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AI and Energy Justice

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Abstract: Artificial intelligence (AI) techniques are increasingly used to address problems in electricity systems that result from the growing supply of energy from dynamic renewable sources. Researchers have started experimenting with data-driven AI technologies to, amongst other uses, forecast energy usage, optimize cost-efficiency, monitor system health, and manage network congestion. These technologies are said to, on the one hand, empower consumers, increase transparency in pricing, and help maintain the affordability of electricity in the energy transition, while, on the other hand, they may decrease transparency, infringe on privacy, or lead to discrimination, to name a few concerns. One key concern is how AI will affect energy justice. Energy justice is a concept that has emerged predominantly in social science research to highlight that energy related decisions—in particular, as part of the energy transition—should produce just outcomes. The concept has been around for more than a decade, but research that investigates energy (in)justice in the context of digitalized and data-driven electricity systems is still rather scarce. In particular, there is a lack of scholarship focusing on the challenges and questions that arise from the use of AI technologies in the management of electricity systems. The central question of this paper is, therefore: what may be the implications of the use of AI in smart electricity systems from the perspective of energy justice, and what does this mean for the design and regulation of these technologies?

Keywords: artificial intelligence; machine learning; energy justice; energy law; PV curtailment; smart grids

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1. Introduction

The use of Artificial intelligence (AI) in electricity systems is part of a broader trend to digitalize these systems to help facilitate and accelerate the energy transition. In fact, it has been advertised as the motor behind the second digitalization wave, the first being primarily focused on interconnection and sensing, resulting in quickly expanding volumes of data (e.g., solar, wind, domestic consumption, demographics) [1]. AI technologies offer the means to address a range of problems that current electricity systems face, such as the integration of renewable and more volatile energy sources, the increased use of the network due to the growing electrification, and a lack of network capacity. AI techniques have been used to forecast and predict energy load, predict consumption and supply, control behind-the-meter appliances and devices, optimize energy storage, schedule battery charging, monitor system health, and support the shift from centralized control to decentralized control of electricity systems [2,3]. These data-driven AI techniques promise a range of benefits including empowerment of consumers and citizens, sustainability, cost-savings, efficiency gains, transparency, and more [2]. Moreover, they promise the facilitation of decentralizing control of electricity systems, making the coordination of the increasingly dynamic grid more manageable.

At the same time, concerns have been raised about the effect that these technologies can have on, amongst other things, safety, privacy, transparency, fairness, and accountability. Niet et al. [3], for instance, noted the following issues. The data hungry character of many AI applications may lead to privacy infringements when increasingly more fine-grained forecasts and predictions of consumer energy demands are made possible by these technologies. Moreover, predicting demand may require various kinds of personal data or data that can reveal a lot about a person's daily schedule and habits. Transparency may be reduced when the complexity of energy systems increases as a result of the integration of AI technologies. The black box character of some AI technologies can be a contributing factor, but the outsourcing of the AI development to private companies and start-ups also makes energy systems less transparent. Moreover, AI-based energy systems that perform a large part of their tasks autonomously can make it more difficult for human operators to intervene effectively because of their complexity and the speed with which they perform their operations. When price negotiations are decentralized—supported by more or less autonomously acting AI-based systems—competition authorities and energy regulators will have a hard time monitoring how prices develop. Moreover, they will have limited means and powers to control these developments (see also [2]).

Many of these concerns are not unique to the use of AI in the energy domain but accompany the development of AI in most of its areas of application. AI technologies enable new relationships, new interconnections, and new activities. As such, they challenge existing norms and regulatory frameworks. These developments have led to a growing number of guidelines and manifestos that identify key principles, such as respect for human dignity and the protection of privacy, to guide the responsible embedding of AI in society [4]. A key principle that occurs in many of these documents is justice: a concept that emphasizes such values as fairness, equality, and non-discrimination, as well as due process. This concern with justice in the development of AI coincides with the growing attention to energy justice in the energy sector as a principle to guide development in the energy transition.

'Energy justice' is a concept that has emerged predominantly in social science research to highlight that energy related decisions, particularly as part of the energy transition, should produce just outcomes. The energy transition entails a move away from fossil fuels to a low-carbon economy driven in large part by the desire to mitigate climate change, through, for example, increasing electrification and the use of renewable energy sources, such as solar and wind. This transition entails significant changes for all stakeholders involved. However, these changes may have adverse effects on certain groups in society as a result of, for example, the replacement of land devoted to farming and food or reliance on forced labor to extract the natural resources for the required electrification [5]. Energy justice is a concept that brings ethical and social concerns to the fore in decisions about energy, in addition to traditional technical and economic aspects. According to Jenkins et al. (2016), energy justice provides a framework to evaluate "(a) where injustices emerge, (b) which affected sections of society are ignored, (c) which processes exist for their remediation in order to (i) reveal, and (ii) reduce such injustices" [6] (p. 175). The concept has been around for more than a decade, but research that investigates energy (in)justice in the context of digitalized and data-driven electricity systems is still rather scarce. In particular, there is a lack of scholarship focusing on the challenges and questions that arise from the use of AI technologies in the management of electricity systems with respect to energy justice (see Section 3.1 below).

