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# Group fairness in power systems computation: Evaluating disparities in grid capacity between households with and without rooftop solar

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ABSTRACT

"Fairness-aware" algorithms are increasingly used to allocate grid capacity in electrical power systems, yet they often overlook existing disparities between household groups, such as those arising from unequal rooftop solar adoption. Through simulations on a stylized low-voltage grid using electricity data from the Netherlands, we apply demographic parity, a group fairness metric, to compare differences in grid access and costs between households with and without rooftop solar. Three objectives are analyzed: minimal intervention, proportional fairness, and min-max fairness. The results indicate that (1) "fairness-aware" allocation does not eliminate group disparities, (2) voltage violations influence the distribution of burdens and benefits, (3) lower curtailment compensation can reduce disparities between households, and (4) common fairness evaluation metrics do not capture these group disparities. This study advances the discussion on fairness in power systems computation by encouraging further research on how to avoid reinforcing existing disparities.

## 1. Introduction

Rooftop solar enables households to reduce energy costs and contribute to decarbonization; however, adoption remains concentrated among those with higher income, greater home value, and increased wealth [1,2]. Several factors contribute to this unequal adoption, including financial barriers to upfront investment, structural housing characteristics such as rental status and roof suitability, and informational barriers in lower-income areas [3,4]. This disparity results in structurally different relationships with the electrical grid: households with rooftop solar benefit from self-generation, supportive adoption policies, and compensation for excess production, while those without rooftop solar have limited opportunities to reduce energy costs [5]. These disparities are well-documented in energy justice literature, which investigates the distribution of benefits and burdens during the energy transition [6,7].

Simultaneously, as electrical grids integrate more distributed energy resources such as rooftop solar, grid operators encounter growing challenges in managing grid capacity constraints. Consequently, grid operators allocate limited grid capacity by curtailing solar generation or reducing household demand during grid operations [8]. Although these decisions are technically motivated, they have distributional consequences that raise concerns about energy justice. Questions regarding which households are requested to reduce their electricity consumption, the frequency of curtailment, and the nature of compensation have direct implications for affected households.

### 1.1. Relevant literature

The literature on grid capacity allocation in operational contexts presents a variety of methodological approaches, including market-based (e.g., [9]), optimization-based (e.g., [10]), and fairness-based (e.g., [11]) approaches. Fairness-based approaches often consider so-called "fairness-aware" algorithms that integrate principles such as proportionality, equality, or min-max optimization to guide resource distribution [12]. To evaluate fairness, aggregate indicators such as Jain's index and the Gini coefficient are commonly used to quantify the distribution of burdens and benefits [13,14].

Although these approaches offer valuable tools for allocating grid capacity, they typically assume that all consumers and producers are equal in terms of needs and capabilities [12]. Specifically, most approaches

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focus on households with rooftop solar, neglecting structural disparities between those with and without it [15,16]. While grid operators may not be responsible for who adopts rooftop solar, their operational decisions can affect the distribution of burdens and benefits. Consequently, we adopt the normative position that such decisions should, at a minimum, avoid exacerbating existing disparities. To the authors' knowledge, no previous research has addressed disparities in grid capacity allocation between households with and without rooftop solar.

### 1.2. Contributions and organization

To bridge this gap, this paper makes three main contributions. First, it applies demographic parity, a group fairness metric commonly used in algorithmic fairness research [17], as a lens to evaluate disparities in grid capacity allocation between households with and without rooftop solar. Second, it evaluates whether commonly used fairness principles, specifically proportional and min-max fairness, mitigate or intensify these disparities. Third, it assesses whether aggregate metrics like Jain's index and the Gini coefficient effectively capture these group disparities. Through this work, we aim to connect research on power systems computation with scholarship on energy justice and algorithmic fairness.

The remainder of this paper is structured as follows. Section 2 introduces group fairness and demographic parity. Section 3 presents the mathematical model for power flow and the fairness principles. Section 4 details the case study, simulation setup, and evaluation method. Section 5 presents the results, followed by a discussion of their implications in Section 6. Section 7 addresses the limitations of this study, and Section 8 provides concluding remarks.

## 2. Group fairness

Group fairness metrics are widely used in algorithmic systems across domains such as public administration, healthcare, and criminal justice [17]. These metrics can be categorized as independence-based, misclassification-based, or calibration-based [18]. Independence-based metrics assess whether outcomes are statistically independent of group membership. Misclassification-based metrics evaluate whether different groups experience similar prediction error rates. Calibration-based metrics determine whether predicted probabilities correspond to actual outcomes across groups.

