantly per phase (Figure 5, b), enabling DSOs to apply non-complex models to infer phase connectivity [40].



(a) Collected smart meter readings. *(b) Breakdown of the meter readings.*

Figure 5: Collected smart meter readings by the DSOs and breakdown into aggregated or per phase measurements.

DSSE illustrates the tension between technical ambition and practical scalability. Academic research on operational data promises near-real-time observability. Yet, DSOs report diminishing returns when pushing accuracy from e.g. 95% to 99%, given the disproportionate investment in monitoring. For utilities using DSSE primarily for situational awareness, such marginal gains offer limited operational benefit. Scaling DSSE is further hindered by incomplete SM rollouts and inconsistent GIS data – although, GIS correction can be achieved with operational data. As priorly discussed, NRAs require validated and explainable methods before DSSE outputs can inform regulated decisions, while algorithms remain opaque.

3.3.4. Discussions on forecasting

According to the survey, DSOs predominantly rely on fixed rule-based methodologies (e.g. Velander's formula, after diversity maximum demand, coincidence factor), which embed conservative approximations [41]. These approaches are increasingly misaligned with evolving grid patterns due to LCTs, prompting a need to leverage operational data for more accurate (peak) load estimation in long-term planning. While academic models for feeder-level load, PV/EV forecasting, and flexibility availability have achieved high accuracy, DSOs tend to favour conservative headroom rules over marginal accuracy gains. Decisions such as maintaining static limits are seldom altered by 1–2% improvements, and the governance or training burden of complex models is non-trivial.

Flexibility solutions have made significant progress, often supported by DSOs (as stakeholder) through short-term forecasting for congestion management. However, being by nature regulated monopolies, DSOs typically delegate implementation to market-based mechanisms [42]. Further, a granularity mismatch also persists: while per-customer forecasts benefit retailers and aggregators, DSOs operate mainly at feeder or transformer level and see limited value in enabling third-party analytics, especially when bearing the privacy, cybersecurity, and reputational risks of data sharing.

3.3.5. Discussions on flexibility management

Despite significant advances, DSOs face persistent implementation barriers. Research approaches often assume seamless access to high-resolution data and interoperable platforms, whereas DSOs operate with legacy systems, limited real-time visibility and are constrained by regulatory frameworks. Privacy concerns and unclear market roles further restrict the use of aggregated flexibility services [43]. While technically feasible, DSOs may lack the regulatory mandate to procure or facilitate such services, highlighting the need for pilot projects and regulatory sandboxes to scale promising solutions found in literature. The latter was also extensively analysed within the ECOFLEX project under deliverables: "*D2.4 Guidelines Legal Enabling Framework for Energy Management Service Providers*" [44] and "*D2.5 A Cost-benefit Analysis of the Energy Management Service Provider's Roles*" [45]. Flexibility management exemplifies incentive misalignment and scalability constraints. Academic work explores optimisation techniques, demand response, and peer-to-peer trading solutions to unlock distributed flexibility. Yet, these are treated by DSOs as short-term/temporary measures until grid reinforcement is viable. Due to the localised nature of congestion, its intrinsic costs (procurement, verification, etc.) can be prohibitive. Under current remuneration models, these costs are treated as operational expenses, offering no return compared to capital investments. Transparency adds further complexity. NRAs emphasise neutrality and consumer protection, requiring clear procurement rules and auditable processes.

3.4. Barriers hindering large-scale adoption of operational data use cases

To conclude this chapter, we categorise the identified barriers by adopting the framework proposed by Monaco *et al.* [46]. Technical barriers primarily stem from legacy infrastructure (and platforms) with interoperability limitations and concerns related to cybersecurity and data protection. Organisational barriers reflect the lack of awareness from DSOs, apprehension about business disruption, cultural misalignment and coordination challenges among stakeholders. Regulatory barriers arise from policy frameworks governing digitalisation, including obligations for data security and explainability. Complemented with the lack of standardisation. Financial investment constraints, compounded by uncertainty regarding the profitability of digital solutions form the economic barriers. Besides, incentive-based regulation often prioritises OPEX-efficiency as noted in [46], thereby intensifying digitalisation challenges. Finally, human factor-based barriers are largely associated with the shortage of skilled personnel required to implement and manage advanced systems. The different categories are visualised in Figure 6.

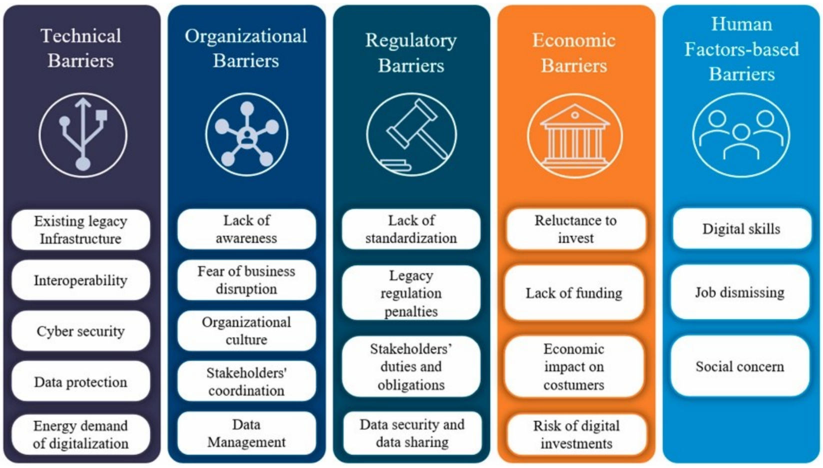


Figure 6: Digitalization barriers and main challenges (Courtesy of Monaco *et al.*)

Table 4 synthesises the different barriers we identified per operational data use cases.

Table 4: Dominant barriers to large-scale adoption by use case.

Use case	Technical Barriers	Organisational Barriers	Regulatory Barriers	Economic Barriers	Human Factor Barriers
Operation & monitoring					
Voltage control	X		●		X
Outage identification	X				●
Faults localisation		●		X	●
NTL detection		●			X
Planning & asset management					
Predictive maintenances	X			●	●
Investment planning	X	X	●		
Hosting capacity	X	●	●		
Operating envelopes			X	●	X
Distribution system state estimation					
Topology identification	●	X	●		●
Impedance estimation	●	X	●	●	X
Phase assignment	X	●			
Forecasting					
Peak load estimation	●	X			
Load demand	●	X			
Generation	●	X			●
Flexibility	X	●	●		X
Flexibility management					
Energy management system		X		●	
Demand response		●	X	●	
Aggregated flex. services	●	●	X	X	
Trading (P2P)	●	●	X	X	

Legend: **X** = primary barrier; ● = secondary barrier.

4. Network planning and grid design

At present, approximately 30% of low-voltage distribution cables are over 40 years old [3] and projections indicate that this figure could rise to 90% by 2050. Conjointly, global and national sustainability goals are accelerating the integration of LCTs. Therefore, a comprehensive reassessment of the validity of the sizing methods employed by DSOs is imperative. Moreover, the substantial expansion of LCTs results in a discrepancy between the anticipated load on the potential loads caused by EVs or the simultaneity of HPs. In addition, the ramifications of reverse power flows resulting from DERs merit explicit consideration. To this end, PLE are considered as crucial to capture the diverse dynamics from the consumers' diversified demand pattern. Depending on the availability of operational data, different methods are valid. For instance, if only annual electricity consumption from the connected customers is at hand, the substation or feeder's maximum demand can be approximated by means of aggregation. Alternatively, a frequently applied method is to convert the annual consumption into standardised (synthetic) load profiles that represent typical customer types based on their annual demand. In contrast, operational data allows to enhance the standardised load profiles by introducing more realistic patterns [47, 48] which results in a more flexible approach.

