

Article

Coupling Scenario-Based Grid Simulations with State Estimation: Measurement Requirements for Low-Voltage Networks Under the German Energy Transition Pathway

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Abstract

Increasing penetration of electric vehicles, heat pumps, and rooftop photovoltaics is creating thermal and voltage stress in low-voltage distribution grids. This work links the German Federal Government energy transition pathway (2025–2045) with state estimation performance requirements, evaluated at five milestone years from 2025 to 2045 on two SimBench reference networks across three equipment size levels (large, medium, small) and three VDE Forum Netztechnik/Netzbetrieb (VDE FNN) measurement constellations that differ in the availability of transformer- and feeder-level instrumentation. Within this work's analysis, congestion is caused exclusively by transformer overloading and voltage-band violations. No individual line exceeds its thermal rating (maximum: 98.6%). Equipment size governs congestion onset for a given deployment trajectory: under large equipment, congestion remains absent through 2045, under medium equipment it emerges from 2035 (4 of 10 scenarios), and under small equipment from 2025 (9 of 10). Without transformer instrumentation, median voltage estimation errors reach 6–42% regardless of smart meter penetration. Adding a single transformer measurement reduces errors by an order of magnitude, achieving median errors of 0.5–1.4%. In urban networks, transformer-level instrumentation meets the VDE FNN voltage accuracy target (99th percentile voltage error below 2%) in all configurations. In rural networks under small equipment, the target is approached but not met. These findings motivate prioritizing transformer instrumentation as an effective first step for grid observability and supplementing the current consumption-driven metering rollout with risk-based deployment criteria linked to local congestion exposure.

Keywords: low-voltage distribution grid; state estimation; energy transition; grid observability; distributed energy resources; regulation-mandated congestion management



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1. Introduction

The transformation of energy systems toward climate neutrality is driven by the extensive electrification of end-use sectors and the large-scale integration of distributed energy resources (DERs) such as rooftop photovoltaics, electric vehicles (EVs), and heat pumps [1]. Because these assets are primarily integrated at the low-voltage (LV) level, a grid tier historically characterized by limited monitoring infrastructure, and a design

centered on unidirectional power flows, their proliferation necessitates a fundamental shift in operational management [2].

In this context, Germany represents a particularly relevant case study due to its advanced energy transition strategy and its legally binding target of achieving climate neutrality by 2045. The German regulatory framework § 14a Energiewirtschaftsgesetz (EnWG) mandates a paradigm shift from *grid follows load* to *load follows grid*, empowering distribution system operators (DSOs) to employ curative control through the temporary curtailment of controllable local systems during periods of acute congestion.

While this regulatory flexibility facilitates a more efficient utilization of existing grid capacity compared to conservative static planning, it remains strictly contingent upon meeting advanced requirements for grid observability and state estimation (SE) [3]. Consequently, these developments make Germany a suitable environment for analyzing the evolving operational and monitoring requirements of increasingly decentralized and bidirectional distribution networks.

Unlike transmission grids, LV distribution networks were originally designed for passive operation with unidirectional power flows and limited simultaneity of high-power loads. The increasing penetration of DERs, combined with flexible and electrified demand, leads to higher transformer and line loading as well as voltage-band violations [4,5]. Reinforcement of distribution infrastructure is capital-intensive and slow, making operational congestion management and improved monitoring essential in the medium term [2,6].

Scenario-based studies frequently analyze alternative energy transition pathways for DER expansion and quantify their impact on congestion frequency, hosting capacity, or flexibility requirements. However, many of these analyses implicitly assume full observability of the network state [7,8]. In practice, LV grids suffer from sparse and heterogeneous measurement coverage, asynchronous data streams, and incomplete knowledge about topology and parameters [9]. This persistent observability gap fundamentally limits the reliable detection, and thus assessment, of emerging congestion situations.

As a key enabler of distribution grid monitoring, SE has therefore gained increasing attention. LV SE approaches typically combine transformer measurements, smart meter data, and pseudo-measurements derived from advanced load profiling of historical consumption data. Many implementations rely on weighted least squares (WLS)-based formulations. However, the demand for higher observability in increasingly active grids highlights the inherent challenges of LV SE [10–12]. While these methods can significantly improve situational awareness, their accuracy strongly depends on the measurement configuration and the statistical properties of pseudo-measurements [13].

At the same time, regulatory frameworks such as § 14a EnWG in Germany introduce new requirements for grid-oriented control of flexible loads via smart meter infrastructures [14]. This regulation mandates agreements for the grid-oriented control of devices such as heat pumps and EV charging points in exchange for reduced network charges. To ensure non-discriminatory operation, it empowers DSOs to manage these loads through economic incentives or direct power limits while simultaneously requiring more precise digital monitoring of the distribution network.

These developments increase both the availability of measurement data and the operational need for reliable grid state assessment. In critical or non-routine situations, insufficient data quality or uncertainty in the estimated grid state may require manual intervention by DSOs [15].

Despite substantial progress in both scenario-based grid studies and LV SE research, the interaction between long-term DER energy transition pathways, resulting congestion patterns, and the measurement requirements for reliable congestion detection remains insufficiently quantified. In particular, it is unclear what measurement configuration

(smart meter penetration together with the availability of transformer- and feeder-level instrumentation) is required to detect congestion events with sufficient accuracy and regulatory compliance as electrification increases.

This work addresses this gap by linking the German Federal Government energy transition pathway for the period 2025–2045 with a systematic evaluation of SE performance under the three VDE Forum Netztechnik/Netzbetrieb (VDE FNN) measurement constellations defined in the VDE FNN 2024 recommendation [16] (K3: smart meter readings only, K2: adding a single transformer total power measurement, and K1: adding per-feeder measurement) at the current regulatory minimum smart meter gateway (SMGW) penetration. Three research questions structure the investigation:

- RQ1:** Considering different grid equipment configurations, at what points in time do thermal and voltage limit violations emerge in representative rural and urban LV distribution grids, how do their frequency and severity evolve, and which grid components are primarily affected?
- RQ2:** How does SE accuracy and congestion detection capability depend on the type of measurement infrastructure (transformer, feeder, and smart meter instrumentation), and which constellation meets established quality targets for the congestion scenarios identified in RQ1?
- RQ3:** What regulatory adjustments to smart meter rollout requirements and grid monitoring standards are necessary to ensure adequate grid observability under the expected DER deployment trajectories, specifically in the context of § 14a EnWG?

To answer these questions, this work proposes a methodological framework that (i) derives congestion events and their characteristics from scenario-based time-series simulations; (ii) evaluates SE accuracy and the detectability of thermal and voltage limits as a function of measurement concepts; and (iii) derives quantitative requirements for measurement infrastructure and monitoring, with direct implications for current German regulations.

To the authors' knowledge, this is the first work to connect long-term deployment planning with operational state estimation under a concrete German energy transition pathway, resolving whether the VDE FNN state-estimation quality targets are achievable across grid equipment size levels and measurement constellations, and translating the outcome into specific regulatory recommendations.

The main contributions of this work are the following:

1. Coupling of the German energy transition pathway (2025–2045) to time-series simulations across three equipment size levels, showing that equipment size governs congestion onset and severity in rural and urban LV reference networks.
2. Accuracy assessment of branch-current-based model (BC-Mod) WLS SE under three VDE FNN measurement constellations, showing that the measurement constellation, not smart meter penetration, governs SE accuracy: a single transformer measurement reduces median voltage errors by an order of magnitude compared to smart meter-only configurations, regardless of penetration.
3. Evidence that congestion is caused exclusively by transformer overloading and voltage-band violations, making voltage estimation the operationally relevant SE contribution. The VDE FNN voltage target ($f_V^{p99} \leq 2\%$) is met by K2 in urban networks.
4. Regulatory recommendations: prioritized transformer instrumentation, risk-based SMGW densification, and alignment of VDE FNN detection metrics with congestion-relevant voltage thresholds.

The remainder of this work is structured as follows: Section 2 reviews related work. Section 3 defines the SE metrics and the algorithm. Section 4 analyzes the impacts of the

energy transition on load limits in LV grids. Section 5 addresses SE quality under varying measurement availability. Section 6 discusses the results, derives regulatory implications, and identifies limitations. Section 7 summarizes the work and outlines directions for future research.

2. Related Work

This work aims to quantify what monitoring infrastructure (the measurement configuration and density) is required to ensure reliable congestion detection via SE as electrified demand and distributed generation grow in LV grids. To position this contribution, prior work is assessed against the following derived requirements (R):

- R1: Pathway-to-feeder downscaling.** The work must translate macro-level technology scenarios (e.g., heat pumps, EVs, rooftop photovoltaics (PV)) into feeder-level load and generation profiling, including spatial uncertainty and simultaneity [17,18].
- R2: Physically grounded congestion characterization.** The work must quantify voltage-band violations and thermal overloads using time-series or probabilistic grid simulations, relating outcomes to the actual topology and parameters of each feeder [18,19].
- R3: Operational consequences and flexibility.** The work must either (i) explicitly model active operation (e.g., active network management, coordinated charging); or (ii) clearly distinguish them from passive *fit-and-forget* scenarios, i.e., scenarios that assume no curtailment or flexibility activation to resolve constraints [20–22].
- R4: Observability-aware monitoring.** SE and monitoring methods for LV grids must cope with sparse, heterogeneous, and potentially asynchronous measurements, including potential dependence on pseudo-measurements [9,23,24].
- R5: Measurement-to-detectability link.** Beyond SE accuracy, the work must connect measurement penetration (and sensor types) to the *detectability* of operational limit violations (congestion events) [24,25].
- R6: Benchmarking and reproducibility.** Evaluation must be grounded on reproducible benchmark grids and time-series datasets (e.g., SimBench) to support systematic comparison of scenario results and SE performance [18,26,27].

The following subsections synthesize work related to these requirements and derive the research gap.

2.1. Scenario Downscaling and Benchmarking

Luo et al. [28] propose an interpretable diffusion model to generate long-term distribution load scenarios. Their method integrates a transformer and temporal decomposition to capture multi-scale load patterns across seasons and years. The generated scenarios achieve high fidelity in the temporal and frequency domains. However, the method operates on aggregate system load data and does not explicitly translate macro-level technology scenarios (heat pumps, EVs) to feeder profiles, so (R1) is only partially met. It also does not simulate grid constraints (R2) or incorporate passive operation, SE, or reproducible benchmark grids (R3–R6). Fakhrooian et al. [18] systematically evaluate EV charging and heat pump impacts on German LV grids using 200 realistic feeder models. They create scenarios of EV and heat pump penetration and run time-series power flows. The study quantifies minimum voltages and maximum transformer/line loadings for each scenario. Thus, it directly addresses (R1) by downscaling national EV/heat pump adoption and using a physical congestion analysis (R2) simultaneously [18]. They use real feeder data (R6). They assume passive operation (R3) but do not tackle SE or measurement issues (R4, R5). Overall, this paper provides rich feeder-level scenarios with stress analysis (R1–R3, R6), but leaves out monitoring and control aspects (R4, R5). Treutlein et al. [26] release the FeederBW dataset, containing two years of measurements from 200 German LV feeders.

This dataset includes one-minute power flows, weather, and detailed metadata (housing count, PV/EV/heat pump capacities). By offering real-world feeder profiles under evolving DER adoption, it fully supports (R6). However, as a data publication it does not perform modeling or downscaling itself (R1–R5). Meinecke et al. [27] introduce SimBench, a benchmark suite of synthetic German power systems. SimBench provides LV/medium voltage (MV)/high voltage (HV) grid models and one-year time series of loads, PV, and EV profiles. The dataset explicitly aims to standardize test cases for research. SimBench “simplifies reproducing study results” by offering scenario data [27], fulfilling (R6). SimBench’s future scenarios can serve as high-level inputs, but the work itself does not generate downscaling or analyze grid congestion (R1–R5).

2.2. Grid Congestion Analysis and Operational Flexibility

Damianakis et al. [20] provide a thorough review of the LV-grid impacts of PVs, EVs, and heat pumps. They summarize studies showing that high DERs penetration can cause voltage-rise violations, phase unbalance, power losses, and overloading. The review also highlights mitigation: violations can be significantly reduced through coordinated voltage/reactive-power control and tap changer optimization, which adjusts the transformation ratio to stabilize the grid voltage. This work addresses grid effects (R2) and operational measures (R3), but as a survey it does not perform new downscaling (R1) or involve SE (R4–R5). Protopapadaki and Saelens [19] simulate multiple LV feeders using stochastic building and load models to study PV and heat pumps effects. They use a Monte Carlo simulation with detailed, Modelica-based building models, which account for the thermal behavior of the building envelope, its orientation, and the window-to-wall ratio to capture realistic heat pump load profiles. Their results show that air-source heat pumps impose larger voltage drops and cable overloads than rooftop PV in the studied feeders. They find rural feeders overload at heat pump penetrations from 20% to 30%. This directly quantifies congestion (R2). No active control (R3) or SE is included (R4–R5). Delchambre et al. [21] present a probabilistic power-flow analysis for a single LV feeder with battery assets. It covers physical congestion due to random frequency containment reserve and automatic frequency restoration reserve injections (R2), and the operational impact of these frequency services (R3). However, it has no scenario downscaling (R1), no SE (R4), and no detection strategy (R5), and it is not based on a public benchmark (R6). Khan et al. [1] review optimization and control methods for LV networks with high DER share. They survey decentralized DERs, demand response, and the regulation of voltage levels through reactive power management, typically provided by smart inverters. Notably, they summarize the quantitative effects of control: coordinated voltage control and optimal tap settings can improve hosting capacity and reduce constraint breaches by 20–67% [1]. This covers active methods (R3) and indirectly less congestion (R2). However, it is a literature review (no new data) and does not perform scenario downscaling or SE (R1, R4, R5).

2.3. Observability and Detectability

Fotopoulou et al. [29] review SE algorithms under sparse measurements. They highlight that limited real-time data in LV grids negatively affects SE accuracy and convergence. This is tackled either with more instruments or with pseudo-measurements [29]. The review covers various SE formulations (WLS, Kalman) and the use of pseudo-measurements to maintain observability. Thus, it addresses observability (R4) and partially discusses pseudo-measurements for unobserved states (R5). It does not involve scenario downscaling or grid simulation (R1–R3, R6). Mattoo et al. [30] present a modular two-level Kalman filter state estimator for distribution grids with asynchronous heterogeneous measurements. In

Stage 1, separate estimators process micro-phasor measurement units, remote terminal units, and smart meter data. Stage 2 fuses these into a global estimate. They explicitly handle different refresh rates and latencies, enabling real-time SE with mixed sensors. This satisfies observability with sparse/heterogeneous data (R4). It does not explicitly address violation detection (R5) nor other requirements (R1–R3, R6). Paruta et al. [23] design a greedy algorithm for meter placement on LV networks. They use an enhanced DistFlow SE model (including cable capacitances) to evaluate observability. Iteratively they place one measurement device that improves SE accuracy the most, until predefined SE error limits are met. On a 75-node Swiss feeder, they achieve full observability with the minimum number of required measurement devices. This work directly addresses (R4) by improving SE observability. It does not deal with violation detection (R5) or other requirements (R1–R3, R6). Buason et al. [24] formulate a bilevel optimization to place a minimal number of voltage sensors and set alarm thresholds so that any violation of voltage limits will be detected. The upper level minimizes sensor count and false alarms, while the lower level computes maximum voltages given uncertain injections. They use linear power-flow approximations to guarantee that no violation escapes detection. Thus, it explicitly ensures detectability of limit violations (R5) and optimizes sensor deployment (R4). Specifically mentioning operation type (R3) and scenario downscaling (R1) is outside its scope. Dehbozorgi et al. [25] develop an SE-based detection scheme for false data injection attacks. They introduce cost functions for misdetection and optimize alarm thresholds for each meter using an autoencoder and largest normalized residual test. This work shows how measurement placement and thresholding affect detection costs. It relies on an SE (R4) and ensures anomalies are caught under limited data (R5). Idlbi and Graeber [31] propose a digital twin framework for LV distribution grids with high DER share, integrating SE with congestion management in a unified operational environment. The digital twin continuously estimates the grid state from heterogeneous measurements and uses the estimated state to identify and resolve thermal and voltage limit violations. It directly uses SE under realistic measurement conditions (R4) and congestion events are detected via estimated state (R5). In addition to that, congestion management is an explicit operational objective (R3). The framework does not perform macro-level scenario downscaling (R1), and no standardized benchmark grids are used (R6). Koch et al. [32] evaluate the substitution of topology-centered measurement infrastructure by smart meters for grid state identification in six SimBench LV grids, showing that substitution becomes feasible at deployment rates between 30% and 60% when both voltage and current deviations are considered. They further integrate this approach into an agent-based local energy and flexibility market use case. Asman et al. [33] extend this line of work by quantifying expected deviations in grid state identification using a smart grid interface module (SGIM) on the same six SimBench LV grids. With SGIM measurements at all transformer distribution lines, voltage deviations range from 0.27% to 0.58% and current deviations from 1.69% to 9.19%. With only a single measurement at the transformer supply line, the deviations significantly exceed the 0.5% voltage accuracy target in five of six grids, rendering the grid state identification unsuitable for curative congestion management. These findings address grid state identification with sparse measurements (R4) and current deviations indicate limits of congestion detectability (R5), but the analysis does not include scenario-based DER projections (R1–R3) and uses SimBench grids (R6). Von der Heyden et al. [34] address a complementary challenge by proposing a privacy-preserving power flow analysis via secure multi-party computation, enabling grid state identification without exposing individual prosumer data. This work tackles the data privacy constraints that limit measurement availability in practice (R4), but does not address congestion detection (R5) or scenario-based analysis (R1–R3, R6).