In this paper, we aim to apply energy justice (as a guiding normative principle for developments in the energy transition) to the design and regulation of AI in the energy sector. A better understanding of the interaction between AI technologies and energy justice is necessary, as these technologies are still in the early stage of development, but may have significant disruptive effects on the energy sector. Moreover, policymakers in the European Union (EU) increasingly see the digital and energy transitions as two interrelated developments, whereby digital technologies are seen as an enabling force to realize the energy transition. To that end, the EU wants to facilitate the digitalization of the electricity sector by stimulating the use of digital technologies and the use and exchange of data, including consumer data [7]. The promise of new coordination mechanisms, new scales of flexibility and complexity, as well the potential new relationships, roles, and responsibilities, require us to reflect on what energy justice in such environments entails and how these AI technologies can facilitate and safeguard this. Ensuring that AI technologies will serve to safeguard energy justice can strengthen a social license, as it places the focus on making sure that the energy transition will leave no one behind.

The central question for this paper is two-fold: what may be the implications of the use of AI in smart electricity systems from the perspective of energy justice, and what does this mean for the design and regulation of these technologies? To address this research question, this paper first presents a conceptual analysis of energy justice. We then explore how legal norms or existing literature can provide a framework to apply this concept to AI technologies. Finally, we perform an initial explorative analysis, applying the notion of energy justice to AI techniques within the electricity sector, focusing on machine learning techniques.

2. Materials and Methods

The analysis is based on a review of academic literature on energy justice and the literature on AI technologies for grid management in the electricity sector. For the sources on energy justice, we searched for literature that conceptualizes and defines the scope of energy justice in general, as well as literature that applies the concept of energy justice in the context of the digitalized electricity sector, using a snowballing approach. Given the scope of this article, we focused predominantly on social science literature, including philosophy and (energy) law. In the latter case, the selection of sources was limited to scholarship studying energy justice in the context of EU law.

Regarding literature on the use of AI in the electricity sector, we focus on AI technologies for smart grid management. There are many kinds of AI technologies that are proposed to tackle the many challenges that sustainable energy distribution is confronted with. However, because we aim to show the relevance of energy justice considerations in the development and deployment of AI rather than give an exhaustive overview, we have narrowed the focus to this domain of application. Moreover, we concentrate on machine learning (ML) technologies—rather than AI in a broad sense—for the same reason. We have gathered literature on relevant ML by searching for the keywords "machine learning", "energy management", and "smart grids" to find comprehensive literature reviews and snowballed from these reviews.

3. Results

This part is structured as follows. Section 3.1 of this paper starts by providing an overview of the predominant conceptualizations and applications of energy justice in academic literature. Particular attention is paid to literature that investigates energy justice in the context of digitalized and data-driven electricity systems. This is followed by a discussion on how the concept can be used as a guiding normative principle. Section 3.2 first provides a short discussion on the use of AI technologies in electricity systems, in particular, for purposes related to grid management. We then zoom in on a particular machine learning application to show how design choices affect energy justice. Section 3.3 brings together the different strands of literature reviewed in the preceding sections to discuss what the implications of the previous analyses are for the design and the regulation of AI technologies used in the energy sector.

3.1. Energy Justice

Energy justice has become an important topic for energy researchers from social sciences, including philosophy and law [8,9]. It is a relatively new concept, which has predominantly been developed in academic circles since 2013, although it has its roots in environmental and climate justice activist movements [10]. The emergence of the notion of energy justice evidences what McHarg terms an "ethical turn" in energy scholarship, as well as in energy law and policy [9]. In a nutshell, this "ethical turn" refers to the growing consensus that energy related decisions should no longer be driven solely by cost–benefit analyses based on technological and economic considerations. According to Sovacool and Dworkin, energy decisions are also "about political power, social cohesion, and even ethical and moral concerns over equity, due process, and justice" [11] (p. 1). In that sense, according to Sovacool and Dworkin, energy decisions should be reframed and understood as justice and ethical concerns.

An important factor that explains why social scientists have become more interested in energy issues, according to McHarg, is the global transition towards a low-carbon energy system [9]. This transition, also known as the energy transition, entails moving away from fossil fuels and involves, among others, more electrification. Shifting to a low-carbon economy does not automatically mean that energy systems will become more just. On the contrary, there is a risk that the energy transition perpetuates or exacerbates the injustices of the fossil fuel economy [5]. Against this background, energy justice is increasingly seen as a normative principle to guide developments in the energy sector, amidst the fundamental changes happening in the context of the energy transition.

The literature provides multiple definitions for energy justice. For example, Sovacool defines energy justice as "the ways in which a society distributes the benefits and burdens of its energy system in terms of an aspiration to be fair" [12] (p. 15). Heffron et al., define it as "a conceptual framework, which seeks to identify when and where injustices occur and how best law and policy can respond" [13] (p. 169). Sovacool et al. characterize it as "a global energy system that fairly disseminates both the benefits and costs of energy services, and one that has representative and impartial energy decision-making" [14] (p. 169).

While there is no broad consensus regarding the specific meaning of "energy justice" in the literature, there seems to be more agreement on the conceptual frameworks used to describe what is covered under the notion of energy justice. For example, there is a well-known conceptual framework proposed by Sovacool et al. [14], based on a set of principles (availability, affordability, due process, transparency and accountability, sustainability, intragenerational equity, intergenerational equity, responsibility, resistance, and intersectionality) which serve as a decision-making framework for different actors making energy related decisions (policymakers, regulators, consumers, businesses, etc.) [11].