Building upon the acquired responses, we classify the network design approaches into four categories, see Figure 7.

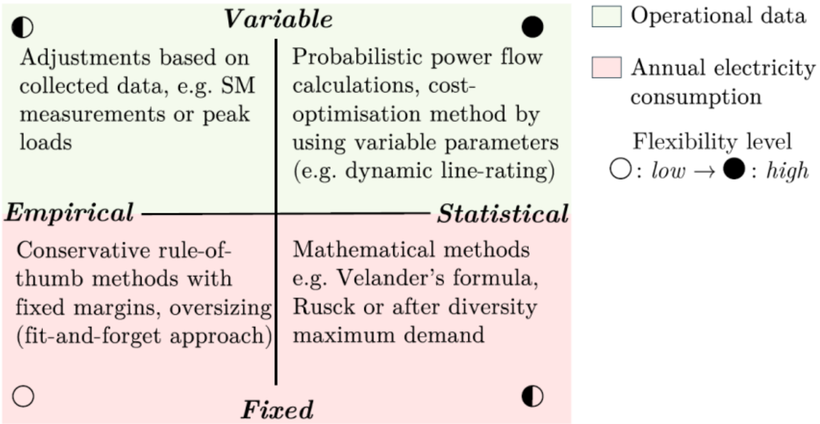


Figure 7: Classification of the network design approaches.

Bearing in mind that the majority of low-voltage cables are buried for a long period, the design of the LVDN must be meticulously conceived. Established design approaches, therefore typically assume worst-case scenarios, aligned with the fit-and-forget doctrine, as a cost-efficient investment strategy. The predefined values depend on: (i) the type of customers; (ii) the operating region; and (iii) the number of dwellings connected to the feeder. Some respondents have specified considering a margin of 30-40% above the expected maximum demand. Moreover, statistical methods like Velander's formula (typically in Scandinavian countries) and/or the Rusck model for the coincidence factor are commonly applied for PLE [41].

In this regard, most DSOs consider a low coincidence factor (0.2 to 0.4) for conventional households, depending on the contractual power of the dwelling. This factor is periodically re-evaluated based on regional aggregated consumption and national regulations. Alternatively, a widely used approach in the United Kingdom for PLE is the *after diversity maximum demand* (or ADMD) index [49, 50], which estimates peak load during the highest demand on the substation. However, this method tends to be less accurate for networks with a limited number of connections. For PV installations, a coincidence factor of unity is regularly assumed – without considering loads – to reflect worst-case injection scenario. The integration of LCTs introduces a trans-axial shift in traditional grid design methodologies (i.e. Figure 7), prompting DSOs to progressively adjust the coincidence factor, or alternatively, incorporate operational data into long-term planning [51]. Becker *et al.* [39] demonstrate that operational data can improve the understanding of LCTs' impact on both the timing and the magnitude of the peak demand. However, the use of operational data remains in its early stages, partly due to a incomplete SM deployment (Table 2) and the limited accessibility of SM data – hindered by privacy and regulatory concerns – which is confined to for R&D purposes. As no one-size-fits-all solution exist, margin criteria vary depending on the region of interest and are applied either through predefined assumptions or based on field expertise. In absence of precautionary measures, the contractual capacity of the connection point, or the HC of the feeder becomes the limiting factor. Meanwhile, smart functions for controlling PV inverters (e.g. DR schemes) are emerging.

5. Evaluation of the grid stability metrics

5.1. Definitions and occurrences

To evaluate the technical impacts of LCTs, a set of grid stability metrics encompassing both voltage and thermal implications is defined, with reference to the limitations imposed by the EN50160:2022. Among them are: overvoltage, undervoltage, voltage unbalance, line overloading and transformer overloading. These were also extensively discussed in deliverable D4.3 [2]. In practice, DSOs with limited visibility rely on customer complaints to identify instances of overvoltage, undervoltage and voltage unbalance. As such, operational data analytics demonstrated to be a promising alternative to proactively detect and mitigate aforementioned issues. To evaluate line overloading, utilities typically rely on digital twin models and power flow analyses. Through periodic assessments based on time-varying load profiles (e.g. SM data), priority regions requiring investment can be identified. Consequently, accurate GIS information is crucial for network operation and targeted expansion, emphasising the applications of GIS correction. Further, survey respondents revealed to monitor the state of the distribution transformers through SCADA systems.

To examine the extent to which the surveyed DSOs encounter the aforementioned power quality metrics, one question was devoted to the frequency at which the various phenomena are experienced. Figure 8 offers from a more aggregated representation the frequency of occurrence of a specified grid stability metric.

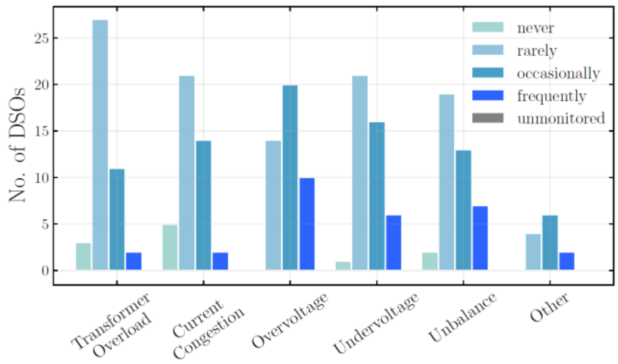


Figure 8: Frequency of occurrences of power quality indicators, based on survey results.

Most DSOs report a lower incidence of transformer overload and intermittent current congestion. In contrast, voltage deterioration; particularly overvoltage is more widespread, with the majority of the DSOs experiencing it occasionally or frequently across their control areas. Interviews revealed growing concerns regarding overvoltage, largely due to increasing PV inverter disconnections caused by elevated voltage levels in areas with high DER penetration. Although undervoltage is currently less prevalent, future projections of LCTs (e.g. electric vehicles or heat pumps) might reverse this tendency due to their substantial load demand. It is therefore incumbent upon regulatory entities to encourage smart charging initiatives [52, 53], supported by appropriate compensation mechanisms. One should note that within the ECOFLEX project, a novel smart charging algorithm has been introduced. We refer to deliverable "*D4.1 Report on different smart charging management structure for electric vehicles*" [54]. Further, we observe that voltage unbalance shows a comparable pattern to undervoltage, with 42% of respondents reporting occasional or frequent occurrences. Since unbalance is mainly driven by the asymmetric load spread over the three phases, §5.2 examines the ratio of single- to three-phase consumers. Regional disparities in grid stability metrics are visualised in Figure 9.

