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Sustainable and Fair Power System Assessment in IEEE Networks via Python-Based Modeling and Simulation

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***Abstract*—This paper assesses steady-state power flow performance in IEEE 9-, 14-, and 39-bus benchmark systems using Python-based simulation tools. Power flow calculations were carried out using Python-based solver settings, including Newton–Raphson and Fast Decoupled Load Flow configurations, to evaluate voltage profiles, line loading, and active and reactive power losses under baseline and modified operating conditions. A renewable integration scenario was then evaluated by introducing distributed generation at selected load buses, with penetration levels defined as a percentage of local demand. The results indicate that appropriately located renewable injections can improve voltage support and reduce total system losses. In the IEEE 39-bus system, active losses decreased from 33.17 MW to 29.71 MW. In addition, voltage deviations and highly loaded lines were used as technical stress indicators to identify areas of potential operational vulnerability. An Optimal Power Flow scenario was examined using fairness-oriented technical indicators to determine whether dispatch decisions can reduce operating cost without increasing voltage or thermal stress. The study shows that conventional power flow analysis can be extended with transparent, reproducible, and equity-sensitive indicators to support sustainable power system planning.**

***Keywords*—Power Flow Analysis, Optimal Power Flow, IEEE Test Systems, Renewable Energy Integration, Fairness-Aware Dispatch**

I. Introduction

Electric power systems are experiencing significant changes due to renewable generation, decentralization, digital control, and greater operational uncertainty. Conventional planning and operation criteria, including cost, losses, voltage stability, and thermal security, remain central to grid assessment. However, recent studies also highlight the importance of examining how technical stress is distributed across the network, particularly when voltage deviations, congestion, or service-quality limitations are concentrated in specific areas [1], [2]. In this context, technical indicators can help identify operational vulnerabilities, even when socioeconomic data are not available.

Steady-state power flow analysis is a fundamental tool for evaluating electrical networks. It provides bus voltage magnitudes and angles, active and reactive power flows, line loading levels, and system losses. These outputs are required for operational assessment, planning studies, and infrastructure reinforcement decisions. Among the most widely used numerical methods, the Newton–Raphson method is recognized for its convergence robustness, while the Fast Decoupled Load Flow method provides computational efficiency in transmission networks where active and reactive power interactions can be approximately decoupled [3], [4]. Both methods remain relevant for benchmark studies and preliminary assessments of systems with renewable generation and variable operating conditions [5], [6].

Distributed renewable generation changes the spatial distribution of injections and power flows. Solar and wind resources are location-dependent and variable, and their connection to load buses may reduce losses and improve local voltage support when properly located. Nevertheless, high renewable penetration can also produce congestion, reverse flows, and voltage regulation problems, especially in weak network areas [7], [8]. Therefore, renewable integration should be evaluated not only through aggregate loss reduction, but also through voltage profiles and thermal loading.

Optimal Power Flow (OPF) extends power flow analysis by determining dispatch decisions subject to operational constraints. OPF is also relevant to discussions on algorithmic transparency and energy justice because optimization objectives may affect the distribution of costs, technical stress, and service quality across the system [9], [10]. Recent research argues that fairness-related objectives should be represented explicitly in power-system models instead of being inferred from efficiency gains alone [2]. In this area, indicators such as locational marginal burden have been proposed to evaluate the equity implications of OPF solutions [11].

This paper evaluates IEEE 9-bus, 14-bus, and 39-bus test systems using Python-based modeling and simulation. Three scenarios are considered: baseline power flow, renewable generation integration, and fairness-oriented OPF. The analysis uses voltage profiles, line loading, active and reactive losses, undervoltage occurrence, and overload incidence as technical indicators. In this study, fairness is not treated as a direct measure of socioeconomic equity. Rather, it is represented through technical stress indicators that identify whether unfavorable operating conditions are concentrated in specific parts of the network.

The contribution of this paper is threefold. First, it compares the steady-state behavior of IEEE test systems under consistent simulation assumptions. Second, it evaluates the effect of renewable injections on voltage support and loss reduction. Third, it interprets OPF results using voltage and thermal stress indicators to support a fairness-oriented technical assessment. The use of open-source tools such as `Pandapower` and `PYPOWER`, which are related to established power-system analysis frameworks, supports reproducibility and transparency in the simulation process [12], [13].