This study focuses on independence-based metrics, which are especially suitable for allocation settings with complete information, where outcomes are determined deterministically rather than probabilistically [19]. Specifically, we use demographic parity, one of the most widely used independence-based metrics in exploratory studies [20]. Eq. (1) shows that demographic parity requires the probability of receiving a positive outcome to be equal across groups [20].

$$\mathrm{DP} = \frac{P(\hat{Y} = 1 \mid A = a)}{P(\hat{Y} = 1 \mid A = b)} \tag{1}$$

Here, $\hat{Y} \in \{0, 1\}$ denotes the assigned outcome, and $A \in \{a, b\}$ represents group membership, where group a corresponds to households without solar and group b to households with solar. A value greater than 1 indicates that solar households are more likely to receive favorable outcomes, whereas a value less than 1 indicates the opposite.

## 3. Mathematical model

A mixed-integer linear program was developed using the LinDistFlow model, which is a linear relaxation of the radial Branch Flow Model [21,22], to analyze the effects of various fairness principles. This approach involves two key simplifications: neglecting line losses and assuming that low-voltage grids are balanced. The consequences of these relaxations are discussed in Section 7.

### 3.1. Model structure

A radial distribution network is modeled as $\mathcal{G} := (\mathcal{N}^+, \mathcal{E})$, where $\mathcal{N}^+$ is the set of nodes and $\mathcal{E}$ the set of branches. The set $\mathcal{N}^+$ is defined as $\mathcal{N} \cup \{n_0\}$, with $n_0$ representing the source node (a low voltage substation) and $\mathcal{N}$ comprising all other nodes. Each node $n \in \mathcal{N}$ is associated with a net power $p_n$, where $p_n > 0$ indicates demand and $p_n < 0$ indicates production. The decision variables are defined as follows:

- $x := \{x_n \mid n \in \mathcal{N}^+\}$: active power control,
- $y := \{y_n \mid n \in \mathcal{N}^+\}$: squared voltage magnitudes,
- $p_0$: active power at source node $n_0$,
- $q_0$: reactive power at source node $n_0$,
- $P := \{P_{mn} \mid (m,n) \in \mathcal{E}\}$: active power flows,
- $Q := \{Q_{mn} \mid (m,n) \in \mathcal{E}\}$: reactive power flows,
- $z$: collection of auxiliary variables for fairness (e.g., $x_n^{\mathrm{abs}}$).

The optimization model is structured as follows:

$$\begin{aligned}
\min \quad & \ell_f(x, z) \\
\text{s.t.} \quad & c_{pf}(x, P, Q, y) \quad (2)\text{–}(5) \\
& c_g(P, y) \quad (6)\text{–}(8) \\
& c_c(x) \quad (10)\text{–}(13) \\
& c_f(x, z) \quad (15), (16), (19), (21)
\end{aligned}$$

Here, $\ell_f(x, z)$ represents the objectives, $c_{pf}(x, P, Q, y)$ the power flow constraints, $c_g(P, y)$ the grid constraints, $c_c(x)$ the control constraints, and $c_f(x, z)$ the fairness constraints.

### 3.2. Power flow constraints

The power flow equations $c_{pf}(x, P, Q, y)$ are based on the LinDistFLow model, comprising the following:

$$P_{mn} = p_n + x_n + \sum_{(n,k)\in\mathcal{E}, k\neq m} P_{nk} \quad \forall n \in \mathcal{N}^+ \tag{2}$$

$$Q_{mn} = q_n + \sum_{(n,k)\in\mathcal{E}, k\neq m} Q_{nk} \quad \forall n \in \mathcal{N}^+ \tag{3}$$

$$y_m = y_n + 2(r_{mn}P_{mn} + \chi_{mn}Q_{mn}) \quad \forall (m,n) \in \mathcal{E} \tag{4}$$

$$y_0 = 1 \tag{5}$$

Here, $P_{mn}$ and $Q_{mn}$ are the real and reactive power flowing from node $m$ to node $n$, $p_n$ and $q_n$ are the initial active power and reactive power at node $n$. For source node $n_0$, $p_0$ and $q_0$ are not initial active or reactive power, but decision variables. Moreover, $y_n$ is the squared voltage at node $n$, $y_0$ the squared voltage at the source node, and $r_{mn}$ and $\chi_{mn}$ are the line resistance and reactance of branch $(m, n)$, respectively.

### 3.3. Grid constraints

The grid constraints $c_g(P, y)$ impose limits on both the lines and the source node (substation) to ensure that power flows and voltages remain within acceptable bounds:

$$-\overline{P}_{mn} \leq P_{mn} \leq \overline{P}_{mn} \quad \forall (m,n) \in \mathcal{E} \tag{6}$$

$$-\overline{p_0} \leq p_0 \leq \overline{p_0} \tag{7}$$

$$\underline{y} \leq y_n \leq \overline{y} \quad \forall n \in \mathcal{N} \tag{8}$$

Here, $\overline{P}_{mn}$ is the maximum active power for branch $(m, n)$, $\underline{y}$ and $\overline{y}$ are the minimum and maximum allowed squared voltage, and $\overline{p_0}$ the maximum active power at the source node.

