Fairness in Demand-Side Energy Management

Jelle T. M. de Haan
University of Twente, Department of EEMCS
Computer Architecture for Embedded Systems (CAES)
Enschede, The Netherlands
June 2025

***Abstract*—Demand-Side Management aims to reduce the increasing pressure on the electricity grid by adjusting the load of the consumer side. An energy management algorithm 'Profile Steering' aims to peak-shave consumer loads by adjusting devices within a neighborhood towards a flat aggregate profile. This algorithm focuses on the biggest improvers. To incentivize people to participate in such programs, the notion of fairness needs to be incorporated. Based on known motivations and barriers, the equality principle is followed. This aims for an equal amount of inconvenience for all participants. An intuitive metric to measure equality is used, the Gini Coefficient. Using these principles, an adaption 'Fairer Profile Steering' is proposed that considers the burden of a participant, based on the deviation from the default operation. A tunable focus variable τ determines the focus between flexibility and fairness. Simulation results show that the notion of fairness can be incorporated in such an algorithm without compromising peak-shaving performance. The adaption can reduce inequality of burdens by 41% compared to regular Profile Steering, but comes as a trade-off for computation speed. A 26% reduction is possible without this compromise.**

***Keywords*—Fairness, Equitable Contribution, Profile Steering, Equality, Gini Coefficient, Burden Distribution, Discomfort**

I. Introduction

During the current energy transition, the increasing need for electricity is unprecedented. Increases in population, usage of Electric Vehicles (EVs) and development of (intermittent) Renewable Energy Sources (RES) result in increased strain on the electricity grid [1]. Most of this infrastructure is not dimensioned for the demanded peak loads of today and face reliability issues. With reinforcements requiring extensive capital investments, this challenge has been calling for different energy management methods.

Instead of the electricity production, Demand-Side Management (DSM) focuses on the side of the consumer. By reducing electricity consumption or flattening peak demand, DSM allows increasingly larger loads to be supplied by a grid without having to reinforce it. In combination with Decentralized Energy Management (DEM), energy production and consumption of a set of physically connected houses can be locally managed within Smart Grids, reducing strain higher up [2]. By local peer-to-peer energy trading within such an Energy Community (EC), participants can collectively reduce their energy bill, share large investment burdens and maintain power quality as a pursued common objective [1].

As a form of Demand Response (DR) to reduce the strain on the grid by consumers within an EC, load shaping techniques such as peak-shaving are available. Profile Steering (PS) is such a DSM algorithm [3]. Rather than dynamic pricing schemes for individual residents, PS is an incentive-based Direct Load Control program. By participating in a collective effort of avoiding blackouts and increasing neighborhood self-sufficiency [4], residents allow the PS algorithm to automatically shift their loads to off-peak hours. Certain appliances, home batteries and electric vehicles (EVs) can be somewhat flexible in the timing or power of their energy consumption. PS calls on and uses this flexibility to peak-shave, spreading the neighborhood's aggregate energy consumption [3]. This allows the grid infrastructure to supply the ever-increasing energy demand, without exceeding the maximum power capacity.

Higher flexibility or more participants can make a greater contribution to reaching shared objectives for grid usage. An equitable distribution of investments, effort, (in)convenience or possible benefits could motivate home-owners to participate in a DR program like PS [4]. To raise participation levels, the PS algorithm needs an objective metric that determines how fairly each house contributes to the shared objective. While several indices for fairness have been widely adopted in other fields, the concept of fairness has not been widely used within the context of energy management yet.

This work addresses the question: *Can existing fairness metrics be incorporated into an energy management algorithm in order to make it fairer?* An analysis is done on the case of Profile Steering, answering three key elements:

- Can an existing fairness metric be used to measure fairness in Profile Steering?
- Can fairness be included in Profile Steering without compromising peak-shaving performance?
- Does the incorporation of fairness make the Profile Steering algorithm fair(er)?

To summarize, the main contributions of this paper are:

- Proposing a suitable fairness approach and metric for a load-shifting energy management algorithm.
- Demonstrating how focusing on fairness by such an algorithm does not compromise peak-shaving performance, given a trade-off with computation speed.

The remainder of this paper is organized as follows. Section II presents a background on Profile Steering and quantification of offered flexibility. Section III analyzes motivations of residents to participate in DR programs and various existing fairness principles and metrics. Section IV elaborates upon a proposed fairness metric and an adaption 'Fairer Profile Steering'. Section V discusses simulation results of this adaption.

II. Background

Before assessing the fairness of the energy management algorithm at hand, some background knowledge is presented. Section II-A elaborates on the PS algorithm [3]. Section II-B expands on earlier work on quantifying flexibility offered to such an algorithm.

A. Profile Steering

Many DSM approaches use (differentiated) dynamic energy pricing as steering signals to shift loads to off-peak hours. Requiring accurate knowledge of the network topology, it also has been demonstrated that such a mechanism hardly reduces peaks or phase imbalance [5]. Instead, the Profile Steering algorithm of Gerards et al. [3] uses desired power profiles as steering signals. Even without grid topology information, it prevents peaks at each hierarchical level in the infrastructure. Simulations have shown that Profile Steering can significantly lower demand peaks at both local and transformer level [3]. The algorithm controls appliances, respecting flexibility constraints such as their latest desired starting time.

1) Algorithm: The PS algorithm [3] aims to make an optimal planning for M time-shiftable devices in N time intervals. Initially, the controller requests every device $m \in M$ to produce a *power profile* $\vec{x}_m$. Each device does this by finding a profile $\vec{x}_m$ that has the minimal Euclidean distance $\|\vec{x}_m - \vec{p}_m\|_2$ to a received *desired profile* $\vec{p}$. This $\vec{p}$ could be a zero-profile, aiming for production-consumption balance. The controller sums these device profiles to an initial total household consumption profile $\vec{x} = \sum_{m \in M} \vec{x}_m$. Then, the PS algorithm iteratively transmits a *difference profile* $\vec{d} = \vec{p} - \vec{x}$ of the leftover peaks to be accounted for. For each device, the new objective is to find a planning that steers towards the *local desired profile* of $\vec{p}_m = -\vec{d} + \vec{x}_m$ that would completely account for all leftover peaks. Each device finds a new *candidate power profile* $\vec{\hat{x}}_m$ that has the minimal $\|\vec{x}_m - \vec{p}_m\|_2$. They calculate the *improvement* e_m their candidate profile $\vec{\hat{x}}_m$ would make if they would replace it for their current profile $\vec{x}_m$. Each device communicates this improvement $e_m = \|\vec{x}_m - \vec{p}_m\|_2 - \left\|\vec{\hat{x}}_m - \vec{p}_m\right\|_2$ to the controller. This selects the device with the largest improvement and this device updates its planning ($\vec{x}_m$ becomes $\vec{\hat{x}}_m$). The controller updates the total consumption ($\vec{x} := \vec{x} - \vec{x}_m + \vec{\hat{x}}_m$) and repeats the process by sending an updated difference profile $\vec{d}$. Iterations are executed as long as a sufficient improvement e_m can be made ($> \epsilon$).