The remainder of the paper is organized as follows. Section II presents the theoretical background on power flow analysis, IEEE test systems, renewable integration, and fairness-oriented grid assessment. Section III describes the modeling environment, assumptions, and scenario design. Section IV reports the simulation results for the baseline, renewable integration, and OPF scenarios. Section V discusses the technical and fairness-related implications of the findings. Section VI presents recommendations for modeling and policy alignment. Finally, Section VII summarizes the main conclusions and future research directions.

II. Theoretical Framework

A. Power Flow Analysis Fundamentals

Power flow analysis determines the steady-state operating point of an electrical network for a specified set of generation, demand, and network parameters. Its main outputs include bus voltage magnitudes, voltage angles, active and reactive power flows, branch loading levels, and system losses. These variables are required to assess voltage adequacy, thermal-limit compliance, and operating losses under a defined system condition [12], [13].

For bus i, the active and reactive power balance equations are expressed as:

$$P_i = V_i \sum_{j=1}^{n} V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right), \tag{1}$$

$$Q_i = V_i \sum_{j=1}^{n} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right), \tag{2}$$

where V_i and V_j are voltage magnitudes, $\theta_{ij} = \theta_i - \theta_j$ is the voltage angle difference between buses i and j, and G_{ij} and B_{ij} are the conductance and susceptance elements of the bus admittance matrix. Equations (1) and (2) define a nonlinear system whose solution depends on the bus-type classification: slack, PV, or PQ.

Power flow studies are particularly relevant in systems with renewable generation because distributed injections modify both the magnitude and direction of power flows. Depending on their location and penetration level, renewable sources may reduce losses and improve voltage support. However, they may also increase congestion or voltage deviations in weak areas of the network [7], [8], [14]. Therefore, renewable integration should be evaluated using both aggregate indicators, such as total system losses, and spatial indicators, such as bus voltage deviations and branch loading distribution.

B. Solution Techniques

The Newton–Raphson (NR) method is widely used to solve the nonlinear power flow problem. It applies a first-order linearization around the current operating point and updates voltage magnitudes and angles through the Jacobian matrix. Its main advantage is robust convergence near the solution, particularly in meshed transmission networks and benchmark systems [3], [13].

The Fast Decoupled Load Flow (FDLF) method simplifies the NR formulation by using the approximate decoupling between active power and voltage angles, and between reactive power and voltage magnitudes. This approximation is generally suitable for high-voltage transmission networks with low resistance-to-reactance ratios. FDLF reduces computational effort, although its accuracy and convergence may deteriorate in systems with stronger coupling, radial configurations, or high penetration of distributed energy resources [4], [15].

In this study, NR and FDLF are used as complementary methods. NR provides a robust reference solution, while FDLF allows the assessment of a computationally lighter alternative. This comparison is relevant because scenario-based grid studies often require repeated simulations under different penetration levels, operating conditions, and system assumptions.

C. IEEE Test Systems

IEEE test systems are commonly used as reference cases for comparing power flow algorithms, optimization models, and control strategies. Their use improves reproducibility because network data, bus classifications, and operating conditions can be implemented consistently across different software environments [12], [13].

This study considers three benchmark systems with different levels of complexity:

- **IEEE 9-bus system:** A compact transmission network commonly used for preliminary validation of power flow solvers and generator-load interactions [5].
- **IEEE 14-bus system:** A medium-sized benchmark with multiple load buses, voltage-control elements, and nonuniform demand distribution. It is suitable for evaluating localized voltage effects and moderate network stress.
- **IEEE 39-bus system:** A larger meshed benchmark, also known as the New England system, frequently used to examine transmission-level behavior, generator dispatch, branch loading, and vulnerability indicators [16].

The number of branches, controllable generators, and equivalent elements may vary depending on the data source and software representation. For this reason, the numerical implementation used in this paper is reported explicitly in Table II.

This avoids ambiguity between the original benchmark descriptions and the specific Pandapower/PYPOWER representation adopted in the simulations.

D. Fairness-Oriented and Sustainable Grid Assessment

Sustainability in power systems is usually associated with efficiency, renewable integration, reliability, and emissions reduction. Recent work on energy justice also emphasizes the distribution of benefits, risks, costs, and service quality among users and territories [1], [2], [17]. From this perspective, power system models can contribute by identifying whether technical stress is concentrated in specific areas of the network.