The line limits $\overline{P}_{mn}$ are determined according to thermal constraints, as specified in (9), where $i_{\max}$ and $u_{\max}$ denote the rated current and voltage of the cable, and pf the power factor.

$$\overline{P}_{mn} = \sqrt{3} \cdot i_{\max} \cdot u_{\max} \cdot \mathrm{pf} \tag{9}$$

### 3.4. Control constraints

The control constraints $c_c(x)$ define the feasible set of control actions $x_n$ at each node $n \in \mathcal{N}$. These constraints are conditional but can be directly enforced because both $p_n$ and $p_{\text{base}}$ are known before the optimization process. The control constraints are specified as follows:

$$\text{if } 0 \le p_n \le p_{\text{base}}: \quad x_n = 0 \tag{10}$$

$$\text{if } p_n > p_{\text{base}}: \quad p_{\text{base}} - p_n \le x_n \le 0 \tag{11}$$

$$\text{if } p_n < 0: \quad 0 \le x_n \le -p_n \tag{12}$$

Here, $p_{\text{base}}$ represents a predefined minimum level of grid access allocated to each household.

At the source node $n_0$, no control actions can be applied:

$$x_0 = 0 \tag{13}$$

The model may become infeasible if the available control actions $x_n$ are inadequate to address violations of substation, line, or voltage constraints. This outcome reflects practical limitations in grid flexibility, where not all operational scenarios can be managed. Potential extensions to address infeasibility, such as introducing slack variables, are acknowledged but remain outside the scope of this study.

### 3.5. Objectives and fairness constraints

This study examines the effects of three distinct allocation objectives on group fairness. The first objective, minimal intervention, does not explicitly target fairness between groups but instead aims to minimize overall grid capacity reductions. In contrast, the proportional fairness and min-max fairness objectives incorporate fairness principles that address the distribution of grid capacity reductions more directly.

#### 3.5.1. Minimal intervention

This objective reflects a system-level approach to fairness, aiming to minimize the aggregate magnitude of control actions across all nodes. Within the optimization model, this objective is formulated as follows:

$$\min \quad \ell_f(x^{\text{abs}}) = \sum_{n \in \mathcal{N}^+} x_n^{\text{abs}} \tag{14}$$

$$\text{s.t.} \quad c_{pf}(x, P, Q, y), \quad c_g(P, y), \quad c_c(x)$$

$$c_f(x, x^{\text{abs}}): \quad x_n^{\text{abs}} \ge x_n \quad \forall n \in \mathcal{N}^+ \tag{15}$$

$$x_n^{\text{abs}} \ge -x_n \quad \forall n \in \mathcal{N}^+ \tag{16}$$

Here, $x_n^{\text{abs}}$ represents the absolute value of $x_n$.

#### 3.5.2. Proportional fairness

This objective aims to allocate control actions in proportion to each household's power, whether for consumption or production. In the model, this is accomplished by minimizing the squared deviation from a proportional allocation, analogous to a least squares approach. The formulation distinguishes between supply nodes $\mathcal{N}^s := \{k \in \mathcal{N} \mid p_k < 0\}$ and demand nodes $\mathcal{N}^d := \{k \in \mathcal{N} \mid p_k \ge 0\}$. The objective is specified as follows:

$$\min \quad \ell_f(x) = \sum_{n \in \mathcal{N}^d} \left( x_n - \frac{p_n}{\sum_{m \in \mathcal{N}^d} p_m} \cdot \sum_{m \in \mathcal{N}^d} x_m \right)^2 + \sum_{n \in \mathcal{N}^s} \left( x_n - \frac{p_n}{\sum_{m \in \mathcal{N}^s} p_m} \cdot \sum_{m \in \mathcal{N}^s} x_m \right)^2 \tag{17}$$

$$\text{s.t.} \quad c_{pf}(x, P, Q, y), \quad c_g(P, y), \quad c_c(x)$$

$$c_f(x, z) := \emptyset \tag{18}$$

#### 3.5.3. Min-max fairness

This objective aims to avoid excessive burdens on any single household by minimizing the maximum intervention required across the network. The approach is implemented as a hierarchical optimization problem: the upper level minimizes the maximum individual intervention, while the lower level reduces the total control to avoid unnecessarily large interventions. The upper level is defined as follows:

$$\min \quad \ell_f^{(1)}(x_{\max}^{\text{abs}}) = x_{\max}^{\text{abs}},$$

$$\text{s.t.} \quad c_{pf}(x, P, Q, y), \quad c_g(P, y), \quad c_c(x),$$

$$c_f(x, x^{\text{abs}}, x_{\max}^{\text{abs}}): \quad (15), \quad (16)$$

$$x_{\max}^{\text{abs}} \ge x_n^{\text{abs}} \quad \forall n \in \mathcal{N}^+ \tag{19}$$