2) Choices and Implications: For this algorithm, the Euclidean distance or also known as 2-norm is used. This norm penalizes peaks quadratically. Minimizing this metric results in better power quality, as losses are closely related to the squared power. There are computationally efficient algorithms available for minimizing such quadratic cost functions, but the perfectly optimal planning requires the very computationally tough task of calculating every single possibility for all devices. Therefore the PS algorithm is a heuristic, meaning it takes educated guesses to converge to a nearly optimal solution quickly.

Only a single appliance is chosen as winner in each iteration to mitigate the risk of overcompensation. Scaling up the number of devices results in low computational efficiency and a quadratic increase in computation time [2]. Adaptions are proposed to make the PS algorithm scalable, enabling a hierarchical tree on multiple levels, with each device (referred to as *child*) being a controller (*parent*) themselves. An extension that accepts multiple candidates each iteration improves the efficiency and makes the computations scale linearly with the number of children [2].

B. Quantifying Flexibility

Moving or adjusting the power profile of an appliance's default operation contributes to the aggregate incentive of the energy management algorithm. Such an action by the controller requires flexibility of a device. To be able to reward participants, distribute discomfort or know which appliances should be focused on, their flexibility should be quantified [6].

1) Quantifying Flexibility of Single Devices: Previous work quantified the ability of a device to influence the cost function for both peak-shaving and self-consumption [7]. This demonstrated how this flexibility value is higher for high energy consumers or default operation times in unfavorable time windows, as there is more potential for an algorithm to lower the cost function. Power-flexible EVs and home batteries are shown to offer a lot of flexibility value. Their smart charging can prevent both PV feed-in and greedy PV charging peaks.

2) Quantifying Flexibility of Device Coalitions: Taking a step further, a method was introduced to quantify the value of flexible assets within a group of devices [6]. This method calculates the average marginal contribution of a controllable device within every possible combination of other devices in a set. Whenever a device is not in the coalition of devices, it is assumed to be uncontrolled. This so-called *Shapley Value* is high for EVs, battery energy storage systems (BESS) and heat pumps (HP), as they can reduce a cost function greatly compared to when they are uncontrolled. In line with [7], dishwashers and washing machines are shown to provide very little potential. This work demonstrates that the marginal contribution of an asset can be influenced by the other assets in a subset: i.e. a battery would be able to make a larger single-handed contribution if there is no EV in that same subset that would contribute as well. An *Interaction Index* is introduced to provide an insight whether the combination of devices results in positive or negative synergy. It shows how appliances or households can greatly influence each others' impact on the aggregate objective. Furthermore, calculations of these Shapley Values scale exponentially with the number of devices. This renders such an approach unscalable for larger communities, even with the expansion discussed before [2].

3) Controlling Based on Flexibility: Previous research has been done to investigate the effect of incorporating the Flexibility Value into the PS algorithm. Aiming to improve the computational efficiency, an adaption to PS is made [8], [9]. This adaption iteratively requests an improvement from one device from a list rather than requesting improvements from all devices. With way less candidate profiles calculated, this adaption increases computation efficiency and speed [8]. One work sorts the devices in ascending order of flexibility to let the flexible compensate for the inflexible, reducing the number of iterations [8]. Flexibility of a device is valued by the allowable time and power window of the operation. Another work uses predetermined Shapley Values of [6] to pick devices based on their potential to make an impact within the group of devices [9]. Surprisingly, the order in which the devices are called has a marginal effect on the peak-shaving performance. These findings allow future adaptions to be more liberate in picking candidate profiles than previously assumed. It should be noted that the order does affect other indicators [9].

III. Analysis

To be able to incorporate a justified fairness metric into the PS algorithm, factors that influence the perspective of residents have to be known, i.e., what is considered to be fair? Section III-A discusses the relevant factors that incentivizes participation. The effect of pooling efforts together as a neighborhood is presented in III-B. Section III-C gives an overview of existing fairness approaches and quantification metrics.

A. Motivations to Participate in Demand Response

Research has been done on the motivations of residents to invest in household RES generation or participate in DR programs. With different mechanisms applied in the field in the past, different stimulants and barriers can be identified.

1) Stimulants: Generally, investing in self-sufficiency to guard against future price rises or power cuts is the main motivation for participants [10]. The incentive to improve the environment can be a decisive factor to take the leap in adopting new environmentally friendly technologies such as installing PV panels. Government policies such as feed-in tariffs add a financial stimulus to this decision-making [10].

2) Barriers: However, it appears that financial holdbacks still generally weigh heavier than the desire to contribute to environmental changes [10]. Electricity bill savings might not be enough to justify the large investments. Implemented policies such as feed-in tariffs are not sufficing, with 'favorable' investment loans sometimes dramatically decreasing house values. Inconvenience also prevents consumers from adopting new technologies, as reducing electricity usage also requires changes in routines [1]. People generally want to spend as little time as possible on actively thinking about their contributions, desiring non-limiting changes in routines and behavior [11], [12]. Some residents show a lack of trust in the technological performance, installment or reliability of new technologies [10]. Demanding administrative procedures and unsatisfactory financial programs fail to convince hesitating participants [12]. Trust in the technology, government and energy suppliers can therefore make or break the objective of ECs.

3) View on Dynamic Pricing: Generally, consumers wish their electricity suppliers to be a trustworthy organization that ensures the basic need for electricity for everyone [13]. In order to be deemed fair, electricity prices should reflect investments or underlying maintenance costs. A pricing scheme that charges for both total energy consumption and peak power usage is found to be the most socially accepted [13]. Such a scheme is predictable and related to network costs. Another socially acceptable pricing scheme scales prices linearly with neighborhood load [14]. As every resident pays more for additional consumption, the total energy bill scales quadratically. This makes sense from a network perspective. Implementing such a pricing scheme in a group effort results in good peak-shaving performance, but highlight its dependency on the flexibility available. Additionally, as mentioned in Section II-A, proper dynamic pricing requires detailed data of the network infrastructure in order to peak-shave sufficiently.