Standard IEEE test systems do not include demographic, geographic, or socioeconomic attributes. Therefore, this paper does not measure social equity directly. Instead, voltage deviations, undervoltage occurrence, branch loading, and overload incidence are used as technical stress indicators. These indicators are interpreted as proxies for operational vulnerability, not as direct evidence of social disadvantage.

Optimal Power Flow (OPF) provides a formal framework for analyzing dispatch decisions under operational constraints. In addition to conventional objectives, such as cost and loss minimization, OPF results can be evaluated or extended using penalty terms associated with voltage deviation, congestion, or uneven stress distribution. Recent studies have proposed equity-oriented metrics, including locational burden and fairness indicators, to evaluate how optimization outcomes affect different areas of a grid [2], [11].

Algorithmic transparency is also relevant in OPF applications because dispatch decisions may affect operating costs, reliability, and service quality. Open-source modeling environments, such as pandapower, PYPOWER, and MATPOWER-compatible tools, support reproducibility by making model assumptions, network data, and simulation procedures easier to verify [12], [13]. This is especially important when optimization models are used to support planning or regulatory decisions.

III. Methodology

A. Modeling Environment

The study follows a simulation-based comparative design. The IEEE 9-bus, 14-bus, and 39-bus systems were implemented in Python using Pandapower and PYPOWER. These libraries support steady-state power flow and OPF studies using data structures compatible with established power-system tools such as MATPOWER [12], [13]. Pandapower was used for network modeling, power flow execution, OPF simulation, result extraction, and visualization. NumPy and Pandas were used to organize numerical outputs and compare the scenarios under consistent assumptions.

B. Assumptions and Computational Setup

The simulations were conducted under balanced, three-phase, steady-state conditions. Loads were modeled as constant PQ demands. Fault events, contingencies, storage devices, demand response actions, and topology changes were not considered. Bus classifications followed the standard representation of slack, PV, and PQ buses. These assumptions restrict the scope of the study to steady-state performance and exclude dynamic stability, transient response, and probabilistic renewable variability.

The IEEE test systems were obtained from open-access benchmark data and verified using the internal consistency checks available in Pandapower. All simulations were executed on a 64-bit Windows 11 system with an AMD Ryzen 7 processor and 16 GB of RAM. The convergence tolerance for power mismatch was set to 10^{-6} p.u. The same computational settings were applied to all systems and scenarios to maintain comparability.

Table I summarizes the simulation scenarios and evaluation indicators used in the study.

TABLE I
SIMULATION SCENARIOS AND EVALUATION INDICATORS

Scenario	Main configuration	Evaluation indicators
Baseline power flow	Original IEEE network data without changes in demand or generation	Voltage profile, branch loading, active losses, reactive losses
Renewable integration	Distributed renewable injections at selected load buses and defined penetration levels	Minimum voltage, loss reduction, branch loading variation, overload incidence
Fairness-oriented OPF	Dispatch optimization under voltage, thermal, and generator constraints	Generation cost, generator outputs, line loading, voltage and thermal feasibility

C. Scenario Design

Three scenarios were defined to evaluate the technical performance of the networks and the distribution of operational stress across buses and branches.

1) Baseline Power Flow: The baseline scenario uses the original configuration of each IEEE test system. No changes were introduced in generation, demand, or topology. This scenario provides reference values for voltage magnitudes, branch loading, active power losses, and reactive power losses. It also allows the identification of technical stress conditions, such as buses operating below 0.95 p.u. and branches loaded above 90% of their rated capacity. These indicators are interpreted as operational vulnerability measures, not as direct evidence of social inequity.

2) Renewable Integration: Renewable generation was added at selected load buses to evaluate its effect on voltage support and system losses. The penetration level was defined as a percentage of the local demand at the selected bus:

$$P_{RES,i}^{\lambda} = \lambda P_{D,i}, \tag{3}$$

where $P_{RES,i}^{\lambda}$ is the renewable active power injection at bus i, $P_{D,i}$ is the active demand at that bus, and $\lambda \in$

$\{0.20, 0.40, 0.60\}$ represents the renewable penetration level. Renewable units were represented as negative PQ injections. This modeling choice is suitable for steady-state sensitivity analysis, but it does not capture intermittency, forecast error, or dynamic control behavior. These limitations should be considered when interpreting the results [7], [8], [14].

For each penetration level, the resulting voltage profile, total active and reactive losses, and branch loading levels were compared with the baseline case. The objective was to determine whether renewable injections reduced system losses without creating additional voltage or thermal stress.