Let $x_{\max}^{\text{abs},*}$ denote the optimal value from the upper level. The lower-level problem is then defined as follows:

$$\min \quad \ell_f^{(2)}(x^{\text{abs}}) = \sum_{n \in \mathcal{N}^+} x_n^{\text{abs}} \tag{20}$$

$$\text{s.t.} \quad c_{pf}(x, P, Q, y), \quad c_g(P, y), \quad c_c(x),$$

$$c_f(x, x^{\text{abs}}, x_{\max}^{\text{abs}}): \quad (15), \quad (16)$$

$$x_n^{\text{abs}} \le x_{\max}^{\text{abs},*} \quad \forall n \in \mathcal{N}^+ \tag{21}$$

## 4. Case study

The case study is based on real-world electricity usage and solar production data from a Dutch neighborhood, collected as part of the GridFlex Heeten project [23]. The 55-node low-voltage grid used in the simulations is based on the real grid in that area, schematically shown in Fig. 1 [24].

### 4.1. Data and simulation environment

Electricity consumption and solar production data from the Gridflex Heeten project (2019) were aggregated from 1-minute to 15-minute intervals using the maximum observed value, consistent with grid operator practices. At each timestep, power flows were computed using the Newton-Raphson method in `PowerGridModel` [25]. When an overload or voltage deviation was detected, the mathematical model allocated grid capacity among households. A safety factor of 0.95 was used for the grid constraint values ($\overline{P}_{mn}$, $\overline{p_0}$, $\underline{y}$ and $\overline{y}$) to mitigate the risk of exceeding limits under nonlinear conditions. Compliance with grid constraints was subsequently verified using Newton-Raphson in `PowerGridModel`. Fig. 2 provides a schematic overview of the simulation process.

All simulations were implemented in Python, with Gurobi serving as the optimization solver. Execution of the baseline scenario across all three principles required approximately 30 minutes on a GitHub Codespaces instance (2-core, 8GB RAM). All code and data used in this study are available at https://doi.org/10.4121/499e4878-22e1-462c-a7f4-e14daa56cded.

### 4.2. Parameters

Table 1 presents the parameters assumed in the case study. Most values were derived from representative low-voltage grid configurations and household electricity pricing in Europe [26,27]. The guaranteed base load and maximum substation power were intentionally set to induce a sufficient number of interventions, although these values may be lower than those typically observed in real-world conditions.

### 4.3. Simulation scenarios

The following three scenario types were analyzed:

1. *Baseline scenario*: All parameters listed in Table 1 were applied, including standard line lengths (10-40m) and compensation for grid capacity reduction of 0.30 €/kWh. This scenario was used to compare the effects of the three allocation methods on group fairness.
2. *Voltage constraint scenarios:* Line lengths were varied to induce different amounts of voltage violations:
   - *Low-violation scenario:* Shorter lines (5-20m) reduce the number of voltage deviations.

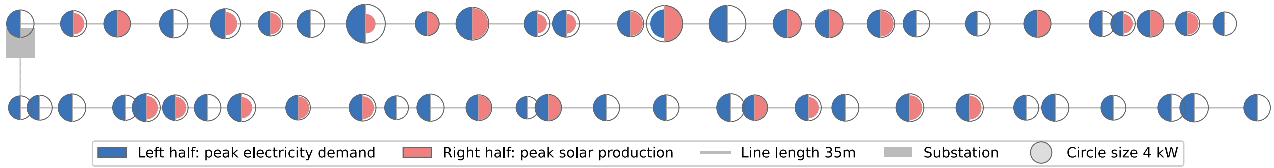


**Fig. 1.** Grid layout for the case study. The left half of the circle (blue) represents the maximum peak electricity demand per household, while the right half (red) represents the maximum peak solar production per household. The distances between households are scaled to reflect the line lengths between them.