B. The Influence of Social Cohesion

As highlighted before, collectively participating as a neighborhood can yield better results than individually [14]. Research also shows that residents are more eager to participate in a socially cohesive neighborhood [12]. Pooling contributions does introduce the additional challenge of dividing potential benefits among participants. Basing this distribution on marginal contribution using Shapley Values is deemed to be the fairest option [15]. However, even though it prevents favoring either passive members or active energy producers, it harshly penalizes ineffectual members of the coalition. This makes the collective energy community unstable as the value of a member is highly dependent on the rest of the group.

1) Additional Stimulants: Local energy cooperatives are positively viewed, being a middle ground between too personally and too distantly involved in an objective [12]. Most people would voluntarily participate and share metering data with peers when incentivized to increase neighborhood autonomy. This altruistic view requires the energy providers to act as an energy exchange institution rather than the currently predominating hierarchical profit structure. [16].

2) Additional Barriers: Despite popular belief that people generally do not care enough for the environment, various barriers prevent ample motivation from becoming visible action. [11]. This leads to the reinforcing spiral of misconception that others do little to mitigate the global challenge, discouraging others even more to single-handedly take on the challenge that requires a large support base. Most residents do not know which actions would contribute most to a better environment either [11]. Additionally, load-shifting requires changing routines and incurring inconvenience. Making this a collective effort can put peer-pressure on how someone schedules their day [16]. Moreover, inequality of financial resources within a group can result in selfishness [17]. Popular belief is that the poor would disproportionately benefit from sustainable investments made by wealthier participants. But it appears that those with lower financial means are willing to contribute proportionally more to a group incentive than those with higher assets [17]. As actions are influenced by other participants, transparency of the fairness of contributions is vital.

C. Existing Fairness Principles and Metrics

In order to propose an approach to make PS fairer, existing fairness principles and metrics are identified below. Unfortunately, reviews indicate that current literature fails to offer a universal approach to fairness in the context of energy management [18], [19]. Most cases suffer from subjectivity and complexity of incorporating fairness into a program.

1) Classifying PS: The case of PS has to be classified as a specific context and scope in order to identify how similar cases have been addressed previously. A review identifies five key contexts within local energy systems in which fairness was considered [18]. It can be argued that the PS algorithm described in Section II-A is not limited to one of these and can be involved in all five. It can be applied to a physical *microgrid* and controlling its appliances including *EVs*. The neighborhood can cooperate as a so-called *local energy community* with the collective effort to peak-shave loads as a form of *demand response*, reducing the burden on the *grid infrastructure*.

Within these five contexts, three main scopes were identified: all reviewed cases aimed to create either a fair *pricing scheme*, a fair *distribution of benefits/burdens* or a fair *distribution of (dis)comfort* [18]. Most load-shifting from their default operation would create inconvenience to some degree. Since the PS algorithm does not contain pricing or benefits yet, the challenge would be to create an equitable distribution of discomfort. Similar cases usually distribute discomfort equally [18]. However, discomfort is subjective and hard to guarantee an objectively fair distribution of it. Burdens on the other hand, can be a quantifiable metric such as money, time or power. Cases like power curtailment scope the fairness problem this way, assuming such metrics are somewhat related to the inconvenience it brings to each consumer [19].

Therefore, the case of profile steering can be viewed as an application-independent algorithm that aims to have a fair distribution of discomfort, which can realistically only be approximated by quantifiable burdens. The next step is to elaborate on previously used fairness principles and metrics to find a suitable approach for PS.

2) Previously Used Principles: The percepted fairness of a system depends on the way fairness is interpreted [19]. There are multiple popular notions of what is regarded to be 'fair':

Equality is an intuitive principle that aims for an equal share for all participants [18]. This uniform approach is popular in cases aiming for a fair (dis)comfort distribution [19]. Following this equality principle for PS by aiming for an uniform distribution of inconvenience makes sense. However, the subjective notion of discomfort is complex and rarely taken into account [20]. Adding intuitive constraints to participation [21] or mapping quantifiable metrics to approximate discomfort levels might be a step in the right direction. Adjusting a certain device incurs a different level of discomfort for a consumer, depending on the type of device or even the persons routines and behavior. Unfortunately, When a completely equal share is forced in contributions, the group will experience the bottleneck of the weakest link [22]. Leftover flexibility might remain unutilized as soon as the most inflexible participant can not offer any more.

Humanistic Min-Max Fairness approaches aim to guarantee basic standards for all participants. This approach tries to maximize the minimal benefit of the group, focusing on the worst-off in the group instead of the average [23]. Such method is implemented in e.g. power curtailment by uniformly adjusting the load of the highest contributors to the problem [22]. While this approach makes sense from a network perspective and protects the smaller and weaker participants, it seems less intuitive for PS. As mentioned in Section II-B, the contribution of a house or appliance to the neighborhood power peaks depends on many factors such as time of the day, type of device and combinations with other devices.

Meritocracy is a popular concept that distributes benefits or burdens proportionally to certain merits or contributions of participants [19], [18]. This approach is mostly used to distribute a predetermined amount of benefit or burden, often using monetary rewards [24], [25]. It should be noted that PS is solely participation-based, with the goal to reach the lowest possible objective score without a predetermined target. Using Shapley Values like [6] could move loads based on their marginal contribution to aggregate peaks. As mentioned before, these calculations are complex. Furthermore, this can cause the coalition to become unstable. It can prompt members to leave as they could be profiting more from participating as an individual rather than in a collective effort [15].

The *Generalized Nash Game* is a cooperative game concept that finds the best result for all participants in a collective effort [25]. In this approach, each participant knows the strategy of the others [18]. Unfortunately, PS is a decentralized approach that aims to control a group of participants without predetermined strategies or peer-to-peer communication.

Some other known principles are seen as not to fit the scope of PS, like the *Supply and Demand Ratio* (SDR) [18] or *Limits and Constraints* [19].

3) Previously Used Metrics: To objectively assess the degree of fairness, several fairness indices have been developed and employed to quantify the fairness of a set of contributions [19], [18]. Desired properties of a fairness metric include a continuous and intuitive scale from 0 to 1 and insensitivity to scale, average value and population size [26].

Jain's Fairness Index (JFI) is a very popular fairness metric, usually used in cases for proportional resource allocation [19], [18]. Unfortunately, it has been shown that it has flaws [26]. An intuitive index would result in 0 for the most unfair system and 1 for the fairest system. But the JFI is bounded by a non-zero minimum and will not result in 0 for the most unfair system. It is also sensitive to the average value and scale and asymmetrical around the average. These flaws make the JFI a suboptimal choice for an intuitive metric.

The *Gini Coefficient* is a simple, intuitive inequality index, often used in economical contexts [19]. Even though it results in 0 for the fairest system and 1 for the most unfair system, it is still a highly recommended metric for fairness in pursuit of equality [27]. The Gini Coefficient has a clear rationale based on the difference between a perfectly uniform distribution in a group, visualized by so-called Lorenz curves [27]. As it is scale-invariant as well, the Gini Coefficient is a suitable metric to evaluate the fairness of a uniform distribution.

