

Towards AC Feasibility of DCOPF Dispatch

Michael A. Boateng*, Russell Bent†, Sidhant Misra†, Parikshit Pareek‡, Pascal Van Hentenryck*, Daniel Molzahn*

* School of Electrical and Computer Engineering, Georgia Institute of Technology
Atlanta, Georgia, USA, {mboateng6, pvh, molzahn}@gatech.edu

† T5: Applied Mathematics and Plasma Physics, Los Alamos National Laboratory
Los Alamos, New Mexico, USA, {rbent, sidhant}@lanl.gov

‡ Department of Electrical Engineering, Indian Institute of Technology Roorkee, India, pareek@ee.iitr.ac.in

Abstract—DC Optimal Power Flow (DCOPF) is widely utilized in power system operations due to its simplicity and computational efficiency. However, its lossless, reactive power-agnostic model often yields dispatches that are infeasible under practical operating scenarios such as the nonlinear AC power flow (ACPF) equations. While theoretical analysis demonstrates that DCOPF solutions are inherently AC-infeasible, their widespread industry adoption suggests substantial practical utility. This paper develops a unified DCOPF \rightarrow ACPF pipeline to recover AC feasible solutions from DCOPF-based dispatches. The pipeline uses four DCOPF variants and applies AC feasibility recovery using both distributed slack allocation and PV/PQ switching. The main objective is to identify the most effective pipeline for restoring AC feasibility. Evaluation across over 10,000 dispatch scenarios on various test cases demonstrates that the structured ACPF model yields solutions that satisfy both the ACPF equations, and all engineering inequality constraints. In a 13,659-bus case, the mean absolute error and cost differences between DCOPF and ACOPF are reduced by 75% and 93%, respectively, compared to conventional single slack bus methods. Under extreme loading conditions, the pipeline reduces inequality constraint violations by a factor of 3 to 5.

Index Terms—AC Feasibility, DC Power Flow (DCPF), Distributed Slack, Loss-Augmented DCOPF, Newton Method.

NOMENCLATURE

\mathcal{N}	Set of buses; $\mathcal{N} = \{1, \dots, N\}$
\mathcal{E}	Set of lines {lines run from $i \rightarrow j$ or $j \rightarrow i$ }
\mathcal{G}, \mathcal{L}	Set of generators and loads $\{\mathcal{G}, \mathcal{L} \subseteq \mathcal{N}\}$
$\mathbf{r}, \mathbf{b}, \mathbf{g}$	Line resistance, susceptance, and conductance
\mathbf{Y}	Complex branch line admittance
Φ	Line-Bus PTDF matrix, size $\mathcal{E} \times \mathcal{N}$
s_{tx}^{\max}	Apparent power transformer limit
i_{line}^{\max}	Current flow line limit
p_g^{\min}, p_g^{\max}	Active power generation limits
p_g, q_g	Active and reactive power generation
s_g	Complex power generation; $p_g + j \cdot q_g$
p_d, q_d	Active and reactive power demand
q_g^{\min}, q_g^{\max}	Reactive power generation limits
v^{\min}, v^{\max}	Voltage magnitude limits, for v_i
θ^{dc}, θ^{ac}	Voltage angles from DC and AC models
π_g	Slack participation factor for generators
ℓ^{tot}, ϵ	Total losses across network, tolerance

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I. INTRODUCTION

The linearity of the DC power flow equations provides the DC Optimal Power Flow (DCOPF) problem with significant computational advantages over the AC Optimal Power Flow (ACOPF) problem [1]. These advantages come at the cost of accuracy relative to ACOPF solutions. Since inaccuracies in DCOPF solutions can lead to suboptimal operation and violations of operational limits, studying DC power flow accuracy is a long-running research topic that includes both empirical and analytical assessments. For instance, [1]–[10] empirically study DC power flow accuracy for various applications. Analytical analyses, e.g., [11]–[13], rigorously bound the worst-case DCPF approximation error, but these bounds are not necessarily indicative of typical accuracy.

Of particular relevance to this paper, Baker in [14] analytically proved that, under nonzero loading conditions in networks with positive resistances and reactances, the feasible regions of DCOPF and ACOPF are disjoint. This implies that the optima of conventional DCOPF problems are never AC feasible, i.e., never satisfy the AC power flow equations. The primary argument in [14] relates to the difference in losses between the DC and AC power flow equations. Baker further shows that even DCOPF variants which incorporate loss-adjustment mechanisms will still fail to provide AC feasible solutions due to a similar argument at the level of individual buses.

The theory in [14] provides an important foundational result regarding the accuracy of DC power flow approximations. However, this theory does not address how frequently the solutions to DCOPF problems can be *easily restored* to acceptable AC feasible operating points, i.e., operating points which satisfy both the AC power flow equations and the limits on generator outputs, voltage magnitudes, and line flows. This paper empirically addresses this question. Solving the AC power flow equations is a natural approach for restoring an AC feasible operating point from a solution to a DCOPF problem. By fixing the generators' active power setpoints to those from the DCOPF solution and the voltage magnitudes to a nominal value such as 1 per unit, one can easily construct a system of AC power flow equations that are frequently solvable via standard Newton-Raphson methods. The resulting power flow solution is feasible with respect to the AC power flow equations by construction. If the power flow solution satisfies limits on generator outputs, voltage magnitudes, and line flow limits, it is

a feasible operating point with respect to the ACOPF problem's constraints. Thus, while the DCOPF problem's solution is not itself AC feasible as shown in [14], it may be the case that an AC feasible solution can often be easily obtained.

Indeed, much of the prior literature on DC power flow accuracy (e.g., [1]–[10]) and restoration of AC feasible solutions (e.g., [15]–[19]) takes this AC power flow approach. However, while existing work performs extensive numerical studies on this topic, there are key gaps in the existing literature. Namely, prior research either 1) focuses on simplistic ACPF models that use a single slack bus or neglect the generators' reactive power limits *and/or* 2) focuses on DC power flow accuracy over a range of power injections as opposed to the solutions to DCOPF problems. Since DCOPF solutions are usually extreme points in the operating region, approximation accuracy at these points is not necessarily aligned with DC power flow accuracy over the entire operating region. To the best of our knowledge, the only other paper that simultaneously considers distributed slack and reactive power limited formulations for ACPF settings similar to ours is [17]. The paper examined reactive power control in ACPF, and addressed a slack distribution formulation – though independently, and only applies distributed slack on a 23-bus system. Further, it does not apply any of the formulations in the context of feasibility restoration for DCOPF solutions.