3) Fairness-Oriented Optimal Power Flow: The third scenario applied an OPF formulation to evaluate whether dispatch decisions can reduce cost and losses while limiting the concentration of technical stress in specific parts of the network. Since IEEE benchmark systems do not include socioeconomic attributes, fairness was represented through technical indicators: voltage deviation, overload incidence, and stress distribution.

For fairness-oriented interpretation, the OPF outcome was assessed using the following weighted performance function:

$$\begin{aligned} J = w_c C_{G,n} + w_l P_{\mathrm{loss},n} + w_v \mathrm{VDI}_n \\ + w_o \mathrm{OLI}_n + w_s \mathrm{SDI}_n, \end{aligned} \tag{4}$$

where $C_{G,n}$, $P_{\mathrm{loss},n}$, VDI_n, OLI_n, and SDI_n are the normalized values of generation cost, active power loss, voltage deviation index, overload index, and stress-distribution index, respectively. The weights w_c, w_l, w_v, w_o, and w_s define the relative importance of each term. Normalization avoids combining variables with different physical units in the same objective function. This assessment function makes the fairness-related assumptions explicit and supports interpretation of the OPF outcome without treating equity as an implicit consequence of efficiency improvement [2], [11], [17].

The voltage deviation index was calculated as:

$$VDI = \frac{1}{N_b} \sum_{i=1}^{N_b} |V_i - V_{ref}|, \tag{5}$$

where N_b is the number of buses, V_i is the voltage magnitude at bus i, and V_{ref} was set to 1.0 p.u. The overload index was computed as:

$$OLI = \frac{1}{N_l} \sum_{l=1}^{N_l} \max\left(0, \frac{S_l}{S_l^{max}} - 0.90\right), \tag{6}$$

where N_l is the number of branches, S_l is the apparent power flow in branch l, and S_l^{max} is its thermal limit. The 90% threshold was used to identify highly loaded branches before reaching the physical limit.

The stress-distribution index was defined as the dispersion of the stress vector s:

$$SDI = \frac{\sigma_s}{\mu_s + \epsilon}, \tag{7}$$

TABLE II
SYSTEM PARAMETERS FOR IEEE TEST NETWORKS

System	Buses	Lines	Loads	Generators
IEEE 9	9	9	3	3
IEEE 14	14	15	11	4
IEEE 39	39	35	21	9

where σ_s and μ_s are the standard deviation and mean of s, and ϵ is a small positive constant used to avoid division by zero. A lower SDI indicates a more even distribution of operational stress across the system.

The optimization was subject to active and reactive power balance, generator limits, voltage limits, and branch thermal limits:

$$P_{G,i} - P_{D,i} + P_{RES,i} = P_i(V, \theta), \tag{8}$$

$$Q_{G,i} - Q_{D,i} = Q_i(V, \theta), \tag{9}$$

$$P_{G,k}^{min} \leq P_{G,k} \leq P_{G,k}^{max}, \tag{10}$$

$$Q_{G,k}^{min} \leq Q_{G,k} \leq Q_{G,k}^{max}, \tag{11}$$

$$V^{min} \leq V_i \leq V^{max}, \tag{12}$$

$$S_l \leq S_l^{max}. \tag{13}$$

The OPF model was solved using the implemented `Pandapower/PYPOWER` workflow. The resulting dispatch was evaluated primarily in terms of generation cost, generator outputs, line loading, and compliance with voltage and thermal limits. Voltage deviation, overload incidence, and stress distribution were retained as conceptual indicators for fairness-oriented interpretation. This approach focuses on the technical interpretation of the OPF outcome rather than on benchmarking different optimization algorithms.

IV. RESULTS

A. Base Case Power Flow Analysis

Table II reports the implemented network representation for the IEEE test systems used in the simulations. The number of buses, lines, loads, and generators corresponds to the `Pandapower/PYPOWER` data structures adopted in this study.

The baseline simulation provides the reference operating point for each network. Figure 1 shows the voltage profile of the IEEE 39-bus system. Most buses operate near the nominal range, although some buses approach or fall below the 0.95 p.u. threshold. This behavior identifies localized voltage stress in the baseline condition.