However, the most predominant framework to understand what energy justice encompasses is that of the **"triumvirate of tenets"**. The "triumvirate of tenets" approach was advanced by McCauley et al., and drew on literature on environmental and climate justice [15]. The authors identify three core themes or tenets of energy justice: distributional (or distributive) justice, procedural justice, and recognition justice (in more recent work, Heffron refers to five dimensions of energy justice, adding two to the existing triumvirate, namely, restorative justice (referred to the rectification of injustices caused by the energy sector) and cosmopolitan justice (which highlights the need of considering the cross-border effects from energy activities) [16]. In this paper, however, considering the scope of our research question, we focus on the three traditional dimensions.).

Distributive justice refers to considerations about the "distribution of benefits, burdens or costs, and responsibilities among stakeholders of an energy system" [17] (p. 1247. See also [15]). The cost and benefits can be financial but can also be expressed in terms of distribution of hazards and externalities, as well as access to energy services [11] (p. 4). The term energy justice has also been used to discuss the distribution of inequalities both locally (for example between rural and urban areas) and globally (for example, between developing and developed countries) [17]. Usual distributive justice issues include, for example, decisions regarding the siting of infrastructure for energy production and energy poverty [6,17].

Procedural justice refers to equitable access to and participation in decision-making processes governing the abovementioned distributive aspects [6,17]. Meaningful participation in and transparency of the decision-making procedures are important elements of procedural justice [18]. This justice dimension also entails that citizens and consumers can have access to information and to legal mechanisms to obtain redress or challenge decision making processes concerning energy issues [9].

Recognition justice refers to the question of who is recognized as a stakeholder with valid concerns and claims [6]. It entails the "equitable appreciation of stakeholder groups involved in energy systems" [17] (p. 1247), where appreciation means both the acknowledgement and respect of the varying needs, rights, and experiences of people affected by energy related decisions [9], taking into consideration, among other factors, social, ethnic, racial, and gender differences [15]. Recognition injustices manifest as lack of recognition and misrecognition [6]. An example of the former is, for instance, failing to recognize that there are groups such as elderly people or people with illnesses or disabilities that need more energy than other groups and cannot easily reduce or adjust their energy consumption [6,9]. Misrecognition entails the distortion or misrepresentation of the claims and concerns of people affected by energy related decisions, in a dismissive or disrespectful way, as exemplified by the use of the "Not-In-My-Backyard" label to delegitimize the concerns of stakeholders opposing to wind park projects [6].

Social science literature attributes different functions to the notion of energy justice. For example, Sovacool and Dworkin refer to it as a conceptual tool for philosophers and ethicists (to integrate distributive and procedural justice concerns); as an analytical tool for energy researchers which aids them in understanding "how values get built into energy systems or to resolve common energy problems"; and as a decision-making tool for energy planners and consumers to make more informed energy choices [19] (p. 435). Jenkins et al. posit that energy justice (research) has an evaluative and normative reach to the extent that it offers "an opportunity to explore where injustices occur, developing new processes of avoidance and remediation and recognizing new sections of society" [6] (p. 176).

In this paper, we will consider energy justice in the latter evaluative and normative sense and use it to explore the choices that AI technologies present about how to promote energy justice and mitigate risks of injustice. Before proceeding to that analysis, we will discuss to which extent the notion of energy justice, as a normative notion, has permeated energy law (Section 3.1.1). Subsequently (Section 3.1.2), we will survey existing literature applying the notion of energy justice to digital technologies used in the electricity sector and identify the research gap that this contribution aims to address.

3.1.1. Energy Justice and Energy Law

As noted by Huhta [20], "energy law" is an expression that has a dual meaning. The first understanding refers to "the collective body of existing legal norms (meaning a binding rule or principle) that govern the energy sector (energy law as a normative system)". This refers to legislation and other types of legally binding rules that apply to the energy sector, as well as court decisions interpreting and applying such legal sources. The second understanding refers to energy law as "an area of research that analyses the collective body of legal norms that govern the energy sector [. . .] (energy law as a legal discipline)" [20] (p. 1.). This refers to the work of legal scholars, who have as their field of study the rules that pertain to energy law as a normative system.

In the context of the EU, the notion of energy justice has permeated more clearly energy law research than the normative system of the energy sector. As of yet, EU legislation does not explicitly incorporate or define energy justice as an objective or principle guiding the energy sector in the EU [21]. For example, the primary source of EU energy law (Article 194 (1) of the Treaty on the Functioning of the European Union) states that the objectives of EU energy policy are "ensuring the functioning of the energy market", "ensure the security of energy supply in the Union", "promote energy efficiency and energy saving and the development of new and renewable forms of energy", and "promote the interconnection of energy networks".

