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Misestimation of Impedance Values Within a Distribution Network Optimal Power Flow

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Abstract—Distribution networks are likely to be significantly impacted by the energy transition as numerous flexible agents will be connected there. Management algorithms within these networks are therefore becoming more complex and must consider the physical constraints of the network. However, line impedances in these networks cannot be assumed to be perfectly known, leading to suboptimal management and constraint violations. Considering the Optimal Power Flow as a reference for optimal management, the consequences of these misestimations are here outlined on an illustrative test case. The performed sensitivity studies indicate that the statistical distribution used to describe impedance errors does not influence the results. A combination of decentralized generators and flexible consumers within the same neighborhood limits the impact of misestimated impedances.

Index Terms—Optimal Power Flow, distribution networks, impedance estimation, voltage limits, social welfare

1 INTRODUCTION

The energy transition requires the generalization of renewable productions [1]. These are mostly decentralized and of small unitary power. Most of these installations are therefore likely to be connected to distribution networks – in terms of the number of installations, if not in terms of connected power [2]. Besides, the issues of predictability and intermittency raised by renewable energies require the implementation of demand side management [3]. The joint management of these decentralized productions and flexible consumptions – both comprising many small power agents – is a major challenge that leads to a rich and dynamic literature [4]–[6].

These investigations are mainly carried out in the context of distribution networks. The modeling of physical quantities in each line and each bus is thus not usually taken into account [7], [8]. Indeed, the design capacity of these networks is currently much higher than the actual flows. Congestion is therefore currently uncommon. The limiting operational constraint is most often voltage limits at the furthest buses from the connection point to a higher-voltage network [9]. But in the future, downstream flows will strongly increase due to electric mobility [10]. Upstream flows will also grow because of distributed generators. In such a context, the challenge will not only be to maintain the power quality, but also to overcome congestion. According

to current state-of-the-art approaches, this evolution should lead to a strengthening of distribution networks. This would result in a considerable consumption of raw material, but also in significant deployment costs. Moreover, such a revision of distribution networks would require extensive periods of work. An alternative to this consolidation would be to apply mechanisms of distributed management that would take into account the physical state of the network [11]. The aim would then be not only to match flexibilities with renewable generation but also to limit network congestion and voltage violations [12]. These mechanisms would then be comparable to optimal power flow (OPF) problems [13], [14].

Distribution networks are yet far more complex than transmission networks in the sense that they include a vast number of connected lines and agents. Moreover, their topology is not perfectly known since they are constantly evolving: it is not always possible to know with certainty on which phase a device is connected. Wear and tear, degradations or weather variations can cause significant fluctuations in the actual impedance of lines compared to their nominal impedance. Furthermore, distribution networks are only very sparsely monitored, compared to transmission networks [15]. This low observability is legitimate in the current situation, as their design capacity is significantly larger than the effective flows and because of the almost complete lack of flexible resources in distribution neighborhoods. Research on the observability of these networks is being developed [16]. Nevertheless, it would appear to be certain that line impedances cannot be considered as known for sure in a distribution network: each node cannot be monitored in a near future and estimators would still commit a residual error [17].

However this lack of knowledge of line impedances cannot but have repercussions on power flow (PF) and OPF results. Consequences may include, in increasing order of criticality, a suboptimality of the proposed management, an increase in losses, non-compliance with voltage limits, or violations of line capacities. The purpose of the present contribution is therefore to assess the consequences of impedance estimation errors on the results of the OPF in distribution networks. This publication is organized as follows: Section 2 will present the methodology and the formulation of

the OPF used. Then section 3 will present the impact of impedance estimation errors on an illustrative distribution network test case. Section 4 will examine the sensitivity of our previous findings by considering the impact of the statistical distribution chosen to describe the impedance estimation errors. It will also explore how the results vary between predominantly consuming and predominantly producing distribution areas.

2 METHODOLOGY AND TEST CASE

This section first introduces the methodology adopted to evaluate the impact of line impedance estimation errors on OPF results. Then, the test case will be presented.