Table III presents the active and reactive power losses obtained in the baseline scenario. Active losses increase from

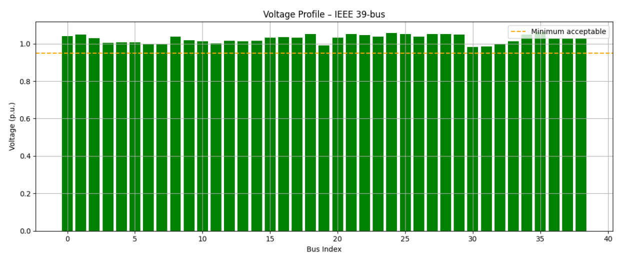

Fig. 1. Voltage profile of the IEEE 39-bus system under baseline conditions.

TABLE III
BASE CASE POWER LOSSES

System	Active Loss (MW)	Reactive Loss (MVar)
IEEE 9	4.95	80.12
IEEE 14	13.39	21.43
IEEE 39	33.17	97.69

TABLE IV
TECHNICAL STRESS METRICS FOR THE IEEE 39-BUS SYSTEM

Metric	Count
Buses with $V < 0.95$ p.u.	2
Lines loaded $> 90\%$	4

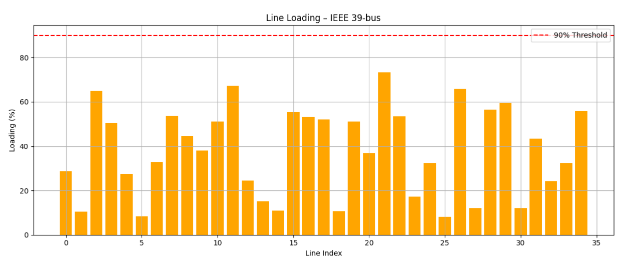

Fig. 2. Line loading distribution of the IEEE 39-bus system under baseline conditions.

the IEEE 9-bus system to the IEEE 39-bus system, reflecting the larger network scale and higher aggregate loading. Reactive losses do not follow a strictly monotonic pattern because they depend on network parameters, voltage-control elements, and the spatial distribution of reactive demand.

B. Voltage and Thermal Stress Indicators

Technical stress indicators were calculated for the IEEE 39-bus baseline simulation. Table IV reports the number of buses with voltage magnitudes below 0.95 p.u. and the number of lines loaded above 90% of their rated capacity. These indicators are used as proxies for operational vulnerability and are not interpreted as direct socioeconomic equity measures.

Figure 2 complements Table IV by showing the line loading distribution across the IEEE 39-bus system. The four lines above the 90% threshold show that thermal stress is concentrated in a limited subset of network elements.

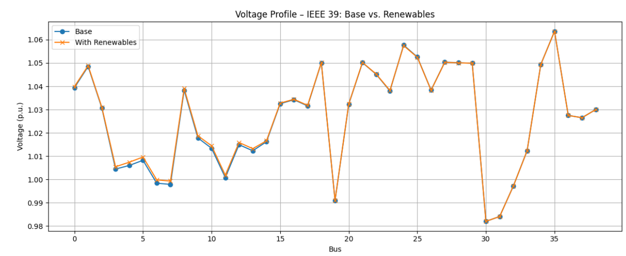

Fig. 3. Voltage profile comparison between baseline and renewable-enhanced scenarios for the IEEE 39-bus system.

TABLE V
LOSS COMPARISON FOR THE IEEE 39-BUS SYSTEM

Scenario	P Loss (MW)	ΔP (%)	Q Loss (MVar)	ΔQ (%)
Base	33.17	–	97.69	–
With renewables	29.71	10.43	91.88	5.95

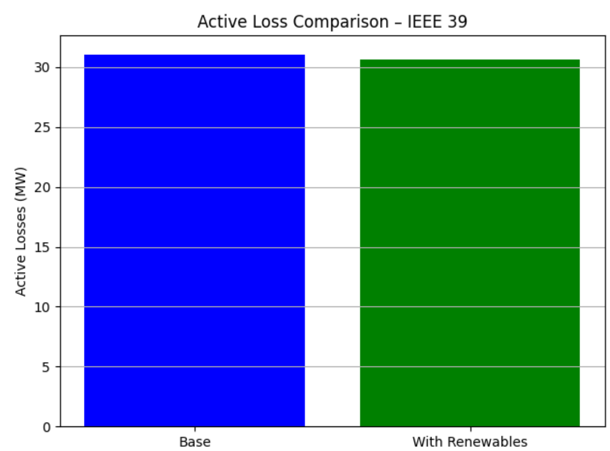

Fig. 4. Active power losses under baseline and renewable integration scenarios for the IEEE 39-bus system.