This does not mean that energy justice is not relevant for EU policymakers. On the contrary, as noted by Kaschny, despite lacking an explicit legal definition, "the objective of establishing a more equitable, just and sustainable energy sector is a widely accepted understanding" in EU energy policy [21]. This is evidenced by secondary legislation (e.g., [22–24]) and policy documents from EU institutions (e.g., [25,26]), which refer to aspects that may fall under energy justice as defined above, such as universal service obligations, requirements of non-discrimination and transparent procedures for consumers (and other market participants), affordable and transparent prices, protection of vulnerable consumers, and energy poverty, among other aspects. These aspects are translated into concrete obligations and values that must be fulfilled by policymakers, network operators, energy suppliers, and other actors in the sector.

Although EU legislation does not specifically refer to energy justice, energy law scholars are increasingly using this notion, as developed by social science literature, as a lens to evaluate existing EU and national laws regulating the energy sector and the energy transition. Energy law researchers have started to acknowledge that energy justice should be the "moral compass" [9] and "overall raison d'être" [16] of energy law as a normative system, and some see in energy justice a specific application of the rule of law in the energy sector [27–29]. This emerging strand of energy law research investigates whether and how the law can aid to realize energy justice and what kinds of legal reforms are necessary to achieve this. This literature includes studies that investigate to what extent EU primary legislation promotes energy justice [21], as well as studies that apply energy justice to topics such as network tariffs [30], energy poverty and the protection of vulnerable consumers [31], the regulation of the heat market [27], energy communities [32], and community benefits in the context of the construction of renewable energy projects [33]. However, superficial attention has been given in energy law research to the energy justice implications of digitalization and the increasing collection and processing of data in the electricity sector. This is different in social science research, as will be explained below.

3.1.2. Energy Justice and the Digitalization of the Electricity Sector

In social science research, there is an emerging strand of energy justice research interested in the issues that arise with the increasing digitalization and datafication in the energy sector. Milchram et al. [17] are among the first authors arguing the importance of applying the concept of energy justice also to smart grids, which they understand as "an umbrella term to capture the digitalization of power systems (focusing on the distribution networks) with the aim to facilitate the transition to more sustainable energy systems" (p. 1245). According to Milchram et al. [17], the convergence between the energy and the information and communication technology (ICT) sectors has as consequence that "ethical challenges including repercussions for energy justice, which are connected to digital systems, become relevant for the energy system" (p. 1247). The authors posit that "energy justice research should be extended by accounting for a broader range of (information technology related) values", such as transparency, control, privacy, and security [17] (p. 1254). This entails, for example, that the examination of distributive justice in the context of smart grids should include aspects such as property and access rights to the data collected in smart grids projects, or that concerns about selection bias in use of algorithms should be studied under procedural justice [17].

Milchram et al. (2020) [18] developed a framework to operationalize and evaluate energy justice in the context of smart grid projects. Their framework is based on the triumvirate of tenets approach described above, but they elaborate the content of each justice tenet taking into account (potential) injustices in smart grid systems identified in Milchram et al. (2018) [17]. In this framework, **distributive justice** encompasses not only the distribution of costs and profits, it includes also aspects related to public funding, knowledge sharing, and data governance. **Recognition justice** pays attention to aspects related to the selection of communities and participants to take part in smart grid projects, as well as how accessible the required technologies are for diverse user groups, and the level of IT literacy required to use the systems of the smart grid project. **Procedural justice** includes aspects related to the participation of users (households) in decision-making processes, both in general and concerning data governance (collection, storage, access, and use of data). It also includes considerations of user control versus automation of the systems used in the projects, and considerations of transparency in general and transparency regarding the use of the data collected in smart grid projects [18].

In recent years, more research has been conducted regarding smart grids and energy justice. Existing research focuses on the (in)justice of smart local energy systems [34,35], domestic demand-side response [36], and variable energy tariffs [37,38]. This literature focuses on smart grids, but does not go into detail about the kinds of technologies used and how they play a particular role regarding energy justice. However, a better understanding of this role can help to inform decisions about future energy systems and the current design of these systems.

Remarkably, there is a lack of research on the implications of the use of AI technologies for energy justice. However, as mentioned earlier, AI technologies are presented as a solution to a range of challenges that the energy transition poses [3]. The developments around machine learning (ML), in particular, have offered promising approaches to addressing these challenges as they are well-suited to deal with high-dimensional, time-varying, non-linear data [39]. At the same time, the way in which AI technologies are designed and used can have implications for energy justice, as we show in the next section.

3.2. AI in the Management of Electricity Systems

To examine how the use of AI interacts with energy justice, we first give a short overview of AI technologies in more detail in this section. Here, we consider AI technologies to refer to a range of technologies that are capable of automated reasoning or learning [40]. Automated reasoning techniques are developed to plan, schedule, or search to, for instance, derive knowledge from sensor data or find the optimal solution for planning tasks. Automated reasoning often involves rule-based systems, but they can also be based on statistical methods. Rule-based systems consist of explicit formalized rules—often expressed in non-numerical symbols—that specify what the system should do.

Automated learning refers to data-driven techniques that make it possible to solve problems that cannot be precisely specified or expressed in explicit rules [2]. Such techniques include artificial neural networks, Bayesian models, and decision trees. These techniques can be used to find patterns, trends, categories, or correlations within (large volumes of) heterogenous data in order to, for instance, predict behavior, process natural language, or classify events. Automated learning techniques include both rule-based systems as well as non-symbolic techniques, such as neural networks and probabilistic or statistical techniques [40,41].