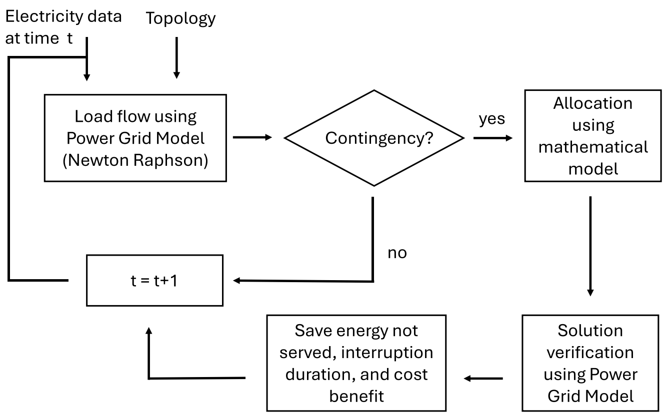


**Fig. 2.** Overview of the simulation process.

**Table 1**
Parameters used in the baseline scenario of the case study.

| Symbol | Value [Unit] | Description |
|---|---|---|
| $p_{\text{base}}$ | 1 [kW] | Guaranteed base load |
| $r_{150}$ | 0.206 [Ω/km] | Resistance of 150mm line |
| $\chi$ | 0.079 [Ω/km] | Reactance per km |
| $c$ | $100 \cdot 10^{-12}$ [F/m] | Capacitance per meter |
| $i_{\text{max},150}$ | 300 [A] | Current capacity of 150mm line |
| $u_{\text{rated}}$ | 230 [V] | Rated voltage |
| $\Delta u$ | 5 [%] | Allowed voltage deviation |
| pf | 0.95 [-] | Power factor |
| $d_{\text{line}}$ | [10,40] [m] | Range of line distances |
| $\overline{p_0}$ | 35 [kW] | Maximum power at substation |
| $\rho_{\text{reimb}}$ | 0.30 [€/kWh] | Compensation for capacity reduction |
| $\rho_{\text{prod}}$ | 0.10 [€/kWh] | Fixed feed-in tariff |

- *High-violation scenario:* Longer lines (20-80m) increase the number of voltage deviations.

These scenarios aimed to assess how grid layouts can influence group disparities.

3. *Net-zero curtailment compensation scenario:* Curtailment compensation was reduced to net zero by aligning it with the feed-in tariff. This scenario explored how financial mechanisms influence group fairness outcomes.

### 4.4. Performance metrics

Three metrics were used to evaluate group fairness:

- *Energy Not Served (ENS):* The total unmet electricity demand for a household, measured in kWh.
- *Interruption Duration (ID):* The cumulative time during which a household experienced reduced or no electricity supply, measured in hours.
- *Cost Benefit (CB):* The financial compensation received by a household due to curtailment or demand response, measured in euros.

ENS and ID were evaluated exclusively on the demand side, as these metrics directly affect household comfort. We excluded curtailment from these metrics because its effects are mainly financial and therefore captured by CB.

### 4.5. Classification of positive outcomes

A household was classified as receiving a positive outcome ($\hat{Y} = 1$) if it meets one of the following criteria:

- *Low interruption:* ENS $\leq \theta_{\text{energy}}$ and ID $\leq \theta_{\text{time}}$, or
- *High compensation:* CB $\geq \theta_{\text{cost}}$

Here, $\theta_{\text{energy}}$, $\theta_{\text{time}}$, and $\theta_{\text{cost}}$ represent the respective thresholds for a beneficial outcome. In the case study, thresholds were set at the 75th percentile of each distribution. This threshold was applied separately in each scenario for consistency.

### 4.6. Jain's index and gini coefficient

Jain's index and the Gini coefficient were calculated according to (22) and (23) to facilitate comparison between the group fairness approach and existing evaluation methods.

$$JI = \frac{\left(\sum_{n\in N} d_n\right)^2}{|N| \cdot \sum_{n\in N} d_n^2} \tag{22}$$

$$G = \frac{\sum_{i=1}^{|N|} \sum_{j=1}^{|N|} |d_i - d_j|}{2 \cdot |N| \cdot \sum_{n\in N} d_n} \tag{23}$$

Here, $d_n$ denotes the burden or benefit allocated to household $n$, and $|N|$ represents the total number of households.

## 5. Results

This section presents four key findings from our simulations.

### 5.1. Fairness principles do not prevent group disparities

In the baseline scenario, the grid operator anticipated 3804 voltage violations and 168 transformer overload events during the simulation year 2019. Fig. 3a shows the deviation from demographic parity between households with and without solar under the different principles. The proportional and min-max objectives resulted in a relative advantage for households with solar, whereas the minimal intervention principle resulted in a smaller advantage for households without solar.

In this scenario, the minimal intervention allocation principle achieves demographic parity values closest to 1.0. This outcome suggests that introducing fairness principles such as proportional or min-max fairness does not address group disparities between households with and without solar. Because the proportional and min-max allocation principles increase the total ENS, ID, and CB compared to the minimal intervention principle, the grid operator would likely prefer the minimal intervention principle in this scenario.