C. Effect of Renewable Injection

The renewable integration scenario was evaluated by adding distributed generation at selected load buses. Figure 3 compares the baseline and renewable-enhanced voltage profiles for the IEEE 39-bus system. The renewable case presents higher voltage magnitudes at several buses, especially near the injection points.

The corresponding loss comparison is reported in Table V and illustrated in Figure 4. Active power losses decreased from 33.17 MW to 29.71 MW after renewable integration, representing a reduction of 3.46 MW, or approximately 10.43%. Reactive losses also decreased, from 97.69 MVar to 91.88 MVar, equivalent to a reduction of 5.81 MVar, or approximately 5.95%.

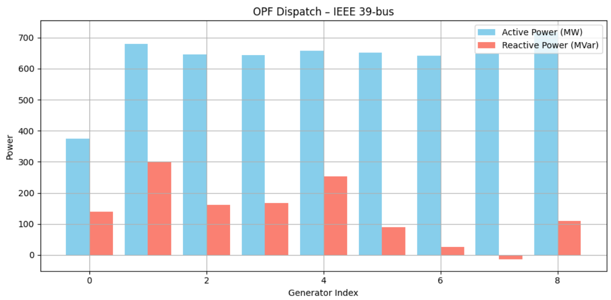

Fig. 5. Generator dispatch after OPF for the IEEE 39-bus system.

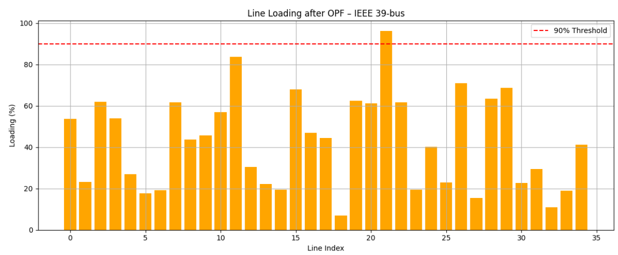

Fig. 6. Line loading after OPF for the IEEE 39-bus system.

D. Optimization Under Fairness-Oriented Constraints

The OPF scenario was used to evaluate whether dispatch decisions could reduce operating cost while maintaining voltage and thermal constraints. The obtained dispatch for the IEEE 39-bus system is shown in Figure 5.

The line loading results after OPF are shown in Figure 6. Under the modeled constraints, the optimized dispatch did not increase line loading beyond the operational limits considered in the study. This result indicates that the OPF solution maintained thermal feasibility while reducing the objective function.

The total generation cost obtained in the OPF scenario was 92963.82 EUR. This value is a scenario-specific result and should not be interpreted as general evidence of equity improvement. Rather, it shows that, under the modeled constraints, a cost-oriented dispatch can be obtained without increasing voltage or thermal stress beyond the defined thresholds.

V. Discussion

A. Summary of Main Findings

The simulations show that the IEEE test systems present different steady-state responses depending on network size, topology, and loading conditions. In the baseline scenario, the IEEE 39-bus system showed localized voltage and thermal stress, with two buses below 0.95 p.u. and four lines loaded above 90%, as reported in Table IV. These results indicate that operational stress was concentrated in specific parts of the network rather than uniformly distributed.

The renewable integration scenario reduced active and reactive losses in the IEEE 39-bus system. As shown in Table V and Figure 4, active losses decreased from 33.17 MW to 29.71 MW, equivalent to a reduction of approximately 10.43%. Figure 3 also shows improved voltage support in several buses after renewable injection. Under the assumptions of this study, these results indicate that distributed renewable generation can improve steady-state performance when properly located.

The OPF scenario produced a feasible dispatch solution under the modeled voltage and thermal constraints. Figure 5 presents the resulting generator outputs, while Figure 6 shows that line loading remained within the operational limits considered in the model. Therefore, the OPF result should be interpreted as evidence of technical feasibility under the proposed constraints, not as direct evidence of social equity.

B. Technical Interpretation

The baseline results confirm the relevance of topology and loading distribution in power flow behavior. Active losses increased from the IEEE 9-bus case to the IEEE 39-bus case, as shown in Table III. Reactive losses did not follow a strictly monotonic pattern, which is consistent with their dependence on voltage-control elements, branch parameters, and the spatial distribution of loads and generation.