2.1 Misestimation Impact Method

The chosen methodology is summarized in Figure 1. ① With \tilde{Z} being the estimated and inaccurate impedances, the first step is to perform an OPF as a DSO might operationally do. Only the active \tilde{P} – and reactive \tilde{Q} when applicable – power injection plans are considered. Indeed, voltages and line flows calculated by this first OPF are incorrect, since they were based on incorrect impedances values. ② The actual values of the network impedances Z are assumed to deviate from \tilde{Z} by an estimation error ΔZ . Since the estimated values can only worsen during the lifetime of the network, ΔZ are strictly positive. They are randomly drawn according to a probability distribution with support in \mathbb{R}^+ . The consequences of the choice of this distribution and its parameters will be evaluated in section 4. ③ These actual impedances Z are then used to assess the physical state of the network, when it is operated under the power injection plan \tilde{P}, \tilde{Q} of the first OPF. This physical state is referred to as \tilde{V} Figure 1 in a concise manner, but refers to both the voltages and the line flows. Social Welfare value \tilde{SW} is jointly assessed. Since step ③ gathers impedance values Z and an injection plan calculated separately, there is no guarantee that the physical values \tilde{V} comply with network limitations. Hence constraint violations may occur. ④ In parallel, these actual impedances Z are used to perform an OPF. The latter being carried out without bias on the estimation of the impedances, it jointly establishes the optimal power injection plan P, Q and the associated physical configuration V and social welfare SW . These results are regarded as a reference since they relate to the optimal management of the real network. Although it cannot be performed operationally, it provides a reference to evaluate the deviations of the injection plan \tilde{P}, \tilde{Q} and the suboptimality of the solution \tilde{SW} .

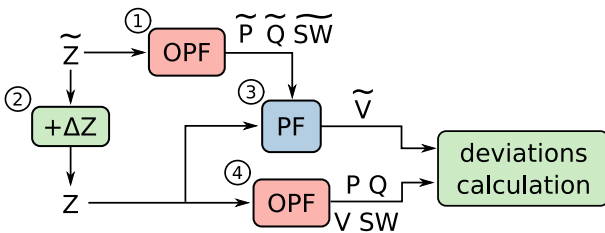


Fig. 1. Methodology used to assess the impact of impedance misestimation. Notations $\tilde{\cdot}$ refers to inaccurate impedances or, any value based upon it.

Since the methodology presented in Figure 1 involves drawing random variables, a Monte Carlo approach is mandatory. Steps ②, ③ and ④ are therefore repeated several times until observed deviations are statistically reproducible.

During this study, only distribution networks will be considered. Indeed, transmission networks are sufficiently instrumented and monitored so that impedance estimation errors can be considered negligible. Therefore, the following formulation is used for the OPF problem [18].

$$\min_{s, S, v, l, s_0} \sum_{i \in \mathcal{N}} f_i(Re(s_i)) \quad (1a)$$

$$\text{s.t. } S_{ij} = s_i + \sum_{h: h \rightarrow i} (S_{hi} - z_{hi} l_{hi}), \quad \forall (i, j) \in \mathcal{E}; \quad (1b)$$

$$0 = s_0 + \sum_{h: h \rightarrow 0} (S_{h0} - z_{h0} l_{h0}); \quad (1c)$$

$$v_i - v_j = 2Re(\tilde{z}_{ij} S_{ij}) - |z_{ij}|^2 l_{ij}, \quad \forall (i, j) \in \mathcal{E}; \quad (1d)$$

$$l_{ij} = |S_{ij}|^2 / v_i, \quad \forall (i, j) \in \mathcal{E}; \quad (1e)$$

$$s_i \in \mathcal{S}_i, \quad i \in \mathcal{N}^+; \quad (1f)$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i, \quad i \in \mathcal{N}^+. \quad (1g)$$

where s_i is the complex injected power at the bus i , S_{ij} is the complex reverse power flow between bus i and j , z_{ij} is the impedance, v_i is the square of the magnitude of the voltage and l_{ij} is the square of the magnitude of the current. The reader is invited to refer to [19] for a complete analysis of this formulation. Its significant features are to allow for a relaxation of the voltage angle (1d) and of the equality constraint determining the flow in the lines (1e) [20]:

$$l_{ij} \geq |S_{ij}|^2 / v_i, \quad \forall (i, j) \in \mathcal{E}; \quad (2)$$