2.4. Summary of the Analysis of Related Work and Research Gap

The systematic review of the literature, summarized in Table 1, reveals a significant fragmentation in current research regarding the monitoring of LV grids, consistent with the broader literature gaps identified by [9]. While each requirement (R1–R6) is addressed individually or in small clusters by existing works, no single study provides an integrated approach that spans the entire chain, from macro-level scenario downscaling to observability-aware congestion detection. In particular, works addressing scenario downscaling and benchmarking (R1, R2, R6) and works addressing observability and detectability (R4, R5) form largely separate groups, so the measurement requirements for congestion detection are never derived from a concrete long-term deployment pathway.

Table 1. Summary of R1–R6 fulfillment for reviewed works across three key categories. ● fulfilled, ◐ partially fulfilled, ○ not fulfilled.

Author	R1	R2	R3	R4	R5	R6
Scenario Downscaling and Benchmarking						
Luo et al. [28]	◐	○	○	○	○	○
Fakhrooeian et al. [18]	●	●	○	○	○	●
Treutlein et al. [26]	○	○	○	○	○	●
Meinecke et al. [27]	○	○	○	○	○	●
Grid Congestion Analysis and Operational Flexibility						
Damianakis et al. [20]	○	●	●	○	○	○
Protopapadaki and Saelens [19]	○	●	○	○	○	○
Delchambre et al. [21]	○	●	●	○	○	○
Khan et al. [1]	○	○	●	○	○	○
Observability and Detectability						
Fotopoulou et al. [29]	○	○	○	●	◐	○
Mattoo et al. [30]	○	○	○	●	○	○
Paruta et al. [23]	○	○	○	●	○	○
Buason et al. [24]	○	○	○	●	●	○
Dehbozorgi et al. [25]	○	○	○	●	●	○
Idlbi and Graeber [31]	○	◐	◐	●	◐	○
Koch et al. [32]	○	○	◐	●	◐	●
Asman et al. [33]	○	○	○	●	◐	●
Von der Heyden et al. [34]	○	○	○	●	○	○

The core research gap lies in the disconnect between long-term grid planning and operational SE. While scenario-based studies often provide detailed pathways for DER expansion, they typically assume a “perfectly observable” grid. Conversely, SE research focuses on algorithmic accuracy but frequently lacks the context of evolving congestion patterns resulting from specific energy transition pathways. To bridge this gap, this work proposes a methodological framework that links the German Federal Government energy transition pathway for the period 2025–2045 with a systematic evaluation of SE performance. This evaluation integrates scenario-based downscaling (R1) and physical grid simulation (R2) with an observability-aware SE (R4). To establish a consistent reference framework for evaluating the detection limits of the SE, active congestion-management measures (e.g., curtailment) are deliberately excluded from the simulation (R3). This “unmitigated baseline” approach ensures that the detectability of thermal and voltage limits (R5) is assessed against the full spectrum of potential grid violations. By utilizing reproducible benchmark grids

(R6), this work provides DSOs with quantitative guidelines for configuring their monitoring infrastructure (the choice of transformer- and feeder-level instrumentation alongside smart meter density) as DER penetration grows, ensuring that reliable SE remains feasible as distribution grids transition from passively operated to actively managed systems.

3. State Estimation: Metrics and Algorithm

LV networks typically lack sufficient measurement infrastructure to achieve full observability. The number of installed sensors rarely meets the mathematical minimum for WLS SE, requiring pseudo-measurements derived from load profiles or consumption models to fill the gap [9,29,35,36]. The accuracy of the resulting state estimate depends on the number, location, and type of real measurements as well as the quality of the pseudo-measurement model [23,24,37].

3.1. Definition and Application of Suitable Quality Metrics

Defining suitable quality metrics for LV distribution grid SE is not trivial. In contrast to transmission system SE, the objective in LV grids is typically not a perfectly accurate reconstruction of the full system state, but rather the reliable detection of operationally critical conditions, such as overloads and voltage limit violations.

A practical basis for the definition of accuracy metrics is provided by VDE FNN guidance on LV grid SE [16,38]. In this context, accuracy targets are formulated explicitly for both voltage and current estimation, and evaluated using robust statistical measures. The voltage estimation accuracy f_V is defined as the absolute deviation between the estimated node voltage V_{est} and the true voltage V_{real} , normalized by the nominal voltage V_n :

$$f_V = \left| \frac{V_{\text{est}} - V_{\text{real}}}{V_n} \right| \cdot 100\%. \quad (1)$$

This work investigates a voltage accuracy threshold of 2% (including measurement inaccuracies). For evaluation, the 99th percentile of node voltage errors is used, which provides a robust metric that focuses on worst-case performance while remaining less sensitive to single extreme outliers.

Similarly, the current estimation accuracy f_I is defined as the deviation between the estimated branch current I_{est} and the true current I_{real} , normalized by the current-carrying capacity I_z :

$$f_I = \left| \frac{I_{\text{est}} - I_{\text{real}}}{I_z} \right| \cdot 100\%. \quad (2)$$

For current estimation, this work investigates a target accuracy of 10% and evaluates the 99th percentile of the current error. In addition, the evaluation is restricted to critical network segments that experience high loading under relevant operating scenarios, reflecting the practical goal of reliably detecting overload risks. The VDE FNN targets therefore represent a practically relevant benchmark if the objective of SE is the avoidance of critical grid states.

For tracking the trend of voltage estimation quality as a function of measurement penetration, independently of regulatory targets, a complementary diagnostic metric is used. The *mean normalized voltage error* $\bar{\varepsilon}$ averages the pointwise voltage deviation across all N_{LV} LV nodes:

$$\bar{\varepsilon} = \frac{1}{N_{\text{LV}}} \sum_{i=1}^{N_{\text{LV}}} \left| \frac{\hat{v}_i - v_{\text{true},i}}{\max_j v_{\text{true},j}} \right| \cdot 100\%, \quad (3)$$

where $\hat{v}_i$ is the SE voltage estimate at node i and $v_{\text{true},i}$ the simulation ground truth. Normalization by the snapshot maximum $\max_j v_{\text{true},j}$ rather than by the nominal voltage V_n

eliminates systematic slack offsets that arise when the substation reference voltage deviates from nominal, and renders the metric sensitive to the *shape* of the estimated voltage profile rather than its absolute level. Unlike $f_{V,p99}$, which targets worst-case compliance, $\bar{\varepsilon}$ summarizes the network-wide average behavior and is therefore suited for sweep analyses in which the measurement penetration is varied continuously.

Beyond pure numerical deviation metrics, it is also useful to evaluate the detection performance of the estimator with respect to critical grid states. In this context, sensitivity (true positive rate, TPR) and specificity (true negative rate, TNR) provide meaningful indicators for assessing how reliably overloads or voltage violations are detected while avoiding false alarms.

In practice, the reference values V_{real} and I_{real} are rarely available across the full network, limiting direct error computation to the few sensor locations. Alternative validation strategies include residual analysis [39], leave-one-out cross-validation [40], and simulation-based evaluation against a known ground truth [41]. This work adopts the simulation-based approach: congestion scenarios from Section 4 provide the ground truth, and the SE is evaluated against the full power-flow solution. Online uncertainty quantification via the gain matrix [13] complements the offline evaluation.

3.2. The BC-Mod Branch-Current WLS Estimator

The SE implementation evaluated in Section 5 is based on the modified branch-current WLS estimator BC-Mod [13,42]. In contrast to the node-voltage WLS formulation, BC-Mod uses complex branch currents as the state variables. This results in a linear measurement Jacobian whose entries depend only on the grid parameters, not on the current measurement set. Compared to node-voltage SE, BC-Mod is therefore less sensitive to measurement errors and pseudo-measurement inaccuracies, a property that is particularly advantageous for LV grids with high pseudo-measurement shares.

The WLS state vector $\hat{\mathbf{x}}$ is constructed from the real and imaginary parts of the complex branch currents for all M lines across all three phases. The estimator minimizes the weighted sum of squared measurement residuals:

$$J(\hat{\mathbf{x}}) = (\mathbf{z} - \mathbf{H}\hat{\mathbf{x}})^T \mathbf{W}(\mathbf{z} - \mathbf{H}\hat{\mathbf{x}}), \quad (4)$$

where $\mathbf{z}$ is the measurement vector, $\mathbf{H}$ is the linear measurement Jacobian, and $\mathbf{W} = \mathbf{R}^{-1}$ is the weight matrix derived from the measurement covariance matrix $\mathbf{R}$. Measurements (substation phasor measurements, smart meter readings) and pseudo-measurements (load-profile estimates) enter $\mathbf{z}$ with weights reflecting their respective uncertainties. In this work, real measurements are assigned $\sigma_{\text{real}} \approx 1.7\%$ and pseudo-measurements $\sigma_{\text{pseudo}} = 40\%$ (see Section 5.1).

Node voltages are not part of the state vector but are recovered in a subsequent forward sweep. Starting from the substation voltage, the voltage drop over each branch is calculated as

$$\mathbf{v}_{\text{drop},l,k} = \mathbf{Z}_{l,k} \cdot \mathbf{i}_{l,k}, \quad \mathbf{v}_l = \mathbf{v}_k - \mathbf{v}_{\text{drop},l,k}, \quad (5)$$

where $\mathbf{Z}_{l,k}$ is the three-phase impedance matrix of branch $l-k$. The distinguishing feature of BC-Mod over the conventional branch-current SE [42] is a backward sweep that incorporates available node voltage measurements: each measured voltage is back-propagated to infer a substation voltage estimate, and the average of these estimates initializes the next forward sweep. This iterative process achieves accuracy comparable to nonlinear SE formulations at significantly lower computational cost.

The implementation also provides uncertainty quantification (UQ) for the estimated branch currents and node voltages [13]. Current uncertainty is derived from the diagonal of

the gain matrix $\mathbf{G} = (\mathbf{H}^T \mathbf{W} \mathbf{H})^{-1}$, which equivalently serves as the covariance matrix of the WLS state vector. Voltage uncertainty is propagated analytically through the forward-sweep equations using the branch impedances and the current covariances. Both uncertainties are expressed as 95% credibility intervals, supporting manual decision making in non-routine grid operation [15].

4. Impacts of the Energy Transition on Load Limits in Low-Voltage Grids

This section quantifies congestion in low-voltage grids under the Federal Government energy transition pathway (2025–2045), covering the scenario definition (Section 4.1), simulation input data (Section 4.2), methodology (Section 4.3), and evaluation (Section 4.4).

4.1. Energy Transition Pathway

All simulations are based on the German Federal Government deployment trajectory for four technology categories: (i) publicly accessible charging stations, (ii) EVs, (iii) heat pumps, and (iv) rooftop PV capacity. The 2025 values are the measured baseline and the 2035 and 2045 values the official targets, with the intermediate years 2030 and 2040 obtained by linear interpolation. Comparable studies by Agora Energiewende [43] and the Fraunhofer Institute for Solar Energy Systems [44] arrive at broadly similar deployment trajectories. The Federal Government figures are drawn from the Renewable Energy Sources Act [45], the Photovoltaic Strategy [46], the Master Plan for Charging Infrastructure II [47], and the Heat Pump Offensive report [48]. Per-100-households (HH) indicators are calculated using [49], which assumes 42.0 million households in 2025 and 42.6 million in 2045. The resulting scenario values are summarized in Table 2.

Table 2. Federal Government national deployment trajectory for public charging stations, EVs, rooftop solar PV, and heat pumps for the years 2025, 2030, 2035, 2040, and 2045 (units per row, # = number of). The 2025 column is the measured baseline. Values for 2030 and 2040 (shown in italics) are obtained by linear interpolation between the 2025, 2035, and 2045 anchor values. The trajectory sets the temporal growth. The spatial allocation per network is settlement-specific (see Section 4.3).

Category	Source	Unit	2025	2030	2035	2040	2045
Public charging stations	[50,51]	#/100 HH	0.22	<i>1.10</i>	1.99	<i>2.85</i>	3.72
Electric vehicles	[52,53]	#/100 HH	3.93	<i>28.0</i>	52.0	<i>68.0</i>	84.1
Rooftop solar PV	[45,54]	GW	76.0	<i>115.5</i>	155	<i>200.5</i>	246
Heat pumps	[55,56]	#/100 HH	3.81	<i>13.9</i>	24.0	<i>33.0</i>	42.0

4.1.1. Baseline (2025)

According to [50], Germany had 91,351 publicly accessible charging stations (comprising 165,295 individual charging points) as of 1 January 2025, corresponding to approximately 0.22 stations per 100 HHs. In [52], it is reported that there are 1,651,643 EVs, equivalent to 3.93 per 100 HHs. After wind energy, solar PV is Germany's second largest renewable source. In 2025, 4,474,362 rooftop systems, with a combined capacity of 76.0 GW, were in operation [54], corresponding to 10.7 systems per 100 HHs. At the end of 2024, approximately 1,600,000 heat pumps were installed [55], equivalent to 3.81 per 100 HHs.

4.1.2. Public Charging Stations

The Federal Government targets 1.38–2.60 charging stations per 100 HHs by 2035 and approximately 3.72 by 2045 [51], complemented by the build-out of a high-power charging network and grid-coordinated charging. Private charging infrastructure is a complementary buffer that limits peak demand on the public grid [51].

4.1.3. Electric Vehicles

The Federal Government has targets of approximately 21.9 million EVs (52.0 per 100 HHs) by 2035 and 35.8 million (84.1 per 100 HHs) by 2045 [53]. These figures imply a large-scale electrification of the passenger car fleet, reaching roughly 70% of the current stock by 2045. Key instruments include direct subsidies, the anticipated 2035 zero-emission mandate for new registrations, and rising CO₂ pricing.

4.1.4. Rooftop Solar PV

Federal Government targets for rooftop PV grow from 76.0 GW in 2025 to 155 GW in 2035 and approximately 246 GW in 2045 [45]. Capacity roughly doubles from 2025 to 2035 and grows by a further 60% to 2045. These values are the rooftop share of the broader Federal PV expansion, which also includes ground-mounted systems.

4.1.5. Heat Pumps

Heat pump deployment rises from 3.81 per 100 HHs in 2025 to 24.0 in 2035 and 42.0 in 2045, reflecting a major shift toward electrified individual space heating [56]. Key drivers are rising CO₂ prices under the EU Emissions Trading System (ETS) and anticipated reductions in network charges and electricity taxes [43].

4.2. Simulation Input Data

Building on the values in Table 2, intermediate years were completed via linear interpolation and the 2025 column is anchored to the empirically observed baseline. Subsequently, existing load profiles were compiled for public [57] and private charging infrastructure [58], rooftop solar PV generation [59,60], households [61], and heat pumps [62]. These load profiles were harmonized to represent a full non-leap year (365 days) at a 15-minute temporal resolution. This resulted in 35,040 intervals, each associated with an average load in kW for the respective 15-minute period.

For public charging stations, in addition to standard weekday and weekend profiles, outliers observed in the raw data were explicitly modeled. The modeling utilized load profiles representing the 70th to 85th percentiles to approximate typical demand conditions. To capture potential peak-load events, a specific high-power profile based on maximum observed utilization was integrated for individual charging units across all scenarios. Distinct load profiles for rural and urban areas were available [57]. For private charging infrastructure, the underlying load profile assumed a daily plug-in factor of 70% with a charging demand of 3.68 kW (16 A, 230 V). Based on empirical measurements, this implies that only 70% of all EVs are charged on a given day [58]. For household demand, the newly updated H25 standard load profile was used. This profile reflects modern consumption patterns by incorporating structural shifts in energy use over the past 25 years to provide a more precise baseline for current residual demand. To adjust the reference single-family-household profile to seasonal variation, a dynamization function was applied [61]. The original normalization to an annual consumption of 1,000,000 kWh was rescaled to a baseline of approximately 3500 kWh per household using a linear adjustment. This value is above the average annual electricity consumption for German households, for a conservative estimate of residential demand [63]. The authors of [64] report that a multi-family building in Germany comprises, on average, 6.76 apartments. This value was rounded down to 6, and the single-family-household load profile was scaled by this factor to approximate a multi-family-building load profile.

For the PV generation profile, Germany's average global horizontal irradiation of 1086 kWh/m² [65] motivated the selection of Frankfurt am Main as the reference location. Frankfurt exhibits approximately 1100 kWh/m², closely matching the national average [66].