This work addresses these gaps using a “structured” ACPF model that more accurately represent generator behavior via distributed slack bus and PV/PQ switching models by imposing realistic generator limits on both active and reactive power outputs. Using the structured ACPF model with several DCPF approximation variants, results from the DCOPF → ACPF pipeline—solving a DCOPF and evaluating the resulting setpoints with an ACPF—demonstrate that different DCPF formulations influence DCOPF dispatch outcomes and the ability to recover AC feasibility with respect to the ACOPF constraints. This provides an important empirical counterpart to the theoretical findings of [14] on the *ease of restoration* for DCOPF solutions. In summary, the paper's contributions are:

- A DCOPF → ACPF recovery pipeline identifying the most effective DC formulation for obtaining AC feasible solutions across a variety of large-scale power systems.
- An assessment of the impacts of ACPF variants—featuring distributed slack and/or PV/PQ switching models—in the context of AC-feasibility restoration.
- A systematic sensitivity analysis of the pipeline to load perturbations and guidance on its importance for improving feasibility-restoration workflows.

The paper is organized as follows. Section II introduces the pipeline with (A) loss-augmented DCOPF models, and (B) a structured ACPF formulation. Section III shows the numerical results, and Section IV concludes with future directions.

II. METHODOLOGY

To investigate the most effective DCOPF → ACPF pipeline as shown in Fig. 1, two components were integrated: (i) a *loss-aware* DCOPF embedding a loss approximation while remaining convex and efficient, and (ii) a *structured* ACPF

Model 1: DC Optimal Power Flow (DCOPF) Formulation

$$\min \sum_{i \in \mathcal{G}} (c_{2i} p_{gi}^2 + c_{1i} p_{gi} + c_{0i}) \quad (\text{Cost Minimization}) \quad (1a)$$

$$\text{s.t. } p_{gi} - p_{di} = \sum_{j \in \mathcal{E}} \vec{p}_{ji} - \sum_{j \in \mathcal{E}} \vec{p}_{ij} \quad \forall i \in \mathcal{N} \quad (\text{Power Balance}) \quad (1b)$$

$$\vec{p}_{ij} = b_{ij} (\theta_i^{\text{dc}} - \theta_j^{\text{dc}}) \quad \forall (i, j) \in \mathcal{E} \quad (\text{DC Flow}) \quad (1c)$$

$$|\vec{p}_{ij}| \leq p_{ij}^{\text{max}} \quad \forall (i, j) \in \mathcal{E} \quad (\text{Line Limit}) \quad (1d)$$

$$p_g^{\text{min}} \leq p_g \leq p_g^{\text{max}} \quad (\text{Gen. Active Power}) \quad (1e)$$

- Different inputs to DCOPF and ACPF variants
- Various DCOPF and ACPF formulations can be paired together
- Recorded inequality constraint violations to observe ACOPF feasibility

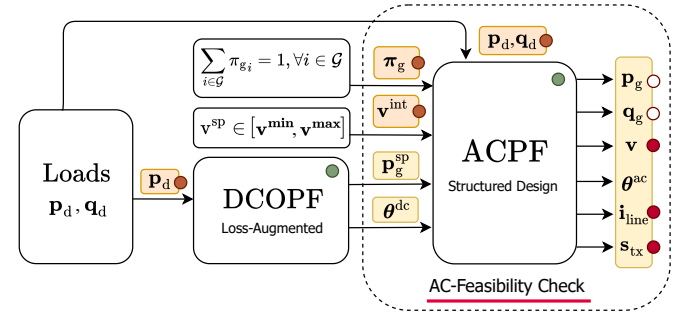


Fig. 1: Pipeline of the DCOPF → ACPF model. The DCOPF gives p_g^{sp} and θ^{dc} from input p_d . The ACPF performs feasibility checks with distributed slack using participation factors (π_g). Voltage initialization (v^{int}) aids in convergence. ACPF constraints are marked with red.

with distributed slack and PV/PQ switching. The stages are coupled: the DCOPF provides generator setpoints, and the ACPF applies minimal adjustments to obtain solutions that are nearly or fully AC feasible — i.e., solutions that satisfy both the ACPF equations and the full ACOPF inequality constraints.

A. DCOPF with Line Loss Approximation

To improve the accuracy of the DCOPF while preserving tractability, several loss-augmented DCOPF variants have been developed in the literature, three of which are described next.

1) *Linear Line Loss Factor Model (LLLF)* [16], [20]: Using the DC PTDF (Φ) matrix from the DC power flow approximation [21], resistive losses are linearized about a reference DC operating point. Total losses are expressed as:

$$\ell^{\text{tot}} = \ell^{\text{ref}} + \lambda^\top \mathbf{p}, \quad (2)$$

where ℓ^{ref} is a scalar offset, λ is the (linear) loss-factor vector, and \mathbf{p} stacks bus active-power injections. The loss factors follow from differentiating the approximate quadratic loss $\sum_{(i,j)} r_{ij} \vec{p}_{ij}^2$ via the chain rule, yielding $\lambda^\top = -2 (\mathbf{R} \odot \vec{\mathbf{p}}^{\text{ref}})^\top \Phi$, and the offset is chosen to match the true loss at the reference, $\ell^{\text{ref}} = -\lambda^\top \mathbf{p}^{\text{ref}} + \sum_{(i,j) \in \mathcal{E}} r_{ij} (\vec{p}_{ij}^{\text{ref}})^2$. Here, \mathbf{R} stacks line resistances r_{ij} , $\vec{\mathbf{p}}^{\text{ref}}$ are oriented reference branch flows, and \odot denotes the Hadamard product [21].

2) *Line Loss Quadratic Convex Program (LQCP)* [16]: This model incorporates line losses directly through convex quadratic constraints. Power balance and operational limits

follow (1d)–(1e). Flows are modeled as being linear in voltage angles via (1c). For each line (i, j) , losses are modeled as:

$$\vec{p}_{ij} + \overleftarrow{p}_{ij} \geq r_{ij} (\vec{p}_{ij})^2. \quad (3)$$

While this formulation is convex, the presence of nonlinear constraints may increase computational burden [16].

3) *Line Loss Outer Approximation (LLOA)* [16]: This approach approximates the nonlinear LQCP loss constraints using supporting hyperplanes. For a given reference flow $\vec{p}_{ij}^{\text{ref}}$, the quadratic loss term is outer-approximated linearly via:

$$\vec{p}_{ij} + \overleftarrow{p}_{ij} \geq r_{ij} \left[-(\vec{p}_{ij}^{\text{ref}})^2 + 2\vec{p}_{ij}^{\text{ref}} \cdot \vec{p}_{ij} \right], \quad (4)$$

which makes the approximation conservative with respect to the LQCP formulation. The total losses $\sum_{(i,j)} \ell_{ij}$ are embedded into the system power balance via $\sum_i p_i = \sum_d p_d + \sum_{(i,j)} \ell_{ij}$, with each ℓ_{ij} lower-bounded by its linear approximation. The LLOA approach allows fast, warm-started dispatch [16].