Substituting it by an inequality constitutes a relaxation on a second order cone (SOC). These relaxations allow us to compute the exact solution of the AC-OPF problem in the case of non-mesh networks and when the reverse power flow is only active or reactive, or none [19]. This happens in most distribution networks and especially in our test case – except when explicitly noted. This formulation will be referred to as AC-OPF-SOC in the rest of this paper.

2.2 Test Case Description

The European Low Voltage Feeder (ELVF) test case [21] has been selected to illustrate the consequences of impedance misestimations. It is representative of European distribution networks and is the framework for many studies [22], [23].

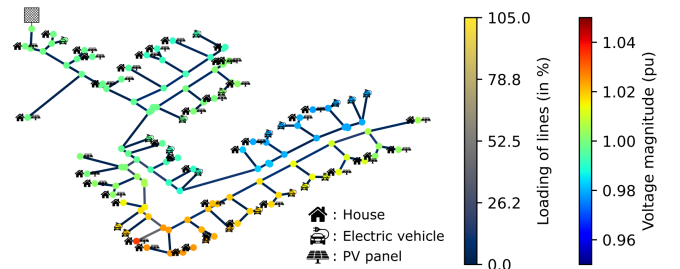


Fig. 2. Power flow example in the European Low Voltage Feeder with distributed generation and flexible consumption.

Although its adoption here does not allow a direct generalization of the results presented, it is a relevant first step to highlight the risks related to impedance estimation errors.

To achieve OPF resolutions, objective functions must be specified for both producers and flexible consumers. These only serve the purpose of creating solicitations on the network used as an example. The remainder of this section describes them for the sake of transparency and reproducibility. The results presented in sections 3 and 4 are not affected by these chosen objective functions.

Energy can be exchanged with the external network, considered of infinite power, either positive or negative. It is connected to the slack bus, whose voltage is fixed to 1 p.u. A history of the EPEXSpot market prices¹ is used for its selling price to the distribution neighborhood. It is assumed to purchase at a price arbitrarily set at 90% of the EPEXSpot price. Not only is this discount representative of current feed-in tariffs, but it also avoids ‘speculative’ buying and selling phenomena within the OPF resolution. The network is randomly populated with production and consumption profiles from the following database [24]. Selling prices of distributed producers are randomly and individually assigned according to a normal distribution with mean value 6 c€/kWh and standard deviation 2 c€/kWh. Since the database provides the power demand of each consumer without any further differentiation between usages, we choose to split the consumption profiles into a non-flexible part and a flexible one. The non-flexible part is set to 90% of the required power P_0 . Below this limit, the consumer is assumed to be willing to pay threefold the grid price. Flexibility bounds are then set at $[0.9P_0; 1.5P_0]$ between which the consumer assigns a purchase price drawn at random according to a normal distribution of mean 15 c€/kWh and standard deviation 5 c€/kWh. Two configurations will be discussed regarding reactive power control. A first case will consider that no reactive power is produced or consumed on the network under study. This configuration is close to the current operation of distribution networks. This will be the configuration adopted in most of the studies presented here, unless otherwise stated. In a second case, all distributed generators will be considered capable of exchanging positive or negative reactive power, within the same limits as their active power. No cost will be associated with this exchanged reactive power. This would correspond to the systematic control of reactive power by the inverters of the distributed generators. This configuration does not correspond to current networks, but is likely to become more widespread, in particular to better handle voltage constraints far away from the slack bus.

The resolution of OPFs and PFs in this study is performed using the implementations proposed by *PowerModels* [25] in Julia and *PandaPower* [26] in Python. In accordance with an open and reproducible science approach, all sources can be accessed on Gitlab².