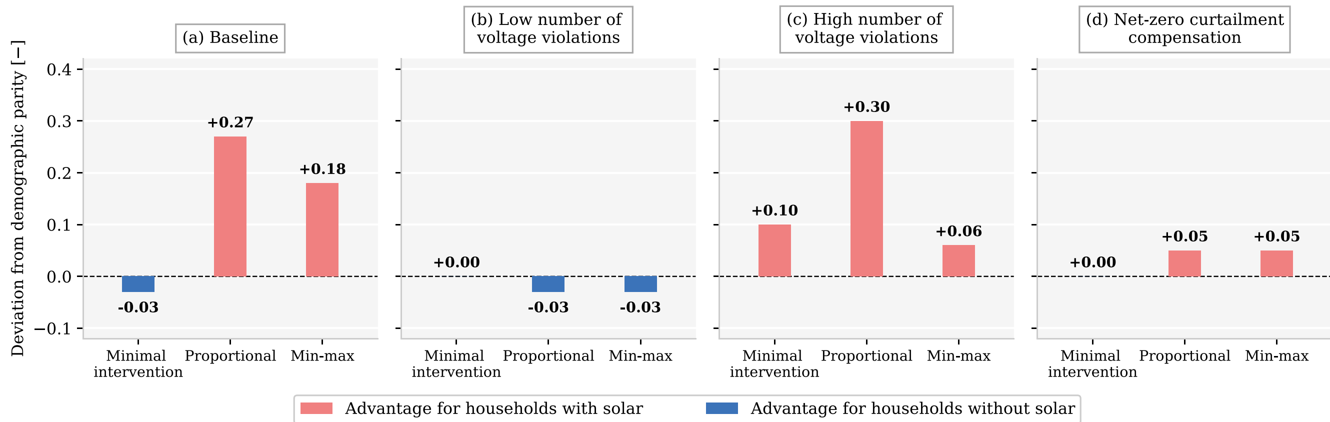


**Fig. 3.** Deviation from demographic parity across four scenarios. Each subplot shows the deviation from the ideal demographic parity value of 1.0 for different principles. Positive values indicate an advantage for households with solar, while negative values indicate an advantage for households without solar.

However, grid losses were 293 kWh for minimal intervention, 319 kWh for proportional, and 272 kWh for min-max allocation. This indicates that minimizing the total amount of interventions for households may result in higher grid losses compared to the min-max principle. The total compensation costs for the minimal intervention and min-max allocation principles were nearly identical, so they would not offset the financial differences in grid losses between these approaches. Nevertheless, if the grid operator seeks to avoid exacerbating group disparities between households with and without rooftop solar, the minimal intervention principle remains preferable.

### 5.2. Voltage constraints influence group disparities

To assess whether the observed disparities remain under different grid configurations, line lengths were varied to simulate changes in the physical layout of the grid. These modifications primarily affected the number of voltage violations, while the number of overload events remained relatively stable.

Short lines between households (5-20m) resulted in zero voltage deviations and 127 overloading events. Fig. 3b shows the deviation from demographic parity for each principle in this scenario. Disparities between households were smaller than in the baseline scenario, indicating that when the number of voltage violations is low, the relative advantage of households with solar is reduced. The minimal intervention principle achieved demographic parity, while the proportional and min-max principles resulted in only a slight advantage for households without solar. Here, the minimal intervention principle remains likely the preferred choice for grid operators.

However, in the high-violation scenario, disparities re-emerge. Longer lines (20-80m) led to increased voltage deviations (5552) and overloading events (197) compared to the baseline scenario. As shown in Fig. 3c, the min-max principle resulted in a smaller deviation from demographic parity than the other principles. Given this finding and the fact that the min-max allocations resulted in the fewest grid losses, the grid operator would likely prefer the min-max principle over minimal intervention in this scenario.

These findings suggest that reducing the number of voltage violations could help mitigate group disparities. However, grid operators may not always have direct control over such structural conditions. In those cases, adjusting compensation mechanisms for curtailment may provide a more practical means to reduce advantages for households with rooftop solar.

### 5.3. Reducing compensation mitigates group disparities

Fig. 3d shows the results of the scenario in which the net benefit of curtailment compensation is reduced to zero compared to the baseline scenario. This adjustment significantly reduced group disparities for all principles. With minimal intervention, demographic parity increases to 1.0. The other two principles also improve, providing a slight advantage for households with rooftop solar.

**Table 2**
Jain's index and Gini coefficient in the baseline scenario.

| | | Minimal intervention | Proportional | Min-max |
|---|---|---|---|---|
| **Jain's index** | *ENS* | 0.08 | 0.14 | 0.20 |
| (higher is more equal) | *ID* | 0.13 | 0.27 | 0.26 |
| | *CB* | 0.22 | 0.28 | 0.28 |
| **Gini coefficient** | *ENS* | 0.88 | 0.75 | 0.72 |
| (lower is more equal) | *ID* | 0.81 | 0.65 | 0.66 |
| | *CB* | 0.74 | 0.69 | 0.71 |

The net-zero compensation for curtailment was also applied in scenarios with low and high levels of voltage violations. In the low-violation scenario, results remained unchanged compared to the initial compensation, likely because the relative advantage for households with solar was primarily induced by their benefit from curtailment. In contrast, the scenario with a high number of violations produced results similar to those in Fig. 3d. These findings indicate that reducing curtailment compensation can mitigate disparities between households, particularly when voltage violations are more frequent.