Fairness Index F was introduced as a proposal to map Quality of Service (QoS) to Quality of Experience (QoE) [26]. It is application-independent as long as the values are on a bounded interval scale. It fulfills desirable properties such as insensitivity to population size, scale and average level [26]. Unfortunately, this index relies on a model to map the value set to a bounded interval scale. PS does not have such a model.

Some other known indices are seen as not to fit the scope of PS, like the *K, SDR, Participation, Averages, RSD* or *Ratios* indices [18], [19].

IV. Incorporating Fairness into Profile Steering

Based on the background knowledge of Section II and analysis in Section III, the following approach to incorporate the notion of fairness into the DSM algorithm 'Profile Steering' of [3] is proposed.

A. Approach to Fairness Principle to Follow

As highlighted in Section III-A, participants are motivated by a simple, understandable approach for reaching equitable contributions. An algorithm that depends on the marginal contributions to actual grid congestion or peak-shaving would be quite complex as mentioned in Sections II-B and III-C. It would also introduce peer-to-peer side-effects and instability as mentioned in Section III-B. Focusing on maximizing the incentive to participate, such effects should be avoided.

An approach deemed intuitive is to aim for a fair distribution of 'flexibility made use of', where participants share an equitable amount of burden. The *Equality Principle* discussed in Section III-C is deemed to be a suitable approach to follow for this, where a completely equal amount of inconvenience for all participants is deemed fair.

This approach requires a mapping of actions (e.g. delaying or adjusting a load) to quantifiable degrees of discomfort it would inflict on a consumer. A comprehensive study on the subjective nature of comfort falls outside the scope of this work. Therefore, an assumed value of discomfort is used for load adjustments in time, power or energy.

Proper mapping would aim to distribute discomfort evenly, rather than require all participants to contribute the same amount of flexibility. As mentioned in Section III-C, demanding equal flexibility can create a major bottleneck once the least flexible participant reaches their limit. Instead, the proposed approach allows some participants to offer more flexibility than others without attaining an unfairly high burden. E.g. load-shifting a home battery does not necessarily yield much inconvenience. In case enforcing perfect fairness turns out to severely hamper peak-shaving performance, a trade-off can be added where some fairness is sacrificed for extra flexibility.

B. Method for Fairness Metric

As touched upon in Section III-C, a metric to quantify the degree of fairness should give an intuitive, reliable result in all cases. An intuitive result for a fairness index would be a range from 0 to 1, where 1 is the fairest case. To ensure reliability, the metric applied to a set of values should be insensitive to the number of values, value scale and the average value [26]. As the approach for PS is to quantify the dispersion of discomfort between users, a simple (in)equality index is suitable.

The *Gini Coefficient* is deemed to be a suitable inequality metric for the case of PS. This metric gives an intuitive result for inequality ranging from 0 to 1 [28]. A Lorenz curve can be made by plotting the cumulative proportion of participants (sorted from lowest to highest contributions) against the cumulative proportion of contributions or discomfort [29]. A completely diagonal line represents perfect uniform distribution. For unequal distributions, there will be some surface area between this fairness line and the Lorenz curve. This bends the Lorenz curve, curving upwards. The Gini Coefficient is the ratio between this inequality area and the total area under the fairness line. A discrete Gini Coefficient calculation for a set x of n values with mean value μ is shown in Equation 1 [29].

$$\text{Gini Coefficient} = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j| \tag{1}$$

The Gini Coefficient is reliable [27], in contrast to the JFI [26]. It is sensitive to drastic outliers [30], but this should not be an issue for an algorithm aiming for equal end results. Another drawback is that 0 represents perfect equality, which is rather non-intuitive. Viewing the Gini Coefficient as an 'inequality index' mitigates this, as a value of 1 represents complete inequality.

C. Algorithm Adaptions for a 'Fairer' Profile Steering

To aim for an equal distribution of discomfort, an adaption to the regular PS algorithm discussed in Section II-A is proposed. 'Fairer PS' will track the total inflicted discomfort for each participant, while steering towards a zero-profile to maximize self-consumption.

Mapping device characteristics to levels of human discomfort is complex and subjective, so some informed assumptions have been made. As an indication of discomfort, the deviation of a device's candidate profile ($\hat{\vec{x}}_m$) from its original profile ($\vec{i_m}$) is taken, using the 1-norm. This value relates to the amount of moved energy consumption, which will be higher for devices with high power rating and capacity. Therefore it is normalized to define a burden value (b_m) of 1 as an action assumed to inflict a similar amount of inconvenience across devices. The burden calculation including normalization (B_m) for several device types is presented in Equation 2. These devices are further elaborated upon in Section V-A.

Each iteration, the winning participant is selected based on a score based on both the possible level of discomfort and the offered flexibility that round. A tunable weight τ between 0 and 1 represents the variable focus between fairness and flexibility. Therefore $\tau = 0$ focuses fully on flexibility, similar to the regular PS. The score function picks the *lowest* scoring participant, as a lower total burden is better. The score part for flexibility is subtracted as higher flexibility makes the participant better, thus lowering the score. Shown in Equation 3, both parts are normalized over the average value to create an even scale around 1. This ensures that discomfort and flexibility hold equal weight in the score, without influence of the actual value.

In contrast to the regular PS, this adaption is likely to pick low improvements in some iterations. As higher improvements can emerge later on, the stopping criterion of the algorithm needs to be adapted. A simple approach is chosen, stopping the simulation after a set number of iterations.

The details of this adapted algorithm are presented in Algorithm 1, with adaptions or additions compared to the regular PS algorithm of [3] in italic.

$$b_m = \frac{\left\|\hat{\vec{x}}_m - \vec{i}_m\right\|_1}{B_m = \begin{cases}\text{Capacity [kWh] for Batteries}\\ \text{Capacity [kWh] for Heatpumps}\\ 2\cdot\text{Requested Charge [kWh] for EVs}\end{cases}} \tag{2}$$