A multitude of AI technologies are applied to electricity systems, including rule-based expert systems, genetic algorithms and machine learning. However, as our aim is to demonstrate the relevance of energy justice considerations to the design and governance of AI in energy systems, we will not give and exhaustive overview but concentrate on ML techniques to explore this relationship in more detail. We have chosen to focus on this subset of AI technologies because it has received increasingly more attention in recent decades as a promising approach to address some of the challenges in current-day energy systems [2,42,43]. Thanks to improvements in methods, computing infrastructure and access to data, the application of these techniques to complex real-world problems using large volumes of heterogeneous data has become a viable approach. In this section, we will give a brief overview of ML techniques and how they are used to address particular challenges in the electricity systems.

There are several different ML methods, each method using different techniques to find some function that optimally maps an input variable to an output variable, given a set of data [39]. Each method will produce a model of the given training data. A good model is able to capture the data to such an extent that it can generalize over new unseen data and predict the appropriate or likely outcome. The different methods can be divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning [39]. Supervised learning techniques make use of labels to learn a function that maps some given input to a desired output or label. It requires that output labels are known when training the model. Supervised learning tends to be applied to high-dimensionality problems with noisy historical data, such as image classification, language recognition, prediction, and forecasting. It has, for instance, been applied to model energy consumption [44]. Unsupervised learning does not require labeled data. That is, an input label does not have to have a given corresponding output label to train the system on. It is used to group data into similar clusters, to find relations between data points, or to reduce the dimensionality of the data space to find some subspace that captures most of the variability in the data. These methods are less common in energy management, but have been used for the development of products and materials [43].

Reinforcement learning techniques follow a sequential process where the results of each action of the algorithm will feedback into the algorithm to gradually improve performance. The algorithm thus learns from the effects on the environment that result from its own actions. This makes these techniques suitable for online process optimization or control in a dynamic environment, such as controlling the charging of a fleet of electric vehicles. Some limitations of reinforcement learning are that it suffers from the curse of dimensionality and had issues with stability.

There are variations of the three categories of ML methods that allow for transfer learning. This entails that models are first partially trained in a setting similar to where they will eventually be deployed, but are then transferred into another setting to be further trained. This kind of technique is useful when in there is not a lot of data for the application domain, or when data cannot be uploaded to a central training server because of privacy or personal data protection reasons.

The choice of a particular method may affect energy justice in different ways. For example, it may affect how much control stakeholders have over their data or the outcome of a coordination mechanism, with implications for procedural justice. Reinforcement learning can adapt to changing environments and is well-equipped for decentralized control in dynamic environments. An advantage of this is that data can be kept locally, allowing for stakeholders to potentially have more control over their own data. However, decentralized control can introduce a new level of complexity, making it harder to interpret the reasons for the behavior of the system and explain why some control measures were taken. This stands in the way of accountability.

The way in which the different methods affect energy justice also depends on the techniques that are used to train models. There are a variety of techniques to train models in either a supervised, unsupervised, or reinforcement learning way. In their overview of the state of the art of ML in energy systems, Mosavi et al. [42] note that there are at least 10 major ML techniques, including artificial neural nets, support vector machines, decision trees, deep learning, and hybrid or ensemble ML techniques. These models differ in various ways and are used differently. For example, decision trees are examples of inductive inference algorithms that extract "if-then-else"-like rules from data. They are used to estimate discrete-valued target functions, such as whether power consumption will be high or low at a certain time in the future. The advantage of these models is that they are more easily interpretable than other techniques, such as neural networks. However, they require discrete values, and can therefore only be used on a specific set of problems. Moreover, they may be less capable of reflecting the complexity of a given underlying problem. Artificial neural networks and deep learning algorithms are used to model complex functions, such as energy consumption per household and weather data [42,45]. They tend to work on historical data and can deal with data from heterogeneous sources. However, they have a high level of complexity and are thus more difficult to interpret than decision trees.

The models reviewed by Mosavi et al. [42] are applied to various problems, such as energy consumption prediction, demand prediction, cost prediction, wind speed estimation, load forecasting, solar radiation prediction, various optimization tasks, power generation forecasting, wind speed forecasting, energy control, peak load management, dynamic energy pricing, and cost minimization. Such applications can contribute to energy justice as they could, for instance, facilitate the integration of renewable energy in the grid, reducing overall energy costs and enabling peer-to-peer sharing between households. The authors note that most research combines several techniques to perform the task at hand. Hybrid models, in particular, perform better in terms of accuracy, user-friendliness, and speed as compared to conventional ML models. These models use several AI techniques and combine them with data preprocessing and optimization tools to produce high accuracy models. These features of hybrid models can be a consideration in addressing energy justice issues, as they may contribute to accountability, transparency, and control.