### 5.4. Common fairness metrics overlook group disparities

Table 2 presents Jain's index and the Gini coefficient for each principle in the baseline scenario. Jain's index ranges from $\frac{1}{|N|}$, indicating the least equality, to 1, indicating the highest equality. In contrast, the Gini coefficient ranges from 0, representing the most equal distribution, to 1, representing the least equal distribution. Although the minimal intervention principle achieves the closest outcome to demographic parity, it records the lowest performance on both Jain's index and the Gini coefficient. This pattern persists across other scenarios as well. These findings indicate that Jain's index and the Gini coefficient are inadequate for evaluating fairness from a group perspective.

## 6. Discussion

This section discusses the implications of our findings.

### 6.1. Group disparities require more than "fair" algorithms

The results indicate that embedding fairness principles in allocation algorithms does not necessarily prevent disparities between household groups. Even with the application of fairness principles, households with rooftop solar receive more favorable outcomes in the case study, primarily because of their advantages in curtailment compensation. Group fairness metrics like demographic parity show these disparities, which remain hidden when using Jain's index or the Gini coefficient.

These findings suggest that addressing fairness in grid capacity allocation may require interventions beyond algorithmic design. For instance, instead of redesigning the allocation algorithm, grid operators could adjust compensation schemes to better account for structural disparities. Such interventions may prove more effective in addressing group disparities than fairness-aware algorithms alone. Understanding how fairness results from interactions across operational, market, and policy levels of the energy system remains an open challenge.

### 6.2. Fairness depends on the grid layout and households

Fairness outcomes in power system operation depend not only on the algorithms used but also on the specific contexts in which they are implemented. The results demonstrate that grid layout and household characteristics influence group fairness outcomes. In most scenarios, the minimal intervention principle produced the most balanced outcomes, whereas the proportional principle often favored households with solar.

However, in the scenario with a high number of voltage violations, the min-max principle resulted in a value closer to demographic parity than the minimal intervention principle. These differences indicate that the results may vary with grid topology as well as households' consumption and production profiles. Future work could investigate whether the minimal intervention principle leads to similarly favorable outcomes across other grid layouts and household compositions. If not, guidance is needed to help grid operators choose objectives for their grid capacity allocation algorithms in specific contexts.

### 6.3. Fairness depends on the design of financial incentives

Financial incentives for grid capacity reduction also influence fairness. In the baseline scenario, curtailment compensation caused households with rooftop solar to receive more favorable outcomes. In practice, dynamic tariffs or differentiated pricing could amplify these effects, particularly when incentives are structured to maximize participation. If not carefully designed, such mechanisms may unintentionally reinforce existing inequalities. Therefore, future research on incentives for curtailment and demand response should consider both their effectiveness in promoting participation as well as their impact on fairness across different household groups.

If curtailment compensation is relatively low, grid operators may be incentivized to curtail households more frequently than necessary, since there are no significant costs associated with these actions. This risk could be mitigated through transparency requirements, including mandatory reporting of curtailment events and the grid conditions that triggered them. Such reporting would enable regulators to verify the necessity of curtailment, ensuring it is used only for grid management.

### 6.4. Defining "positive outcomes" requires normative choices

Defining a positive outcome within the group fairness approach is not straightforward, as it involves deciding which burdens and benefits are relevant and how to measure and compare them across households. This study focused on three burdens and benefits (interruption duration, energy not served, and cost benefit) and used the 75th percentile within each scenario as a threshold for household classification. Sensitivity analysis demonstrated that threshold selection influences group disparities: using the 50th percentile revealed more disparities, while the 90th percentile reduced them.

The selection of burdens and benefits also requires further reflection. Certain burdens may be considered justified under specific conditions. For instance, households with high electricity consumption may be interrupted more frequently because they contribute more to grid congestion. In such cases, conditional fairness metrics could help assess whether disparities are acceptable given relevant household characteristics [28]. Future research could explore other definitions of positive outcomes or group fairness metrics, and assess whether stakeholders agree with these definitions.

### 6.5. Practical implications for grid operators and regulators

The results of this study lead to several recommendations for grid operators and regulators. Grid operators are encouraged to monitor group fairness in curtailment and demand response across multiple locations. They could start with monitoring differences between households with and without solar and subsequently consider other groups, such as near- versus end-of-line households. When disparities are identified, grid operators should assess whether adjustments to grid capacity allocation algorithms are needed. Regulators may require reporting of these disparities and establish acceptable thresholds for deviations from demographic parity across groups.