B. Structured AC Power Flow Model

Following the DCOPF, a structured ACPF is solved via the Newton–Raphson method, with a distributed slack to allocate active-power imbalances across generators and PV/PQ switching to handle reactive-power limits. For a comprehensive pipeline analysis, a total of four AC variants are utilized.

1) *Distributed Slack Model*: A conventional ACPF assigns all active-power imbalance to a single slack generator, often producing unrealistic dispatch and voltage bias. To address this, a *headroom-based* distributed slack formulation is used, sharing the total mismatch ℓ^{tot} —the signed active-power deficit or surplus between the DCOPF setpoints p_{gi}^{sp} , and the current AC state (θ, \mathbf{V}) —across generators in proportion to their available headroom (i.e., margin to their upper active power output limit). This adaptive allocation prevents infeasible loading during AC feasibility recovery, unlike equal or maximum-capacity participation schemes that disregard operating limits. As shown in Model 2, (5a) defines each generator’s headroom h_i as the upward margin to the active-power limit; generators at their upper limits have $h_i = 0$ and thus do not absorb further deficit. The participation factor π_{gi} defined in (5b) allocates a fraction of ℓ^{tot} to each unit, and a capacity-proportional fallback ensures feasibility when $\sum_i h_i = 0$. Updated injections follow (5c), with π_{gi} recomputed and normalized at each Newton–Raphson iteration to maintain $\pi_{gi} \geq 0$ and $\sum_i \pi_{gi} = 1$. This weighting preserves realism under load perturbations, enhances numerical stability, and improves cost allocation accuracy [22].

2) *Reactive Power Control*: The ACPF also utilizes a reactive power control mechanism via bus-type switching—a standard method for representing generator behavior in power flow analysis. As shown in Fig. 2, the bus transitions between PQ^{max} , PV , and PQ^{min} states based on $(q_{gi}, v_i^{\text{sp}})$. In practice, most solvers apply small tolerances to avoid oscillatory switching during Newton–Raphson iterations. Accordingly, a deadband (ϵ_q, ϵ_v) is imposed such that $|\mathbf{q}_g - \mathbf{q}_g^{\text{lim}}| \leq \epsilon_q$ and $|\mathbf{v}^* - \mathbf{v}^{\text{sp}}| \leq \epsilon_v$, preventing transitions within this range. When reactive power violations exceed ϵ_q , PV buses switch to PQ , clamping reactive power at its bound. Reversion occurs only

Model 2: Headroom-Based Slack Distribution

$$h_i = \max(p_{gi}^{\text{max}} - p_{gi}^{\text{sp}}, 0), \quad \forall i \in \mathcal{G} \text{ (Headroom)} \quad (5a)$$

$$\pi_{gi} = \begin{cases} \frac{h_i}{\sum_{i \in \mathcal{G}} h_i}, & \text{if } \sum_{i \in \mathcal{G}} h_i > 0, \\ \frac{p_{gi}^{\text{max}}}{\sum_{i \in \mathcal{G}} p_{gi}^{\text{max}}}, & \text{otherwise,} \end{cases} \quad \forall i \in \mathcal{G} \text{ (Slack share)} \quad (5b)$$

$$p_{gi} = p_{gi}^{\text{sp}} + \pi_{gi} \ell^{\text{tot}}, \quad \forall i \in \mathcal{G} \text{ (New dispatch)} \quad (5c)$$

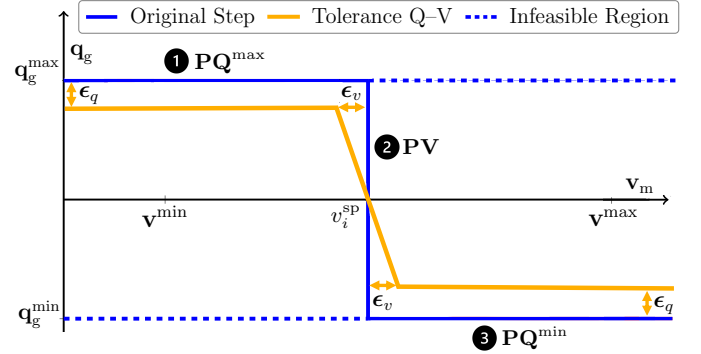


Fig. 2: The generator bus-type switching logic. The **blue curve** is the discrete logic. The bus transitions between PQ^{max} , PV , and PQ^{min} states, based on q_{gi} and v_i^{sp} . The **blue dashed lines** are infeasible regions where the generator cannot maintain voltage control while obeying reactive power limits. The **orange curve** is the tolerance-based control, with tolerances ϵ_q and ϵ_v on reactive power and voltage.

when voltages move beyond ϵ_v . This practical scheme limits switching per Newton solve, enforces reactive power feasibility, and improves convergence by reducing oscillations. Although it does not guarantee voltage-limit satisfaction, it maintains feasible reactive injections and numerically stable operation.

Unstable and erratic iterations from discrete PV/PQ switching noted in prior studies [23], [24] were rarely observed in AC_{SPF} , and while homotopy-based methods [17] can further reduce iterations, the tolerance-based deadband offers sufficient robustness and integrates seamlessly with the ACPF framework.

In Newton–Raphson ACPF, *total iteration count* records all inner iterations needed for convergence under fixed bus types, while the *PV/PQ switching count* tracks outer iterations where generator buses change type as reactive limits are enforced or released. Both iteration counts are recorded in Section III.

For the sake of notational brevity, the paper hereafter denote four ACPF variants as follows: AC_{BASE} uses a single slack bus with no generator control, AC_{BTS} applies discrete PV/PQ switching (blue curve in Fig. 2), AC_{DS} employs distributed slack control only, and AC_{SPF} (Structured Power Flow) combines headroom-based distributed slack (Model 2) with tolerance-based PV/PQ switching (orange curve in Fig. 2).