Besides the possible contributions that the various methods and models can make in support of energy justice, they can also pose challenges for energy justice. Donti and Kotler [2] note several relevant limitations of ML techniques. First, they are highly dependent on the data they are fed: "garbage in, garbage out". They note: "machine learning is fundamentally an amplifier of the system in which it is deployed, meaning that while it is capable of amplyfying the benefits of these systems, it is also equally capable of exacerbating biases, inequities, and market failures through its data, design and applications" [2] (p. 726). In addition, ML techniques have a problem with distribution shift: they are not well suited to deal with situations where the historical data no longer accurately reflect the current state of affairs, which can have implications for recognition justice. Moreover, they have difficulty enforcing any physics or hard constraints associated with the domains in which they operate, such as satisfying power flow equations in power system optimization and control contexts. This, the authors note, may increase operational costs or even lead to blackouts. ML techniques are closely related to statistics and suffer from the same long standing limitations as statical methods that may effect procedural and recognition justice, including that they find correlations instead of causal relationships (see also [46]). Finally, many methods also suffer from a lack of interpretability, which can stand in the way of procedural justice.

Although their direct social and ethical impacts may not always be immediately clear, the choice of a particular algorithm, model, or technique will have different effects on different parties involved when it comes to energy justice. These technologies affect, for example, how energy is distributed or who gets to participate in the decision-making about energy systems. In their discussion of energy justice in smart grids, Milchram et al. (2018) point out that distributive, recognition, and procedural justice are at the core of many benefits and drawbacks of these grids [17]. Those with more access to knowledge, skills, and technology will have a significant head start in making new technologies, such as photovoltaic panels, electrical vehicles (EV), and batteries, work for their benefit, while placing those with less access to those resources further behind. Similarly, ML technologies that facilitate and support these smart grids and electricity networks in general may, for example, contribute to more equitable access of citizens in general to energy networks, but they may also disproportionality benefit more affluent parts of society at the cost of more vulnerable groups.

To show how technical design choices can be relevant for energy justice, we will take a closer look at specific applications of ML technologies for grid management. Concretely, we will consider the three dimensions of energy justice (distributive, procedural, and recognition justice) in the context of the curtailment of solar photovoltaic systems in low voltage networks (hereafter, "PV curtailment"), as this provides an example of the application of ML techniques to address grid management issues that directly impact citizens. When applying the three dimensions of energy justice, we are mindful of the close interrelation between them, as noted by Milchram et al. (2020) [18]. In that sense, we acknowledge that some of the issues we identify below have implications for more than one dimension of energy justice.

3.3. Energy Justice Considerations in the Use of AI for PV Curtailment

PV curtailment is one of multiple strategies to deal with the challenges that the fast growing number of renewable energy sources in low voltage (LV) networks has posed. When the voltage in the LV network becomes too high due to peak generation—for example on sunny days—and low demand, the active power injection of certain PV systems can be temporally decreased to prevent overvoltage [47]. Other strategies include storing excess energy in batteries, electric vehicles or other energy demanding appliances, demand response management through pricing mechanisms, or grid reinforcement. The latter comes with relatively high cost, while introducing more flexibility in the grid through measures such as PV curtailment or demand response can provide more cost-effective solutions. Yet, the costs and benefits of these methods may play out differently for the various actors in the system.

Curtailment is a relatively easy option, but one that can lead to unfair outcomes [47,48]. Those curtailed might lose out on reimbursements for the energy they produced or they have to incur additional costs because they will have to draw energy from the grid. This is the case for the relatively crude mechanism of curtailing systems furthest from the medium voltage to low voltage transformer, where overvoltage is the highest. This creates unfair advantages to those prosumers near to the transformer, as they may still be compensated for their supply of energy or save costs as they can still use their own generated energy. Curtailment can also have consequences for other users, non-users, and the broader public, because curtailment means an overall loss of energy.

To address unfair curtailment, some researchers have used machine learning techniques, such as reinforcement learning, to develop centralized or distributed curtailment strategies that are intended to spread out voltage constraints over the different PV connections to the grid [49,50]. This can be achieved through a centralized control strategy that takes different PV connections into account and computes an optimum at which the total curtailment is minimized, and local voltage issues are mitigated fairly. Yap et al. [51], for example, use a neural network approach to accurately predict curtailed power to determine the optimized inverter power. The neural network learns from historical data, including household power usage and PV power, to predict curtailed power. In this approach all PV inverters are curtailed according to the same percentage. This approach can be computationally expensive and requires considerable transfer of data, including personal data, between the PV connections and the centralized controller, such as data about PV forecasts. Another approach is to perform most of the computations locally at the PV connections and through direct communication between the PVs. Although computationally less expensive and potentially more privacy-friendly, this may come at the cost of finding an overall optimal solution.

Some researchers have attempted to find a balance between centralized and decentralized coordination. Vergara et al. [50] developed a reinforcement learning approach that combines a decentralized architecture with centralized coordination. PV inverters are operated by processes (agents) that perform computations locally and communicate with a central agent to coordinate voltage regulation. Through iterative steps, the best actions for each PV agent are computed at particular time intervals. A PV agent is rewarded for minimizing the power curtailed. This approach assumes that curtailment should be distributed more across the different PV connections, but does not provide an explicit way of doing this fairly. Indeed, the algorithm might reinforce geographic inequalities in the historical data.