Algorithm 1 Fairer Profile Steering

for each appliance $m \in \{1, \dots, M\}$ **do**
  Find $\vec{x}_m$ minimizing $\|\vec{x}_m\|_2$ {Initial profile}
  $\vec{i}_m := \vec{x}_m$ {*Save initial profile*}
  $b_m := 0$ {*Initialize burden*}
end for
$\vec{x} := \sum_{m=1}^{M} \vec{x}_m$ {Total aggregate consumption}

for $n \leq N$ **do** {*Repeat for N iterations*}
  $\vec{d} := \vec{x} - \vec{p}$ {Difference vector}
  for $m \in \{1, \dots, M\}$ **do**
    $\vec{p}_m := \vec{x}_m - \vec{d}$ {Local desired profile}
    Find $\hat{\vec{x}}_m$ minimizing $\|\hat{\vec{x}}_m - \vec{p}_m\|_2$ {Candidate}
    $e_m := \|\vec{x}_m - \vec{p}_m\|_2 - \|\hat{\vec{x}}_m - \vec{p}_m\|_2$ {Improvement}
    $\hat{b}_m := \|\hat{\vec{x}}_m - \vec{i}_m\|_1 \cdot \frac{1}{B_m}$ {*Candidate burden*}
  end for
  Score each appliance $m \in \{1, \dots, M\}$ using:

$$s_m = \tau \cdot \frac{\hat{b}_m}{\mu_{\hat{b_m}}} - (1 - \tau) \cdot \frac{e_m}{\mu_{e_m}}$$

  Find the appliance m with the lowest score s_m
  $\vec{x} := \vec{x} - \vec{x}_m + \hat{\vec{x}}_m$ {Update total consumption}
  $\vec{x}_m := \hat{\vec{x}}_m$ {Update profile of appliance m}
  $b_m := \hat{b}_m$ {*Update burden of appliance m*}
end for

$$\mu_{\hat{b_m}} = \frac{1}{M} \sum_{m \in M} \hat{b_m} \quad \text{and} \quad \mu_{e_m} = \frac{1}{M} \sum_{m \in M} e_m \tag{3}$$

D. Hypotheses

The Gini Coefficient can be calculated for the outcome of each profile optimization, with a lower score indicating a fairer algorithm. As it has been demonstrated before in a somewhat similar case [25], it is expected that it should be possible to incorporate fairness into PS without significant peak-shaving performance loss. This does require a large total amount of available flexibility [28]. Therefore, it is expected that fairness would increase when the burdens are tracked for multiple days, allowing more room to equalize all contributions.

However, a severe bottleneck is to be expected when a perfect fair system is enforced, where flexibility is left unused as soon as the most inflexible participant cannot offer any more. This would only be acceptable if all flexibility is correctly mapped to discomfort, to guarantee a uniform distribution of discomfort as a justification for sacrificed performance.

The results of a fairness-flexibility trade-off depend on the focus [31]. When fully focusing on flexibility, peak-shaving performance will be similar to the regular PS of [3]. When increasing focus on flexibility, the performance is expected to suffer gradually more. Especially when most focus is on fairness, the bottleneck is expected to decrease performance significantly. The optimal point would be up to a network provider to choose.

Lastly, a slight increase in computation time is expected as more data communication is required for this adaption between the child nodes and the PS controller, with additional computations at the controller as well.

V. Simulation Results & Discussion

A simulation is carried out to evaluate the proposed adaption and compare for different τ. The effects on peak-shaving performance, fairness and computation time are studied.

A. Evaluation Method & Reproducibility

To simulate a realistic neighborhood scenario, a 'PS Light' framework is used. This Python framework implements the Profile Steering algorithm from [3], utilizing device optimization code from DEMKit [32] that implements planning algorithms from [33]. A simulation consists of several devices that create an initial planning without control. Controllable devices are then steered iteratively by the algorithm. This aims towards a flat aggregate power profile. The following devices are added to each house in the simulations:

- *100 base loads*, uncontrollable 0-5 kWh electricity demand.
- *25 batteries*, fully available to be (dis)charged by PS, capacity of 3.5 kWh with a maximum (dis)charge power of 5 kW. We set $b_m = 1$ for a full capacity (dis)charge.
- *25 EVs*, each with 40 kWh capacity of which a 4-22 kWh charge is requested, starting charge between 7:00-12:00 and maximum end time between 15:00-22:00. They can charge with approximately 4-11 kW, assuming general EV chargers allowing 6-16A (in steps of 1A) at three phases of 230V [34]. We set $b_m = 1$ for the full charging request moved away from original window.
- *25 heatpumps*, required to fulfill a 0-7.5 $\text{kW}_{\text{electric}}$ heat demand. They can be charged up to 3.5 $\text{kWh}_{\text{electric}}$ heat capacity to store some energy. Maximum power of 5 $\text{kW}_{\text{electric}}$. We set $b_m = 1$ for a full capacity charge.

The PS Light framework is adapted to incorporate the 'Fairer PS' of Section IV-C. The Gini Coefficient of the controllable devices' burdens is calculated each iteration. The devices are altered to communicate a candidate burden $\hat{b_m}$ along with their candidate improvement e_m. Both are taken into account in the new scoring system s_m, with a tunable focus on fairness τ. In case of a tie, a random tie-participant is picked. A sweep is carried out for different values of τ. The usage of random seeds makes sure that this sweep uses the same randomly generated device characteristics throughout this sweep. A simulation is stopped after $N = 2000$ iterations. This value is based on empirical results of the convergence for this set of devices. Several plots are implemented to visualize the convergence of the 2-norm objective and Gini Coefficient for fairness each iteration. This 'Fairer PS' Python framework is openly available via GitHub [35].

B. Effect of Fairness Incorporation on Peak-Shaving Performance

After simulating, the effects of this adaption 'Fairer PS' are studied. Various τ's are simulated, where $\tau = 1$ represents full focus on fairness and $\tau = 0$ represents the regular PS algorithm that fully focuses on flexibility. The first indication is to verify whether fairness can be incorporated without compromising peak-shaving performance.

1) Effect on the Power Profile: Figure 1 shows the aggregate power profile of the full simulated day before and after optimization. It shows how all simulation runs are able to significantly spread the energy consumption, with negligible differences in the final aggregate profile. The highest peak in power demand is reduced by 14% for all τ's. This greatly aids in reducing grid congestion.

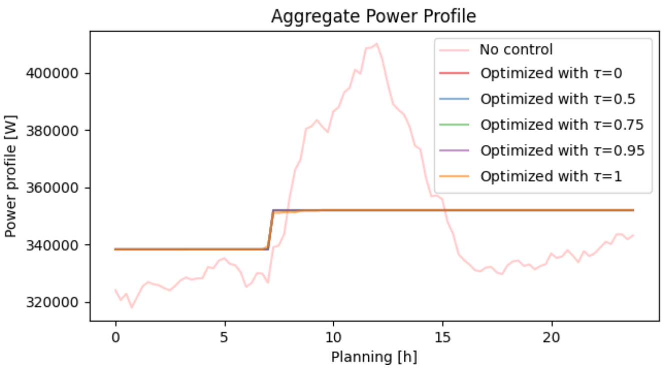

Fig. 1. Aggregate power profile before and after optimization, for various τ's

2) Convergence of Peak-Shaving Metric: As Figure 1 shows, all runs result in virtually identical power profiles and therefore the same objective score of the 2-norm. However, Figure 2 shows the evolution of the 2-norm during the iterative phase. This clearly demonstrates that the algorithm exhibits slow convergence toward this final result for high τ's. The run with $\tau = 0$ reaches its potential in less than hundred iterations, while $\tau = 1$ needs almost two thousand. Runs with lower τ's focus more on offered flexibility and making big improvements, so this result is not surprising. It indicates that a higher focus on fairness comes at the cost of additional computational complexity in order to reach the same peak-shaving performance.