III. NUMERICAL EXPERIMENTS

The various combinations of DCOPFs and ACPFs described in Section II were evaluated on a diverse suite of MATPOWER 8.1 test cases [25]. This includes IEEE cases $\{\text{ieee_30}, \text{ieee_ne_39}, \text{ieee_118}\}$, ACTIVSg grids $\{\text{South_Carolina_500}, \text{Texas_2000}\}$, PEGASE networks $\{\text{pegase_89}, \text{pegase_1354}, \text{pegase_2869},$

TABLE I: NUMBER OF VIOLATIONS IN BASE CASE FOR DCOPF \rightarrow ACPF PIPELINES USING STANDARD TEST CASES

Test case	AC type	Active Power Violations				Reactive Power Violations				Voltage Violations				Thermal Violations			
		DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}
case_118	AC _{BASE}	1	1	0	1	22	21	18	16	0	1	0	0	0	0	0	0
	AC _{BTS}	1	1	0	1	0	0	0	0	1	1	0	0	1	1	1	1
	AC _{DS}	0	0	0	0	19	20	25	26	0	1	0	0	0	0	0	0
	AC _{SPF}	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
case_1354	AC _{BASE}	1	1	1	1	91	70	85	76	2	1	1	1	3	17	5	11
	AC _{BTS}	1	1	0	1	0	0	0	0	1	1	1	1	6	13	5	10
	AC _{DS}	0	0	0	0	82	67	87	89	0	1	1	1	5	15	1	4
	AC _{SPF}	0	0	0	0	0	0	0	0	0	1	1	0	0	13	2	0
case_2869	AC _{BASE}	1	1	1	1	310	190	87	115	2	1	1	1	12	4	3	16
	AC _{BTS}	1	1	1	1	0	0	0	0	14	7	4	2	12	25	13	22
	AC _{DS}	0	0	0	0	365	213	164	96	2	2	3	2	18	17	5	11
	AC _{SPF}	0	0	0	0	0	0	0	0	0	1	0	0	0	6	1	0
case_13659	AC _{BASE}	1	1	1	0	1215	1028	971	1012	19	6	6	5	68	65	62	62
	AC _{BTS}	1	1	0	1	0	0	0	0	213	170	69	62	93	55	52	60
	AC _{DS}	0	0	0	0	1003	980	956	940	22	16	17	16	40	42	32	33
	AC _{SPF}	0	0	0	0	0	0	0	0	0	7	0	3	0	24	0	21

 TABLE II: MAXIMUM VIOLATION VALUE IN BASE CASE FOR DCOPF \rightarrow ACPF PIPELINES USING STANDARD TEST CASES

Test case	AC type	Active Power Violations (p.u.)				Reactive Power Violations (p.u.)				Voltage Violations (p.u.)				Thermal Violations (%)			
		DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}	DC _{BASE}	DC _{LLLF}	DC _{LQCP}	DC _{LLOA}
case_118	AC _{BASE}	0.002	0.001	0.000	0.001	1.538	1.528	1.489	1.469	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.000
	AC _{BTS}	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.008	0.005	0.000	0.000	4.472	4.470	4.100	4.001
	AC _{DS}	0.000	0.000	0.000	0.000	1.234	1.202	1.113	1.110	0.000	0.020	0.000	0.000	0.000	0.000	0.000	0.000
	AC _{SPF}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000	0.000	0.000
case_1354	AC _{BASE}	0.024	0.016	0.012	0.012	14.29	15.78	13.72	13.88	0.030	0.024	0.016	0.009	14.16	12.59	11.73	11.83
	AC _{BTS}	0.014	0.013	0.000	0.014	0.000	0.000	0.000	0.000	0.017	0.015	0.014	0.012	18.85	16.60	17.14	19.07
	AC _{DS}	0.000	0.000	0.000	0.000	12.78	12.35	12.10	12.12	0.021	0.016	0.011	0.000	15.42	11.23	8.433	9.761
	AC _{SPF}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.020	0.010	0.000	0.000	15.65	3.810	0.000
case_2869	AC _{BASE}	2.522	1.714	1.131	1.362	14.51	14.62	14.08	14.53	0.026	0.021	0.024	0.024	27.56	17.42	12.53	11.67
	AC _{BTS}	2.121	1.032	2.116	1.089	0.000	0.000	0.000	0.000	0.039	0.027	0.023	0.025	24.37	19.62	14.09	20.96
	AC _{DS}	0.000	0.000	0.000	0.000	16.02	14.39	11.76	11.76	0.033	0.020	0.017	0.002	26.78	14.34	9.051	9.803
	AC _{SPF}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000	0.000	6.732	4.329	0.000
case_13659	AC _{BASE}	43.10	42.05	44.30	0.000	8.790	7.322	6.999	6.704	0.063	0.055	0.053	0.042	55.45	56.01	48.67	46.34
	AC _{BTS}	44.52	43.46	0.000	33.80	0.000	0.000	0.000	0.000	0.150	0.129	0.112	0.122	75.43	70.13	62.24	67.60
	AC _{DS}	0.000	0.000	0.000	0.000	9.334	7.592	6.178	6.207	0.071	0.067	0.066	0.061	46.73	41.28	40.01	40.13
	AC _{SPF}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.007	0.000	15.65	0.000	13.81

pegase_9241, pegase_13659}, and a large-scale RTE case {rte_6468}. Computations were carried out on the Darwin high-performance computing system at Los Alamos National Laboratory. Experiments used a single 24-core compute node equipped with 32 GB of RAM. The ACOPFs and DCOPFs variants were solved using `PowerModels.jl` [26]. The design and implementation of the custom ACPF was formulated using `pandapower.py` [27]. Active power demands (p_d) at load buses were perturbed using Gaussian multiplicative noise, where each positive demand was scaled by $\xi \sim \mathcal{N}(1.0, \sigma^2)$ with $\sigma \in (5\%, 15\%)$. Reactive power (q_d) was recomputed from randomly sampled power factors in $[0.95, 1.0]$, and 1000 samples were evaluated per testcase. Since distributed slack and bus-type switching can change the Jacobian's structure across iterations, we rebuild the sparse system when the active set changes while exploiting sparsity at each step. These optimizations yield a scalable Newton-Raphson solver. The solver tolerance was set to 10^{-6} p.u., while the tolerances for reactive power control were 10^{-4} p.u. for ϵ_q (reactive power) and 10^{-5} p.u. for ϵ_v (voltage). All results reported correspond to samples that converged. The mean absolute error (MAE) and percent cost difference (CD) are computed as follows:

$$\text{MAE} = \frac{1}{G} \|\mathbf{p}_g^{\text{DC} \rightarrow \text{AC}} - \mathbf{p}_g^{\text{O}}\|_1, \quad (6)$$

$$\text{CD} = \frac{|\text{Cost}^{\text{DC} \rightarrow \text{AC}} - \text{Cost}^{\text{O}}|}{\text{Cost}^{\text{O}}} \cdot 100, \quad (7)$$

where G is the number of generators, $\mathbf{p}_g^{\text{DC} \rightarrow \text{AC}}$ is the generation vector after the DCOPF \rightarrow ACPF pipeline, and \mathbf{p}_g^{O} is the ACOF-based reference used as a ground truth.

A. ACOPF Feasibility Study with DCOPF \rightarrow ACPF Variants

This section evaluates violations of the ACOPF constraints in Fig. 1 across the different DCOPF \rightarrow ACPF pipelines. Tables and charts summarize these violations and their reduction factors under loss-augmented DCOPFs and the ACPF variants.