3 ASSESSMENT OF MISESTIMATION IMPACT

The methodology described in section 2.1 is applied in this section to the test case described section 2.2. Initially,

1. <https://ewoken.github.io/epex-spot-data/>
2. https://gitlab.com/satie.sete/opf_misestimation_impedance

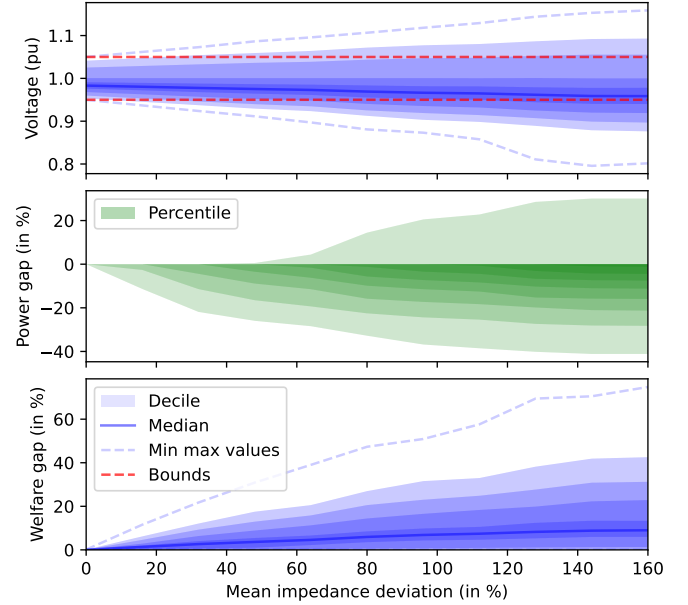


Fig. 3. Sensitivity of AC-OPF-SOC results depending on the average of impedance estimation errors. Top: repartition of voltages at each bus; middle: repartition of power injection deviation; bottom: suboptimality of social welfare. Permissible limits in red, deciles and percentiles in colored areas, extreme values observed in dotted blue line. Results observed on ELVF under a truncated normal distribution.

estimation errors are assumed to follow a truncated normal distribution. Effective impedances Z are then deduced from a random variable ε ,

$$Z = \tilde{Z} + \Delta Z = (1 + \varepsilon) \cdot \tilde{Z} \quad (3)$$

This random variable being only positive, it will be characterized by its distribution and its expectation, the standard deviation being its consequence. Different draws are made while shifting the mean of this law by steps of 10%. For each considered mean value, 10 networks are randomly generated, each of 130 lines, that is 1300 random variables in total. For each of these networks, the OPF is simulated for 12 time steps over 36 days evenly distributed over the year. The statistical variations of the obtained electrical quantities are then represented Figure 3.

On the left end of Figure 3, impedances are perfectly known. Thus, the OPF resolution allows setting voltages of the most solicited buses to the admissible limit values – the test case being designed to activate these limits. In contrast, moving to the right means impedances are more and more poorly estimated. More and more buses violate voltage limits, with several deciles passing one after the other the tolerated limits, indicated in red. Simultaneously, a global decrease in network voltages can be noticed while impedances increase. This is due to the test case including more consumers than producers: the energy flow being then overall consumed, the impedance increase leads to a voltage decrease at the end of lines.

Besides the allocation between consumers and decentralized producers adopted for this study, the voltage decrease is also the consequence of the choice to consider here only impedance errors causing degradations rather than improvements. Typically, this refers to the case of a

DSO estimating its impedances \tilde{Z} by their nominal values before wear. In contrast, impedance values provided by a data assimilating estimator would generate a positively and negatively distributed error. Here, when the impedances are incorrectly estimated by an average of 40%, the average voltage is reduced to 0.97 p.u. and a third of the buses violate the specified limits. It should be noted that extreme values can be observed in the experimental statistical distribution, both positively and negatively.