Surprisingly, all simulation runs achieve a virtually identical result despite the change in focus. This indicates that the algorithm manages to always extract all the flexibility potential of the device set, regardless of the focus. This might be due to the fact that each device will have a high chance to be picked at least once in all cases. Additionally, the substantial flexibility of the batteries is able to address the smallest of deviations. With the high number of iterations, a device that has not yet optimized for the local desired profile and thus a burden of 0 will have a high chance of contributing its full potential, scoring well on both parts regardless the focus.

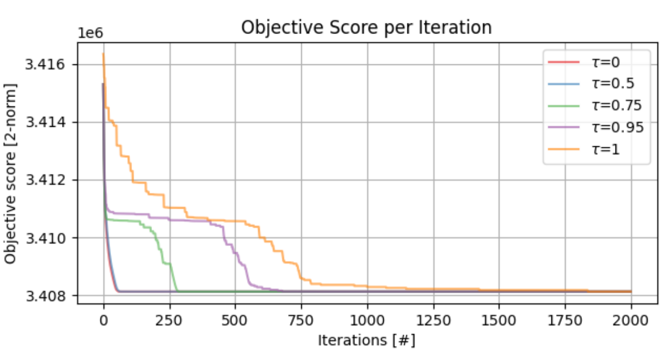

Fig. 2. Convergence of the objective score, for various τ's

The vast difference in objective score convergence is visualized by Figure 3. Where low τ's are focused on picking the highest improvement, higher focus on fairness results in an iteration's improvement to vary greatly during the simulated runs. It shows how higher τ's continue to improve their objective score after hundreds of iterations, slowly converging to the same 2-norm as the lower τ's. The lower τ's actually stop making any improvement after barely two hundred iterations as they make the biggest improvements in their first few iterations already.

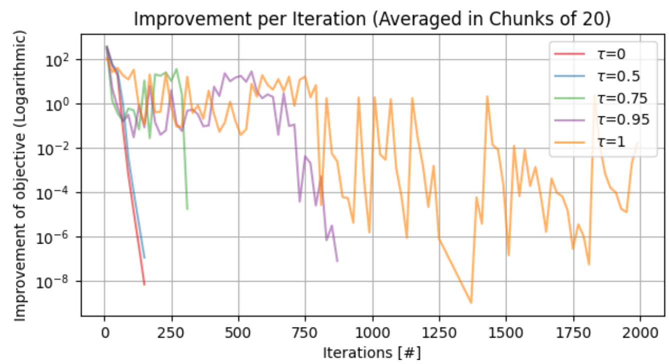

Fig. 3. Convergence of the improvement each iteration, for various τ's

C. Effect of Fairness Incorporation on Fairness Metric

With the impact on peak-shaving performance analyzed, the main question is whether 'Fairer PS' has actually made Profile Steering fair(er). For this, the total accumulated burden of each controllable device is studied. The Gini Coefficient provides an intuitive value for the inequality of its distribution.

1) Device Burden Distribution: Figure 4 shows the final distribution of burdens of all controllable devices for different τ's. The violin plot gives an intuitive insight, outlining the minimum, maximum and median burden for each device type. It shows how runs with higher τ's result in less extreme outliers and a more uniform distribution of burdens. This is reflected by the Gini Coefficient that indicates a lower inequality for higher τ's.

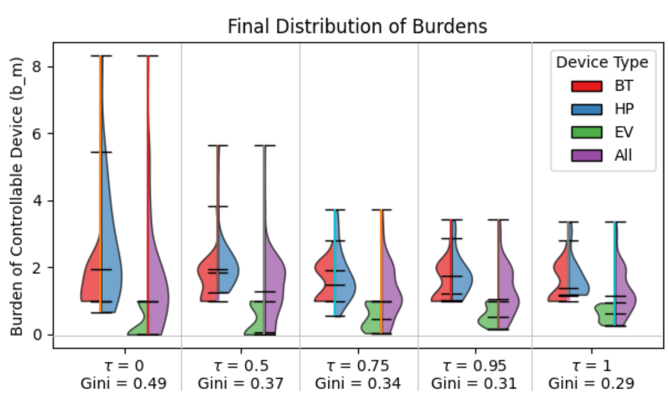

Fig. 4. Resulting burden distribution of the controlled devices, for various τ's

Regular PS ($\tau = 0$) has many devices carrying a somewhat similar burden, but has extreme outliers. Its Gini Coefficient of 0.49 and its violin plot indicate that some controllable devices carry significantly more burden than others. Fully focusing on fairness ($\tau = 1$) instead of flexibility ($\tau = 0$) decreases the inequality by 41%. The emergence of different shapes for higher τ's is assumed to be the result of picking similar specific actions across devices that inflict low burden. This plot shows a shortcoming of the burden mapping, with EVs unable to accumulate a burden higher than 1 while batteries and heatpumps can be (dis)charged several times more. A possible improvement could be to normalize a device's burden based on the maximal flexibility it could provide in a full day.

2) Convergence of Fairness Metric: In similar fashion as Figure 2 for the 2-norm, Figure 5 shows the evolution of the Gini Coefficient during the simulation runs. It shows a similar phenomenon. Lower τ's converge significantly faster to their full potential than higher τ's. Higher τ's eventually converge to a Gini Coefficient that is lower than the maximum capability of lower τ's. This shows the lower inequality and therefore higher fairness as eventual result. This plot also shows that it is vital to allow a large number of iterations in order to reach low inequality, as the higher τ's are significantly less fair than the lower τ's in the first few hundred iterations.