1) *Violation Tables Analysis:* Tables I and II show that the distributed-slack reconciliation AC_{SPF} delivers the fewest violations across all DC initializations and systems. In case_13659, reactive-power violations are noticeably high for AC_{BASE} and AC_{DS}, since these lack reactive control. The counts are 1215/1028/971/1012 for AC_{BASE} across DC_{BASE}/DC_{LLLF}/DC_{LQCP}/DC_{LLOA}, and 1003/980/956/940 for AC_{DS}. By contrast, both AC_{BTS} and AC_{SPF} keep reactive violations at zero, with AC_{SPF} also maintaining voltage violations low (0/7/0/3) and thermal violations modest (0/24/0/21). For active-power violations, the distributed slack in AC_{DS} and AC_{SPF} again drives violations to zero across all DC variants. However, AC_{BASE} and AC_{BTS} struggle: in case_13659, maximum per-unit active-power violations reach 43.10/42.05/44.30/0.000 p.u. under AC_{BASE} and 44.52/43.46/0.000/33.80 p.u. under AC_{BTS}. For AC_{SPF}, maximum active- and reactive-power violations remain 0.000 p.u. in every case and DC variant. Thus, AC_{SPF} combines the best of both worlds, eliminating active and reactive violations. AC_{SPF} also seems to restore feasibility for DC_{BASE} consistently. This will be revisited in the sensitivity analysis, later in this section.

Looking horizontally within any fixed AC reconciliation, violations generally fall as we move from the lossless DC_{BASE} to the lossy DC_{LQCP}/DC_{LLOA}. DC_{LLLF} usually improves on DC_{BASE} but less reliably. As summarized in Section II, the

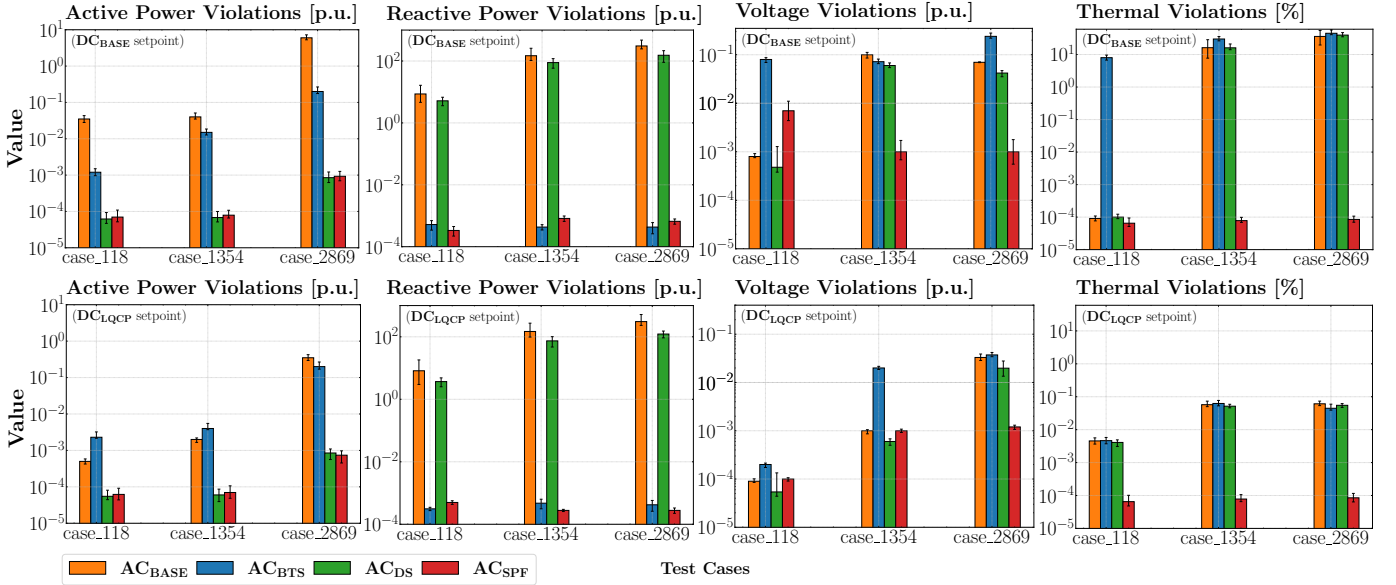


Fig. 3: Comparison of the sum total of violations in different AC power flow formulations across various cases: case_118, case_1354, and case_2869 (with mean and min-max error bars). The pipelines shown have different DC setpoints: (top) DC_{BASE} and (bottom) DC_{LQCP} . The plots are taken over load uncertainty with $\sigma = 15\%$, for 1000 samples per case. Shown are the active power, reactive power, voltage, and thermal violations, with y-axes on log-scales. Results are reported for AC_{BASE} (orange), AC_{BTS} (blue), AC_{DS} (green), and AC_{SPF} (red).

superior accuracy of DC_{LQCP} and DC_{LLOA} arises because they include lossy formulations that more faithfully capture I^2R effects, whereas DC_{LLLF} , being a simpler linear formulation, neglects higher-order terms and therefore underperforms. Ultimately, when observing the AC_{SPF} results horizontally for each case, the DC_{LQCP} was revealed to generalize better and be more consistent with violation reduction, at scale. DC_{LLOA} did have the lowest violations sparingly compared to the others, but performed poorly at scale (e.g., for case_13659 in AC_{SPF} , complete AC feasibility was achieved in DC_{LQCP} , with DC_{LLOA} recording violations closer to the linearized DC_{LLLF}).

2) *Bar Graph Sensitivity Analysis*: Following the realization of DC_{LQCP} 's better generalizeable performance, imperative sensitivity analysis was conducted. Fig. 3 provides a visual reflection of the numerical trends, presenting the *sum of violation magnitudes* across all buses, branches, and limits. Unlike Tables I–II, which details violation *counts* and *maxima*, these plots capture the aggregate severity. The top panels correspond to $DC_{BASE} \rightarrow AC$ pipelines, while the bottom panels use lossy DC_{LQCP} initializations. Across most test systems, the distributed-slack AC_{SPF} reconciliation yields the lowest summed violations in every category. From the upper plots, moving from AC_{BASE} to AC_{SPF} reduces both active- and reactive-power violation magnitudes by roughly *four orders of magnitude* (from 10^{-3} – 10^2 , down to 10^{-4} – 10^{-3} p.u.). The same trend extends to voltage and thermal violations, which remain low under AC_{SPF} . In contrast, AC_{BTS} and AC_{BASE} show higher aggregate magnitudes. AC_{DS} performed well in active power and voltage violation reduction, but performed poorly in reducing reactive power and thermal violations.

Comparing the upper and lower rows, lossy initializations (DC_{LQCP}) further reduce total violation magnitudes by an additional one-to-two orders of magnitude across all AC types.