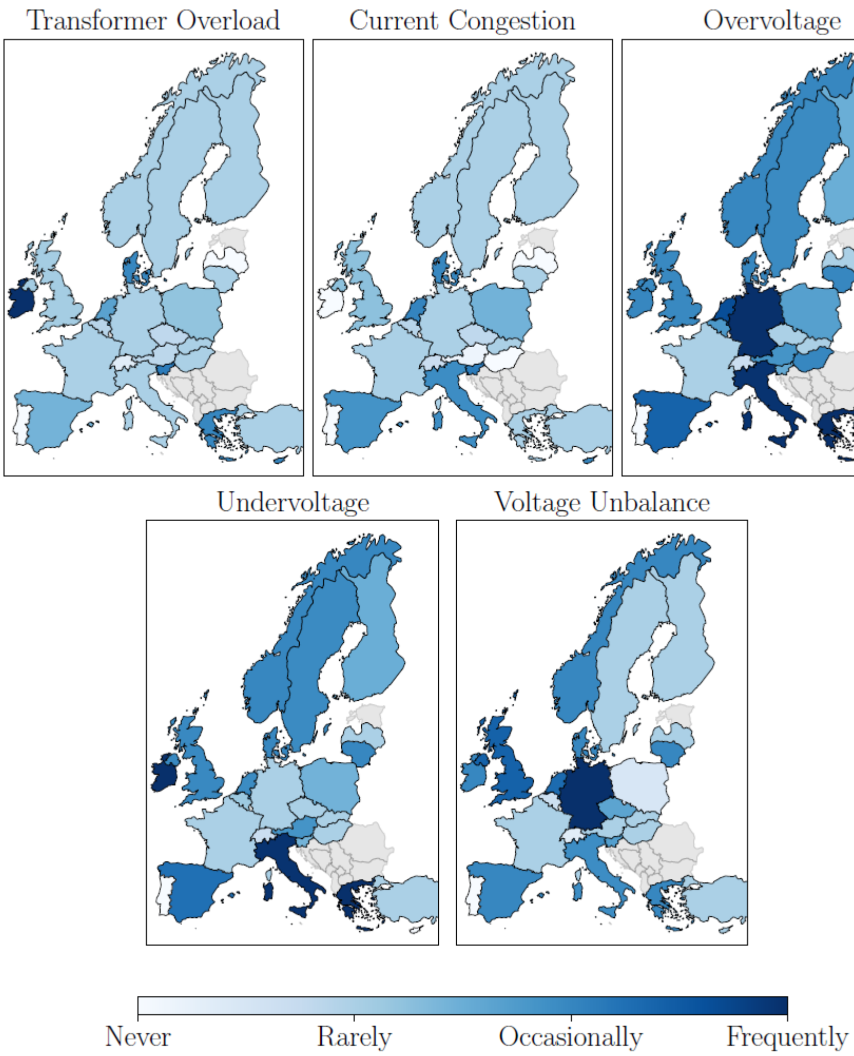


Figure 9: Spatial distribution of the investigated power quality parameters, mapped occurrence frequency and weighted by customers per country.

Finally, among the responses categorised as `Other', harmonic distortion was most often reported as an occasional issue, while load and reactive power unbalance were frequently cited deviations.

5.2. Root causes of the various grid stability metrics

According to the survey results, voltage quality problems are currently the most pressing concern, as shown in Figure 8 and Figure 9. Overvoltage, undervoltage and voltage unbalance are the prominent aspects DSOs do encounter. On the one hand, the emergence of high loads including EVs and HPs increases the risk of undervoltage or even unbalance [55, 56] in LVDNs, unless anticipatory measures are implemented. On the other hand, the advent of DERs has introduced reverse power flows resulting in overvoltage events [57, 58]. Reasons for voltage unbalance have been extensively studied in [59], which identified four main causes: (i) random phase and loads allocation, (ii) use of single-phase service cables, (iii) asymmetrical load behaviour and (iv) unbalanced faults (e.g. line-to-line short circuit). While (i) and (ii) relate to power system planning, (iii) and (iv) are less predictable. Several respondents reported to investigate the practicability of operational data to mitigate the asymmetrical load behaviour, such as the applications in [28, 60, 61].

To identify causal relationships with the power quality issues, we examined the proportion of single-phase consumers (Figure 10). Results were subject to a weighted average filter at country level, based on the DSO coverage (i.e. connected customers).

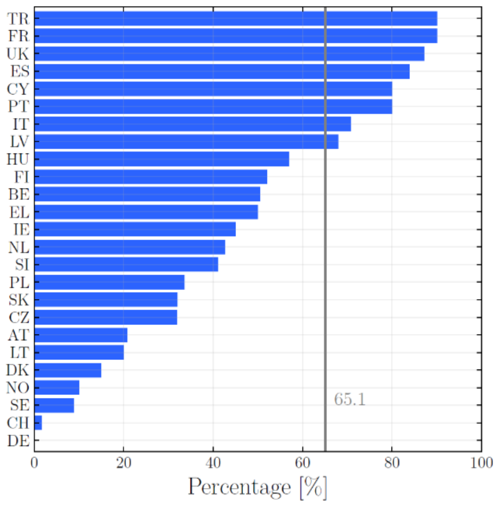


Figure 10: Indicative proportions of single-phase connections at LV-side. Median: 65.1%, considering the number of customers as weight.

Linking the results of the single-phase percentage with the power quality occurrences was not compelling. For example, France, with a high proportion of single-phase connections, reports few voltage violations, whereas the United Kingdom (with similar ratio) experiences frequent voltage unbalance despite comparable LCT penetration. As the initial survey did not aim to identify root causes, isolating contributing factors remained challenging. Especially given the diversity among DSOs. Instead, to quantify influencing factors, a follow-up survey was conducted with the same respondents. The objective was to discover the most significant proxies (e.g. network design, seasonal pattern, regulation) affecting power quality metrics. For each metric, predefined causes – according to expert knowledge – were rated on a severity scale from 0 ('no influence') to 5 ('critical'). Seventeen DSOs participated, comprising: 3 urban; 4 small; 9 medium; and 1 big DSO. Figure 11 displays the results.

Transformer overload is influenced equally by peak demand and uneven phase loading (unbalanced situation). But, loading patterns vary significantly depending on the operating regions (i.e. rural, sub-urban and urban areas), making it important to consider in this context. The fit-and-forget principle has proven to be an adequate design method to mitigate overload risks. DSOs monitor substations periodically and take corrective actions to prevent an escalation in overload. Moreover, some respondents quoted that: `LV transformers are usually kept in stock', allowing rapid intervention if needed. *Current congestion* is loosely associated with voltage deviations. For instance, overvoltage incentivise DSOs to implement measures such as voltage regulators, which can enable additional connections and potentially lead to current congestion. Furthermore, network design and peak load simultaneity cannot be overlooked, alongside the operational region.

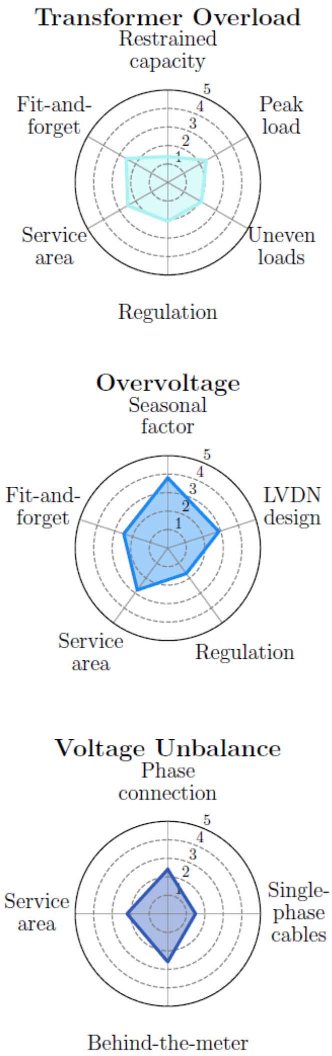


Figure 11: Ranking of the power quality origins according to DSO expert interviews.