The voltage profile of the IEEE 39-bus system in Figure 1 shows that most buses operated near nominal values, although a limited number of buses approached or crossed the 0.95 p.u. threshold. Similarly, Figure 2 shows that high loading was concentrated in a subset of lines. These results support the use of voltage deviation and line loading as technical stress indicators.

The renewable integration scenario reduced losses and improved voltage support in the modeled case. This behavior is consistent with studies showing that distributed energy resources can reduce network losses and improve local voltage conditions when their location and penetration level are suitable [7], [8], [14]. However, the results should not be generalized to all renewable integration cases because the present study used deterministic injections and did not model intermittency, forecast errors, storage, or time-varying demand.

C. Fairness-Oriented Interpretation

The fairness-oriented component of this study is based on the distribution of technical stress indicators. Since IEEE test systems do not include socioeconomic, demographic, or consumer-class data, the analysis does not measure social equity directly. Instead, undervoltage occurrence, high line loading, voltage deviation, and overload incidence are used to identify areas exposed to less favorable operating conditions.

This distinction is necessary for methodological consistency. Energy justice literature emphasizes that equity-oriented assessment requires explicit metrics, transparent assumptions, and, when available, social or territorial data [1], [2], [17]. In this paper, the proposed approach represents a technical layer for fairness-oriented grid assessment. It identifies where operational stress appears in the electrical model, but it does not determine whether those areas correspond to vulnerable populations or disadvantaged territories.

The OPF results indicate that voltage and thermal constraints can be incorporated into dispatch decisions without increasing operational stress beyond the defined thresholds. This is consistent with recent work suggesting that OPF formulations can include fairness-related indicators, such as locational burden, voltage-deviation penalties, and stress-distribution terms [2], [11]. Stronger conclusions would require a broader validation process, including additional operating points, uncertainty analysis, and real contextual data.

D. Comparison with Related Studies

The loss reduction obtained under renewable integration is consistent with prior studies on distributed generation and renewable-supported power flow analysis [5], [7], [8]. The contribution of this study is not the development of a new power flow algorithm. Rather, it combines conventional steady-state analysis with technical stress indicators that can support a fairness-oriented interpretation of grid performance.

The use of Python-based tools is also aligned with reproducibility-oriented power-system research. Open-source frameworks such as `Pandapower`, `PYPOWER`, and MATPOWER-compatible environments facilitate the inspection of model assumptions, network data, and computational procedures [12], [13]. This is relevant when simulation or optimization results are used to support planning studies, since transparency is required for external verification.

Compared with equity-aware power-system modeling studies, the main limitation of this paper is that fairness is evaluated only through technical indicators. Studies on energy justice and fairness in local energy systems emphasize the need to connect technical performance with affordability, access, reliability, geographic exposure, or social vulnerability indicators [1], [2], [17]. Therefore, the present framework should be understood as a technical basis that can later be extended with socioeconomic and geographic layers.

E. Limitations and Future Work

Several limitations should be considered. First, the study is restricted to steady-state power flow and OPF simulations. Dynamic stability, transient response, contingency conditions, and protection behavior were not evaluated. Second, renewable generation was modeled as deterministic negative PQ injection. This simplification is useful for sensitivity analysis, but it does not represent renewable variability, forecast uncertainty, or control interactions.

Third, the fairness-oriented assessment is limited to voltage and thermal stress indicators. These metrics identify operational vulnerabilities within the network model, but they do not capture affordability, demographic exposure, reliability interruptions, or locational marginal pricing. Fourth, the OPF result is reported as a scenario-specific dispatch outcome. Therefore, it should not be interpreted as a full algorithmic benchmark or as a generalized proof of equity improvement.

Future work should extend the model in four directions. First, stochastic simulations should be used to represent renewable uncertainty and load variability. Second, contingency analysis should be incorporated to evaluate whether stress concentration persists under line or generator outages. Third, the technical stress indicators should be connected with geographic or socioeconomic datasets when moving from IEEE benchmarks to real grid models. Fourth, interpretable optimization or machine-learning methods could be explored, provided that objective functions, constraints, and model assumptions remain auditable [9], [10], [18].