The DC_{LQCP} formulation captures loss and angle effects more accurately than DC_{BASE} , producing better-aligned initializations and greater AC feasibility. Consequently, the $DC_{LQCP} \rightarrow AC_{SPF}$ pipeline is the most consistent at violation reduction across test cases. These plots reinforce the trends in Tables I–II: incorporating lossy DC models and distributed slack improves both constraint satisfaction and numerical stability.

B. Key Metrics for ACPF Variants Assessment

The following study gives an extensive comparative analysis of the ACPF variants from Section II. After demonstrating that $DC_{LQCP} \rightarrow AC_{SPF}$ reduces violations and often fully restores AC feasibility, further performance analysis is required.

1) *Performance Metrics Table*: Table III summarizes key performance metrics for 10 core test cases, comparing cost deviation, mean absolute error, iteration behavior, and solving time across all ACPF variants. Clear trends show that distributed-slack formulations, AC_{DS} and AC_{SPF} , yield the lowest cost deviation and error magnitudes through improved active-power balancing. Cost differences drop by up to 93% relative to AC_{BASE} , while mean absolute errors approach zero for most systems (e.g., AC_{SPF} maintains ≤ 0.05 p.u.). Iteration metrics reflect the effects of tolerance-based PV/PQ switching: both AC_{BTS} and AC_{SPF} reach zero reactive power violations, though AC_{SPF} consistently converges faster—reducing total iterations by about 50% in case_2869. In contrast, AC_{BASE} and AC_{DS} complete in a single recalculation loop but require longer inner iterations, at times. Full feasibility was not restored only for case_2000, likely due to high line impedance ratios (r/x) limiting reactive controllability. As feasibility restoration is the pipeline's focus, convergence rate was not prioritized, though future work will address it [24]. Solving times align with iteration behavior: smaller systems (e.g., case_89,

TABLE III: PERFORMANCE METRICS IN BASE CASE DCOPF FOR ACPF VARIANTS ACROSS MULTIPLE TEST CASES

Test case	Cost Difference (%)					Mean Absolute Error (p.u.)					Iteration Count (Total)				Solving Time (s)	
	AC _{BASE}	AC _{BTS}	AC _{DS}	AC _{SPF}	Improv. (%)	AC _{BASE}	AC _{BTS}	AC _{DS}	AC _{SPF}	Improv. (%)	AC _{BASE}	AC _{BTS}	AC _{DS}	AC _{SPF}	ACOPF	AC _{SPF}
case_30	1.21	1.71	0.36	0.32	(74, 81, 11)	0.00	0.02	0.01	0.00	(0, 100, 100)	4	19	4	3	1.79	0.21
case_39	1.38	1.43	0.30	0.26	(81, 82, 13)	0.01	0.03	0.01	0.00	(100, 100, 100)	3	20	3	8	0.41	0.13
case_89	0.33	0.36	0.19	0.20	(39, 44, -5)	0.02	0.04	0.02	0.00	(100, 100, 100)	4	42	4	12	0.42	0.23
case_118	2.19	2.82	0.24	0.18	(92, 94, 25)	0.01	0.04	0.00	0.01	(0, 75, -100)	4	60	3	18	0.19	0.22
case_1354	0.41	0.58	0.12	0.28	(32, 52, -133)	0.01	0.05	0.03	0.02	(0, 60, 33)	4	357	3	152	2.78	64.10
case_2000 ^o	2.11	2.14	0.91	0.82	(61, 62, 10)	0.23	0.20	0.02	0.05	(78, 75, -150)	3	208	4	81	3.24	36.10
case_2869	0.54	0.62	0.31	0.37	(31, 40, -19)	0.04	0.14	0.03	0.04	(0, 71, -33)	4	777	3	380	4.88	187
case_6468	1.65	1.89	0.26	0.24	(85, 87, 8)	0.07	0.12	0.04	0.05	(29, 58, -25)	4	3396	4	1670	59.05	2213
case_9241	1.60	1.11	0.21	0.20	(88, 82, 5)	0.02	0.13	0.02	0.02	(0, 85, 0)	3	2204	3	1356	30.18	6104
case_13659	1.81	1.31	0.15	0.13	(93, 90, 13)	0.01	0.04	0.01	0.01	(0, 75, 0)	4	6452	3	3320	127.14	7170

* AC variants have higher iteration counts due to PV/PQ switching. ^o case_2000 incurred violations of inequality constraints.

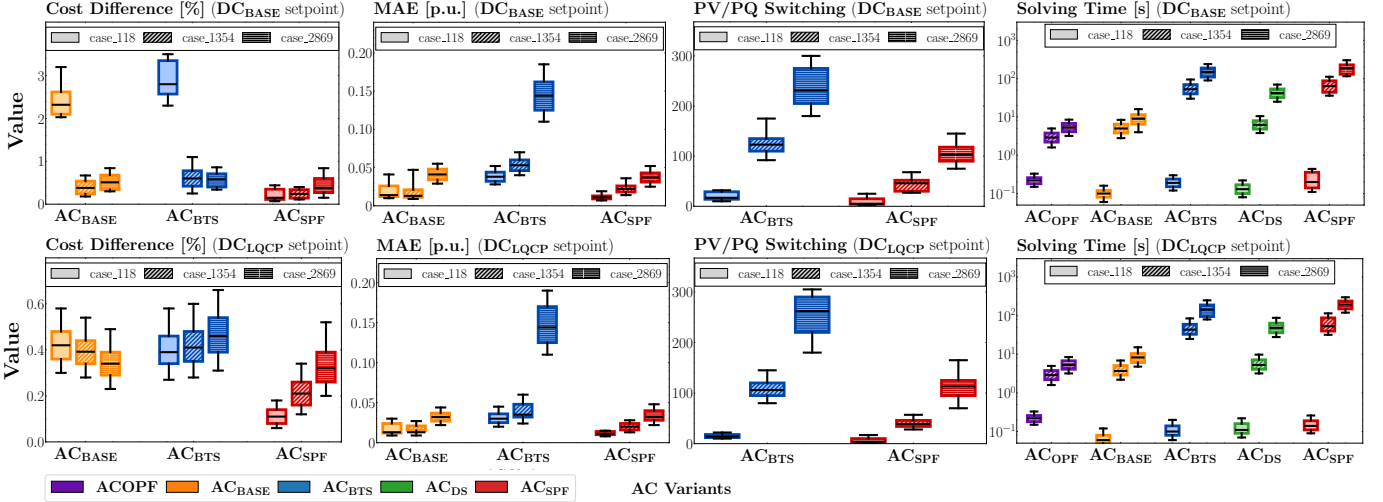


Fig. 4: Boxplot comparison of different AC variants' metrics across test cases: case_118, case_1354, and case_2869 (with mean and min-max extremes). The AC variants shown have different DC setpoints: (top) DC_{BASE} and (bottom) DC_{LQCP}. The plots are taken over load uncertainty with $\sigma = 15\%$, for 1000 samples per case. Metrics shown (left to right): cost difference, mean absolute error, iteration count, and solving time. Results are reported for AC_{OPF} (purple), AC_{BASE} (orange), AC_{BTS} (blue), AC_{DS} (green), and AC_{SPF} (red).