LVDNs primarily experience *overvoltage* during summer months (or periods of high solar irradiance and simultaneity) driven by DERs' intermittent nature. Network design did not fully account for high penetrations of DERs, as evidenced by the survey respondents. Service area will also influence the root origin in this case, as longer LV lines (typically found in rural areas) manifest greater voltage rises. In contrast, *undervoltage* shows less seasonal variation, likely due to lower prevalence of flexible LCTs such as EVs and HPs. Overall, results reveal a clear pattern, with network design and the operating area being the predominant contributing factors. As noted earlier, the proportion of single-phase connections does not directly correlate with *voltage unbalance*. First, two small DSOs attributed frequent occurrences to single-phase service cables. Second, end-user phase connectivity and behind-the-meter configuration (e.g. three-phase connection with single-phase PV systems) were cited by other respondents.

6. Discussions

The questionnaire, combined with a systematic review, addresses different topics related to DSOs. Despite the valuable insights, it is also subject to a series of limitations. First, responses collected from small DSOs are assumed to be representative of a specific demographic area, e.g. rural network. This assumption may not hold for DSOs covering larger territories, typically spanning multiple demographic regions including rural, suburban and urban areas. Consequently, some of the obtained figures may reflect aggregated averages or highlights from specific regions. Accordingly, the severity of certain responses could vary, potentially appearing milder or more pronounced. Second, several respondents were affiliated with inter-municipal companies (or umbrella organisations) representing several *small* DSOs. While it is not expected to significantly influence the operational status in the field, subtle differences in interpretation between the inter-municipal entity and its constituent regional DSOs may nonetheless arise, obscuring the heterogeneity. Third, the diversity in respondents' roles and departmental affiliations also constitutes a limitation. Although the majority were positioned within innovation departments, a smaller subset represented regulatory affairs, strategy, or planning divisions. Regardless of their formal roles, respondents indicated to consult internally for technical questions, which may have introduced variability in the depth or framing of certain responses. Finally, it can be observed that responses are representative at national level unless a restricted quantity of responses were obtained.

Several limitations also arose from the included studies themselves. One is the scale or representativeness, such as in [39] where the authors acknowledge a bias in the used SM data. Another is the lack of standardised definitions or methodologies to measure them. For instance, a salient observation of the study pertains to the ambiguity surrounding LCT adoption. In the case of PV installations, some DSOs rely on rough estimates based on subsidy applications, or mandatory reporting. The EV-landscape is similarly fragmented, with DSOs having low visibility into residential charging infrastructure, mainly inferred from connection upgrade requests or subsidies applied for. Despite growing interest in LCTs, conventional technologies such as ICE vehicles, gas boilers and traditional air conditioning units remain dominant. LCT penetration levels are illustrated in Figure 12. Note that the figures are subjective, insofar as they do not always cover the whole country. Additionally, our survey employed a multiple-choice format, with penetration levels segmented in 20% intervals (e.g. 0-20% and so forth).

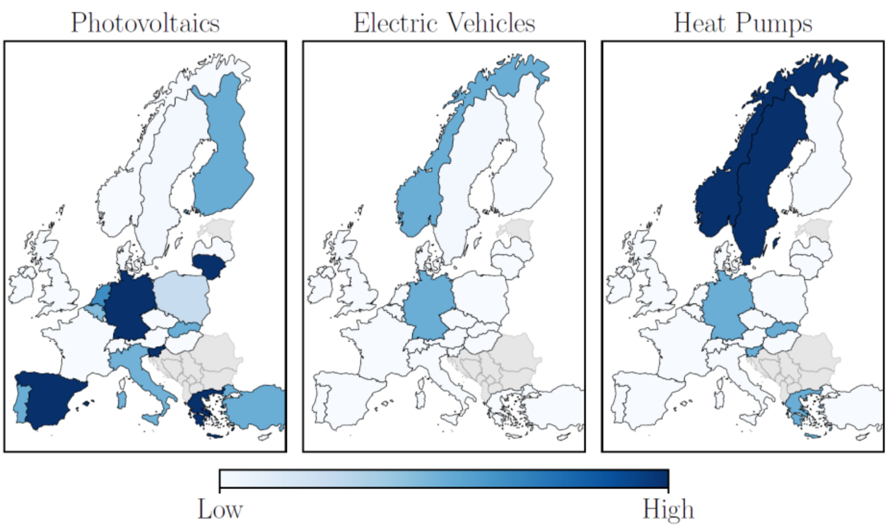


Figure 12: LCT penetration rates according to the respondents.

Nonetheless, we observed analogous trends to those documented in other studies, e.g. the PV shares [62]; the EV penetration (Eurostat [63]) which is predominantly below 3%, expected from Norway, reporting a 20% share. Scandinavian countries dominate the adoption of HPs, and in the absence of official numbers, the residential HP sales reported in [64] were used to validate our findings. It should be noted that air conditioning units are excluded from this analysis, although these significantly impact the distribution grid (i.e. Italy, Spain). Finally, the absence of a unified definition for the frequency of the various power quality issues hinders cross-border comparability. While quality of supply is quantified by both, the *system average interruption duration index* (SAIDI) and the *system average interruption frequency index* (SAIFI), their interpretation and application vary significantly. For example, voltage levels are not always distinguished when reporting these indices [65]. Moreover, the origins of the interruption are region-specific: heavy snowfall impacting overhead lines will more prevalent in Nordic countries, whereas wildfires in Southern Europe, can lead to widespread regional outages.

Aforementioned methodological variability complicates direct comparisons and to generalise on a European level. We therefore recommend European DSO associations and NRAs undertake a comprehensive study using standardised definitions to quantify: the digitalisation among DSOs and the current power quality state and challenges, with the 2050 targets in mind. Notwithstanding these limitations, this article provides valuable insights into the extent LVDNs are currently facing power quality deterioration. Overall, no clear trend emerged between power quality indicators and potential influencing factors (including LCTs adoption). Several reasons may contribute to the lack of a discernible pattern: (i) the considerable diversity in operating regions, (ii) differing network design and expansion criteria across DSOs, (iii) regulatory framework such as tariff structures that incentivise consumer behaviour (e.g. peak demand reduction) and impact transformer loading, current and voltages congestion, (iv) the spatial and temporal variability of DERs, which can mask underlying patterns, and (v) the relatively early stage of LCT adoption in many member states. While a strong correlation between voltage unbalance and the proportion of single-phase connections might be expected, the findings did not support this assumption. Voltage unbalance was observed across networks with both low and high single-phase rates, suggesting that additional factors must be considered to draw meaningful conclusions. To this end, the follow-up survey provided valuable insights.

Overall, the findings highlight a significant diversity among DSOs and reveal a lack of regulatory consistency across regions. In our opinion, this should be addressed by fostering best-practice sharing among DSOs, alongside increased transparency and involvement from DSOs in academic research. To narrow the gap between academic innovation and DSO implementation, coordinated actions are essential. Such collaborations would not only support the development of harmonised approaches for effective LCT integration, but also ensure that academic efforts are more consistently aligned with DSO practices and operational needs. For DSOs, open-source benchmark networks and realistic synthetic SM data, co-developed with academia, can mitigate data-sharing barriers while preserving privacy and cybersecurity. For policy-makers and NRAs, mandating clear frameworks that support controlled data-sharing mechanisms, and clarify DSOs' roles in flexibility procurement are essential. Moreover, they should address the transparency in network development plans, distinguishing acceptable descriptive or probabilistic methods from non-explainable black-box models. Finally, academic research should consider scalability and computational burdens, which forms barriers for DSO implementation. Table 5 outlines our recommendations, highlighting actions each actor should address to strengthen collaboration and reduce implementation barriers.