A typical PV system size of 11.5 kWp was assumed [67]. Based on data from [68], the following distribution of PV array orientations was adopted: south (62.3%), west (21.0%), and east (16.7%), obtained by excluding north-facing systems and scaling the remaining south, west, and east shares to 100% of the simulated capacity. To account for regional differences in building stock, the electric load of urban heat pumps was assumed to be four times that of rural heat pumps. This factor of four accounts for the difference in heating loads between urban multi-family buildings and rural single-family houses [69].

4.3. Methodology

This section investigates when and how severely grid congestion occurs in LV distribution networks under the Federal Government energy transition pathway, considering three levels of grid equipment size and passive network operation. This work applies time-series power-flow analysis based on standardized SimBench reference networks, scenario-specific equipment at network connection points (NCPs), and a formalized detection and classification of congestion events.

Active congestion-management measures (storage systems, bidirectional charging, load shifting, dynamic tariffs, intelligent control strategies) are deliberately excluded. At each NCP, PV generation and demand are represented as separate elements at the same bus and netted by the power flow, so local generation offsets local demand and only the residual is exchanged with the grid. The analysis thus quantifies when purely passive operation reaches its limits.

4.3.1. Selection and Modeling of Network Structures

The analysis is based on standardized LV reference networks from the SimBench dataset [27]. To represent contrasting settlement structures, two different networks are used. For the simulation of urban scenarios, the open-access SimBench code 1-LV-urban6-0-no_sw is used. It is characterized by densely built areas with predominantly multi-family homes. The rural scenarios are based on the SimBench code 1-LV-rural13-0-no_sw, which represents single-family-home areas with low connection density. Both networks are shown in Figure 1.

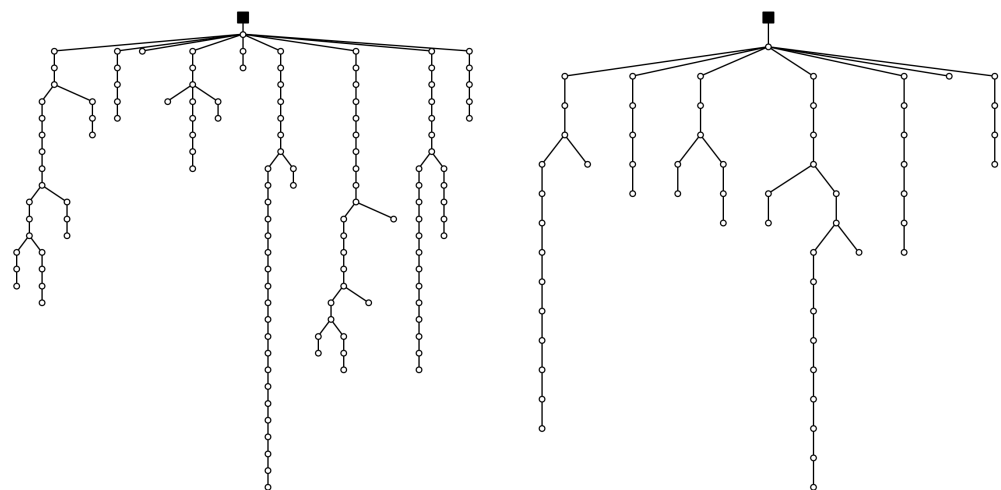


Figure 1. Schematic visualization of the two LV SimBench networks used in this work: 1-LV-rural13-0-no_sw (left) and 1-LV-urban6-0-no_sw (right).

The network topology (lines, transformers, buses) and all electrical parameters of the original SimBench data correspond to the *large* equipment level described below and remain unchanged for that level, apart from a minimum-impedance floor. All load and generation elements originally contained in the reference networks are removed and fully replaced by scenario-based load and generation data to ensure that observed congestion results exclusively from the defined scenarios (a minimum line resistance and reactance of $0.001\ \Omega$ is enforced to avoid quasi-zero impedances in the SimBench data; these values are orders of magnitude below realistic line impedances and do not materially affect the results).

To investigate the sensitivity of congestion patterns to the existing network infrastructure, three equipment size levels are considered. These levels vary the distribution transformer rating and the cable type (and thus the thermal current limit) while preserving the network topology; i.e., all bus positions, line lengths, and connection points remain identical. Table 3 summarizes the parameterization for both area types.

Table 3. Grid equipment size levels for rural and urban low-voltage networks.

Level	Area	Transformer	Cable Type	Thermal Limit
Large	Rural	400 kVA	NAYY 4 × 150	270 A
Large	Urban	630 kVA	NAYY 4 × 240	357 A
Medium	Rural	250 kVA	NAYY 4 × 120	242 A
Medium	Urban	400 kVA	NAYY 4 × 150	270 A
Small	Rural	160 kVA	NAYY 4 × 50	142 A
Small	Urban	250 kVA	NAYY 4 × 120	242 A

The *large* level corresponds to the original SimBench default parameterization and thus to the transformer ratings and cable cross-sections specified in the respective reference networks. The *medium* and *small* levels represent progressively smaller equipment by reducing both the transformer rating and the cable cross-section. The selected transformer ratings are consistent with real German LV grids. Across 87 analyzed real-world networks, characteristic transformer size distributions can be observed for both rural and urban grids [70]. The ratings used in this work therefore correspond to the three most frequent types for the respective settlement structures. The chosen cable cross-sections likewise reflect differentiated rural and urban equipment levels, with 150, 120, and 50 mm² (large, medium, and small) for rural networks and 240, 150, and 120 mm² for urban networks [71,72]. In the *small* rural case, for example, the transformer capacity is reduced by 60% relative to the *large* baseline, and the cable thermal limit decreases by approximately 47%. These variations allow the analysis to capture the range of grid headroom that may exist in practice, as real LV grids exhibit considerable heterogeneity in their installed equipment.

4.3.2. Scenario Setup

Future developments are represented by the Federal Government energy transition pathway described in Section 4.1. The current state in 2025 serves as the reference. The target years are 2030, 2035, 2040, and 2045. Each year is analyzed for both the urban and the rural network, yielding the ten scenarios listed in Table 4.

Each of the ten scenarios is simulated for all three equipment size levels defined in Table 3, yielding a total of $10 \times 3 = 30$ scenario–equipment combinations.

Table 4. Simulated test scenarios by area type and year.

Scenario	Area Type	Year
1	Rural	2025 (baseline)
2	Rural	2030
3	Rural	2035
4	Rural	2040
5	Rural	2045
6	Urban	2025 (baseline)
7	Urban	2030
8	Urban	2035
9	Urban	2040
10	Urban	2045

4.3.3. Mapping of Network Connection Points and Component Modeling

NCPs are uniquely mapped to the load buses of the respective SimBench network. This preserves the spatial distribution of loads while ensuring a consistent one-to-one assignment between NCPs and buses. If a direct assignment is not possible, NCPs are assigned to available free load buses as a documented fallback. NCPs that cannot be assigned are not simulated.

In the rural network with 109 NCPs, each NCP corresponds to one household (single-family home). In the urban network, one NCP is an aggregate of multiple dwelling units (multi-family home). It includes 53 NCPs. The SimBench topologies provide 118 (rural) and 53 (urban) load buses. In the rural network, 109 of these are assigned to NCPs and the remaining 9 stay load-free throughout all simulated time steps, while in the urban network all 53 load buses are assigned.

Depending on the scenario, the following elements are modeled per single-family or multi-family home and assigned based on input data sheets including household electricity demand, public charging stations, EVs, rooftop solar PV generation, and heat pumps. For clarity, public charging stations are coupled directly to households rather than introducing additional intermediate buses.

Table 2 defines the national deployment trajectory, which sets the temporal growth of each technology over the period 2025–2045. The allocation within each network is settlement-specific: starting from this trajectory, devices are distributed across the NCPs by randomized assignment up to the maximum per-NCP configurations shown in Figure 2. A rural single-family home is assigned at least household demand and at most two EVs, one PV system, one heat pump, and one charging station. An urban NCP, which aggregates six dwellings, is assigned at most six EVs, one PV system, one heat pump, and two charging stations. Intermediate configurations follow from the randomized allocation. This settlement-specific intensity reflects the higher per-home car ownership in single-family areas, about 1.3 cars per rural household against 0.8 in metropolitan areas [73], and the limited rooftop area per dwelling in multi-family buildings. Heat pumps are allocated per NCP, as one heat pump serves one building. The two reference networks are therefore deliberately contrasting cases of settlement structure rather than a statistically averaged national sample.

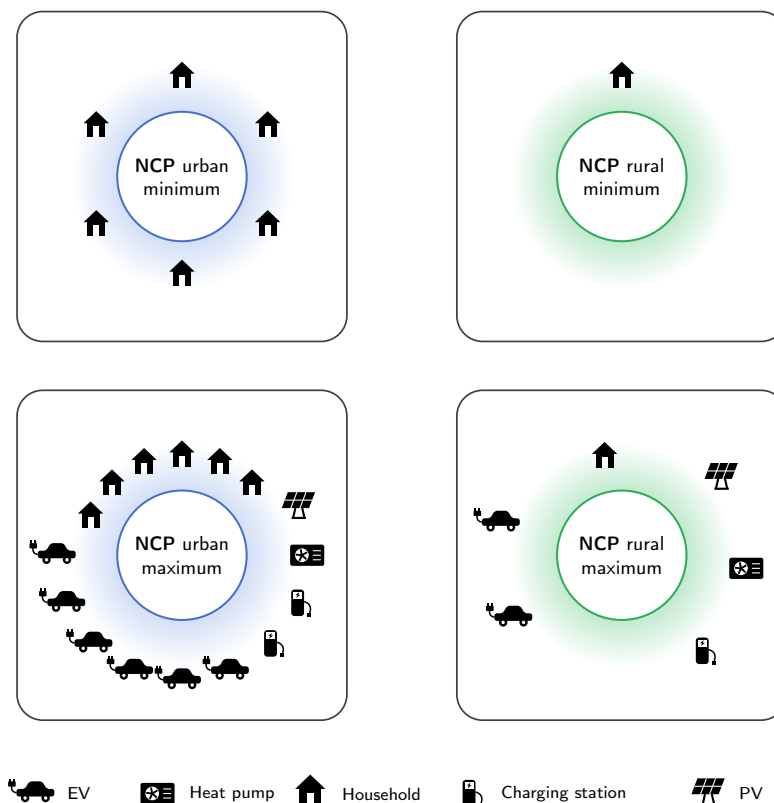


Figure 2. Minimum and maximum per-NCP equipment configurations for the urban and rural scenarios. An urban NCP aggregates six dwellings. Its maximum configuration adds six EVs, one PV system, one heat pump, and two charging stations. A rural NCP is a single-family home. Its maximum configuration adds two EVs, one PV system, one heat pump, and one charging station.

To account for the voltage sensitivity of real-world devices, voltage-dependent ZIP (constant impedance, current and power) load models with specified power factors are used. Household loads are represented as a mixture of constant-impedance, constant-current and constant-power components ($\text{ZIP} = 20\%/10\%/70\%$), with a power factor of $\cos \varphi = 0.98$. Private EV charging is modeled predominantly as near-constant power ($\text{ZIP} = 5\%/5\%/90\%$, $\cos \varphi = 0.99$), consistent with the power-electronics-controlled behavior of typical chargers. Heat pump loads are modeled with $\text{ZIP} = 10\%/10\%/80\%$ and $\cos \varphi = 0.97$. Their reactive power demand is slightly higher than that of household loads, but constant-power behavior still dominates. PV generation is modeled as active-power injection with $\cos \varphi = 1.0$. Reactive power provision by inverters (e.g., $Q(U)$ or $\cos \varphi(P)$ control) is intentionally not considered, in line with the passive business-as-usual assumption.

4.3.4. Congestion Events

A time step is classified as a congestion period if at least one of the following conditions is met: (i) thermal overload, i.e., loading of a line or transformer exceeding 100%; (ii) voltage-band violation with $U < 0.95$ per unit (p.u.) or $U > 1.05$ p.u.; or (iii) non-convergence of the power-flow calculation. For each congestion period, affected elements (lines, transformers and buses) are recorded together with the corresponding loading or voltage values.

To separately report near-limit operating states, a *gray zone* is defined. The *gray zone* includes line and transformer loadings between 100% and 110% and voltage deviations in the ranges 0.90–0.95 p.u. (undervoltage) and 1.05–1.10 p.u. (overvoltage). Operating states outside these ranges are classified as *hard* congestion, i.e., loadings above 110% or voltages $V < 0.90$ p.u. or $V > 1.10$ p.u.

The root-cause classification for congestion is performed per time step. If PV generation exceeds total demand in the generation–load balance, the period is classified as generation-dominant. Otherwise it is classified as load-dominant. Thermal overloads are interpreted according to this dominance. Overloads under generation dominance are classified as generation-side congestion, whereas overloads under load dominance are classified as load-side congestion. Voltage violations follow the same balance-based label, which in practice coincides with the deviation direction: overvoltage ($V_{\max} > 1.05$ p.u.) arises under generation dominance, and undervoltage ($V_{\min} < 0.95$ p.u.) under load dominance. Non-convergent periods are handled separately and reported as *not converged*, as affected elements cannot be uniquely identified in these cases.

4.3.5. Simulation Setup

For each of the 30 scenario–equipment combinations (10 scenarios $\times$ 3 equipment size levels), a time-series simulation is performed over a full non-leap year with 15-min resolution (35,040 time steps). At each time step, all network elements are updated and a power-flow calculation is executed using pandapower (Newton–Raphson, maximum 50 iterations). Non-convergent time steps are classified as *non-converged* congestion events. No element-level overload data are available for these cases.

Detailed element outputs are retained only for time steps containing at least one congestion event. Key scenario-level metrics, including congestion period counts, loading extremes, temporal distributions, and element-wise overload shares, are aggregated across all retained time steps.

4.3.6. Simulation Verification

A targeted validation study was conducted using one urban and one rural test network with the same topology and number of NCPs as the main simulation. Synthetic input data for eight time steps were constructed with known demand and generation values, covering the full range of operating conditions: no-congestion baselines, isolated high loads from each technology (PV, EVs, public charging, heat pumps), simultaneous extreme demand triggering solver non-convergence, and balanced high-load/high-generation cases. All eight test cases produced results consistent with the expected outcomes. These results confirm the correctness of scenario-to-network mapping, device penetration scaling, congestion detection, and root-cause classification.

4.4. Grid-Side Congestion Under Passive Network Operation

This section analyzes grid-side congestion in urban and rural LV networks under passive operation up to 2045, systematically varying the grid equipment level (Table 3). Device penetration rates are summarized in Table 2 (Section 4.1).

4.4.1. Development of Congestion Frequency

Figure 3 illustrates the development of the share of congestion periods in urban and rural grids over the period 2025–2045, differentiated by equipment level. A distinction is made between gray-zone periods and hard-congestion events, as defined in Section 4.3.4.

Under large equipment, no congestion occurs throughout the entire simulation horizon in either network type. Under medium equipment, congestion first appears in 2035 in the urban network and in 2045 in the rural network. All observed events are exclusively load-driven. Under small equipment, congestion is present from the 2025 baseline in both area types and intensifies substantially toward 2045, with hard-congestion events increasingly dominating over gray-zone periods. In the rural network under small equipment, generation-side congestion driven by PV feed-in first appears in 2025, whereas the urban network exhibits exclusively load-side congestion across all years. In the *small* rural

network, total congestion grows from 8.9% of time steps in 2035 to 26.8% by 2045 and is overwhelmingly load-driven, with the superimposed generation-side overvoltage signal (the downward bars) never exceeding about 4.5% of time steps. This signal is threshold-sensitive: the peak midday bus voltage sits just at the 1.05 p.u. limit, dropping below it in 2030 (1.042 p.u.) and rising clearly above only in 2045 (1.066 p.u.). The 2030 valley is therefore congestion-free, with both regimes sub-threshold that year (peak transformer loading 95.4%, minimum voltage 0.958 p.u.). In other words, 2030 falls in the window between the early generation-side overvoltage, a marginal gray-zone signal that recedes just below its threshold that year, and the onset of load-side congestion, which becomes dominant only from 2035 onward.