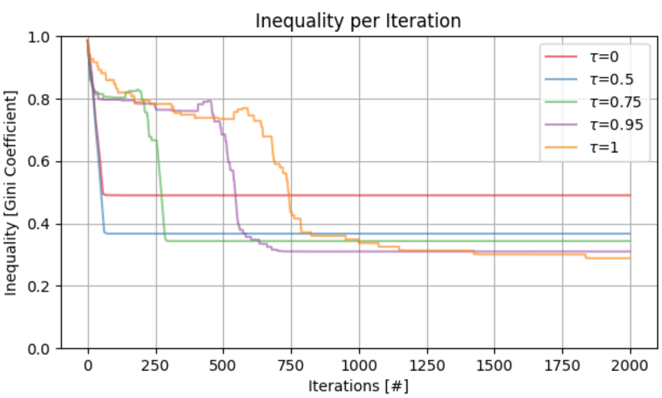

Fig. 5. Convergence of the Gini Coefficient for inequality, for various τ's

D. Comparing Tunable Focus τ

A full sweep across τ from 0 to 1 in steps of 0.05 showed that the inequality measured by the Gini Coefficient gradually decreases for higher τ's, similar to Figure 5. All simulations converge to the same 2-norm and power peak reduction after a high number of iterations, similar to Figure 2. However, runs for higher τ's runs converge a lot slower to this result than others. Based on plotting Figure 2 for the full range of τ, an approximation is made of the number of iterations needed to converge to this final objective score. Showing the trade-off of fairness for convergence speed, Figure 6 shows the resulting Gini Coefficient and required iterations for each choice of τ.

With 'Fairer PS' always simulating a large number of iterations, its computation time is generally a lot higher than the regular PS, which finishes in under a hundred iterations in the studied use case. The slowest convergence appears at $\tau = 1$, taking over thirty times longer than $\tau = 0$. Should one wish to lay focus on achieving low computation time as well, a fairly balanced choice of $\tau = 0.55$ could provide a 26% decrease in inequality without hindering convergence speed.

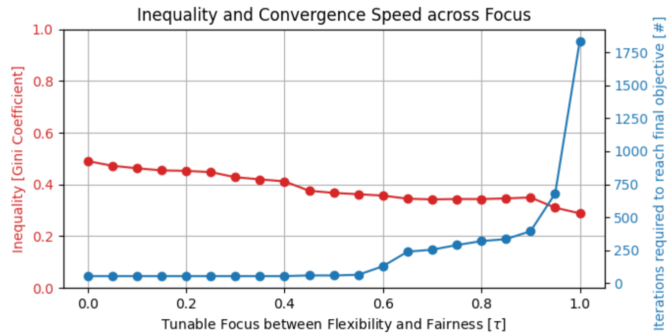

Fig. 6. Inequality and iterations needed to converge to final objective score across τ

VI. Conclusions and Future Work

We have shown that an existing metric like the Gini Coefficient can be incorporated into an energy management algorithm such as Profile Steering to make it fairer. This will incentivize residents more to participate in collective efforts to reduce grid congestion. In the scenario of the conducted simulation, it is shown that each variation of the proposed 'Fairer' algorithm is able to reach similar peak-shaving performance as regular PS. Noted that the current device set offers a lot of flexibility, a bottleneck does not emerge, even for high focus on fairness. Therefore, fairness can be included in PS without compromising peak-shaving performance. As the equality principle is followed to aim for an equal amount of inconvenience for all participants, the Gini Coefficient is a suitable metric to measure equality in Profile Steering. The regular PS does not focus on fairness and results in a rather poor Gini Coefficient of 0.49. Changing the focus results in a fairer distribution of device burdens. Fully focusing on fairness instead of flexibility can decrease the Gini Coefficient to 0.29. Thus, the incorporation of fairness can make the Profile Steering algorithm 41% fairer. Although the final objective score is the same for all focus divisions between flexibility and fairness, the algorithm requires considerably more iterations to reach this value. Fully focusing on fairness is the slowest converging simulation run, taking over thirty times longer than regular PS. Without hurting convergence speed, the maximum fairness increase is 26%, which comes at a rather balanced focus on both fairness and flexibility.

It would be interesting for future research to dive into the fairness across different device types and their role in the convergence of the algorithm. Further work can be done on improving the mapping of quantifiable device characteristics to actual human subjected discomfort levels, like [20]. Different adaptions such as more sophisticated stopping criteria or scenarios with little available flexibility are interesting to study the effects of. The same holds for other implications of different efficiency-fairness trade-offs, continuing in line of [31]. Furthermore, adding other schemes to PS such as monetary rewards or saving goals could incentivize participation even more.

Acknowledgment

I would like to thank Aditya Pappu, Gerwin Hoogsteen and Nataly Bañol Arias for being my supervisors during my research. My discussions with Gerwin and Aditya have been of tremendous help in shaping ideas, direction and solutions. They allowed the freedom to pursue the concepts that sparked my interest.

Declarations

During the preparation of this work the author used OpenAI's language model ChatGPT (GPT-4, 2025) in order to clarify key differences between researched concepts, aid in writing mathematical LaTeX equations, give examples of Python code structures and aid in data plotting with Matplotlib. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

References

[1] M. Bakare, A. Abdulkarim, M. Zeeshan, and A. Nuhu, "A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction," *Energy Informatics*, vol. 6, 03 2023.

[2] G. Hoogsteen, M. E. T. Gerards, and J. L. Hurink, "On the Scalability of Decentralized Energy Management using Profile Steering," in *2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, 2018, pp. 1–6.

[3] M. E. T. Gerards, H. A. Toersche, G. Hoogsteen, T. van der Klauw, J. L. Hurink, and G. J. M. Smit, "Demand Side Management using Profile Steering," in *2015 IEEE PowerTech Eindhoven*. United States: IEEE, Jun. 2015, pp. 457 759:1–457 759:6, iEEE PowerTech 2015 ; Conference date: 29-06-2015 Through 02-07-2015.

[4] P. Siano, "Demand response and smart grids—A survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

[5] C. N. Almeida, A. Narayanan, M. Hussain, and P. H. J. Nardelli, "Pricing Mechanisms versus Non-Pricing Mechanisms for Demand Side Management in Microgrids," in *2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, 2024, pp. 1–5.

[6] I. A. M. Varenhorst, J. Hurink, and M. E. T. Gerards, "Quantifying Device Flexibility With Shapley Values in Demand Side Management," in *Proceedings of the 15th ACM International Conference on Future and Sustainable Energy Systems*, ser. e-Energy '24. New York, NY, USA: Association for Computing Machinery, 2024, p. 147–157.

[7] M. E. T. Gerards and J. L. Hurink, "On the value of device flexibility in smart grid applications," in *2017 IEEE Manchester PowerTech*, Jun. 2017, pp. 1–6, 12th IEEE PES PowerTech Conference : Towards and Beyond Sustainable Energy Systems, PowerTech 2017 ; Conference date: 18-06-2017 Through 22-07-2017.