All voltages are thus affected by fluctuations of varying magnitude. The observation is, however, very different concerning the injected powers – middle panel of Figure 3. Here are shown the deviations between the injected powers calculated by an OPF using the true impedance values Z (block ④ on Figure 1) and those from an OPF using erroneous values \tilde{Z} (block ①). Only a few percent of the injected powers show deviations, although these are rapidly very significant. Actually, the only agents likely to modify their injection plans between these two OPFs are those concerned by the activation of a voltage constraint. In particular, these limits may compel distributed generators not to inject all their available power. This must then be compensated by the external network, whose purchase price is significantly more expensive. The impact of these few percentiles of deviation is therefore critical on the fluctuations of the social welfare – visible on the third panel. Comparing social welfare $\tilde{SW} - SW$ (according to Figure 1 notations) does not make sense when the constraints of a problem are not fully respected. Here with misestimated impedances, no configuration resulted in an improved social welfare taking advantage of constraint violation. Under this clarification, the suboptimality is represented to illustrate that severe decreases come along with impedance errors. With minimal deviations in injected power leading to large shifts in voltages and social welfare, a misestimated network appears to behave as an uncertainty amplifier that magnifies errors.

Figure 3 does not display line flows for two reasons. First, the limiting constraint within the ELVF case is the voltage limit, which is consistent with current distribution networks. Regardless of the load imposed on the network, power constraints on the lines cannot be activated because the power flows would be beforehand limited to comply with voltage constraints. Besides, the network has been completely controlled by power set points. Therefore, impedance fluctuations cannot cause any modification of the flows, which are imposed by end-of-line producers and consumers. Only the value of the losses can be impacted: it is assumed here that the external network compensates for any disequilibrium.

Four modifications are therefore made to the test case for the rest of this section. First, consumers are no longer specified by cost functions depending on their power consumption, but rather by load impedances (wards according to PandaPower formalism). These impedances are set so that the rated power consumed by each load is equal to the previous case. Second, decentralized generators are allowed to exchange reactive power. Third, all power exchanges are multiplied by 30. Finally, AC-OPF-SOC may lead to unfeasible solution since reverse active and reactive PF of

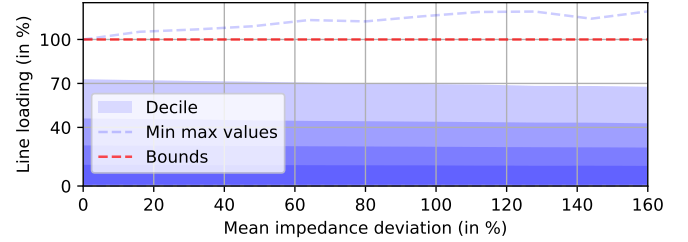


Fig. 4. Sensitivity of line flows computed by an AC-OPF depending on the average of impedance estimation errors.

may occur. Thus, we will use the AC-OPF formulation. It is then possible to reach line capacity constraints, as illustrated on the left end of Figure 4. When consumers are specified by impedances, the deviation of the power consumed will vary with the squared voltage. Voltage fluctuations then affect the line flows. This effect is measurable but statistically very marginal. Nonetheless, the risk of a line being in overcapacity is real, as illustrated by the most heavily loaded line. We notice that the evolution of the flow in this line is not monotonous with the increase of the impedance estimation error. Indeed, when using a Monte Carlo approach, it is much more difficult to estimate extreme events than average behaviors. Due to the high computational cost, the number of draws performed here cannot ensure the accurate estimation of extreme events.

4 SENSITIVITY AND DISCUSSIONS

The previous section highlighted the risks associated with incorrect estimation of line impedances when using an OPF. The purpose of this section is to discuss the various parameters which have been used arbitrarily so far. Specifically section 4.1 will consider the sensitivity to the probability density describing the estimation errors. Section 4.2 will describe the differences between high-consuming and high-producing distribution networks.