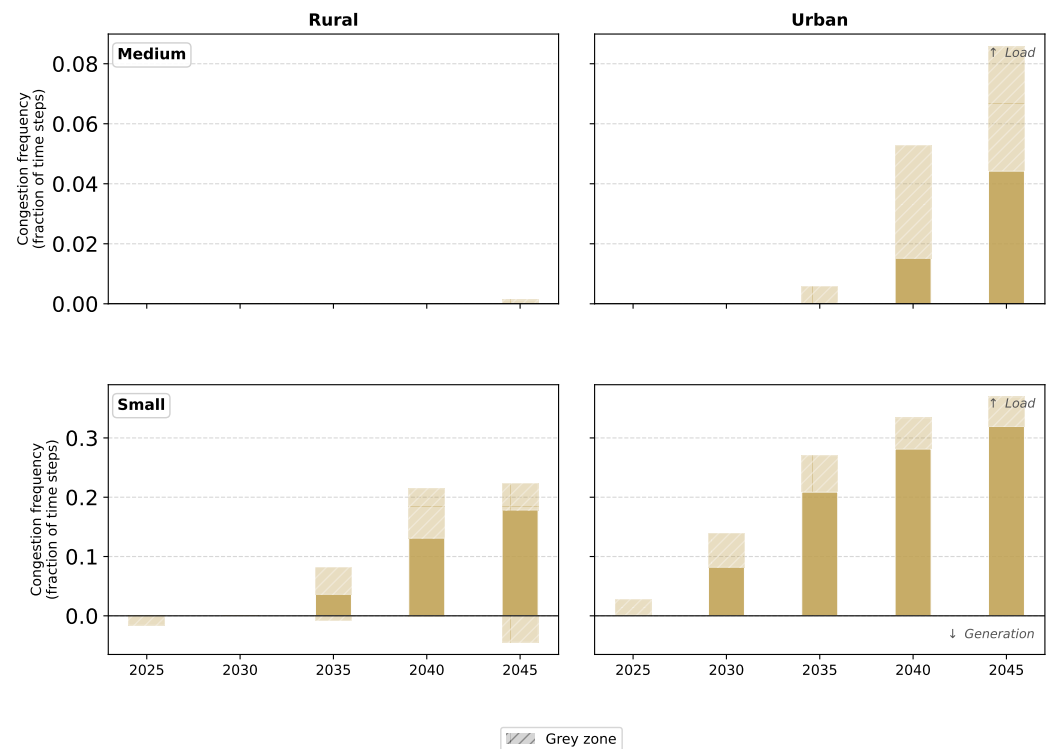


Figure 3. Development of congestion frequency in urban and rural grids by year, energy transition pathway, and equipment level. Bars show the fraction of all 35 040 time steps per year with at least one congestion event, split into hard-congestion (solid) and gray-zone periods (hatched). Bars above the zero line indicate load-side, below it generation-side congestion.

4.4.2. Limit Violations at Network Components

Figure 4 quantifies which violation type drives congestion, showing for each year the fraction of congestion periods affected by transformer overload and by voltage-band violation.

Figure 4 confirms that congestion is driven by two distinct mechanisms: transformer overloading and voltage-band violations. Under medium equipment, transformer overloading is the sole violation type in urban networks from 2035, while rural congestion at 2045 is also driven exclusively by transformer overloading. Under small equipment, transformer overloading dominates in urban networks across all years, consistent with the higher per-transformer demand density in multi-family-home areas. In rural networks, voltage-band violations are the primary mechanism in 2025 (PV-driven overvoltage), as the reduced transformer and cable capacity lowers the threshold at which PV backfeed causes voltage rise at peripheral nodes. From 2035 onward, rising EV and heat pump penetration makes transformer overloading the most frequent violation type (present in 83 to 91% of congestion periods), while the accompanying voltage violations shift in character from the PV-driven overvoltage of 2025 to load-side undervoltage at remote feeder ends. This un-

dervoltage is not a secondary effect; it accompanies nearly every congestion period in 2040. By 2045, it affects a smaller share, as PV-driven overvoltage also returns at midday, when the peak bus voltage again exceeds the 1.05 p.u. limit (see Section 4.4.4). No individual line exceeds its thermal rating in any of the evaluated scenarios (maximum observed: 98.6% in the 2040 urban network under small equipment). The radial topology concentrates thermal stress at the transformer rather than distributing it across line segments.

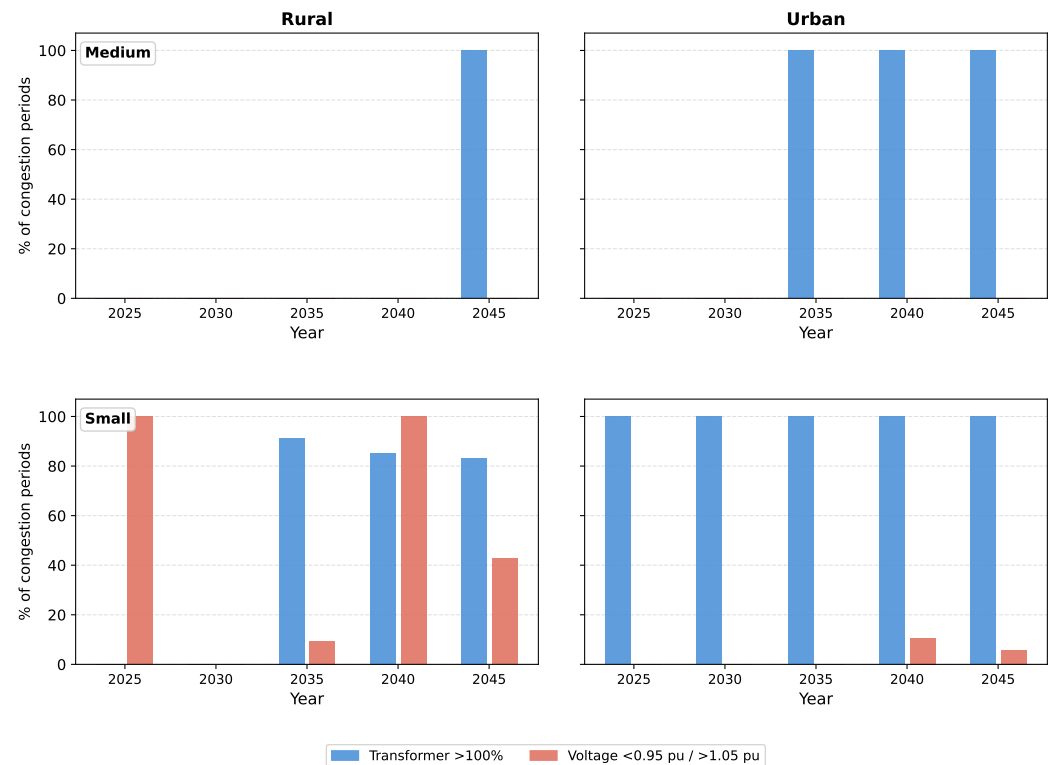


Figure 4. Component-level limit violations during congestion periods, by equipment size level (rows: medium, small) and network type (columns: rural, urban). For each year, grouped bars show the fraction of congestion periods with transformer loading >100% (blue) and with at least one bus voltage outside 0.95–1.05 p.u. (red). Empty bars indicate years without congestion events.

4.4.3. Congestion Severity

Figure 5 extends the frequency analysis to severity, showing the distribution of maximum transformer loading exclusively during time steps classified as congestion events (Section 4.3.4). While Figure 3 quantifies how often congestion occurs, Figure 5 characterizes how severe it is. Large equipment is omitted from the figure because no congestion events occur under this equipment level in any of the ten scenarios, as established in Section 4.4.1.

Under small equipment, the distribution of transformer loading during congestion periods in Figure 5 shifts markedly upward over time. In the urban network, the median loading rises from approximately 104% in 2025 to approximately 139% by 2045, with the interquartile range widening substantially, so congestion becomes both more frequent and more severe. The rural network follows the same trend from a lower base: its 2025 events are generation-side at low transformer loading; load-driven severity emerges only from 2035 and reaches about 119% by 2045; and 2030 is congestion-free. Under medium equipment, congestion severity remains moderate, with the median only just above the 100% threshold (about 110% in the urban network by 2045).

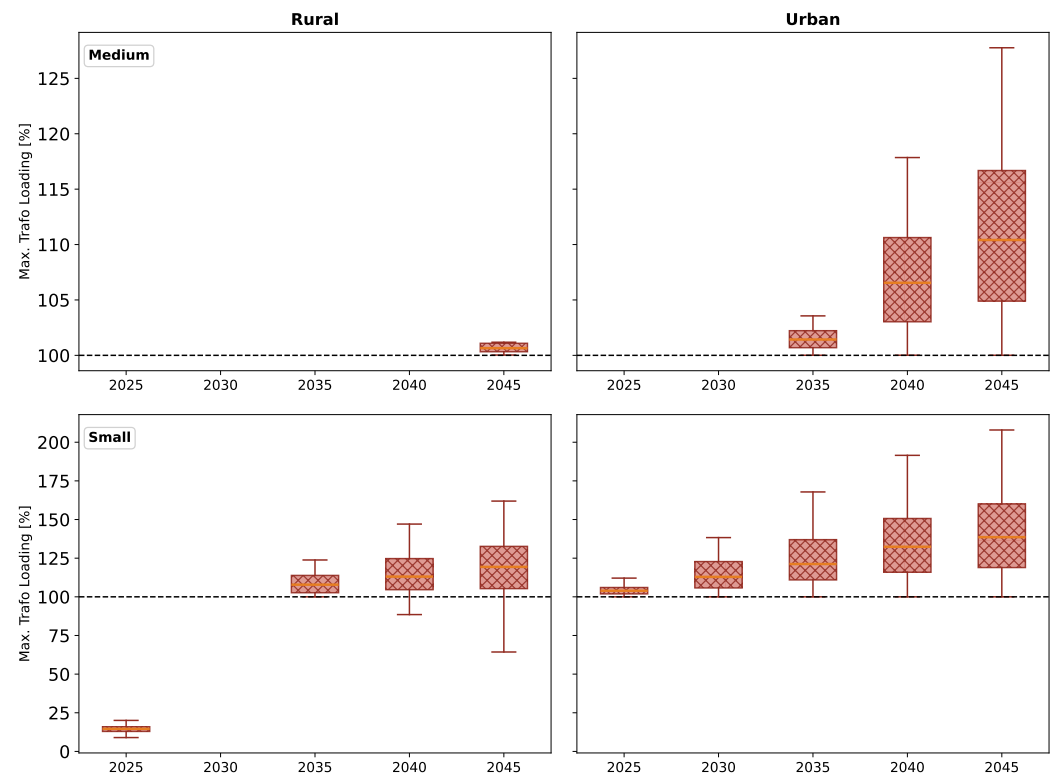


Figure 5. Distribution of maximum transformer loading during congestion periods by year, equipment level, and area type. Box plots show one distribution per year for medium and small equipment and both network types. Large equipment is omitted (no congestion events). Dashed line: 100% overload threshold. Missing boxes indicate years without congestion events.

4.4.4. Seasonal Distribution of Congestion Periods

This section examines the seasonal structure of congestion events to identify in which months and under which conditions the load- and generation-side mechanisms dominate.

Figures 6 and 7 show the monthly distribution of transformer loading and bus voltages exclusively during congestion periods for the *small* rural network.

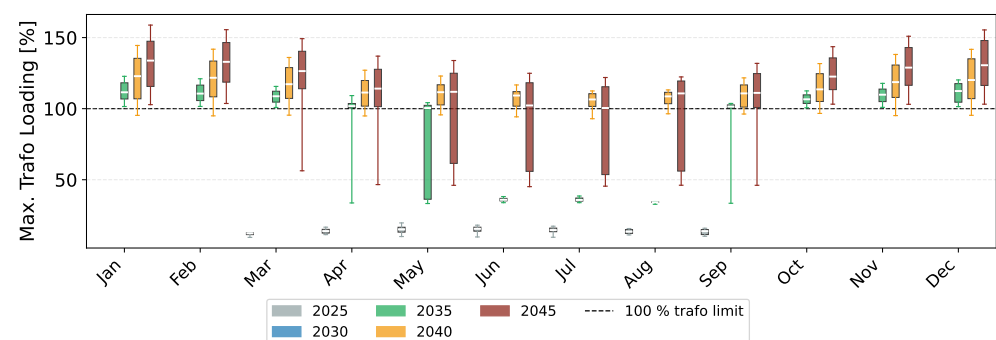


Figure 6. Monthly distribution of transformer loading during congestion periods for small equipment and a rural network (2025–2045). Whiskers span the 5th–95th percentile. Dashed line marks the 100% thermal limit. Missing boxes indicate months without congestion events.

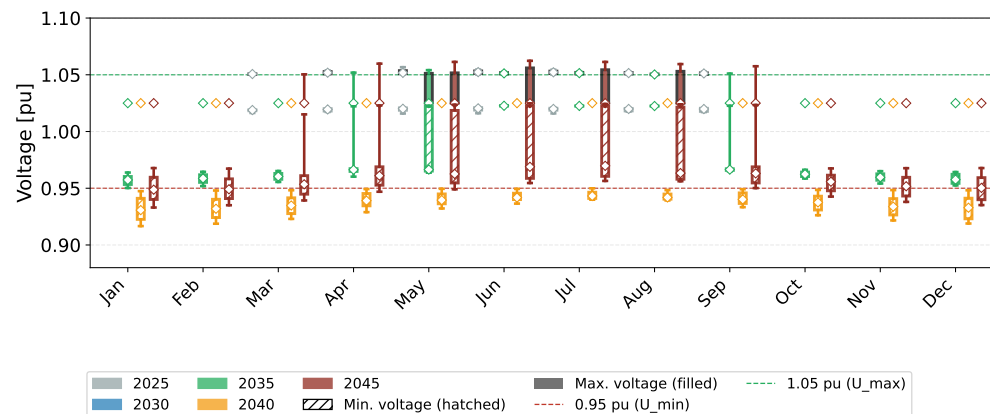


Figure 7. Monthly distribution of bus voltage during congestion periods for small equipment and a rural network (2025–2045). Minimum voltage (hatched) and maximum voltage (filled) are overlaid at the same position, with diamond markers indicating the median where boxes are compact. Whiskers span the 5th–95th percentile. Dashed lines mark the 0.95 and 1.05 p.u. voltage limits. Missing boxes indicate months without congestion events.

Figures 6 and 7 jointly reveal a pronounced bimodal seasonal structure in which two distinct congestion regimes alternate over the year. The 2030 columns are empty throughout, reflecting the congestion-free year identified in the frequency analysis (see Section 4.4.1).

During winter months (November–March), congestion is predominantly load-driven. In 2025, the rural network has essentially no load-driven winter congestion: January, February, November, and December show no boxes at all, and the only winter-month events are a few generation-side ones in March (the low-loading box) in Figure 6. From 2035 onward, winter congestion emerges with median transformer loading around 105–115%, rising to about 125–135% by 2045 as EV and heat pump penetration increases. Simultaneously, minimum bus voltages (hatched boxes) fall to and below the 0.95 p.u. limit as EVs and heat pumps draw power at remote feeder nodes: their median during congestion drops from about 0.96 p.u. in 2035 to 0.93 to 0.95 p.u. from 2040, while maximum voltages (filled boxes) stay near 1.025 p.u., well below the 1.05 p.u. limit, as PV generation is low. These load-driven evening peaks are confirmed in Section 4.4.5.

In summer months (May–August), the congestion character depends on the target year. In 2025, all summer congestion events are generation-driven: transformer loading remains low, around 10 to 20% (Figure 6), reflecting events in which PV backfeed triggers overvoltage at peripheral nodes while the transformer is only lightly loaded. In 2035, the picture is mixed, with transformer loading spanning a wide range from approximately 30% to above 100%, indicating the coexistence of generation- and load-side events within the same season. By 2040, this transitional pattern has resolved into load-side dominance: median transformer loading during congestion exceeds 100% in every month, including June–August, so that the low-loading generation-side summer cluster still visible in 2035 has all but disappeared (only a handful of low-loading generation events remain). By 2045, the summer is load-dominant, with median transformer loading around 100 to 112% across the summer months while a substantial generation-side cluster reappears at midday (roughly 40% of summer congestion events), as growing EV and heat pump demand produces evening congestion even in summer months. Correspondingly, the maximum voltage values in Figure 7 rise toward and beyond the 1.05 p.u. upper limit during generation-side events, while minimum voltages fall toward 0.95 p.u. when load-side events occur. The load-side share grows strongly through 2040. In 2045, however, a

generation-side summer cluster re-emerges as PV backfeed grows, so the shift toward load dominance is not strictly monotonic.

The transition months, April and September/October, mark the boundary between the two regimes. In April 2035, the transformer loading distribution in Figure 6 spans from approximately 35% to above 100%, and Figure 7 shows both overvoltage (maximum voltage near 1.05 p.u.) and a load-side minimum-voltage depression to about 0.96 p.u. (still above the 0.95 p.u. limit) within the same month. By 2040, April has shifted to predominantly load-driven congestion (median loading above 100%), and the generation-side signal has largely disappeared. A similar transition is visible in September, where the generation-side events of 2025 give way to load-driven congestion by 2045. October, by contrast, is load-driven in every year in which it shows congestion (from 2035 onward). Load-driven congestion progressively encroaches on the spring and autumn shoulder months. The generation-dominated summer window narrows through 2040 but partially re-widens in 2045 as PV backfeed grows.

Across the congestion-affected years, the transformer-loading distributions intensify and their winter interquartile range widens (about 25 percentage points in 2040 and 29 in 2045). The summer spread is wide only where both regimes coexist within a month: about 60 to 64 percentage points in every summer month of 2045 (midday generation events at 45 to 55% alongside evening load events above 110%), and about 66 percentage points in 2035 but only in the mixed month of May. In 2040, with generation-side congestion largely absent, the summer boxes are narrow (about 9 to 14 percentage points) and sit above the 100% threshold.