Table 5: Recommendations to bridge gaps between academic research and DSO practices.

Area	NRAs	DSOs	Academia
Data governance and access	Enable controlled research access to anonymised and/or aggregated SM data; set privacy baseline	Publish a field-level data dictionary for operational data used in decisions	Focus on privacy-preserving analytics
Model acceptance and explainability	Issue acceptance checklists with diagnostics	Adopt model-risk management	Deliver auditable methods with uncertainty; benchmark against heuristic baselines; Consider scalability and computational burden
Digitalisation and observability	Incentivise min. observability and annual digitalisation performance	Prioritise GIS and topology/phase reconciliation; deploy DSSE-lite where feasible	Create robust methods for missing and noisy data
Planning incentives	Move toward TOTEX-style treatment; define transparency rules; launch regulatory sandboxes	Provide criteria for reinforcement vs. flexibility cases	Conduct techno-economic and data-quality sensitivity analysis
Power quality	Incentivise data-driven instead of complaint-led detection	Pilot alternative solutions instead of grid reinforcement; Organise competitions to solve in-field problems	Provide open-source code for the solutions

7. Concluding remarks regarding the survey

Distribution networks are at the core of the energy transition, as most decentralised generation and the electrification will take place at the low-voltage levels. In this context, operational data from SMs could accelerate the shift towards a carbon-free future, serving as a cornerstone of this transformation. However, LVDNs are often considered the black boxes of the power system due to the low visibility network operators have, compared to transmission grids. To address this, we conducted a questionnaire-based survey addressing DSOs. The collected data covers 63.6% of the European connected customers at distribution level and provides beneficial understanding into the contemporary state of LVDNs and the modus operandi of DSOs. This deliverable overviews the SM roll-out and discusses the challenges utilities face during the data gathering process and examines the applications of operational data by DSOs. At present, besides enhancing the power system operation and monitoring aspect, DSOs are particularly focussed on DSSE applications, especially topology identification and the phase connectivity. Accordingly, SM data significantly enhances strategic planning – both in terms of short- and long-term investments and maintenances – by improving the accuracy of PLE and evaluating the available HC. Nonetheless, differences were identified between academic progress and DSO practices, due to regulatory barriers, computational burden and transparency concerns.

In this context, the findings indicate that DSOs step away from the conventional fit-and-forget dogma, and embrace more dynamic approaches that leverage SM data. The latter also proved to be an invaluable tool for monitoring and proactively mitigating power quality problems. At present, overvoltage, undervoltage and voltage unbalance are the most occurring power quality problems at low-voltage. So far, voltage violations have shown a strong correlation with seasonal trends and demographic factor. However, nowadays' penetration level of LCTs is relatively minor compared to the scale required to meet net-zero targets. Moreover, as quoted by respondents, voltage stability issues are regularly identified only through customer complaints. Though operational data use cases could increase the visibility. Our findings stress the evolving role of DSOs as active distribution networks coordinators. It is therefore indispensable not only to invest in infrastructure, but also to develop innovative solutions with a focus on cost-efficiency to accommodate LCTs. Furthermore, access to open-source representative LVDNs would enhance the scalability of the state-of-the art solutions.

8. Phase swapping as solution to grid stability problems

This part of the deliverable has been presented at an international conference: IEEE PES Innovative Smart Grid Technologies, i.e.: Cleenwerck, Rémy, et al. "Smart Meter-Based Re-Phasing for Voltage Imbalance Enhancement Through Topology Reconstruction." *2023 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*. IEEE, 2023.

8.1. Scope of the proposed solution

As discussed in §5, the major grid stability issues that DSOs encounter to this day are: overvoltage, undervoltage and voltage unbalance. On the other hand, it was also observed through the literature and confirmed by the survey respondents that the low-visibility (i.e. incomplete GIS software platforms etc.) bring numerous challenges. Therefore, a we propose a multi-objective optimization of the phase connection, in order to improve the voltage unbalance and increase the explicit hosting capacity of low-voltage distribution networks. To achieve this, we proceed as follows:

- The network topology is reconstructed by using a hierarchical agglomerative clustering algorithm to identify feeders, while phase connections are obtained through a voltage correlation approach.
- Machine learning regression models are trained to forecast the influence of SDGEs. These can be employed to identify violations in terms of (i) under- and over-voltages and (ii) local hosting capacity.
- To address the congestion problem, we propose a stochastic optimization with permutations through brute force to optimize the phase connection of the infringing smart meter IDs.

In this Section, we use the terms phase-swaps and permutation interchangeably to refer to the re-phasing approach. The objective function of these phase-swaps is to reduce the amount of voltage violations (overvoltage and undervoltage) with respect to the grid standard IEC EN50160:2022, hence increasing the HC without major investments.

8.2. Methodology

In this section, we discuss the architecture of the optimization problem. Overall, the presented approach allows for a retrospective solution to voltage violations in LVDN by (i) reconstructing the topology, (ii) identifying perturbing house-units through forecasting where the influence of SDGEs is assessed, and finally (iii) implementing a re-phasing algorithm (see Figure 13).

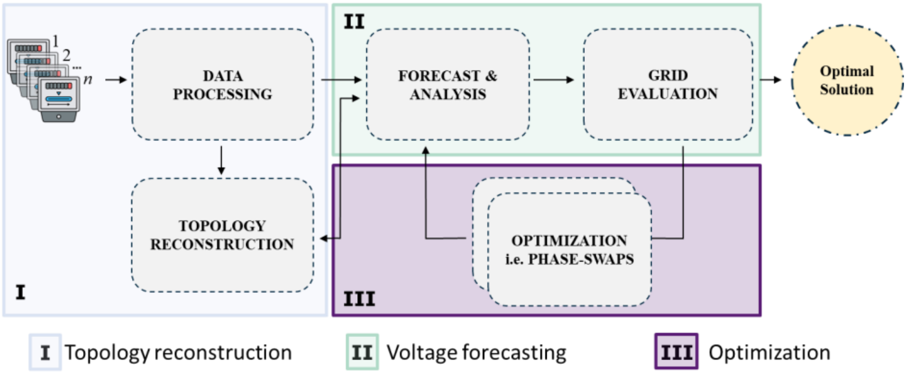


Figure 13: Phase-swapping approach.

8.3. Problem description

System operators combine distribution grid specifications with geographic GIS to accurately assess location-based effects on the network. Accordingly, datasets including grid parameters, and GIS must be available, which is not always the case [66] or not correct [67]. Furthermore, in the case of time series power flow simulations, an additional time dependent feature should be added as shown in Figure 14.

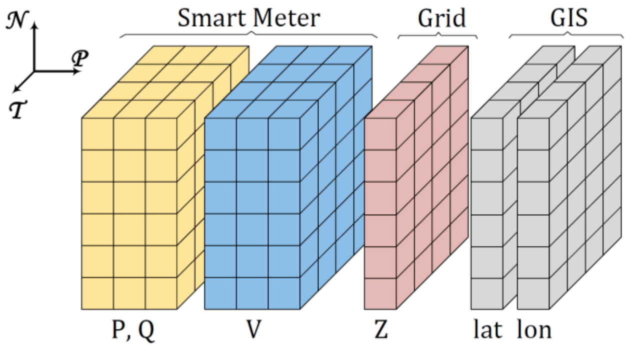


Figure 14: Illustrative representation of the various datasets used by utilities, with: nodal data provided by SMs (left); grid impedance (center) and GIS data (right).