In addition to operational monitoring, group fairness could be considered when designing mechanisms to manage grid congestion. When developing curtailment compensation schemes or dynamic tariffs, grid operators and regulators could assess the distributional impacts of these mechanisms across household groups using a group fairness approach. Demographic parity offers an advantage over aggregate fairness metrics because it is more intuitive, making it particularly useful for communication with policymakers and citizens.

## 7. Limitations

While this study has offered a structured comparison of fairness principles and metrics, it has three main limitations.

### 7.1. Scope and assumptions of the case study

The first limitation is that our case study relies on several simplifying assumptions regarding household behavior. In particular, we assume that households do not adjust their electricity consumption during grid capacity allocation, even though in practice they may change their consumption in response to prior demand response events or time-of-use tariffs. The case study also uses simplified financial parameters, including a stylized feed-in tariff and compensation scheme, and considers only a limited set of grid topologies.

Furthermore, the analysis is based on 2019 consumption and production data, even though electricity usage patterns and solar output can vary from year to year. More recent data may better capture current household behavior and the increased adoption of electric vehicles or residential batteries. While these choices facilitated controlled comparisons across fairness principles, they may limit the generalizability of the results to other grid layouts, market conditions, or time periods. Future research should examine a broader range of grid configurations and tariff structures to assess the robustness of these findings.

### 7.2. Balanced and linearized modeling assumptions

Another limitation is that the mathematical model adopts the LinDistFlow approximation, which assumes a balanced single-phase network and does not account for phase unbalance or line losses. Single-phase balanced calculations were selected for mathematical tractability, and this approach is standard in practice for many grid operators in low-voltage grids due to the historical absence of per-household phase-connection records. However, phase imbalance can cause localized voltage issues on specific feeders, which may influence fairness outcomes under certain conditions. As most residential grids are reasonably balanced at the feeder level, both our modeling approach and the resulting fairness outcomes are most applicable to such grid conditions. Nevertheless, future research should examine whether group fairness outcomes differ in unbalanced feeders.

Line losses could, in principle, create a structural disadvantage for end-of-line households. Our analysis indicates that LinDistFlow systematically overestimates voltages and underestimates line flows compared to DistFlow. This may result in curtailment being triggered more frequently than necessary. Curtailment affects only households with rooftop solar, which may increase their benefit in the baseline scenario. Sensitivity analysis, reducing curtailment compensation by 10%, 25%, and 50%, confirmed that these overestimates do not affect demographic parity outcomes. The second-order cone programming (SOCP) DistFlow formulation was also explored to relax this approximation, but its conic constraints did not become tight under the fairness objectives. Further methodological development is needed to address these limitations.

### 7.3. Group definitions and regulatory context

The analysis is also limited to a single household grouping, distinguishing between households with and without rooftop solar. Many other potentially relevant (sub)groups remain unexplored, such as those defined by socioeconomic status, feeder location, or the presence of flexible assets like home batteries or electric vehicles. Examining fairness across such groups would be a valuable direction for future research.

Furthermore, the approach assumes that all households participate in grid capacity allocation under a centralized coordination framework. Such top-down control by the grid operator is most applicable in systems where the grid operator has the authority to directly allocate capacity to households. In contexts where this role is absent or delegated to market parties, alternative allocation mechanisms and grouping axes may be more relevant. Extending the approach to other groups definitions and regulatory settings is an important area for future research.

## 8. Conclusion

This paper contributes to the growing discourse on fairness in power system computation by explicitly accounting for group disparities between households with and without solar. It adopts the normative stance that grid operators should, at a minimum, avoid exacerbating existing disparities in the energy system. To evaluate this, demographic parity, a common group fairness metric, was used to assess differences in grid capacity allocation between households with and without rooftop solar.

The results indicate that fairness-aware algorithms alone do not guarantee fair outcomes among households. Group fairness was influenced not only by the fairness principles embedded in the algorithms but also by the number of voltage violations and the compensation levels for curtailment. Therefore, addressing fairness in power systems computation requires attention not only to algorithm design but also to the contextual conditions that determine how fairness is realized in practice.

To our knowledge, this work represents an initial step toward integrating group fairness perspectives into power systems computation. We encourage further research that builds on this approach to better account for existing disparities among household groups in this field.

## CRediT authorship contribution statement

**Eva de Winkel:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Data curation, Conceptualization; **Flin Verdaasdonk:** Writing – review & editing, Validation, Methodology; **Zofia Lukszo:** Validation, Supervision, Conceptualization; **Werner van Westering:** Writing – review & editing, Validation, Funding acquisition; **Mark Neerincx:** Validation, Supervision; **Roel Dobbe:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

## Declaration of Generative AI and AI-assisted technologies

During the preparation of this work the authors used Claude to assist with code development and Grammarly to improve the manuscript's grammar. Following the use of these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

The data and code can be found at: https://doi.org/10.4121/499e4878-22e1-462c-a7f4-e14daa56cded.

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