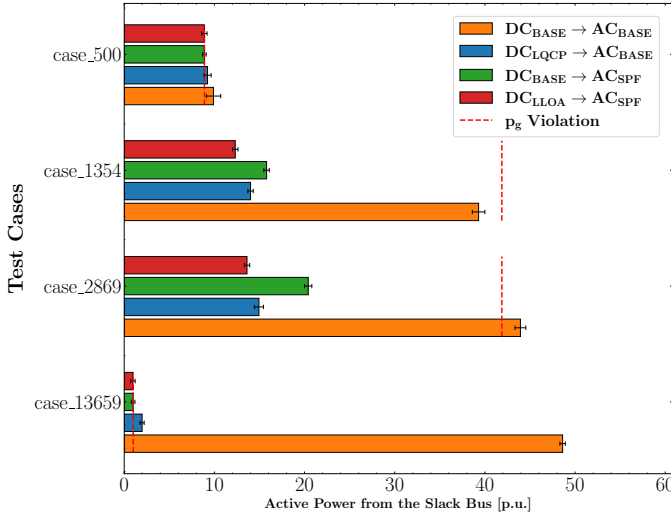
case_118) run comparably or slightly faster under AC_{SPF}, while larger networks slow down due to iterative refinement. Still, the gains in cost and feasibility confirm AC_{SPF} has a good balance between accuracy and computational efficiency.

2) *Box Plot Sensitivity Analysis*: Fig. 4 illustrates the statistical distribution of performance metrics for three cases, revealing the robustness and variability of each ACPF variant. The upper plots correspond to DC_{BASE} → AC pipelines, while the lower plots represent DC_{LQCP} setpoints. The lossy DC generally yields a lower average cost difference and MAE, though with slightly higher variability across realizations. The DC_{LQCP} initialization also reduces iteration counts and solving times—particularly for case_118 and case_1354—owing to its pre-accounting of power losses and generator redispatch. Since the AC reconciliation must only distribute the residual loss (i.e., remaining mismatch after DC loss approximation), convergence is faster. However, reactive-power control adjustments still dominate iteration requirements in larger networks. Across all metrics, AC_{SPF} achieves the tightest distributions with the lowest mean values for both cost difference and MAE. The reduced interquartile ranges in AC_{SPF} indicate superior consistency and robustness. For iteration count and solving time, AC_{SPF} exhibits apparent higher computational effort, but remains competitive—with improved accuracy and reliability.

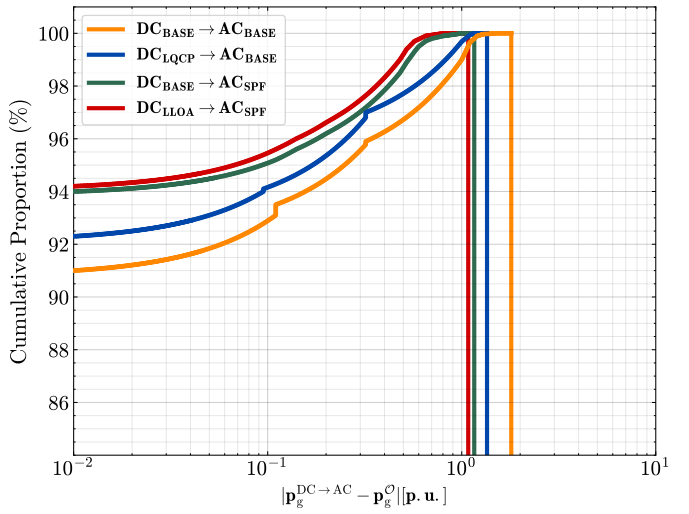
C. Distributed Slack Effects on Active Power

The analysis examines distributed- versus single-slack-bus modeling in ACPF, isolating how DC and AC variants separately affect loss handling. It also evaluates whether DC models with higher degrees of freedom paired with simpler AC models (and vice versa) can yield acceptable performances.

1) *Bar Plot Sensitivity Analysis*: The horizontal bar plots in Fig. 5(a) reveal significant differences in slack-bus active-power requirements across four pipeline combinations. The red and green pipelines using AC_{SPF} consistently yield active-power violations below 10^{-3} p.u. Among them, DC_{LLOA} → AC_{SPF} produces the smallest active-power changes across all test cases. This behavior arises from the distributed-slack mechanism, which shares losses in proportion to generator reserve capability, rather than a single slack bus. By contrast, DC_{BASE} → AC_{BASE} exhibits the largest slack-bus injections, since a single slack must absorb losses after a lossless DCOPF—pushing loss accountability to that unit. The pipeline DC_{LQCP} → AC_{BASE} also employs a single slack, *but* its setpoints originate from a DCOPF that accounts for losses, yielding a notable reduction relative to DC_{BASE}. Consequently, using DC_{LQCP} or DC_{LLOA} improves AC reconciliation compared with DC_{BASE} (seen in the reduction from orange to blue, and green to red). With low perturbations of $\sigma = 5\%$, single-slack pipelines may converge



(a) Active power from the slack-bus (mean with min-max error bars)



(b) Cumulative plot of generator output errors in a case_1354

Fig. 5: Pipeline comparison across different DC and AC variants, over load uncertainty with $\sigma = 5\%$. (a) Slack-bus active power using 100 per case, for: case_500, case_1354, case_2869, and case_13659 under $DC_{BASE} \rightarrow AC_{BASE}$ (orange), $DC_{LQCP} \rightarrow AC_{BASE}$ (blue), $DC_{BASE} \rightarrow AC_{SPF}$ (green), and $DC_{LLOA} \rightarrow AC_{SPF}$ (red). Dashed (red) line is the active power violation. (b) Cumulative density factor (CDF) plot of unit-wise active-power deviation $|p_g^{DC \rightarrow AC} - p_g^O|$ across generators in case_1354, using 1000 per case, with an x-axis log-scale.

without active-power violations, yet the slack generator remains stressed, underscoring its inherent fragility.

2) *Cumulative Density Function Analysis*: Fig. 5(b) compares $|p_g^{DC \rightarrow AC} - p_g^O|$ (p.u.) across pipelines on a logarithmic scale. The two distributed-slack recoveries, $DC_{LLOA} \rightarrow AC_{SPF}$ and $DC_{BASE} \rightarrow AC_{SPF}$, dominate: for any error threshold, their curves lie above the single-slack ones, indicating fewer large generator-setpoint deviations. At 10^{-2} p.u., about 94.5%, 94%, 92.3%, and 91% of generators lie below this error for the four pipelines, respectively. A notch near 10^{-1} p.u. on the AC_{BASE} curves reflects loss aggregation under a single slack, producing a cluster of similar deviations. The right tails confirm the same ordering: AC_{SPF} pipelines saturate near 1 p.u., whereas AC_{BASE} ones require larger errors (~ 1.2 – 1.3 p.u.) to reach 100%. These results underscore the advantage of distributed slack and advanced AC recovery in minimizing generator output errors and mitigating the limitations of single-slack aggregation.