To investigate the LCT's effects on a radial DN, one can rely on methods such as the branch flow models, Eq. (1) and Eq. (2). Let $\mathcal{N}$ be the set of nodes of the network and $p_{j,t}$, $q_{j,t}$ denote the active and reactive power exchange at each node $j \in \mathcal{N}$,one models the power flows in a radial network through the branch flow equations:

$$p_{j,t} = P_{ij,t} - r_{ij}\ell_{ij,t} - \sum_{k:j\to k} P_{jk,t} \qquad \forall j \tag{1}$$

similarly, we obtain for the reactive power flow:

$$q_{j,t} = Q_{ij,t} - x_{ij}\ell_{ij,t} - \sum_{k:j\to k} Q_{jk,t} \qquad \forall j \tag{2}$$

with r_{ij}, x_{ij} as the resistance and reactance of the line (i,j) and $\ell_{ij,t}$ as the squared current magnitudes of bus i at timestep t and let $P_{ij,t}$, $Q_{ij,t}$ be the active and reactive power flowing from bus i to j, respectively. Unfortunately, in the event that grid parameters (r_{ij}, x_{ij}) are unknown, this method cannot be applied. As a result, alternatives must be found (i) to reconstruct the network topology and (ii) to identify the house-unit and/or smart meter ID causing voltage congestion. Within this work, we achieve this by only considering smart meter data (limited to voltage and power values) and divide the two objectives into several steps. Firstly, the topology of the distribution network is reconstructed at feeder level. Then, a phase identification process is applied. Using predictive techniques, the specific house-units causing voltage congestion are identified. Finally, an innovative re-phasing algorithm is used to provide a solution to the congestion problem.

8.4. Methodology

8.4.1. Voltage forecasting

To estimate the impact of SDGEs on the distribution network we reduce the branch flow equations Eq. (1) and Eq. (2) to a multiple regression problem, such as described in deliverable D4.3 [2]. Given the linearity one can describe a multivariable linear regression as:

$$\sum_{i=1}^{n} \hat{v}_{i,t} = \alpha + \sum_{i=1}^{n} \beta_i \cdot x_{i,t} + \epsilon_{i,t} \qquad \text{s.t.} \quad x_{i,t} = [p_{i,t}, q_{i,t}] \tag{3}$$

with $\hat{v}_{i,t}$ being the predicted voltage of the i-th component of the dependent variable $v_{i,t}$ at timestep t, α the intercept term, β_i the regression coefficients (n -dimensional), $\epsilon_{i,t}$ the error term and let $x_{i,t}$ represent independent variables $p_{i,t}$ or $q_{i,t}$. Thus, a machine learning model can be trained using historical smart meter data. However, prior to fitting the model, all independent variables are normalized into a range of [0,1]. To avoid over-fitting, cross-validation is applied and models are evaluated through quantifying the root mean square error (RMSE). If $\hat{v}_{i,t}$ is the predicted voltage for the i-th bus at timestep t and $v_{i,t}$ is the corresponding true value for a total number of observations n, the RMSE is defined as:

$$\text{RMSE} = \sqrt{\sum_{n=1}^{n} \frac{\left(\hat{v}_{i,t} - v_{i,t}\right)^2}{n}} \tag{4}$$

8.4.2. Feeder partitioning problem

To start, unstructured smart meter data needs to be partitioned into several clusters where each of these clusters represent a distribution feeder of the LVDN. As a first condition, obtained smart meter data must be from the same substation. Ignoring this condition yields a model that suggests non-existent relationships. By virtue of the physical properties of a distribution network, one can assume that electrically neighbouring house-units will be strongly correlated. However, in the event that house-units are connected to the same phase but on a different feeder, the similarity in their voltage pattern will deteriorate due to the increase in line impedances. It is therefore important to reconstruct the feeder topology before extracting the phase connections of the house-units.

Within this study, we adopt the method from [68] to assess the similarity between house-units through a hierarchical clustering algorithm. Therefore, groups of house-units are recursively clustered according to their individual distance. This iterative process excludes house-units causing a correlation deterioration and clusters the remaining house-units within a set $\mathcal{C}$. Given a data set of smart meters containing the power and corresponding voltage profiles of each house-unit, let $\boldsymbol{X}$ be the Pearson correlation matrix of the voltages. We define the correlation coefficients (ρ) by:

$$\rho(V_i, V_j) = \sum_{i=1,j=1}^{n} \frac{(V_i - \overline{V_i})(V_j - \overline{V_j})}{\sqrt{(V_i - \overline{V_i})^2 (V_j - \overline{V_j})^2}} \tag{5}$$

where $i, j \in \mathcal{N}$ are the indices of the load buses, $\overline{V_i}$ and $\overline{V_j}$ denote the mean values of V_i and V_j respectively. This step allows to visually define the number of clusters that will later be used as hyperparameter. Hereafter, the Pearson correlation matrix is converted into a distance matrix $\boldsymbol{\mathcal{D}}$ as follows:

$$d_{ij} = 1 - \boldsymbol{\mathcal{X}} \tag{6}$$

We then apply a distance metric among the clusters g and h that is based on the average linkage between two clusters. Distances between every possible element pair (i, j) are computed with $i \in g$ and $j \in h$. The hierarchical clustering based on average linkage yields:

$$\xi_{gh} = \frac{\sum_{i \in \mathfrak{C}_g} \sum_{j \in \mathfrak{C}_h} d_{gh}}{n_g n_h} \tag{7}$$

where the numerator of the fraction denotes the sum of all pairwise distances between g and h. Therefore, $\mathfrak{C}_g$ and $\mathfrak{C}_h$ are the sets of elements belonging to the clusters g and h, respectively. Finally, n_g and n_h are their cardinality. Initially, each element is defined by its own cluster (bottom-up approach). At each iteration, pairs of clusters where the distance ξ_{gh} is minimum are merged into a new cluster m such that $C_m = \mathfrak{C}_g \cup \mathfrak{C}_h$ until all elements fall into a unique cluster. Let C be the resulting set of clusters.

The next step consists of ranking the IDs in accordance with their actual adjacent ID or position towards the point of common coupling (PCC). First, the individual impact of each consumer is determined through a sensitivity analysis using Eq. (3). Then, a pairwise list is generated by adding each ID i and its most impacted counterpart j. Subsequently, these lists are combined based on common elements until no more common elements exist, yielding lists that accurately reflect the physical interconnections within the respective clusters. The farthest located ID can be discerned by its lowest voltage under the assumption of an identical load profile being imposed on all consumers within a cluster. The intersection of each sub-feeder into the main branch is determined as a function of voltage drop created by imposing a load profile on the farthest located consumer within each sub-feeder.

8.4.3. Phase identification

In analogy, the correlation approach described previously is a satisfying approach to discern phase connections [69]. Since currents induce voltage drops across lines as a function of the line impedances, the voltage drop at the feeder-end will correspond to the accumulated sum of all the voltage drops through that feeder. Thus, in case one phase experiences a greater load than the other phases, the voltage drop across that phase (along the feeder) will be more significant. Similar voltage profiles within the same feeder suggest that phases are identical. Although, it should be noted that the accuracy of the feeder partitioning and phase identification can be affected by factors such as: missing data or unmetered loads, synchronization between smart meters and/or AMI, the sample resolution or even line losses across the grid [70].

8.4.4. Identification of the violating consumers

Once the grid topology is reconstructed and the phase connections are reestablished, we adopt the voltage forecasting approach defined in Eq. (3) to accentuate smart meter IDs where grid violations are observed. This by summing up profiles of LCTs on top of the load profiles.