[8] D. Pinto, "Investigating the Effects of Changing the Optimization Order in Profile Steering," July 2024. [Online]. Available: http://essay.utwente.nl/101617/

[9] F. W. J. van der Waals, "Flexibility Informed Profile Steering using Shapley Values," July 2024. [Online]. Available: http://essay.utwente.nl/101035/

[10] P. Balcombe, D. Rigby, and A. Azapagic, "Investigating the importance of motivations and barriers related to microgeneration uptake in the UK," *Applied Energy*, vol. 130, p. 403–418, 10 2014.

[11] T. Bouman and L. Steg, "A spiral of (in)action: Empowering people to translate their values in climate action," *One Earth*, vol. 5, no. 9, pp. 975–978, Sep. 2022.

[12] J. Naus, B. J. M. van Vliet, and A. Hendriksen, "Households as change agents in a Dutch smart energy transition: On power, privacy and participation," *Energy Research Social Science*, vol. 9, pp. 125–136, 2015, special Issue on Smart Grids and the Social Sciences.

[13] S. Neuteleers, M. Mulder, and F. Hindriks, "Assessing fairness of dynamic grid tariffs," *Energy Policy*, vol. 108, pp. 111–120, 2017.

[14] V. M. J. J. Reijnders, M. E. T. Gerards, and J. L. Hurink, "A hybrid electricity pricing mechanism for joint system optimization and social acceptance within energy communities," *Energy Reports*, vol. 8, pp. 13 281–13 292, 2022.

[15] M. Baranauskas, A. Keski-Koukkari, P. Astero, A. Safdarian, and A. Kulmala, "Value creation and sharing methods in household energy communities," in *2022 IEEE International Conference on Power Electronics, Smart Grid, and Renewable Energy (PESGRE)*, 2022, pp. 1–8.

[16] M. Goulden, B. Bedwell, S. Rennick-Egglestone, T. Rodden, and A. Spence, "Smart grids, smart users? The role of the user in demand side management," *Energy Research Social Science*, vol. 2, pp. 21–29, 2014.

[17] J. Vicens, N. Guerra, M. Gutiérrez-Roig, C. Gracia-Lázaro, J. Gómez-Gardeñes, J. Perelló, A. Sánchez, Y. Moreno, and J. Duch, "Resource heterogeneity leads to unjust effort distribution in climate change mitigation," *PLoS ONE*, vol. 13, p. e0204369, 10 2018.

[18] J. Soares, F. Lezama, R. Faia, S. Limmer, M. Dietrich, T. Rodemann, S. Ramos, and Z. Vale, "Review on fairness in local energy systems," *Applied Energy*, vol. 374, p. 123933, 2024.

[19] E. de Winkel, Z. Lukszo, M. Neerincx, and R. Dobbe, "A Review of Fairness Conceptualizations in Electrical Distribution Grid Congestion Management," in *2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, 2024, pp. 1–5.

[20] L. Hurtado Muñoz, E. Mocanu, P. Nguyen, M. Gibescu, and R. Kamphuis, "Enabling Cooperative Behavior for Building Demand Response Based on Extended Joint Action Learning," *IEEE transactions on industrial informatics*, vol. 14, no. 1, pp. 127–136, Jan. 2018.

[21] M. Vanin, T. Van Acker, H. Ergun, R. D'hulst, K. Vanthournout, and D. Van Hertem, "Congestion mitigation in unbalanced residential networks with OPF-based demand management," *Sustainable Energy, Grids and Networks*, vol. 32, p. 100936, 2022.

[22] A. Vadavathi, G. Hoogsteen, and J. Hurink, "Fair and Efficient Congestion Management for Low Voltage Distribution Networks," in *2024 IEEE 8th Energy Conference (ENERGYCON)*. United States: IEEE, Apr. 2024, iEEE 8th Energy Conference, ENERGYCON 2024, ENERGYCON 2024 ; Conference date: 04-03-2024 Through 07-03-2024.

[23] R. Hernandez, J. Giraldo, G. Tsaousoglou, M. J. Rider, and N. Paterakis, "Fair Congestion Management in Distribution Systems using Virtual Power Lines," in *2021 International Conference on Smart Energy Systems and Technologies (SEST)*, 09 2021, pp. 1–6.

[24] E. Jamil and B. Hayes, "Fair Prosumer Participation in P2P Energy Markets: An Iterative Water–Filling Algorithm for Congestion Control," in *2023 58th International Universities Power Engineering Conference (UPEC)*, 2023, pp. 1–6.

[25] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad, "Achieving Optimality and Fairness in Autonomous Demand Response: Benchmarks and Billing Mechanisms," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 968–975, 06 2013.

[26] T. Hoßfeld, L. Skorin-Kapov, P. Heegaard, and M. Varela, "A new QoE fairness index for QoE management," *Quality and User Experience*, vol. 3, 02 2018.

[27] E. Heylen, M. Ovaere, S. Proost, G. Deconinck, and D. Van Hertem, "Fairness and inequality in power system reliability: Summarizing indices," *Electric Power Systems Research*, vol. 168, pp. 313–323, 2019.

[28] M. Vassallo, A. Benzerga, A. Bahmanyar, and D. Ernst, "Fair Reinforcement Learning Algorithm for PV Active Control in LV Distribution Networks," in *2023 International Conference on Clean Electrical Power (ICCEP)*. IEEE, Jun. 2023, p. 796–802.

[29] A. Sen, *On Economic Inequality*. Clarendon Press, 1997, pp. 29-31. [Online]. Available: https://books.google.nl/books?id=Kb03KNreUqcC

[30] M. Shirli, C. Louen, and D. Vallée, "Exploring mobility equity in a society undergoing changes in travel behavior: A case study of Aachen, Germany," *Transport Policy*, vol. 46, pp. 32–39, 02 2016.

[31] Z. Baharlouei and M. Hashemi, "Efficiency-Fairness Trade-off in Privacy-Preserving Autonomous Demand Side Management," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 799–808, 03 2014.

[32] G. Hoogsteen, J. L. Hurink, and G. J. M. Smit, "DEMKit: a Decentralized Energy Management Simulation and Demonstration Toolkit," in *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 2019, pp. 1–5.

[33] T. van der Klauw, "Decentralized Energy Management with Profile Steering: Resource Allocation Problems in Energy Management," PhD Thesis - Research UT, graduation UT, University of Twente, Netherlands, May 2017, cTIT Ph.D. thesis series no. 17-424.

[34] V. Schwarzer and R. Ghorbani, "Current State-of-the-Art of EV Chargers," 2015, Hawaii Natural Energy Institute. [Online]. Available: https://api.semanticscholar.org/CorpusID:11339502

[35] J. T. M. de Haan, "GitHub repository: Fairer Profile Steering," https://github.com/J3ll3H/fairerprofilesteering, 2025.