VI. Recommendations and Guidelines

A. Technical Recommendations

The results support the combined use of conventional power flow tools and technical stress indicators. For similar studies, the following practices are recommended:

- **Report voltage and thermal stress explicitly:** In addition to total active and reactive losses, studies should report buses operating below the voltage threshold and lines operating near their thermal limits. These indicators help identify whether operational stress is concentrated in specific parts of the network.
- **Avoid interpreting technical stress as direct social equity:** In IEEE benchmark systems, voltage deviation and line loading should be interpreted as indicators of operational vulnerability rather than direct measures of social equity. Direct equity claims require additional information, such as consumer type, geographic location, affordability, outage frequency, or socioeconomic characteristics [2], [17].
- **Define OPF fairness terms mathematically:** If fairness-oriented OPF is included, the objective function should explicitly specify the cost, loss, voltage-deviation, overload, and stress-distribution components. The weights and constraints should also be reported to support reproducibility and interpretation [11].
- **Report OPF outputs consistently:** OPF results should include, at minimum, generation cost, active losses, voltage deviation, overload incidence, stress-distribution indicators, and compliance with voltage and thermal limits.
- **Use reproducible workflows:** Simulation scripts, system parameters, and modeling assumptions should be shared through a repository or appendix when possible. This practice is consistent with open-source environments such as `pandapower` and MATPOWER-compatible tools [12], [13].

B. Planning and Policy Implications

Although the simulations are based on benchmark networks, the results suggest implications for planning-oriented studies.

Renewable integration should be evaluated not only by total loss reduction, but also by its effect on voltage profiles and line loading. A renewable injection that reduces aggregate losses may still create localized congestion if it is poorly sited.

Technical stress indicators may also support the prioritization of grid reinforcement. Buses with recurrent undervoltage and lines with persistent high loading should be examined before defining expansion, compensation, or distributed-generation placement strategies. In real systems, this analysis should be complemented with geographic and consumer-level data.

OPF-based decision tools should be transparent when used in planning or regulatory contexts. The objective function, constraints, input data, and algorithmic assumptions should be documented, especially when optimization results may influence dispatch, investment priorities, or service-quality decisions [9], [10], [18].

C. Alignment with Sustainable Development Goals

The proposed approach is related to Sustainable Development Goal 7 because it evaluates efficiency, reliability-related indicators, and renewable integration. However, the contribution should be framed carefully. The study does not measure universal energy access directly. Instead, it provides a technical assessment framework that can support SDG-related analysis when combined with real service-quality, geographic, and socioeconomic data.

The main contribution to sustainability is methodological. The framework shows how steady-state power flow, renewable integration analysis, and OPF can be combined with stress indicators to identify operational vulnerabilities. This information can support future studies on equitable infrastructure planning, especially when benchmark simulations are replaced by real grid models and contextual data.

VII. CONCLUSION

This paper evaluated the steady-state performance of IEEE 9-bus, 14-bus, and 39-bus test systems using Python-based power flow and OPF simulations. Three scenarios were considered: baseline operation, renewable integration, and fairness-oriented OPF. The IEEE 39-bus baseline case presented localized technical stress, including two buses below 0.95 p.u. and four lines loaded above 90%. These indicators show that voltage and thermal stress may be concentrated in specific parts of a network, even when the system remains feasible.

The renewable integration scenario reduced active losses in the IEEE 39-bus system from 33.17 MW to 29.71 MW, equivalent to a reduction of approximately 10.43%. Reactive losses also decreased from 97.69 MVar to 91.88 MVar. The voltage profile comparison indicated improved voltage support in several buses after renewable injection. These findings support the technical relevance of distributed renewable placement, although the deterministic modeling approach limits conclusions regarding variability and uncertainty.

The OPF scenario produced a feasible dispatch solution with a total generation cost of 92963.82 EUR under the modeled constraints. The post-optimization line loading results indicate that the solution did not increase thermal stress beyond the defined operational limits. These findings should be interpreted as evidence of technical feasibility, not as proof of social equity. Since IEEE test systems do not contain demographic or socioeconomic attributes, fairness was represented through technical stress indicators.

The study provides a reproducible workflow for combining power flow analysis, renewable integration assessment, and fairness-oriented technical indicators. Its main value lies in showing how conventional simulation tools can be extended to identify voltage and thermal stress patterns that may inform more detailed grid-planning studies. Future research should incorporate stochastic renewable behavior, contingency analysis, storage, time-varying demand, and real socioeconomic or geographic data. These extensions would allow the proposed technical indicators to be connected with broader energy justice and infrastructure-planning objectives.

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