4.1 Impact of the Probability Distribution

With no real large-scale experimental data, it is relatively difficult to motivate the adoption of one distribution rather than another. Hence the adopted approach is to compare results obtained using several different distributions. A truncated normal distribution, a Weibull distribution and an exponential distribution are used here. They are adjusted to have the same mean – 160% of nominal impedance values, corresponding to the right end of Figure 3. The top panel of Figure 5 shows voltages experimental density – histogram normalized to make its integral unitary. On all configurations, a peak is observed at 1 p.u.: in the time series used for this test case, some periods present little to no power exchanges, at night for instance. Voltages are thereby not disturbed at all. The distribution based on perfectly known impedances – in purple – reads on the right side as the density reaches much higher values. As explained for Figure 3, the test case involves more consumption than production. Voltages are therefore pulled down. An OPF with perfect knowledge of the impedances manages to activate the voltage constraint of numerous buses. However,

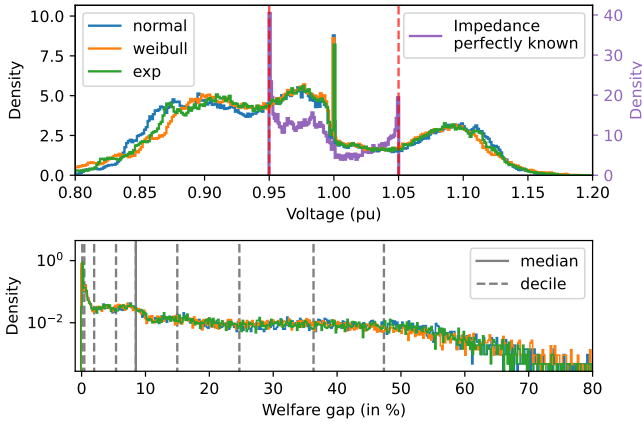


Fig. 5. Experimental distributions of bus voltages (top) and suboptimality of the social welfare (bottom) according to the probability distribution used to describe impedance misestimations. Mean impedance errors are set at 160%. AC-OPF-SOC formulation is used.

when impedances become poorly known, this distribution is spread over a wider voltage range. Peaks corresponding to initially active constraints can still be identified, around 0.9 p.u. and 1.1 p.u. On the bottom panel, the distribution of social welfare suboptimalities is represented in logarithmic scale for better visualization. A significant part of the tested configurations do not show any suboptimality, although significant values can be obtained infrequently. It can be observed that the three probability laws produce very similar outcomes. The choice of a particular distribution does not seem to have any impact on the state of the network, characterizing the average error is enough.

4.2 Producers versus consumers share

To obtain the previous results, the ELVF test case has been populated with production and consumption time series. However, these results are significantly impacted by the ratio between producers and consumers. These impacts are depicted Figure 6: with a 160% mean impedance error, a scaling factor is applied on all productions of the test case – *scale gen* – and another one on all consumptions – *scale load*.

The point (0,0) means that no production or consumption is exchanged. The point (1,1) refers to the configuration used in all previous studies. 400 points constitute this grid which is represented Figure 6 as pixels without interpolations. 15 random networks were sampled for each pixel. On the top panel, the frequency of voltage constraint violation is displayed in color scale. Under full load without any production – (1,0) bottom right corner – 70 % of all studied buses have a voltage violating the power quality constraints. Since these results are obtained using a Monte Carlo approach, non-monotonic fluctuations can be observed. Although, trends are clearly marked. Starting from the origin point (0,0), an increase in consumption (right shift) or in production (up shift) are both associated with voltage violations. The increase is sharper for consumption due to the selected time series: the max to average ratio is greater for the consumption profiles, resulting in more frequent violations. The coexistence of generation and consumption appears not to be the worst configuration with respect to