D. Bus-type Switching Effects on Voltage and Reactive Power

As discussed in Section II-B, reactive power and voltage are tightly coupled in ACPF. Fig. 6 shows this relationship across five test cases under load uncertainty $\sigma = 5\%$. The upper box plots show voltage magnitudes with dashed limits, while the lower plots depict mean reactive violations. AC_{BTS} eliminates most reactive violations through dynamic PV/PQ switching, maintaining feasibility but causing larger voltage deviations—particularly in case_1354 and case_2869, where voltages approach their upper limits. While voltage-reactive coupling allows PV/PQ switching to restore most voltage setpoints, near-limit voltages may demand reactive support beyond generator capability, leading to increased violations. AC_{BASE} enforces setpoints rigidly, yielding more reactive-limit breaches, whereas loss-aware DC_{LQCP} and DC_{LLOA} pre-account for losses and phase angles, reducing voltage deviations

and violations. Among DC variants, DC_{LQCP} best maintained voltages within limits, even with AC_{BASE} . Overall, AC_{BTS} demonstrates the benefits of reactive flexibility, while lossy DC pipelines help keep bus voltages near nominal values. These results highlight the voltage-reactive trade-off in AC feasibility recovery and the value of loss-aware setpoints for balanced operation. Voltage initializations from AC_{BASE} also improved convergence and reduced violations relative to a flat start.

IV. CONCLUSION

This paper investigates AC feasibility restoration pipelines for DCOPF dispatches. A comprehensive empirical study is conducted, applying various DCOPF and ACPF variants. The most effective and consistent pipeline for restoring AC feasibility from DC solutions is found to be $DC_{LQCP} \rightarrow AC_{SPF}$. The results show that integrating a structured ACPF—featuring distributed slack and reactive power limited generators—with loss-augmented DCOPF dispatches, can yield ACOPF feasible outcomes. This workflow reduces violations in active power, voltage, reactive power, and thermal limits while lowering the cost difference. For reference, applying the structured pipeline to the 13,659-bus case achieved improvements of 93% in cost difference, 75% in mean absolute error, and an improved convergence rate compared to single-slack methods. The link between voltage and reactive power violations is also examined. Future work will focus on improving the pipeline's computational efficiency, with a promising direction being the integration of parameterized DCOPF and structured ACPF in an end-to-end self-supervised learning framework to enhance AC feasibility, and scalability for DC-operated markets.

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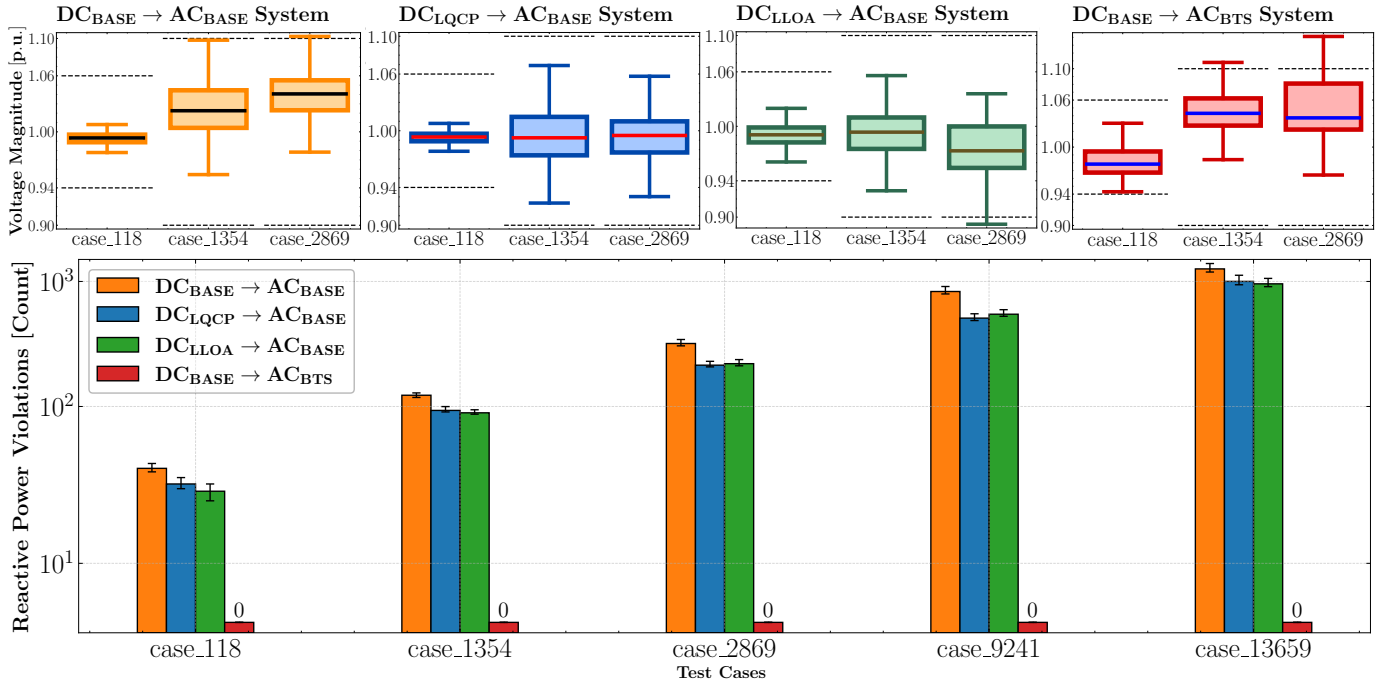


Fig. 6: Interplay between voltage magnitude and reactive power for various pipelines. The plots are taken over load uncertainty with $\sigma = 5\%$, for 1000 samples per case. The top box plots (mean with min-max extremes) show the voltage distributions for three cases (case_118, case_1354, and case_2869). Dashed lines are voltage limits. The bottom plots show mean reactive power violations (with min-max error bars), with a y-axis log-scale, using: $\text{DC}_{\text{BASE}} \rightarrow \text{AC}_{\text{BASE}}$ (orange), $\text{DC}_{\text{LQCP}} \rightarrow \text{AC}_{\text{BASE}}$ (blue), $\text{DC}_{\text{LLOA}} \rightarrow \text{AC}_{\text{BASE}}$ (green), and $\text{DC}_{\text{BASE}} \rightarrow \text{AC}_{\text{BTS}}$ (red).

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