Large equipment shows no congestion in any month. The other three network–equipment combinations differ qualitatively. In the *small urban* network, congestion is exclusively load-driven: no summer generation cluster appears in either the loading or voltage distributions, and congestion occurs in every month, with transformer loading consistently above 100% and the highest event counts in winter. Maximum voltage deviations remain negligible throughout, as the high baseline load suppresses PV surplus at the network level.

For the *medium* equipment level, congestion is entirely absent in the early target years and emerges only from 2035 onward. When congestion does occur, it is exclusively load-dominated in both rural and urban networks: transformer loading during congestion periods is clustered near and above the 100% threshold without a low-loading summer cluster, while bus voltages remain within their limits (no undervoltage violation occurs under medium equipment, as the minimum voltage stays above 0.95 p.u.). This is consistent with Figure 3, confirming that PV-driven overvoltage requires substantial prior exhaustion of transformer and cable headroom, which medium equipment does not reach within the simulation horizon.

4.4.5. Intraday Distribution of Congestion Periods

To interpret *when* congestion occurs, hourly congestion statistics must be related to the intraday composition of demand and generation. Figure 8 illustrates the aggregated instantaneous power for the rural scenarios for the years 2025 (current state), 2035, and 2045 (shown as three representative snapshots of the trajectory, with the intervening years 2030 and 2040 lying between them in load and generation magnitude). For each year, the upper panel represents a summer day (2 July) characterized by high PV generation and comparatively low heat pump demand, whereas the lower panel depicts a winter day (26 January) with low PV generation and elevated heat pump demand. Positive stacks disaggregate household electricity demand, private and public EV charging, and heat pump demand, while PV generation is shown below the zero line. Figure 8 reveals a clear temporal decoupling between midday PV generation and demand components, which peak

predominantly in the evening hours. Across the considered years, the positive and negative magnitude increases, indicating a progressive intensification of structural network loading.

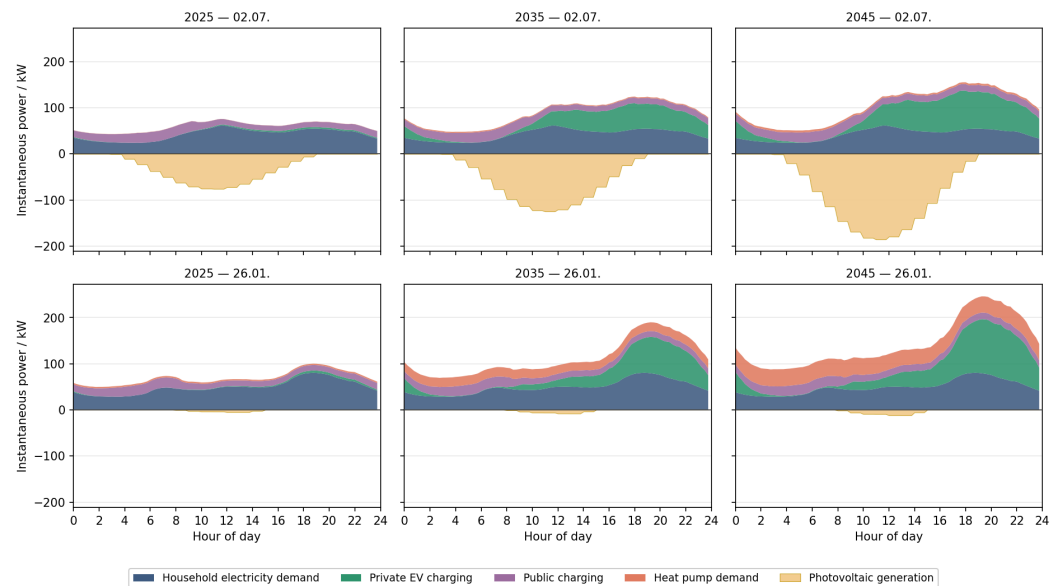


Figure 8. Aggregated instantaneous power for the rural network from 2025 through 2035 to 2045. For each year, the upper panel shows a summer day (2 July), and the lower panel a winter day (26 January). Positive stacks represent household demand, private and public EV charging, and heat pump demand, while PV generation is plotted below the zero line.

As EV penetration increases, a pronounced evening charging peak emerges (approximately 18–22 h) that is only weakly developed in the 2025 baseline. This peak structurally reshapes the daily load profile rather than merely scaling it. As it develops, peak demand shifts into the evening and decouples from the midday PV generation. In the 2025 baseline, peak demand still falls around midday. Summer and winter profiles differ in component magnitude (reduced PV in winter, lower heat pump demand in summer), driven by seasonal solar irradiance and heating demand, respectively.

Building on this decomposition, congestion periods were aggregated on an hourly basis and separated into load-side and generation-side events (Figure 9). A congestion period is classified as generation-dominated when PV generation exceeds total demand at the transformer level. Load-side congestion is plotted upward and generation-side congestion downward.

The results reveal that the intraday structure of congestion depends on both the equipment level and the type of congestion. In urban grids, all congestion is exclusively load-driven. Under *small* equipment in the urban network, load-side congestion concentrates in the late afternoon and evening hours, with peaks between 18:00 and 22:00. This pattern is consistent with simultaneous load peaks from household consumption and, in particular, EVs. As DER penetration increases, the urban congestion window broadens substantially: the evening peak grows from about 25% of time steps in 2025 through 68% in 2030 to 100% from 2035 onward, while its onset shifts from the early evening toward the late morning, until congestion spans almost the entire day by 2045. Under *medium* equipment, a similar but attenuated intraday structure emerges from 2035 onward, predominantly in the urban network (peak congestion share approximately 10%, 41%, and 54% in 2035, 2040, and 2045). Under *large* equipment, no intraday congestion structure is observable.

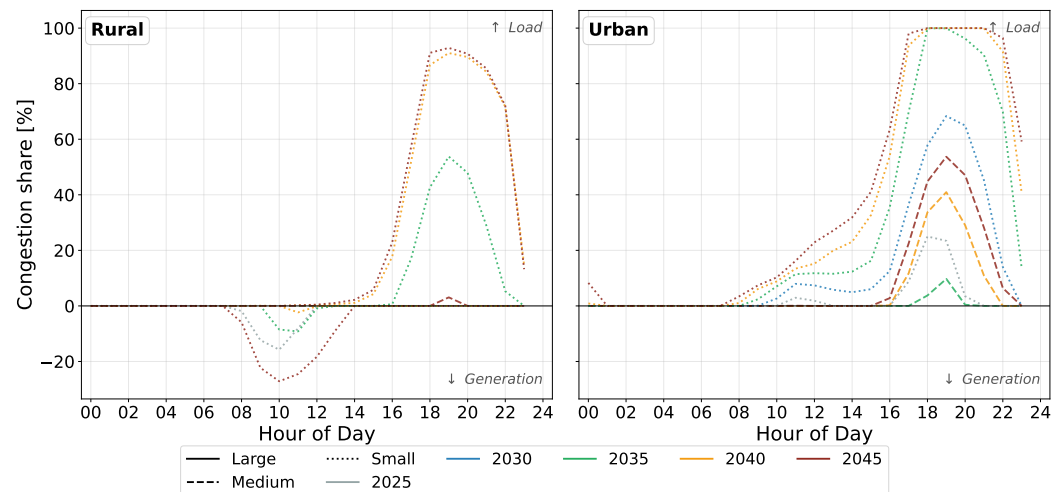


Figure 9. Intraday congestion profiles comparing all three equipment levels in one panel per network type. Lines are differentiated by equipment level (solid: large, dashed: medium, dotted: small) and colored by year (2025–2045). Each point shows the percentage of quarter-hour time steps at that hour containing at least one congestion event. Positive (upward) values indicate load-side, negative (downward) generation-side congestion. Lines with zero congestion are omitted.

In rural grids, by contrast, a fundamentally different and bidirectional congestion pattern emerges under small equipment. Generation-side congestion, driven by PV-induced overvoltage, is concentrated during midday hours (approximately 8:00–14:00), forming a pronounced downward peak that is temporally complementary to the load-side evening peak. Under small equipment in 2025, generation-side congestion at midday already reaches approximately 15% of time steps, while no load-side congestion is present. This generation-side midday signal is non-monotonic: as a marginal gray-zone signal that sits close to the 1.05 p.u. limit, it recedes just below the limit in 2030, stays minor through 2040, and resurges to its deepest level in 2045. By 2045, generation-side congestion intensifies to approximately 27% during peak PV hours (9:00–13:00), while load-side congestion simultaneously grows to approximately 90% during evening hours (18:00–21:00). This creates two distinct congestion windows per day: a midday generation-side window and an evening load-side window, with a brief transition period around 14:00–16:00 in which congestion of either type is rare.

Under medium and large equipment in rural grids, generation-side congestion is absent or negligible, and the intraday pattern, where congestion occurs, resembles the purely load-driven urban profile.

The bidirectional pattern in rural grids with small equipment reflects two structurally independent mechanisms: midday PV surplus causes overvoltage at peripheral nodes despite low transformer loading, while the superposition of household, EV, and heat pump demand drives evening overloads.

Combined with the winter dominance of load-side congestion (Section 4.4.4), winter evening hours constitute the highest load-side congestion risk, while summer midday hours pose the highest generation-side risk, particularly for rural grids with small equipment.

4.4.6. Spatial Distribution and Persistence of Congestion at the Component Level

The central finding is that the spatial persistence of congestion hotspots is strongly modulated by the equipment level. Under *large* equipment, no congestion corridors form across the entire simulation horizon. Under *medium* equipment, identifiable hotspots emerge from 2035 onward in the urban network, concentrated at the transformer and immediately adjacent feeder sections. Under *small* equipment, clearly identifiable hotspots

appear already in 2025 in both area types, although the rural network is congestion-free in 2030. From 2035 onward the rural hotspots are predominantly load-driven. By 2045, these hotspots intensify and expand spatially.

To quantify this spatial persistence, the frequency with which each individual line and bus was affected by congestion was evaluated across all simulated scenarios. The results confirm a systematic, topology-determined pattern that is most pronounced under small equipment. Thermal overloads occur at the distribution transformer, while the lines themselves do not experience overloads but show varying degrees of utilization. Aggregated across congestion-affected scenarios and years, the most heavily loaded line segments are located within the first few segments downstream of the transformer in both network types. This reflects the accumulation of downstream power flows at the feeder-entry section, where lines carry the combined load of all downstream NCPs. By contrast, voltage limit violations concentrate toward the remote end of the feeders, consistent with the additive voltage drop that accumulates along the feeder path. In the *small* rural network this separation is pronounced: the undervoltage violations concentrate at the remote feeder ends (median hop distance about 14 of 27 from the transformer, with the most frequently affected buses near hop 20), whereas the highest-loaded line sits directly at the feeder entry (median hop distance 0 to 1). The structural implication is that both thermally critical nodes and voltage-critical buses are topologically predictable and recurrent. Targeted monitoring can therefore be concentrated at the transformer, the only thermally overloaded element, and at the remote feeder ends, where the undervoltage occurs. The feeder-entry lines carry the highest current but stay within their thermal rating (maximum line loading 70% rural, 98.6% urban).

Figure 10 illustrates this progression for the rural network under small equipment. The 2025 snapshot shows a representative generation-side gray-zone event: at 10:15 on 12 May, PV backfeed exceeds local demand and drives overvoltage at peripheral nodes (max: 1.057 p.u., just above the 1.05 p.u. threshold), while the transformer itself is only lightly loaded (20%) and all line segments remain well below their thermal limits (max: 30%). This event is characteristic of the 2025 rural congestion pattern, which consists exclusively of mild PV-driven overvoltage without any thermal overloads. The 2045 panel shows the most severe congestion period, i.e., the time step with the highest transformer loading. By 2045, the worst-case period is load-driven: on 17 January at 19:15, simultaneous EV charging and heat pump demand drives the transformer to 162% loading and causes voltage drops at remote feeder ends (min: 0.931 p.u.), while line segments remain below their thermal ratings (max: 70%). Under large and medium equipment, this spatial progression is either entirely absent or confined to the transformer vicinity in late target years.

4.4.7. Combined Temporal Risk Map

Figure 11 combines seasonal and intraday patterns in a two-dimensional representation, showing the fraction of quarter-hour intervals with congestion for each combination of month and hour of day.

Under small equipment, congestion occurs in every month and is concentrated in the afternoon and evening hours (approximately 12:00–24:00). This timing is consistent with the load-driven evening peaks established in Section 4.4.5, in particular EV charging. In winter months (November to March) the evening load congestion persists later into the night and, in the urban network, reaches just past midnight (the 00:00 hour is congested in up to 44 percent of winter intervals), while the early-morning hours (01:00 to 07:00) stay congestion-free in both networks. Because the heatmap resolves the seasonal dimension that Figure 9 averages over, congestion probabilities at late evening hours (21:00–24:00) appear

substantially higher in individual winter months than in the annual-average intraday profile, where they are diluted by congestion-free summer months at the same hours.

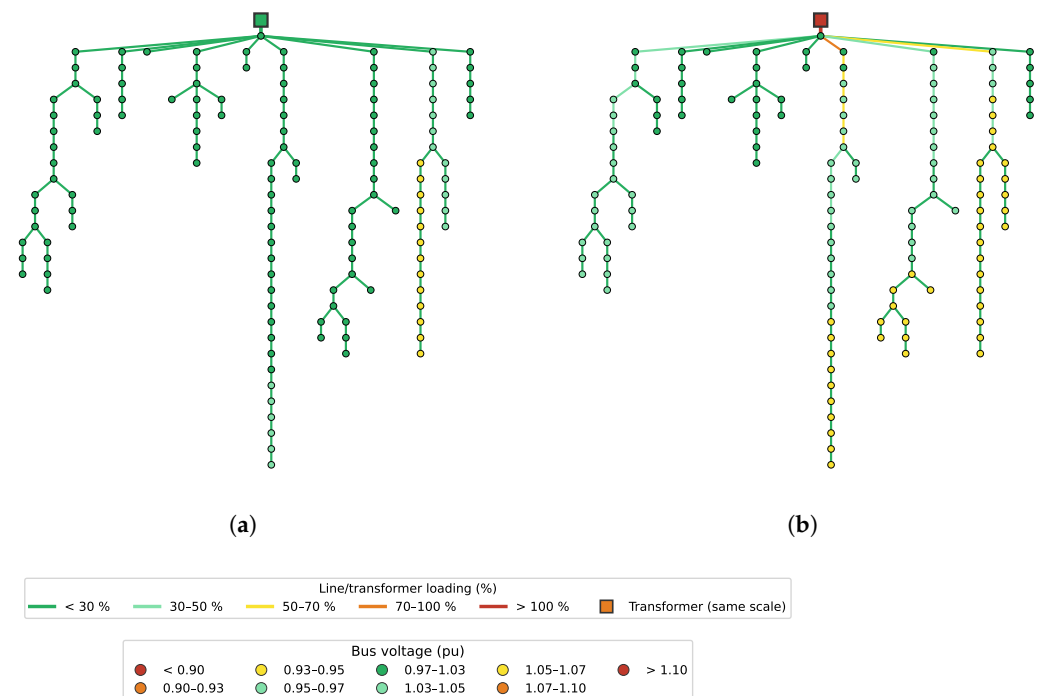


Figure 10. Spatial progression of congestion in the rural SimBench LV grid (1-LV-rural3, 129 buses) under small equipment. The 2025 panel shows a representative generation-side gray-zone event (overvoltage only, no thermal overload). The 2045 panel shows the most severe congestion period (highest transformer loading). (a) 2025—mild generation-side event (gray zone): transformer: 20%, max. line loading: 30%, max $V = 1.057$ p.u. (12 May, 10:15); (b) 2045—severe load-side: transformer: 162%, max. line loading: 70%, min $V = 0.931$ p.u. (17 January, 19:15).

In the 2045 snapshot, the winter congestion window extends only to the hour just after midnight in the urban network and ends at 23:00 in the rural network, with the early-morning hours staying congestion-free. In summer, the rural network additionally shows the midday generation-side stress identified earlier (peaking near 77 percent around 10:00 in July), whereas the urban network has no generation-side congestion in any month. Summer morning hours remain congestion-free in both.

Under medium equipment, congestion is confined to a narrow evening window (roughly 17:00 to 23:00) and is predominantly urban: it appears from around 2035 in the urban network, whereas the rural network shows only isolated evening congestion from 2045 onward. Large equipment is omitted from Figure 11, as no congestion events occur across the entire simulation horizon, consistent with the findings in Figure 3.

These differences across equipment levels have direct operational implications: grids with small equipment require monitoring over a broad temporal range, whereas grids with large equipment remain congestion-free across the simulated scenarios, indicating correspondingly lower monitoring and control needs.

4.4.8. Structural Synthesis

The analysis shows that, under the assumption of passive network operation, the grid equipment level is the primary determinant of whether and when congestion occurs, while the stage of DER deployment, together with the settlement type, raises its severity. While grids with large equipment remain congestion-free throughout the horizon, the onset of load-driven congestion is delayed under medium equipment, whereas under small

equipment congestion is present already in the 2025 baseline and reaches high levels by 2045. In 2025, the urban network already shows load-side transformer overload, while the rural baseline is only mild PV-driven overvoltage at low transformer loading.