Both ML approaches implicitly assume that every PV connection should have the same amount of curtailment. In practice, however, this may turn out to be a too narrow view of fairness. It might be the case, for instance, that those households with more PV panels would benefit more from this strategy than others. Moreover, it might be preferable to make exceptions for certain prosumers, such as individual households. Gebbran et al. [52] introduce a distributed approach, which is not based on ML techniques, that can use different fairness conceptions: egalitarian, proportional, and uniform dynamic photovoltaic curtailment redistribution. Egalitarian redistribution entails that curtailment is distributed equally across all prosumers. The second fairness conception entails that curtailment is distributed proportional to how much a prosumer would be able to feedback into the grid in an uncongested situation. In the uniform dynamic case, the highest power-exporting prosumers are curtailed first. Although Gebbran et al.'s [52] distributed approach does not use ML to implement fair curtailment strategies, it does illustrate that different conceptions of fairness can lead to different outcomes. Moreover, they show that there are trade-offs to be made between the different conceptions of fairness.

Fairness in the approaches discussed is about **distributive justice**. How will the costs and benefits of curtailment be distributed across the different prosumers? Fairness here is narrowly defined in terms of economic costs for prosumers. However, there are also others costs to take into account. Some of these approaches require additional communication infrastructures to enable the communication between local PV agents or other specialized hardware, requiring investments in equipment, which raises questions about (public) funding to cover those costs.

The fair distribution of economic costs says little about what the described approaches mean in terms of other costs and benefits considered under distributive justice, such as knowledge or access to data or energy services. In part, this is because the approaches described are intended to work in the background and will only serve as a small part of the energy management system. The direct relevance of knowledge sharing or data governance is not self-evident. However, design choices made in these approaches can have broader implications for distributive justice in this respect. For example, ML approaches may require additional (more granular) data on household energy uses to forecast PV power. Depending on who controls what happens with the data (including who has access to the data), such approaches can help to empower consumers vis-a-vis energy utility companies. However, they may also lead to overly intrusive data collection and the concentration of knowledge in the utility and technology companies deploying ML solutions in the electricity sector [17,34].

As explained above, there are more aspects to justice than fair distribution of costs and benefits, in particular those aspects associated with **procedural** and **recognition** justice. The choices in the design of an algorithm for curtailment are relevant with regard to **procedural justice** as they affect how transparency and accountability can take shape and the extent to which citizens can participate and control their energy activities. Reinforcement learning can complicate the task of accounting for the decisions made as a distribution of PV curtailment is the result of multiple iterative computing steps that are sensitive to changing contexts. This can make it more difficult to trace and explain the reason why certain actions have been taken. However, some scholars have explored explainability methods to make reinforcement learning approaches interpretable for designers [53]. Such methods may contribute to **procedural justice**.

Accountability is intimately connected to the control that citizens have over the decisions that affect them. The less direct control they have, the more important accountability of decision makers becomes. The approaches described are intended to automate how PV inverters respond to events in the network. They delegate control to these systems to find optimal solutions in a complex network of interacting factors. However, this leaves citizens with little control over what to do with excess energy and places it in the hands of those in charge of the automated systems. Moreover, in the approaches described, the question of who will decide on how to interpret fairness is left to the designers and researchers. From a **procedural justice** point of view, however, the voices of those affected should be somehow represented in this decision making. This highlights the need to consider how mechanisms for deliberation and decision-making in and around the AI technology can enhance procedural fairness. How should multiple voices be included in discussions about how to delegate coordination to automated systems and how should decisions be made? For example, is there room for citizen participation or some form of interest group representation in negotiating values to be built into machine learning models? Moreover, the described approaches raise the question of whether and how citizens can object to such design decisions. To what extent can decisions be reversed or be objected to when they are a built-in element of an algorithm? For a reinforcement-based learning approach, a different fairness measure might mean retraining the algorithm.

Recognition justice also plays a key role in developing just algorithms for renewable energy networks. It is complementary to distribution and procedural justice, as it emphasizes the question of which voices should be included in decision-making about the distribution of costs and benefits of the algorithms and how those voices should be included. Several PV curtailment approaches rely on data about the functioning of the system and also on energy consumption of households. In the approaches described, only those citizens, businesses, or organizations with solar panels are considered. This excludes other relevant stakeholders from consideration. For example, will those that do not own PV panels incur similar benefits and costs in these local networks? The amount of total PV curtailment will affect electricity prices in the grid. A suboptimal total PV curtailment, but with fairer distribution between PV owners, may have negative consequences for the consumers without PV panels. Moreover, the described approaches do not consider what lies behind a PV connection and therefore provide no information on how those behind the connection will be affected by the algorithm. It can be a homeowner with a set of PV panels on their roof, but it might also be a social housing estate or an elderly home. The effects of curtailment may weigh heavier on some stakeholders than on others. The ML algorithms discussed leave no room to consider such disparities.

Finally, as mentioned, PV curtailment is but one of a range of different options to address the effects of a growing penetration of decentralized energy sources in the grid. Other measures will be of influence on any considerations about energy justice in curtailment approaches. Thus, the presence of local batteries or algorithms to coordinate EV charging will affect the performance, the effectiveness, and the fairness of these approaches. In order to understand how design decisions may contribute to or inhibit energy justice, the assumptions underlying the problem definition for the development of ML in energy management must be regularly interrogated.