Within this work, voltage violations are defined by exceeding the upper and lower bound limits, i.e., ±10% of the nominal voltage according to the IEC EN50160:2022. We define this constraint as:

$$v^{-} \leq v_{n,t} \leq v^{+} \tag{8}$$

where the minimum and maximum values correspond to 0.9 p.u. and 1.1 p.u. Further, we define the portion of violations ($\boldsymbol{\Omega}$) for a given scenario (σ) – e.g. an EV penetration degree of 75% – at a house-unit n by recalling (Eq. (8)):

$$\boldsymbol{\Omega}_{n,t}(\sigma) = \sum_{n \in N} \begin{cases} 0, & \text{if } v^{-} \leq \hat{v}_{n,t}(\sigma) \leq v^{+} \\ 1, & \text{otherwise} \end{cases} \tag{9}$$

where for each timestep $t \in \mathcal{T}$, the number of violations at a load bus n is computed, with $\boldsymbol{\Omega}_{n,t} \in \{0, 1\}$ determines whether a violation is registered for case σ at timestep t of load bus n or not. However, one should note that the referred standard considers a voltage violations when the 10-minute rms value is exceeded for 95% of the time.

In contrast, datasets used for the validation and demonstration of this methodology have a 15 minute resolution, hence we contemplate voltage measurement exceeding the limit as a violation. Finally, the total amount of violations for a given scenario ($\Psi(\sigma)$) can be defined as:

$$\Psi(\sigma) = \sum_{i=1}^{n} \boldsymbol{\Omega}_{i}(\sigma) \tag{10}$$

9. Optimisation of the voltage imbalance

9.1. Optimisation algorithm

To mitigate the voltage violations, we define the objective function as a minimization of (Eq. (10)). This can be achieved by reassigning consumers to a different phase (Ψ) within their respective cluster ($\mathcal{C}_s$). First, we define the consumer (ι) with the largest positive residual error ($\Delta\boldsymbol{\Omega}_n(\sigma)$) within their respective cluster. This by setting his consumption to zero, and subsequently evaluating the total number of remaining violations. After identifying the interfering user (ι), we append his power exchange profile (X) to a candidate permutation (i). The criterium opposed to be a candidate relies on: it (i) must belong to the same subfeeder, and (ii) must be a single-phase meter connected to a different phase. Additionally, a distance constraint is applied to the permutations, such that the candidate with the shortest Euclidean distance (i.e. closest neighbour) is favoured. An overview is given in **Algorithm 1**. This iterative process is repeated until the optimal phase-swap with respect to the boundary constraints is found.

9.2. Simulation and results

To validate the proposed approach, models have been applied on smart meter data (active power exchange only) with a 15-minute resolution from a typical LVDN with a radial layout (presented in Figure 15), where multiple LV feeders are starting from the PCC. We assume the LVDN to be balanced, i.e. all phase-to-neutral voltages at the PCC are considered to be 230V.

Algorithm 1 Re-phasing optimization

Input: $x_{i,t} = [p_{i,t}; q_{i,t}]$ and $v_{i,t}$

Calculate $\boldsymbol{\Omega}_n(\sigma) \forall\ n \in \mathcal{N}$, using (9)
Identification of user with highest residual error ($\imath$) :
while $\exists C_s \in \mathcal{C}, s = 1, ..., m :\ n_s \in C_s$ **do**
  for each load bus $i = 1, ..., n_s \quad \forall\ n_s \in \mathcal{N}$ **do**
    $X_i \leftarrow 0$
    Calculate $\boldsymbol{\Omega}_{n_s}(\sigma)$, using (9)
    $\imath \leftarrow i$ where $\max\limits_{i \in n_s} \Delta\boldsymbol{\Omega}_i(\sigma)$
    $\mathcal{I} \leftarrow \imath$, where $\mathcal{I} = \{\imath^{max}, .., \imath^{min}\}$
  end for
  Phase-swap algorithm
  for each $\imath \in \mathcal{I}$ **do**
    for each $i \in C_s : i = 1, ..., n_s$ **where** $\min\|\imath - i\|$ **do**
      if $\phi_i \neq \phi_\imath \wedge \phi_i =$ single-phased **then**
        $X_i = X_\imath + X_i$,
        $X_\imath \leftarrow 0$
        Calculate $\hat{V}_i(\sigma)$, using (3a)
        Calculate $\Psi(\sigma)$, using (10)
      end if
    end for
  end for
  Re-phase $\phi_\imath \leftarrow \phi_i$ where $\min\limits_{\imath \in n_s} f(\boldsymbol{\Psi}(\sigma))$
end while

Some of these feeders, in turn, include multiple sub-feeders that together comprise of 91 load buses to which traditional loads and/or SDGEs are connected. For validation purposes, properties of the network such as cable lengths and impedances were modelled in OpenDSS. Voltage measurements resulting from the simulation of the network in OpenDSS are used to train the models. This is to allow a fair comparison of the network's behaviour.

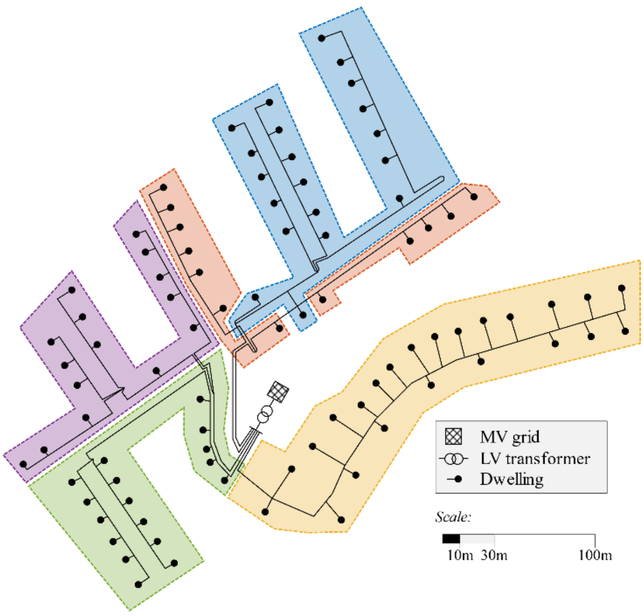


Figure 15: Representation of the low-voltage distribution network used to validate the models. Each colour represents on the feeders

We consider both (i) single-phase and (ii) three-phase house-units within the employed LVDN. However, the matrix dimensions of the obtained datasets differ. Consumption profiles are regardless of the house-unit being single- or three-phased, given by one value at each timestep t. Thus we assume all three-phase loads are balanced. While voltages are depending of the connection type (single- or three-phased) represented individually. Finally, the simulation has been conducted by solely considering active power, as reactive power was not present in the acquired datasets.

9.2.1. Topology reconstruction

Using the correlation matrix as described in Section 8.4.2, we are able to derive five different clusters for the studied case which corresponds to the representation of the LVDN given in Figure 15. Subsequently, the obtained amount of clusters is utilized as a hyperparameter for the algorithm that partitions smart meter IDs into their respective clusters. Upon the restoration of the clusters, the phase connections can be identified. A representation of the topology reconstruction for feeder 1 (marked in blue) is shown in the figure below.