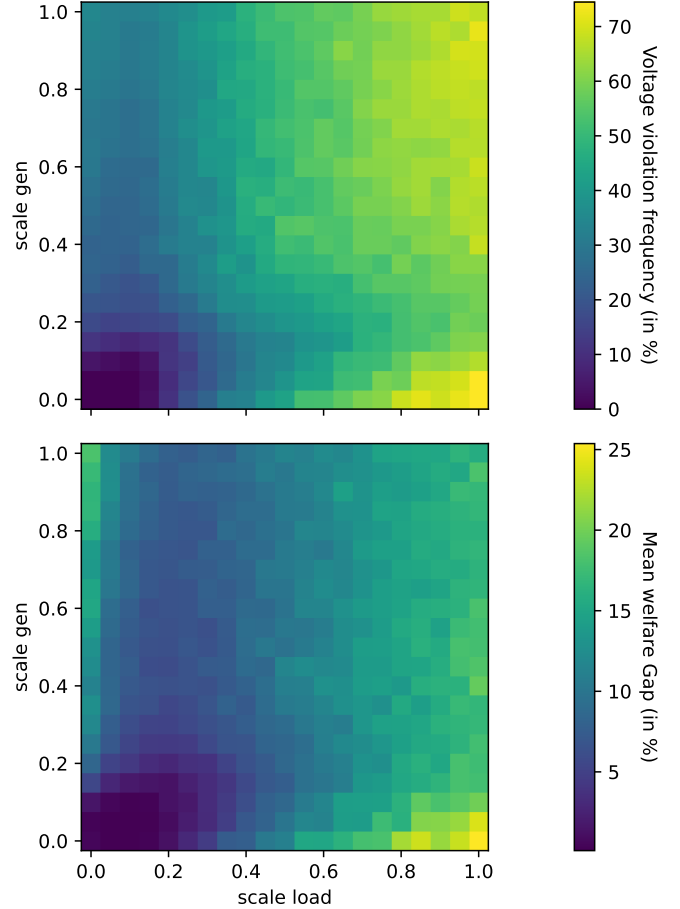


Fig. 6. Impact of the production-consumption ratio – x-axis: consumption, y-axis production – on the frequency of voltage violation (top) and on the welfare suboptimality (bottom) using an AC-OPF-SOC.

the frequency of voltage violations. This is an uplifting indication as this configuration is the most likely to become widespread in the future. For each *scale load* value, there is an optimal *scale gen* value for which voltage violations are less frequent – although this needs to be confirmed as this case study may not represent all distribution networks.

The bottom panel represents the average suboptimality of the obtained solution. Similar trends can be observed, although the comparison of social welfare cannot be straightforward when constraints are not respected as previously mentioned. Yet configurations with only generators – the left side of the figure – show significant suboptimalities that diminish as soon as some consumers are involved. Indeed, voltage constraints restrict exports from the distribution neighborhood. Local consumption prevents producers from being compelled to curtail their production. Here again, the effects of the lack of knowledge regarding impedances seem to be limited by the coexistence of producers and consumers in the same distribution neighborhood.

5 CONCLUSION AND PERSPECTIVES

This contribution sought to estimate the impact of misestimated impedances on the results of an OPF in distribution networks. Indeed, such networks include a large number of lines and are sparsely instrumented, while their production

and consumption flows are likely to increase in the future. The proposed methodology has shown on a case study that non-compliance with voltage constraints could appear across the network while only a few agents modify their injection plan. Lines as a whole are much less affected, although dangerous configurations can quickly appear on the most stressed lines. The statistical distribution chosen to describe the impedance errors does not seem to impact the observed results, characterizing the average error is enough. However, the proportion of producers and consumers in the distribution neighborhood significantly affects the frequency of constraint violations and suboptimalities. The coexistence of distributed consumers and producers seems to be an element to mitigate the hazards of impedance misestimations in distribution networks.

This contribution needs to be pursued in several directions. First, it is crucial to overcome the dependence of the obtained results to a specific case. A generalization to any distribution network – characterized by metrics to be identified – would be a powerful tool to anticipate the sensitivity of a neighborhood to impedance misestimations. The local control, or the distributed instrumentation, could then be adapted. Furthermore, impedance estimation errors are an additional source of uncertainty in the OPF literature. Already investigated in areas where the stochastic distribution of uncertainties is available –renewable generation, line failure–, the development of a robust or chance constraint approach on line impedances would allow to optimally define the margins necessary to respect the operating limits of the network. If necessary, a generalization to a distributionally robust optimization approach could be implemented.

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