4. Discussion

As discussed throughout this paper, energy justice is increasingly seen as a normative principle that should guide the energy sector and the decisions taken therein, particularly in the context of the transition to a low-carbon economy. As decision-making tasks in the energy sector are progressively delegated to opaque and complex AI systems, the use of these technologies has implications for energy justice. However, as the discussion of energy justice in energy law and social science shows, operationalizations of the concept in terms of legal norms or design guidelines applied to AI technologies in the energy sector are lacking. This contribution is a first step to filling that gap. In this section, we therefore reflect on the main findings of our analysis regarding the design and regulation of AI technologies to achieve energy justice and set an initial agenda for further research.

In this paper, we first explored the implications of the use of AI technology in smart grids from the perspective of energy justice. As our analysis shows, the implications can be viewed along the **three axes of energy justice**: distributive, procedural, and recognition. The three axes, as discussed in Milchram et al. (2020) [18], provide a framework to consider energy justice in projects related to the smart grid. The framework uses energy justice as an evaluative and normative concept to pinpoint the choices in the design and development of smart grids that can either enhance or limit the ultimate aim of making the benefits of the technologically driven energy transition work for all. We have shown that this tripartite concept is also directly relevant to the design of AI technologies.

We first described the different ML methods and techniques to show that considerations about energy justice not only play out during the deployment phase of an ML-based system but are already relevant in decision-making about the design and development of ML algorithms. The discussion of ML techniques and methods highlights how choices, for instance, between an algorithm that facilitates decentralized control or one that is centralized but more interpretable, can have implications for energy justice along the three dimensions. Decentralized control may empower prosumers to participate in local energy markets and thereby enable them to benefit more from energy generation. However, it may come at the cost of accountability and control over how energy is distributed. The analysis also shows that energy justice considerations can guide the selection of methods and models for particular problems. To contribute to procedural justice, for example, one may opt for the use hybrid models to improve accountability and transparency.

The subsequent analysis of ML techniques applied to PV curtailment demonstrated in more detail how choices, such as which data or which fairness metrics to use, are relevant for energy justice along the three axes. With regard to distributive justice, they can affect how costs and benefits are distributed across relevant stakeholders, including economic costs, but also cost and benefits in terms of power or knowledge. As discussed, a curtailment algorithm may disproportionately benefit some prosumers, in particular those close to the transformer, as compared to those furthest away. ML algorithms can correct this existing inequality, but there are multiple ways of translating fairness into the design of the algorithm. Different approaches will thus have different effects on the costs and benefits of curtailment strategies. With regard to procedural justice, the way that these approaches are designed and implemented is directly related to how much and in what way stakeholders, including prosumers and non-users, can be involved in the choices that directly affect them. The opaqueness, complexity, or their enabling functions, for example, affect the extent to which accountability is possible or whether or not interventions can be made at any time. Finally, in modelling contingent environments, ML techniques are based on abstractions that include or exclude aspects of the world. Such choices have implications for recognition justice, as this may lead to the misrecognition of certain groups and their particular needs. Using more fine-grained data could mitigate this to some extent, but this, too, is not without trade-offs, as it may, for example, lead to privacy and/or personal data protection concerns.

As we have argued in this paper, it is important to take energy justice in consideration from an early stage in the development or design of AI techniques. As an analytical tool, it can help bring potential societal and ethical risks and concerns into view, guide the framing of the problem, and facilitate the selection of the data, algorithms, models, and metrics. It also highlights the need to be aware of the context and the environmental contingencies that affect the performance of AI-based systems as well as their effectiveness and acceptance. Further empirical research in different contexts is, therefore, needed on how this principle can best be operationalized to guide AI development practices.

Another point that should be further explored is the role of the law to prevent or mitigate injustices resulting from the use of AI technologies in the energy sector. As discussed above, energy justice is not yet explicitly recognized as a formal principle of EU energy law. Nevertheless, EU energy law pursues objectives and values that must be safeguarded by policymakers, network operators, energy suppliers, and other actors in the sector, and can therefore guide various energy-related decisions, including in the development and use of AI technologies. Examples of these objectives/values are affordability, consumer empowerment and participation, non-discrimination, and protection of vulnerable consumers, which can be linked to the distributive, procedural, and recognition dimensions of energy justice. However, the lack of an explicit energy law framework requiring that energy justice considerations are taken into account when developing AI technologies might limit the normative reach of this notion.

Looking beyond energy law, including energy justice as a consideration in the design of AI technologies in the energy sector aligns with broader discussions on regulating AI more generally. For example, the EU has taken steps to regulate the development, marketing, and use of AI technologies. The proposed "AI Regulation" [54] includes prohibitions of certain uses of AI, as well as special requirements for high-risk AI systems, such as putting in place a risk management system, requirements related to the (governance of the) data needed to train AI technologies, and requirements concerning transparency and provision of information. The proposed regulation may provide some directions for energy justice considerations as applied to AI technologies, particularly regarding procedural and recognition justice. Interestingly, it lists AI systems used for the management and operation of critical infrastructure (including energy infrastructure) as high-risk, although the scope is limited to AI systems to be used "as safety components". In future research, these connections between energy justice, energy law, and the regulation of AI technologies should be further explored.

This paper set out to bring the twin digital and green transitions together through the lens of energy justice. As these transitions change the way in which energy has been governed, energy justice should be a key consideration in the digitalization of the energy system, even on the level of technical design, to ensure no one is left behind.

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