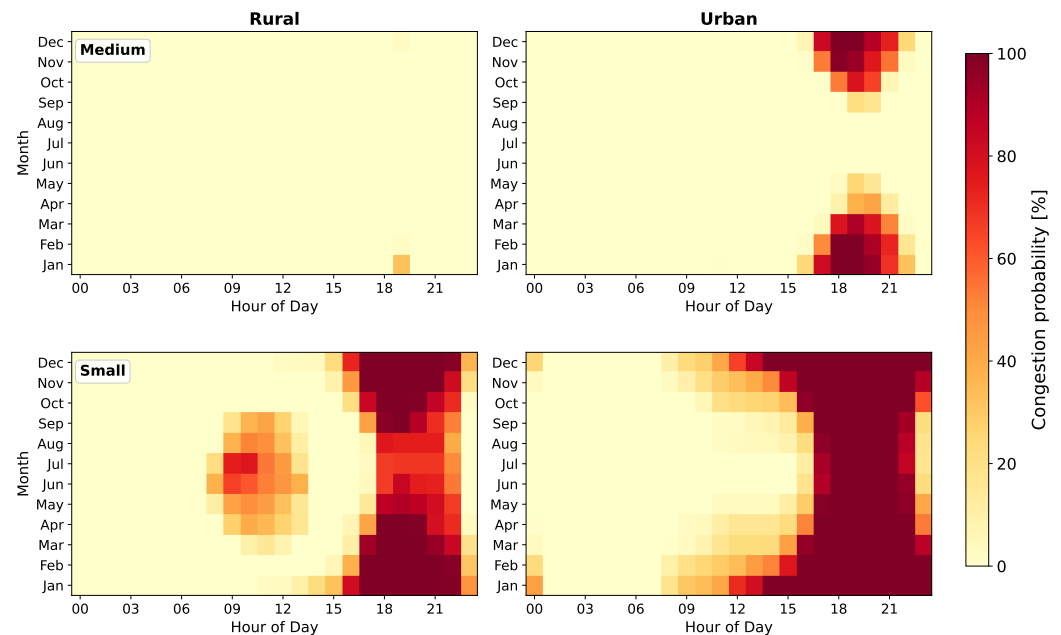


Figure 11. Congestion probability heatmap by month and hour of day for the 2045 target year, comparing medium and small equipment levels (rows) and both network types (columns: rural/urban). Cell color indicates the fraction of quarter-hour time steps in a given month–hour combination with at least one congestion event, from 0% to the maximum observed, consistent across panels. Large equipment is omitted as no congestion events occur.

Increasing DER penetration modulates the severity and the seasonal and intraday character of congestion within a given equipment class and can switch congestion on or off over time, as in the *small* rural network (congested in 2025, congestion-free in 2030, congested again from 2035). In that case the early generation-side overvoltage is a marginal gray-zone signal that recedes just below its threshold in 2030, before load-driven congestion takes over as deployment continues. The equipment level sets the overall susceptibility to congestion. The following section investigates whether the available measurement infrastructure is sufficient to detect these congestion events via SE.

5. State Estimation Quality Under Varying Measurement Availability

This section evaluates the quality of LV grid SE using the BC-Mod branch-current WLS estimator (Section 3.2) across the congestion scenarios identified in Section 4, against the accuracy and detection metrics defined in Section 3.1. The evaluation covers all three equipment size levels and the three VDE FNN 2024 measurement constellations K3 (SMGW-only), K2 (transformer total power measurement), and K1 (per-feeder measurement). The base scenario set comprises ten combinations (5 years $\times$ 2 network types). Whether a scenario produces congestion depends on the equipment size level: large equipment yields no congestion in any scenario (0 out of 10), medium equipment produces congestion in 4 scenarios, and small equipment in 9 of 10 (the 2030 rural network remains congestion-free), resulting in 13 congestion scenarios in total across all equipment levels.

5.1. Measurement Configurations and Input Data

5.1.1. Measurement Model and VDE FNN Constellations

Real measurements represent values acquired by installed SMGWs, as defined under the German Metering Point Operation Act (Messstellenbetriebsgesetz, MsbG [74]). Each real measurement delivers the active and reactive power injection at an NCP for the preceding 15-min interval. These measurements are modeled with a relative standard deviation of $\sigma_{\text{real}} \approx 1.7\%$ of the measured value [13]. This accounts for both sensor inaccuracy and communication jitter.

The transformer secondary bus (slack bus) serves as the voltage reference node. Its magnitude is taken from the simulation rather than fixed at nominal: in the evaluated SimBench scenarios the upstream medium-voltage bus is set to 1.025 p.u. and the on-load tap changer of the transformer remains at its neutral position, so the secondary reference equals 1.025 p.u. ($\cong 236$ V per phase). Aligning the reference to this value avoids a systematic offset between the assumed and the actual slack voltage. The slack voltage standard deviation of $\sigma_{\text{slack}} = 0.5\%$ accounts for the residual uncertainty in the secondary voltage, primarily its load-dependent variation across the transformer impedance.

The VDE FNN 2024 study [16] defines three measurement constellations for LV SE. All three include SMGW real measurements at equipped nodes and differ in the availability of additional grid-level metering:

- K3—SMGW-only (no transformer measurement): No transformer or feeder measurements are available. Pseudo-measurements for non-metered nodes are derived exclusively from standard load profiles scaled by each node's annual energy consumption proxy. The VDE FNN recommends a minimum SMGW penetration of 70%.
- K2—Transformer total power measurement: In addition to SMGW readings, the total active power at the transformer secondary is measured. This aggregate value is distributed across all non-metered nodes proportionally to their annual energy consumption to form pseudo-measurements. The VDE FNN recommends a minimum SMGW penetration of 30%.
- K1—Feeder-level transformer measurement: In addition to SMGW readings, each outgoing feeder is individually metered at the transformer secondary. Pseudo-measurements for non-metered nodes are generated by distributing the feeder's measured active power proportionally to the nodes' annual energy consumption within that feeder. The VDE FNN recommends a minimum SMGW penetration of 15% for radial feeders.

Feeder membership is derived algorithmically from the SimBench LV network topology (breadth-first traversal from the transformer LV bus), yielding nine feeders (rural, 1–29 buses each) and seven feeders (urban, 1–18 buses each).

5.1.2. Pseudo-Measurement Model

Pseudo-measurements follow the proportional load distribution approach specified in VDE FNN [16,35,75]. An estimated or measured total active power is distributed proportionally to each node's annual energy consumption $E_{a,i}$, obtainable from metering data:

$$w_i = \frac{E_{a,i}}{\sum_{j \in \mathcal{N}} E_{a,j}}, \quad (6)$$

where $\mathcal{N}$ is the set of all load nodes and w_i is the proportional weight assigned to node i . The two measurement-anchored constellations K2 and K1 differ in how the total active

power that is subsequently distributed is obtained (K3 must additionally estimate the total load from load profiles, as described below).

K3 (SMGW-only)

Without a transformer measurement, the total grid load must itself be estimated. Under K3, all non-metered nodes are assigned pseudo-measurements based on a single generic H0 household load profile $f_{H0}(t)$ (normalized to unit mean), scaled by each node's consumption proxy:

$$\hat{P}_i^{(K3)}(t) = f_{H0}(t) \cdot w_i \cdot \frac{\sum_{j \in \mathcal{N}} E_{a,j}}{\bar{T}}, \quad (7)$$

where $\bar{T}$ is the number of hours per year and $\hat{P}_i^{(K3)}(t)$ is the estimated active power consumption of node i at time t . In practice, this simplifies to $\hat{P}_i^{(K3)}(t) = f_{H0}(t) \cdot \bar{p}_i$, where $\bar{p}_i$ is the average annual demand rate of node i . The H0 profile is a generic household consumption pattern and does not capture the load patterns of EV charging, heat pumps, or PV feed-in. During congestion periods, which are driven precisely by these devices, the H0-based estimate systematically mis-estimates the true net demand (underestimating load during load-driven periods and missing PV feed-in during generation-driven periods). Accordingly, pseudo-measurements under K3 are assigned $\sigma_{\text{pseudo}}^{(K3)} = 40\%$ [13,42,76].

K2 (Transformer Total Power Measurement)

With the transformer secondary total active power P_{trafo} available as a real measurement, the distribution step replaces the profile-based estimate. Let $\mathcal{M}$ denote the set of SMGW-equipped nodes with real measurements P_j^{real} . The residual power after subtracting the known metered injections is distributed proportionally across the unmetered nodes $i \notin \mathcal{M}$:

$$\hat{P}_i^{(K2)} = \frac{P_{\text{trafo}} - \sum_{j \in \mathcal{M}} P_j^{\text{real}}}{\sum_{k \notin \mathcal{M}} w_k} \cdot w_i. \quad (8)$$

At zero SMGW penetration ($\mathcal{M} = \emptyset$), this reduces to $\hat{P}_i^{(K2)} = P_{\text{trafo}} \cdot w_i / \sum_k w_k$, i.e., proportional distribution of the full transformer power. Because the absolute load level is anchored to the measured total, primarily the distributional uncertainty of the consumption-based weights remains (alongside the reactive-power approximation via a constant power factor). This justifies a reduced standard deviation of $\sigma_{\text{pseudo}}^{(K2)} = 25\%$ [16].

K1 (Feeder-Level Measurement)

With per-feeder active power measurements $P_{\text{feeder},f}$ available at the transformer secondary, the distribution step is performed independently for each feeder f . Let F_f denote the set of all load nodes belonging to feeder f , and $\mathcal{M}_f = \mathcal{M} \cap F_f$ the subset equipped with SMGWs. The pseudo-measurement for an unmetered node $i \in F_f \setminus \mathcal{M}$ is

$$\hat{P}_i^{(K1)} = \frac{P_{\text{feeder},f(i)} - \sum_{j \in \mathcal{M}_{f(i)}} P_j^{\text{real}}}{\sum_{k \in F_{f(i)} \setminus \mathcal{M}} w_k} \cdot w_i, \quad (9)$$

where $f(i)$ denotes the feeder of node i . The balance constraint is enforced at feeder level rather than grid level. This confines distributional uncertainty to a smaller group of nodes, which justifies $\sigma_{\text{pseudo}}^{(K1)} = 15\%$ [16].

Annual Consumption Proxy

The proxy $E_{a,i}$ is computed as the sum of all active power load entries at each node, corresponding to metering data available to the DSO via the metering point operator. Public charging points are coupled to household buses (see Section 4) and are implicitly captured in $E_{a,i}$.

Reactive Power Modeling

Reactive power is derived from active power via a constant power factor $\cos \varphi = 0.95$. Power values are expressed as single-phase watts, consistent with the BC-Mod formulation [13].

5.1.3. SMGW Penetration Configurations

The fraction of NCPs equipped with real measurements is referred to as the *measurement penetration* $n_{\text{real}}/N_{\text{LV}}$, where N_{LV} denotes the number of *NCP-occupied* load buses in the LV network (excluding the MV slack bus and transformer tap node). The two SimBench reference networks have $N_{\text{LV}} = 109$ (rural) and $N_{\text{LV}} = 53$ (urban).

The evaluation uses the regulatory minimum SMGW penetration under the MsbG [74] ($\approx 15\%$) as the primary reference point, translating to $n_{\text{real}} = 16$ equipped nodes in the rural network and $n_{\text{real}} = 8$ in the urban network. This level matches the VDE FNN minimum for K1 but falls below the recommendations for K2 (30%) and K3 (70%). The choice reflects the current (2025) rollout status. While SMGW penetration will increase under the ongoing MsbG rollout, evaluating at this lower bound establishes the worst-case baseline for SE accuracy.

Three SMGW placement strategies are evaluated: *power-first* selects the nodes with the highest instantaneous apparent power (oracle upper bound); *consumption-first* selects by annual energy consumption (feasible DSO deployment based on metering data); and *random* selects uniformly at random (averaged over ten draws to reduce sampling variance). The random strategy simulates an uncoordinated rollout.

The reported accuracy metric throughout this section is the mean normalized voltage error $\bar{\varepsilon}$ (Equation (3), defined in Section 3.1), averaged over the set $\mathcal{T}$ of evaluated congestion periods. This ensures that reported penetration thresholds reflect typical congestion conditions rather than a single extreme snapshot.

To keep the evaluation computationally tractable, up to $|\mathcal{T}| = 200$ congestion periods are selected per scenario. The selection uses stratified sampling to ensure that the sample covers a representative range of operating conditions: periods are binned by transformer loading severity (four quartile bins) and by which line is most heavily loaded (five most frequent lines plus a residual group), and each bin contributes proportionally to the sample. Scenarios with fewer than 200 congestion periods are evaluated exhaustively.

5.2. Algorithm Verification

Two correctness tests verify BC-Mod under complete real-measurement coverage (all load nodes instrumented, $\sigma_{\text{real}} = 1.7\%$), which bypasses pseudo-measurement uncertainty.

A synthetic three-bus network reproduces the reference power-flow voltages with a maximum error of $< 0.0001\%$. The same test on the full SimBench rural network (127 LV nodes, 30% nominal loading) achieves a mean voltage error of 0.0001% (max: 0.0002%). This confirms algorithmic correctness. The ground-truth values are obtained from the time-series simulations described in Section 4.

A mirror test with full measurement coverage (real power and voltage at all nodes) is applied to the first three congestion periods of each base scenario. All scenarios pass the 0.1% acceptance criterion (Table A1, Appendix A). The largest deviations (up to 0.09% ,

2045 rural) remain well within the acceptance criterion and reflect residual numerical effects of the WLS solution rather than a systematic bias.

5.3. Estimation Accuracy: K3, K2, and K1 over All Congestion Scenarios

This subsection evaluates the mean normalized voltage error $\bar{\varepsilon}$ (Equation (3)) for K3, K2, and K1 across all congestion scenarios using power-first placement and up to 200 stratified congestion periods per scenario.

Figure 12 visualizes the cross-equipment comparison by showing the median voltage error at the regulatory minimum ($\approx 15\%$) for each equipment level and measurement constellation, separated by network type.

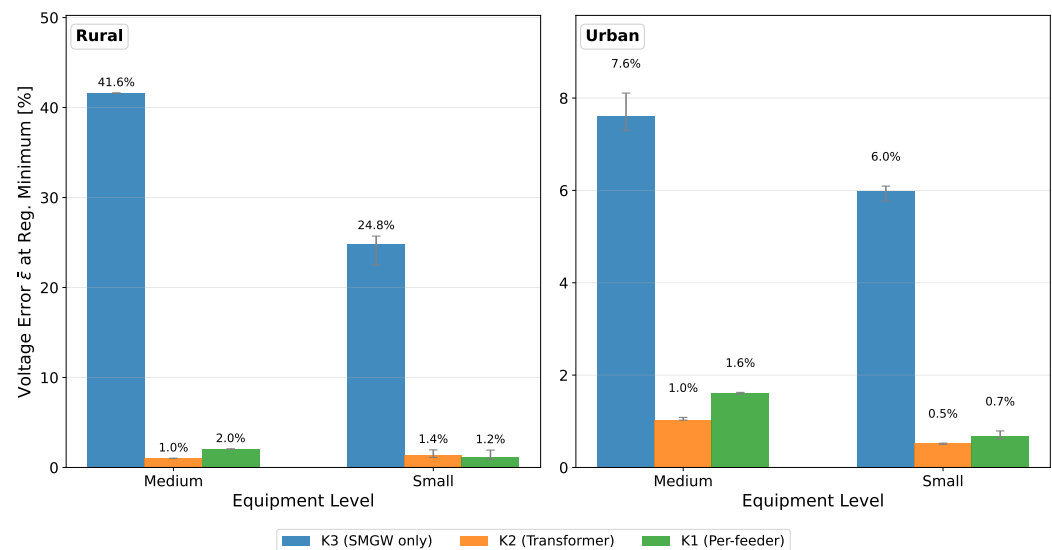


Figure 12. Median voltage error $\bar{\varepsilon}$ at the regulatory minimum ($\approx 15\%$ penetration, power-first placement) by equipment size level and measurement constellation (K3/K2/K1), for rural (left) and urban (right) networks. Bars show the median across congestion scenarios, error bars the interquartile range. Large equipment is omitted.

Across all equipment levels, K2 and K1 reduce the median voltage error by roughly an order of magnitude compared to K3, with reductions ranging from about fivefold in the already-low-error urban networks to over fortyfold in the rural networks. Under small equipment, K2 achieves 1.4% (rural) and 0.5% (urban) at the regulatory minimum, while K3 remains at 24.8% and 6.0%, respectively. A single transformer power measurement eliminates the dominant source of pseudo-measurement error (the unknown absolute load level), leaving primarily the distributional uncertainty of the consumption-based weights. This pattern holds under both equipment levels evaluated, although the medium-equipment medians rest on few congestion scenarios (a single rural scenario).