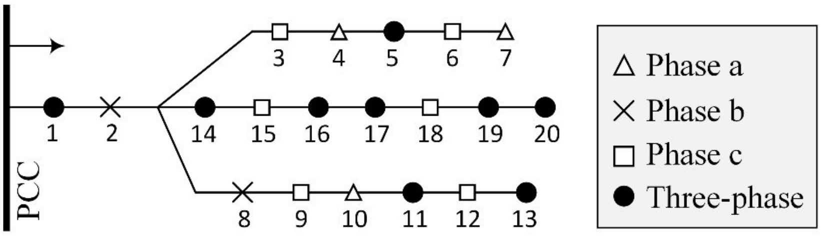


Figure 16: Single-line diagram of Feeder 1, marked in Blue on Fig. 15

9.2.2. Congestion forecast and application of the phase-swaps

To demonstrate the effectiveness of the phase-swap algorithm, we consider a scenario with a penetration degree of 75% for the electric vehicles and the PV systems. For this particular scenario (σ), the interfering house-unit of Feeder 1 was identified as being number 18, which is connected to phase 3. Provided there are no suitable candidates for this branch, no permutation can occur on that sub-feeder. In return, the model looks within another branch/sub-feeder for a suitable candidate that does meet the requirements, and in this case changing house-unit 3 from phase c to the identical phase as house-unit 4 (i.e. phase a) appeared to be the solution, see Figure 17. Applying the suggested phase-swap, resulted in a decrease of 90% in the total amount of voltage violations. However, since the model excluded phase-swaps on three-phased consumers, the first solution which tends to be the optimal was not selected. Hence, it can be depicted from the selected candidates as well as from Figure 17, that swapping smart meter IDs connected to phase c will mitigate the voltage violations corresponding to that specific scenario.

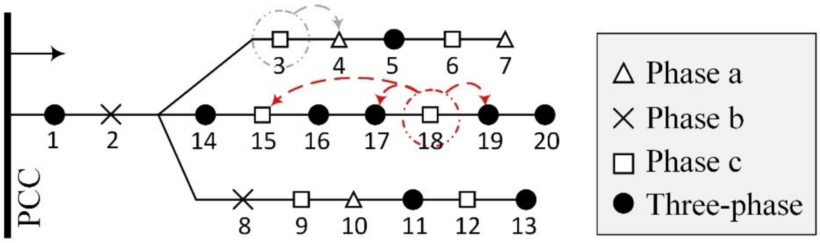


Figure 17: Two potential phase-swaps are depicted, where the first option (red) fails to meet the criteria, while the second alternative (grey) corresponds to the qualified phase-swap.

An instance for that particular case is exemplified in Figure 18 (solid line), where it is noticeable that an increase in power withdrawal – attributed to EV charging – intensifies the voltage drop at house-unit 20. Figure 18 (dashed line) showcases the resulting voltage after performing the proposed permutation on the other branch (phase-swap of house-unit 3 with 4).

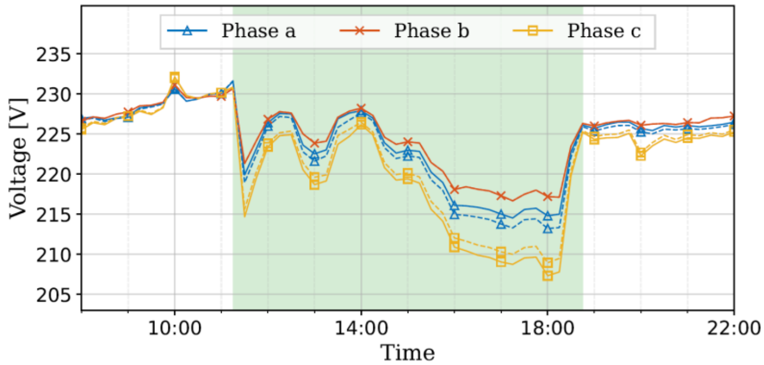
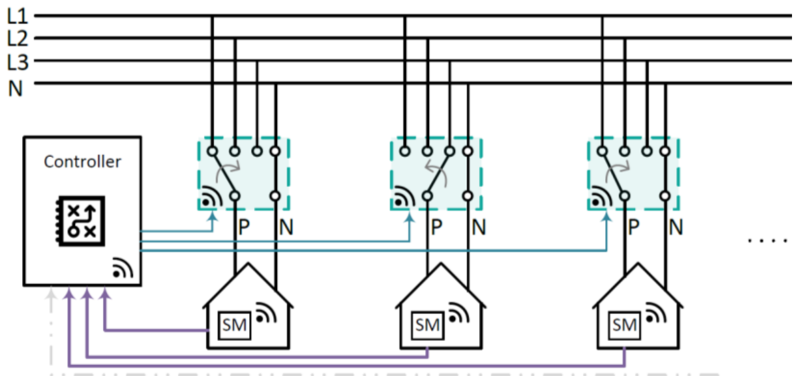
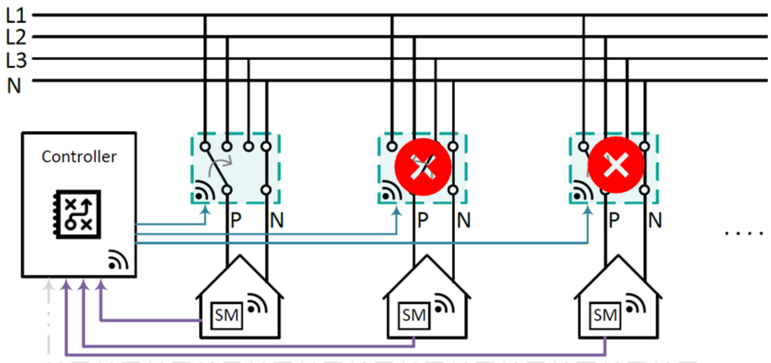


Figure 18: Voltage profile before (solid line) and after phase-swapping (dashed line).

Below (see Figure 19), is an example of how the phase-swapping would be executed in field. Therefore, devices should be installed at the house-units themselves which can perform a phase selection based on the proposed algorithm. Moreover, since SM already have the communication (which is centralised via the DSOs, the ideal location to install such phase-swapping device would be close to the SM.



(a) Candidates for phase-swapping



(b) Candidates that meet the criteria for phase-swapping

Figure 19: Example of how the phase-swapping would be in practice.

For the given permutation, it can be concluded that applying a phase-swap on house-unit 3 helps mitigating the voltage drop of *phase c* in the branch of house-unit 20. The figure shows a voltage imbalance improvement on *phase c* while *phase a* experiences a voltage drop. gives an overview of the observed amount of violations before implementation of the phase-swap algorithm Ω_{prior} and after Ω_{after}.

Table 6: Number of violations before and after performing a phase-swap on house-unit 3.

	Smart meter ID					
	15	***16***	***17***	***18***	***19***	***20***
Ω_{prior}	9	16	18	22	23	23
Ω_{after}	0	1	1	3	3	3

10. Concluding remarks for the phase-swapping approach

A proof-of-concept approach to address the issue of voltage violations occurring in low-voltage distribution networks is proposed, via a novel phase-swap concept. The methodology involves a smart meter-driven framework to reconstruct the network topology, and the use of forecasting techniques to accurately determine the composition of each feeder, as well as to identify interfering house-units. The proposed solution reduces the total amount of voltage violations across the grid by applying phase-swaps on the identified house-units. Via a case study, we demonstrate that the proposed approach effectively mitigates voltage congestion within the network and increases the explicit hosting capacity. As a result, the novel approach has the potential to provide an economically feasible solution for the voltage unbalance by reducing the need for grid reinforcements. The robustness of the proposed methodology, particularly in cases where not all the smart meter data is available is subject to further investigation. Nevertheless, this present work describes a promising solution for the ongoing challenges that low-voltage distribution networks are facing.

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