Under K3, the total grid load is estimated from the H0 standard load profile (Equation (7)), which does not reflect EV charging, heat pump, or PV feed-in patterns and systematically mis-estimates net demand during congestion periods. Because all pseudo-measurements are derived by distributing this biased total via the weights w_i , installing additional SMGWs corrects individual nodes but does not fix the systematic total load error. Even increasing SMGW penetration to the VDE FNN-recommended 70% for K3 would not resolve this bias, because the total load estimate remains anchored to the mismatched H0 profile. Under K2, a single transformer measurement eliminates this bias at its source.

The relative performance of K1 and K2 depends on network topology. Under small equipment, K1 achieves 1.2% vs. K2's 1.4% in the rural network: the nine rural feeders (up

to 29 buses) carry unevenly distributed loads during congestion, and per-feeder metering captures this spatial heterogeneity. In the urban network, K2 remains slightly better (0.5% vs. 0.7%), as the seven shorter feeders (up to 18 buses) are more homogeneously loaded, so per-feeder metering adds measurement noise without proportional information gain. Under medium equipment, congestion is milder and the load distribution during congestion periods deviates less from annual averages, so the proportional weights w_i already approximate the true distribution well. K1's additional feeder constraints provide little benefit in this regime, and K2 outperforms K1 in both networks ($\bar{\varepsilon}$: 1.0% vs. 2.0% rural). Urban networks show lower $\bar{\varepsilon}$ in nearly all configurations due to shorter electrical distances and the resulting flatter voltage profile, which limits error propagation from individual pseudo-measurement inaccuracies.

Under K2 and K1, the three placement strategies (power-first, consumption-first, random) yield nearly identical $\bar{\varepsilon}$ values, because the transformer- or feeder-level measurement anchors the total load level and reduces the influence of individual node placement. Under K3, power-first outperforms random placement, but the improvement does not compensate for the systematic H0 bias.

Qualitative Illustration

Figure 13 shows the ground truth and the three state estimates for the most heavily loaded congestion period in the 2045 rural scenario under small equipment.

K3 (Figure 13b) produces large voltage errors ($\bar{\varepsilon} = 39.0\%$) and mis-estimates line currents due to H0 profile mismatch. K2 (Figure 13c) reconstructs voltages accurately ($\bar{\varepsilon} = 2.3\%$) by anchoring the total load level. K1 (Figure 13d) achieves the lowest error ($\bar{\varepsilon} = 1.3\%$) through tighter per-feeder constraints.

5.4. Voltage and Current Accuracy for Congestion Assessment

This subsection evaluates SE accuracy against VDE FNN targets [16] under medium and small equipment. Congestion is exclusively transformer- and voltage-driven (see Section 4). No line exceeds its thermal rating (max: 98.6%). Under K2 and K1, the transformer power is directly measured, so the operationally relevant SE contribution is the estimation of bus voltages for detecting voltage-band violations. Two VDE FNN accuracy metrics (defined in Section 3.1) are evaluated at the regulatory minimum ($\approx 15\%$ penetration, power-first): the 99th percentile voltage error f_V^{p99} (target: $\leq 2\%$) and the 99th percentile current error f_I^{p99} across lines with ground-truth loading $> 20\%$ (target: $\leq 10\%$) [16]. Detection performance is assessed through the sensitivity (TPR) and specificity (TNR), defined in the same subsection. Since no line overload occurs, the VDE FNN overload TPR cannot be evaluated. The TNR is 100% for K2 and K1 (no false alarms), while K3 TNR ranges from 36% (small, rural) to 88% (small, urban).

5.4.1. Voltage and Current Accuracy at the Regulatory Minimum

Figures 14 and 15 visualize the f_V^{p99} and f_I^{p99} distributions at the regulatory minimum across all equipment levels and constellations, with individual scenario values shown as dots where multiple scenarios are available.

Voltage Accuracy (f_V^{p99})

K3's median f_V^{p99} reaches 33–44% (rural) and 8–10% (urban), far from the 2% target and unsuitable for voltage violation detection.

K2 meets the 2% target in urban networks (0.9% small, 1.6% medium) and under medium rural equipment (1.4%), but reaches 3.6% under small rural equipment, which is sufficient for detecting severe violations (< 0.90 p.u.) but not for reliable detection at 0.95 p.u. The higher error in rural networks is consistent with their longer feeders and

larger impedance, which amplify voltage deviations caused by pseudo-measurement errors. Under small equipment, K1 outperforms K2 in the rural network (2.6% vs. 3.6%), where per-feeder metering better captures the spatially uneven load distribution across feeders, but is slightly worse in the urban network (1.1% vs. 0.9%), where the shorter, more homogeneous feeders do not benefit from the additional measurement granularity. Under medium equipment, K2 outperforms K1 in both network types, as the milder congestion conditions produce a more uniform load distribution that the proportional weights already approximate well.

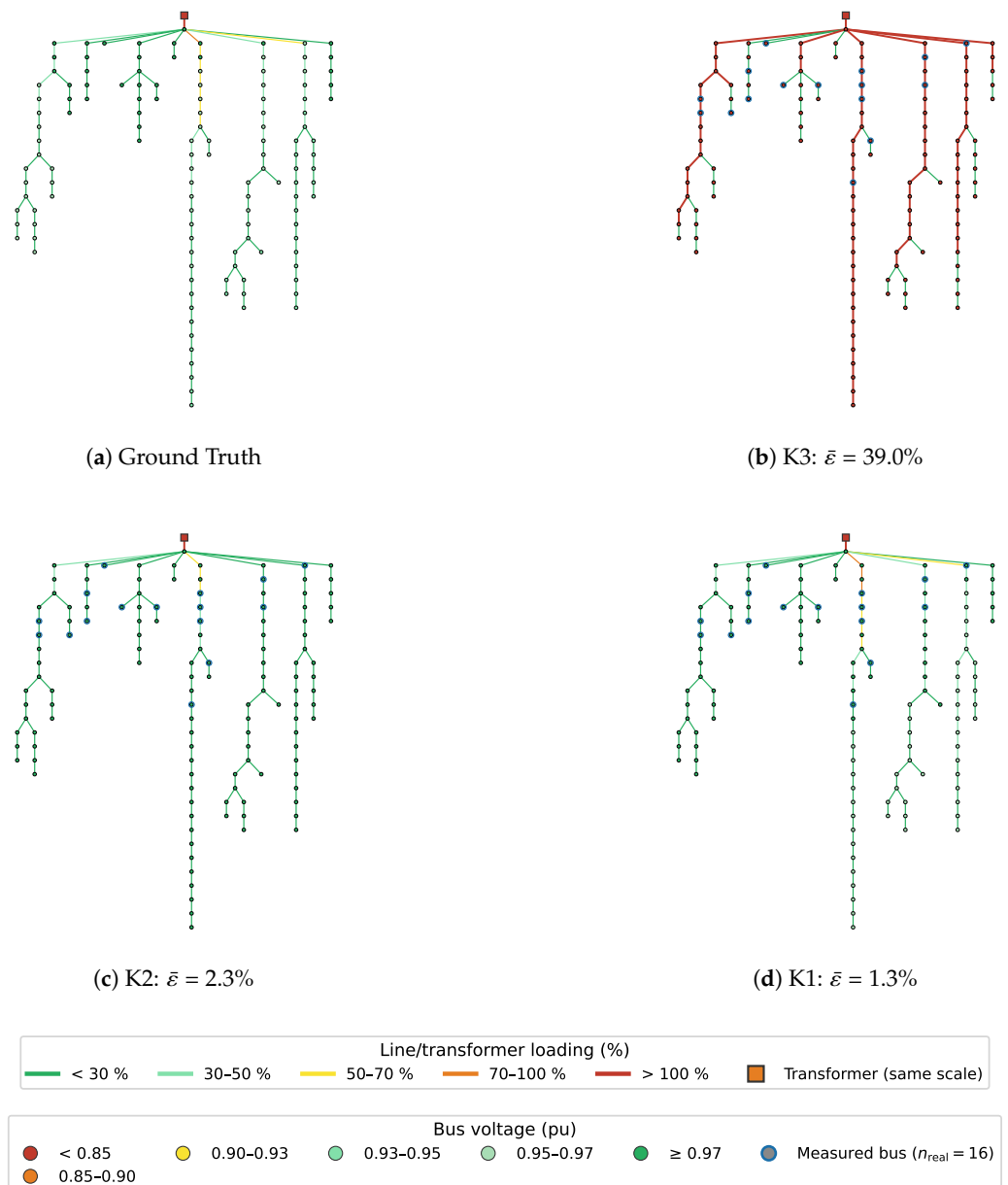


Figure 13. Network state estimation at the regulatory minimum ($n_{\text{real}} = 16$, $\approx 15\%$ penetration, power-first) for the most heavily loaded congestion period in the 2045 rural scenario under small equipment. Subfigure captions give the mean normalized voltage error $\bar{\varepsilon}$. Blue ring: bus with real SMGW measurement.

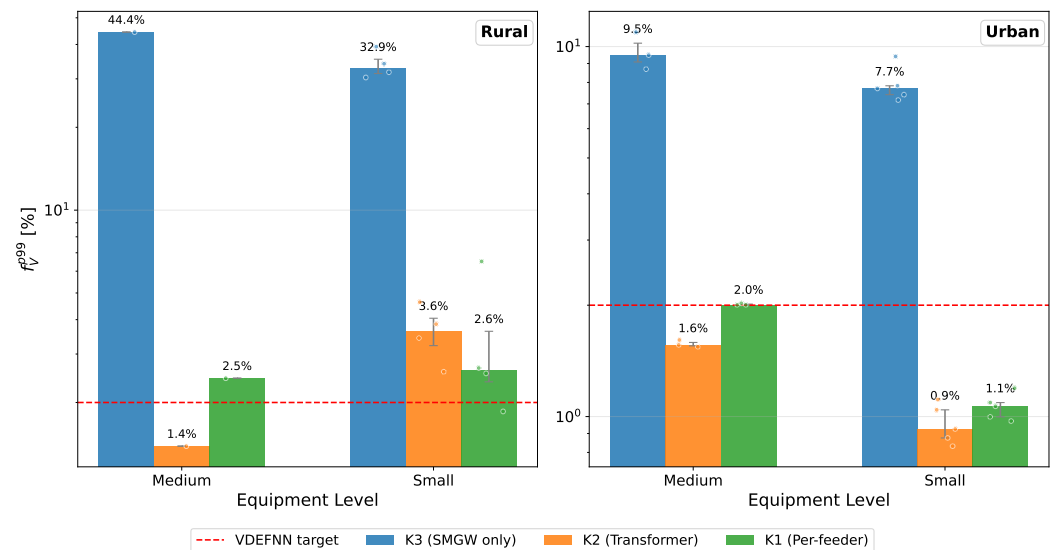


Figure 14. The 99th percentile voltage error f_V^{p99} at the regulatory minimum ($\approx 15\%$ penetration, power-first) by equipment size level and measurement constellation, for rural (left) and urban (right) networks. Bars show the median across congestion scenarios, error bars the interquartile range, and dots the individual scenarios. Dashed red line: VDE FNN target ($f_V^{p99} \leq 2\%$). Large equipment is omitted. Logarithmic y-axis, different for rural and urban.

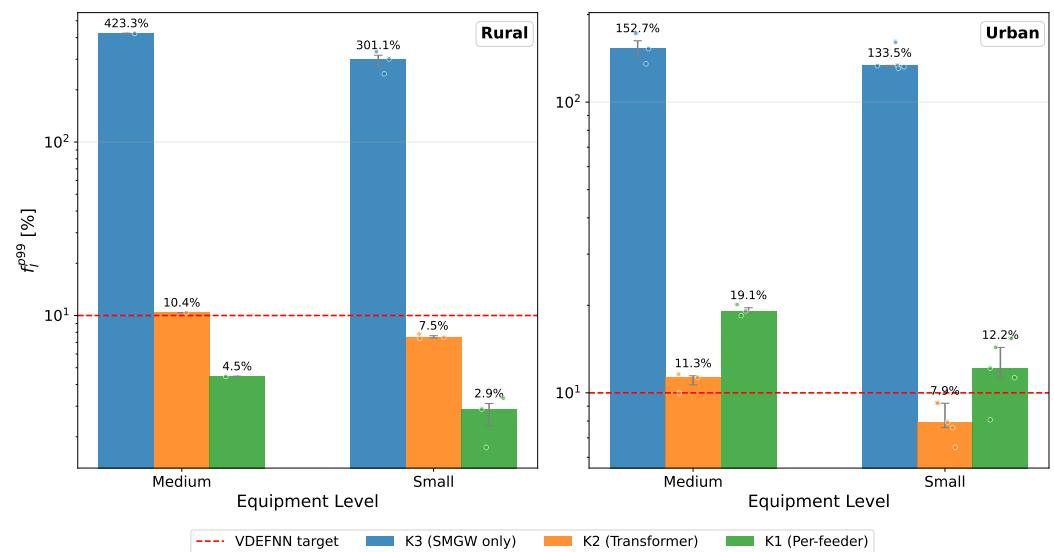


Figure 15. The 99th percentile current error f_I^{p99} at the regulatory minimum ($\approx 15\%$ penetration, power-first) by equipment size level and measurement constellation, for rural (left) and urban (right) networks. Bars show the median, error bars the interquartile range, and dots the individual scenarios. Dashed red line: VDE FNN target ($f_I^{p99} \leq 10\%$). Large equipment is omitted. Logarithmic y-axis, different for rural and urban.

Current Accuracy (f_I^{p99})

K3's current estimation is unusable (median f_I^{p99} : 133–423%). K2 meets or approaches the 10% target under small equipment (7.5% rural, 7.9% urban) and narrowly exceeds it under medium equipment (10.4–11.3%). K1 achieves 2.9% in the rural network under small equipment, where the long feeders carry unevenly distributed currents that per-feeder metering resolves well. In urban networks, K1 reaches 12–19%, because the short feeders provide less current differentiation between nodes, so the per-feeder constraint adds little beyond what K2 already captures.

No constellation consistently meets $f_I^{p99} \leq 10\%$ across all configurations, but current accuracy is less operationally relevant since the transformer power is directly measured under K2 and K1.

Implications for Voltage-Band Violation Detection

A violation at 0.95 p.u. can be reliably detected only if f_V^{p99} is substantially smaller than 5%. K2 in urban networks ($f_V^{p99} = 0.9\text{--}1.6\%$) and under medium rural equipment (1.4%) meets this criterion. Under small rural equipment ($f_V^{p99} \approx 2.6\text{--}3.6\%$), deep undervoltages (<0.90 p.u.) are detectable but marginal violations near 0.95 p.u. may be missed. K3 cannot support voltage violation detection.

5.4.2. Positioning Relative to State-of-the-Art Methods

Node-voltage-based and branch-current-based estimators achieve comparable accuracy in the literature. Performance depends primarily on observability and pseudo-measurement quality, not on the choice of state representation [77,78]. The K3 errors observed here ($\bar{\varepsilon} \approx 6\text{--}42\%$) are consistent with H0-based estimators reported by Angioni et al. [76] (10–30% at 15% penetration) and with the uncertainty bounds in Strobel et al. [13]. K2's median $\bar{\varepsilon}$ of 0.5–1.4% matches state-of-the-art results for estimators with measured transformer injection [35]. A recent systematic review [9] identifies transformer-based anchoring as the single most impactful instrumentation decision for LV SE accuracy, which matches the findings of the present work.

6. Discussion

6.1. Synthesis of Results

The combined results of Sections 4 and 5 reveal a structural mismatch between the pace of DER-driven congestion emergence and the measurement infrastructure available for its detection. Grid equipment size governs congestion onset (no congestion scenarios under large, four under medium, nine under small equipment), while the measurement constellation governs whether these congestion events can be detected. A single transformer power measurement (K2) reduces the median voltage error by an order of magnitude compared to K3 and meets the VDE FNN voltage target in urban networks. In rural networks under small equipment, neither K2 nor K1 meets the target, leaving marginal voltage violations near 0.95 p.u. undetectable. K3 cannot support congestion detection at any SMGW penetration level due to the systematic H0-based total load bias.

Transferability

The analysis is based on two SimBench reference networks (rural and urban) under a single energy transition pathway (Federal Government). While the absolute congestion thresholds and SE error magnitudes are network-specific, the structural findings (dominance of transformer overloading and voltage-band violations over line overloads, order-of-magnitude improvement from K3 to K2, K3 stagnation under increasing SMGW penetration) are properties of radial LV topologies with sparse metering and are expected to hold across networks with similar structural characteristics.

6.2. Positioning Relative to Existing Regulation and Literature

6.2.1. § 14a EnWG

The German Energy Industry Act, § 14a EnWG [3], permits DSOs to curtail controllable loads (EV charging stations, heat pumps) in congestion situations in exchange for reduced grid fees. The practical exercise of this right requires the DSO to identify congestion reliably and in near real time. The present results indicate that, at the current SMGW rollout

minimum ($\approx 15\%$ penetration), a DSO relying on K3-based SE would observe median voltage errors of 6–42%, so reliable congestion identification is impossible. Even under K2, voltage-band violations near the 0.95 p.u. threshold may go undetected in rural networks where f_V^{p99} exceeds 3% (3.6% under small equipment). The § 14a mechanism therefore presupposes a level of grid observability that the current rollout trajectory does not provide in DER-dense scenarios.

6.2.2. MsbG

The MsbG [74] defines mandatory SMGW rollout for end consumers exceeding specific annual consumption thresholds. While this creates a bottom-up trajectory for SMGW deployment, it is decoupled from DER expansion: rollout obligations are triggered by consumption, not by congestion risk. A household with an EV charger and a heat pump may consume less annual energy than the statutory threshold yet generate disproportionate peak loads that drive transformer overloading. As DER penetration increases, more scenarios will require grid monitoring, but the MsbG rollout trajectory does not account for this.

6.2.3. VDE FNN 2024

The VDE FNN technical specification [16] establishes $f_V^{p99} \leq 2\%$ and $f_I^{p99} \leq 10\%$ as SE quality targets for LV grids. This work provides, to the authors' knowledge, the first systematic assessment of their achievability under a concrete DER deployment scenario across three equipment size levels. The results show that the voltage target is met by K2 in urban networks under both equipment levels ($f_V^{p99} = 0.9\text{--}1.6\%$) and in rural networks under medium equipment (1.4%). K1 meets the target under small urban equipment (1.1%) but narrowly exceeds it under medium urban equipment (2.0%). Neither K1 nor K2 meets the target in rural networks under small equipment (2.6–3.6%). K3 is far from the target in all configurations. The current target ($f_I^{p99} \leq 10\%$) is met by K2 under small equipment (7.5–7.9%) but narrowly exceeded under medium equipment (10.4–11.3%), and not consistently met by any constellation across all configurations.

The VDE FNN study also reports large differences between measurement constellations: the required SMGW penetration for radial networks increases from 15% with feeder-level measurement to 70% with SMGW-only setups [16]. This is qualitatively consistent with the present finding that K3 (no transformer measurement) requires fundamentally higher penetration levels than K2 or K1. The two analyses differ in their evaluation methodology: the VDE FNN study restricts accuracy evaluation to the top 1% of time steps with highest loading across a full year, whereas the present work evaluates exclusively during congestion periods identified from scenario-based simulations with pathway-specific DER deployment. Both approaches focus on high-stress conditions, but the present analysis conditions on actual congestion events rather than a fixed percentile of loading.

The VDE FNN specification defines detection metrics (sensitivity and specificity) for three congestion types: transformer overloading, cable overloading, and voltage-band violations [16]. In the evaluated scenarios, no line exceeds its thermal rating, so cable overload detection cannot be evaluated. The dominant congestion mechanisms in these radial LV networks are transformer overloading and voltage-band violations, consistent with the congestion types in the VDE FNN framework.

6.2.4. LV State Estimation Literature

The BC-Mod branch-current formulation belongs to the class of WLS state estimators for radial LV networks. The mean errors observed under K3 ($\bar{\epsilon} \approx 6\text{--}42\%$) are consistent with the range reported for profile-based pseudo-measurement approaches: Angioni et al. [76] report mean errors of 10–30% for H0-based estimators in radial feeders at 15% penetration.

Koch et al. [32] show that smart meter substitution becomes feasible only at deployment rates of 30–60%, consistent with the finding that K3 accuracy does not improve meaningfully below these levels. Von der Heyden et al. [34] address the complementary problem of data privacy by demonstrating that power-flow analysis can be performed on cryptographically hidden prosumer data, which may help overcome regulatory barriers to higher measurement penetration.

A recent systematic review [9] emphasizes that state estimation accuracy in LV grids is primarily driven by observability and the joint design of sensing, data fusion, and estimation. The present finding that transformer-based anchoring substantially reduces voltage errors across all equipment levels confirms this.

This work couples SE performance to explicit DER deployment scenarios across three equipment size levels. The number of scenarios requiring SE-based monitoring grows with increasing electrification, while per-scenario accuracy is primarily determined by the measurement constellation.

6.3. Derived Regulatory Implications

The quantitative findings directly motivate three regulatory adjustments to the current German metering and monitoring framework.

6.3.1. Transformer Instrumentation as a Universally Effective First Step

A single transformer power measurement (K2) reduces the median voltage error at the regulatory minimum by an order of magnitude compared to K3 (see Section 5.3), and in urban networks under both small and medium equipment K2 achieves the VDE FNN voltage target ($f_V^{p99} \leq 2\%$). Under K2 and K1, the transformer power is directly measured, providing immediate congestion detection for the dominant congestion mechanism (transformer overloading). This confirms that transformer instrumentation provides the largest marginal gain per additional device.

6.3.2. Risk-Based Supplement to the MsbG Rollout

The current SMGW rollout minimum ($\approx 15\%$ penetration) does not provide sufficient voltage accuracy for reliable voltage-band violation detection in rural networks under small equipment (K2: $f_V^{p99} = 3.6\%$, K1: 2.6%), although K2 meets the target under medium equipment (1.4%). Because the MsbG ties rollout obligations to annual consumption thresholds rather than congestion risk, SMGW density lags behind measurement requirements as DER penetration increases. A risk-based supplement that mandates higher rollout densities in feeders with high DER penetration or modeled congestion probability is necessary to close this gap.

6.3.3. Alignment of Quality Targets with Observed Congestion Mechanisms

The VDE FNN framework defines accuracy targets (f_V^{p99} , f_I^{p99}) and detection metrics (sensitivity, specificity) for transformer overloading, cable overloading, and voltage-band violations [16]. In the evaluated scenarios, congestion is caused exclusively by transformer overloading and voltage-band violations and no cable overloads occur. Under K2 and K1, the transformer power is directly measured rather than estimated. The operationally relevant SE contribution is therefore the detection of voltage-band violations at the 0.95/1.05 p.u. thresholds. Detection metrics should be evaluated at these operationally relevant thresholds to ensure that the monitoring system is assessed against the congestion mechanisms that actually occur in radial LV networks.

The introduction of three equipment size levels adds a further dimension. DSO operating grids with small equipment face a trade-off between network reinforcement (installing larger transformers and cables to delay congestion onset) and digitalization

(deploying measurement infrastructure to detect and manage congestion in the existing grid). Under large equipment, congestion is absent and measurement deployment is less urgent. Under small equipment, nine of the ten scenarios produce congestion, the 2030 rural network being the only exception, and K2 provides sufficient voltage monitoring in urban networks without any SMGW deployment. The optimal strategy for SMGW densification depends on the local grid condition, the expected pace of DER adoption, and the relative cost of physical reinforcement versus sensor deployment.

6.4. Limitations

The evaluation is based on SimBench reference networks (1-LV-rural3, 1-LV-urban6) and normalized service curve (NSC)-based load profiles generated within the same simulation environment. While these networks are designed to be representative of German LV grid topologies, absolute results such as congestion thresholds, voltage profiles, and SE error magnitudes will differ for specific real-world grids. The two networks are contrasting settlement-specific cases rather than a statistically representative sample of the national stock. The rural network in particular is a single-family area with correspondingly high per-home EV intensity, so absolute rural congestion magnitudes represent a high-electrification case rather than a national average. Validation of the reported thresholds against field measurement data from operational LV grids remains outstanding.

The pseudo-measurements used in Section 5 derive their consumption weights from the same NSC annual energy values that underlie the simulation ground truth. In operational LV grids, these weights would be constructed from billing data or standard load profiles, which would introduce additional distributional uncertainty. The qualitative conclusions (K3 insufficiency, K2/K1 superiority) would therefore be reinforced rather than weakened under real-world conditions, as the dominant error source under K3 (the H0-based total load estimate) is independent of the weight accuracy.

The BC-Mod algorithm linearizes the branch current equations around nominal voltage. The mirror test (Section Algorithm Mirror Test Results) confirms that the linearization error remains below 0.1% under full measurement coverage, but this error grows under extreme loading conditions, where voltages deviate substantially from nominal (<0.93 p.u. in the 2045 rural scenario under small equipment). The reported SE errors therefore include a linearization component that a nonlinear solver would avoid. Nonlinear or hybrid SE formulations could improve performance at higher computational cost.

Finally, while the grid-side analysis in Section 4 covers both load-driven and generation-driven congestion, the SE evaluation in Section 5 focuses on load-driven congestion periods. Generation-driven congestion (e.g., PV reverse power flow causing over-voltage) occurs in the rural network under small equipment from 2025 onward. The SE accuracy under these conditions warrants further investigation, as pseudo-measurement uncertainty may differ when the H0 load profile does not account for generation. No line overloads occur in any scenario (maximum line loading: 98.6%) and networks with higher cable utilization may exhibit different estimation characteristics.

A further error source, distinct from measurement availability, is the accuracy of the assumed network model. This work presumes correct topology and line impedances. In operational grids, feeder models may be outdated and fail to reflect recent expansions or reconfigurations, so estimation errors can persist even at high measurement penetration [79]. Because the same network model underlies both the simulated ground truth and the estimator, this error does not affect the results reported here. It would affect the estimation under any measurement constellation, not only those evaluated here.

Consistent with the passive-operation baseline used throughout this work, the analysis does not model battery storage, coordinated or price-responsive electric vehicle charging,

Volt/VAR control, demand response, or on-load tap changer voltage regulation. This baseline is realistic under present conditions, since coordinating such resources for congestion relief presupposes a level of grid observability that low-voltage grids currently lack [9]. Each of these mechanisms would be expected to relieve at least one of the congestion types considered here, thermal overloading or voltage-band violations, so the reported congestion frequency and severity can be regarded as a conservative upper bound for a given deployment trajectory. Quantifying how such active operation shifts the measurement requirements is a direction for future work.

6.5. Answers to Research Questions

The three research questions posed in the introduction can now be answered.

RQ1 asks at what points in time thermal and voltage limit violations emerge under different equipment configurations, how they evolve, and which components are primarily affected. The results show that congestion onset and severity are governed by the interaction between DER penetration and equipment size. Under small equipment, congestion is present from the 2025 baseline in both network types and intensifies substantially by 2045, with hard-congestion events increasingly dominating over gray-zone periods. The rural onset is non-monotonic, however: the early PV-driven midday overvoltage is a marginal gray-zone signal that recedes just below its threshold in 2030, leaving that year congestion-free, before load-driven congestion takes over. Under medium equipment, congestion first appears in 2035 (urban) and 2045 (rural). The dominant congestion mechanisms are transformer overloading and voltage-band violations, with no line overloads in any scenario (maximum line loading: 98.6%). In rural networks, generation-side congestion driven by PV feed-in is visible from 2025 under small equipment, while urban networks exhibit exclusively load-side congestion.

RQ2 asks how SE accuracy and congestion detection capability depend on the type of measurement infrastructure, and which constellation meets quality targets for the identified congestion scenarios. The results show that the measurement constellation (K3/K2/K1) is the dominant factor determining SE accuracy at the current regulatory minimum ($\approx 15\%$ penetration). K3-based SE produces median voltage errors of 6–42% and cannot support congestion detection. K2 reduces errors to 0.5–1.4% (median $\bar{\varepsilon}$) and meets the VDE FNN voltage target in urban networks ($f_V^{p99} = 0.9\text{--}1.6\%$). In rural networks under small equipment, K2 achieves $f_V^{p99} = 3.6\%$, sufficient for detecting severe voltage violations but not marginal ones near the 0.95 p.u. threshold. K1 provides additional benefit in rural networks under small equipment ($f_V^{p99} = 2.6\%$) but does not outperform K2 in urban networks.

RQ3 asks which regulatory adjustments are necessary to close the observability gap. The results motivate three adjustments (detailed in Section 6.3). First, transformer instrumentation should be mandated as a minimum requirement, since K2 provides the largest marginal gain in observability per additional device. Second, the consumption-based MsbG rollout should be supplemented with risk-based criteria tied to DER penetration and congestion probability. Third, VDE FNN detection metrics should be evaluated at the 0.95/1.05 p.u. voltage thresholds used in congestion definitions, so that the monitoring system is assessed against the violations that actually trigger operational responses.

7. Conclusions

This work couples the German Federal Government energy transition pathway (2025–2045) with time-series simulations of rural and urban LV reference networks and evaluates BC-Mod WLS state estimation under the three VDE FNN measurement constellations.

The grid-side analysis shows that congestion onset and severity are governed by the interaction between DER penetration and equipment size. Under small equipment,

congestion occurs from 2025 onward and intensifies substantially by 2045. Congestion is caused exclusively by transformer overloading and voltage-band violations, with no line overloads (maximum line loading: 98.6%). The dominant congestion mechanism shifts from generation-side overvoltage (rural, 2025) to load-side transformer overloading (both networks, 2035–2045) as EV and heat pump penetration increases.

The SE evaluation reveals that the measurement constellation determines estimation accuracy far more than SMGW penetration at the current regulatory minimum ($\approx 15\%$ penetration). K3-based estimation produces median voltage errors of 6–42% and stagnates regardless of smart meter density due to the systematic H0-based total load bias (see Section 5.3). A single transformer power measurement (K2) reduces the median voltage error by an order of magnitude (1.4% vs. 24.8% in rural networks under small equipment) and meets the VDE FNN voltage accuracy target ($f_V^{p99} \leq 2\%$) in urban networks. In rural networks under small equipment the target is approached but not met. The per-configuration accuracy values are reported in Section 6. Since the transformer power is directly measured under K2 and K1, the operationally relevant SE contribution is the detection of voltage-band violations.

Three regulatory implications follow from these findings. First, transformer instrumentation should be prioritized, as it provides the largest marginal gain in grid observability per additional device. Second, the consumption-based MsBG rollout should be supplemented with risk-based criteria tied to DER penetration and local congestion probability. Third, VDE FNN detection metrics should be evaluated at the 0.95/1.05 p.u. voltage thresholds used in congestion definitions, so that the monitoring system is assessed against the violations that actually trigger operational responses in radial LV networks.

While the grid-side analysis covers both load-driven and generation-driven congestion, the SE evaluation focuses on load-driven congestion periods. Extending the SE assessment to generation-dominant periods, where pseudo-measurement uncertainty may differ due to PV reverse power flow, remains open. Further priorities include validating the derived thresholds on real feeder data from multiple DSOs, developing device-type-aware pseudo-measurement models that use smart meter metadata [80], and incorporating nonlinear SE formulations to improve accuracy under extreme loading conditions where the BC-Mod linearization introduces systematic error.

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Abbreviations

The following abbreviations are used in this work:

COP	Coefficient of performance
DSO	Distribution system operator
EV	Electric vehicle
NCP	Network connection point
DER	Distributed energy resource
HH	Household
LV	Low voltage
SMGW	Smart meter gateway
MV	Medium voltage
HV	High voltage
PV	Photovoltaics
SE	State estimation
WLS	Weighted least squares
AC	Alternating current
KVS	Distribution cabinet/switching point
PM	Pseudo-measurement
BC-Mod	Branch-current-based model
UQ	Uncertainty quantification
MsbG	Messstellenbetriebsgesetz
EnWG	Energiewirtschaftsgesetz
VDE FNN	VDE Forum Netztechnik/Netzbetrieb
iMSys	Intelligentes Messsystem
SGIM	Smart grid interface module
NSC	Normalized service curve
LCT	Low-carbon technology
FCR	Frequency containment reserve
p.u.	Per unit
ZIP	Constant impedance, constant current, and constant power
aFRR	Automatic frequency restoration reserve
PMU	Phasor measurement unit
RTU	Remote terminal unit
LNR	Largest normalized residual
SLP	Standard load profile
TPR	True positive rate
TNR	True negative rate
IQR	Interquartile range

Appendix A.

Algorithm Mirror Test Results

Table A1 reports the normalized mean voltage deviation for each of the ten scenarios under complete real measurement coverage (mirror test), evaluated over the first three congestion periods per scenario. The acceptance criterion is a deviation below 0.1%. All scenarios pass. The 2035, 2040, and 2045 rural scenarios exhibit slightly elevated deviations (up to 0.09%) that remain well within the acceptance criterion and reflect residual numerical effects of the WLS solution rather than a systematic bias (see Section 5.2).

Table A1. Mirror test: normalized mean voltage deviation per scenario (mean over three periods). Criterion: <0.1%. All scenarios pass.

Scenario	Period 1	Period 2	Period 3	Status
2025 rural	<0.05%	<0.05%	<0.05%	✓
2025 urban	<0.05%	<0.05%	<0.05%	✓
2030 rural	<0.05%	<0.05%	<0.05%	✓
2030 urban	<0.05%	<0.05%	<0.05%	✓
2035 rural	0.06%	0.05%	<0.05%	✓
2035 urban	<0.05%	<0.05%	<0.05%	✓
2040 rural	0.07%	0.06%	0.05%	✓
2040 urban	<0.05%	<0.05%	<0.05%	✓
2045 rural	0.09%	0.08%	0.06%	✓
2045 urban	<0.05%	<0.05%	<0.05%	✓

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