MY AWESOME PRELIM TITLE

BY

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Abstract

This is a comprehensive study of caffeine consumption by graduate students at the University of Illinois who are in the very final stages of completing their doctoral degrees. A study group of six hundred doctoral students. . . .

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List of Abbreviations

ESOM energy system optimization model 2

LP linear programming 11

MILP mixed-integer linear programming 10

`Osier` Open source multi-objective energy system framework 18

`Temoa` Tools for Energy Model Optimization and Analysis 20

`PyGenesys` Python for Generating Energy Systems 19

`Pymoo` Multi-Objective Optimization in Python 15

HSJ Hop-Skip-Jump algorithm 30

MGA Modeling-to-Generate-Alternatives 14

MOO multi-objective optimization 10

GHG greenhouse gas 5

SP stochastic programming 14

MC Monte Carlo 13

PA parametric analysis 13

NSGA-II Non-Dominated Sorting Genetic Algorithm-II 16

NSGA-III Non-Dominated Sorting Genetic Algorithm-III 24

UNSGA-III Unified Non-Dominated Sorting Genetic Algorithm 24

GA genetic algorithm 16

WS weighted-sum 15

EC ϵ-constraint 15

IPCC International Panel on Climate Change 2

VRE variable renewable energy 7

NRC Nuclear Regulatory Commission 7

CCS carbon capture and storage 5

PVE participatory value evaluation 20

IPCC International Panel on Climate Change 2

UN United Nations 5

GVA gross value added 18

GDP gross domestic product 18

WTP willingness to pay 20

WPE weighted permutation entropy 28

IGD+ inverted generational distance plus 26

`DEAP` Deep Evolutionary Algorithms in Python 26

UIUC University of Illinois Urbana-Champaign 33

Chapter 1

Motivation and Introduction

Chapter 2

Literature Review

Every year, world leaders meet to discuss plans to address climate change at the COP summit (cite). In 1995, world leaders established a set of targets with the Kyoto Protocol (cite) and again with the 2016 Paris Climate Agreement. Every few years, the United Nations releases a report from the International Panel on Climate Change (IPCC) assessing the current impacts of climate change and forecasting future scenarios. Most of the world understands that anthropogenic climate change is an existential threat to society. Indeed, many studies in the energy system optimization model (ESOM) literature begin with a statement about the urgency of climate change. This chapter reviews the extant literature for both quantitative and qualitative analyses of the problem considered in this thesis – primarily bridging the gap between feasibility or planning studies to address the climate crisis and the current pattern of missed targets and growing carbon emissions. First, I draw from the risk assessment literature to characterize and situate the problem of climate change and demonstrate the necessity of a holistic analysis. Second, I build upon the central issue of disproportionality of climate change risk by reviewing the energy and environmental justice literature. Third, I develop an encompassing definition of an "energy system" using technical and social perspectives. Finally, I review the energy system literature for gaps in conventional modeling practices and identify previous attempts to incorporate social science and justice concepts into energy system models.

2.1 Characterizing the Problem of Climate Change

Risk is generally understood as the "potential for adverse consequences" [1]. However, due to the complexity of climate change, the IPCC developed a three-tenet framework to discuss risk [1]: hazard, exposure, and vulnerability. *Hazards* are mediated by physical features, such as climate and topography [2], [3]. Climate change is already producing more significant hazards, like forest fires, hurricanes, storms, floods, droughts, and heat waves [4]–[6]. *Exposure* refers to the scale and duration of the subjection of people, infrastructure, and social wealth to a particular hazard [1], [3], [7]. *Vulnerability* is the ability of a system to cope, recover, and adapt after exposure to a hazard. Although climate change is a worldwide phenomenon, vulnerabilities to its hazards are not uniformly distributed. On the contrary, the people and communities most likely to be harmed by climate change are already harmed by social inequities [8]. Recent work from Simpson et al. [3] expanded on this definition of risk by including *responses* to risk as itself a driver of risk. This framework is illustrated in Figure 2.1 using infrastructure risk as an instructive example. Considering the actions taken (or not) in response to climate change is vital for a holistic understanding of risk because it encompasses benefits

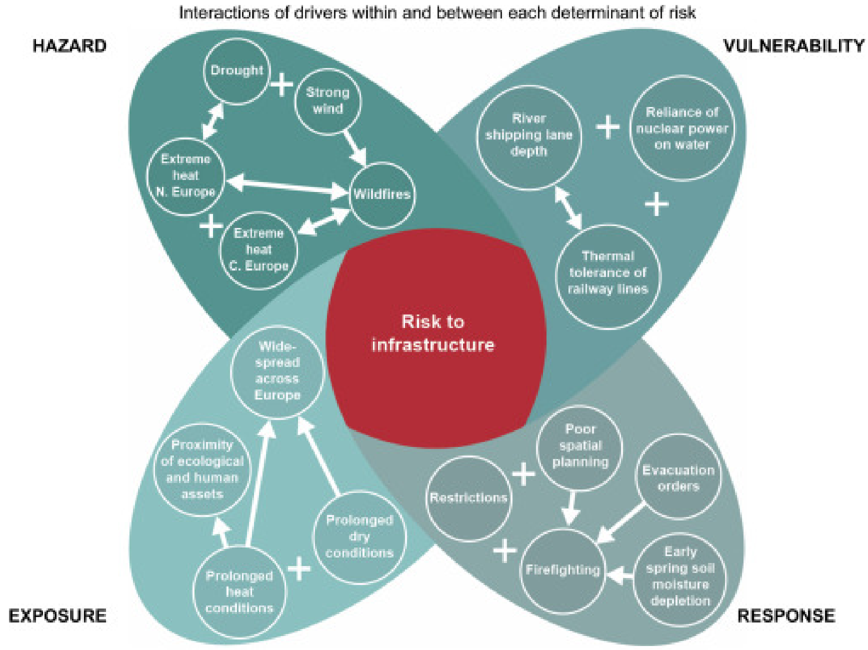

Figure 2.1: A framework for decomposing risk into its parts: hazard, exposure, vulnerability, and response, using risk to infrastructure as an illustrative example. Reproduced from Simpson et al. (2021) [3].

and mitigating outcomes, not just negative, inflammatory ones. Additionally, heterogeneous stakeholders perceive the costs and benefits of (in)action differently. Therefore, including response as a driver of risk is essential for making choices more transparent and actionable within decision-making structures [3]. Responses to climate change risk come in myriad forms, and at multiple scales, from individual choices (e.g., demand response) [9]–[11] to community responses [12], [13], and national level policies [14], [15]. Paterson and Charles [12] developed a descriptive typology for community-based hazard responses that also applies to national and global scales. The five response categories making up this typology are: [12]

1. individual and material well-being, which seek to meet individuals' basic needs such as food, water, and shelter, as well as livelihood and health.
2. relational well-being emphasizes community and support networks and could include evacuation or relocation.
3. awareness involves monitoring and stock-taking of potential hazards.
4. governance relates to decision-making structures around human-hazard interactions.
5. infrastructure refers to the physical defense against hazards using engineered tools or ecological characteristics.

Figure 2.2 shows the breakdown of the categories. Although this framework could help assess policies to mitigate climate change, these response categories are related to specific climatic hazards rather than climate change mitigation.

Based on the net-zero carbon emissions target set by the 2016 Paris Agreement, myriad countries, states, and companies have set climate policies covering two-thirds of the global economy [16]. Reducing CO_2 (or

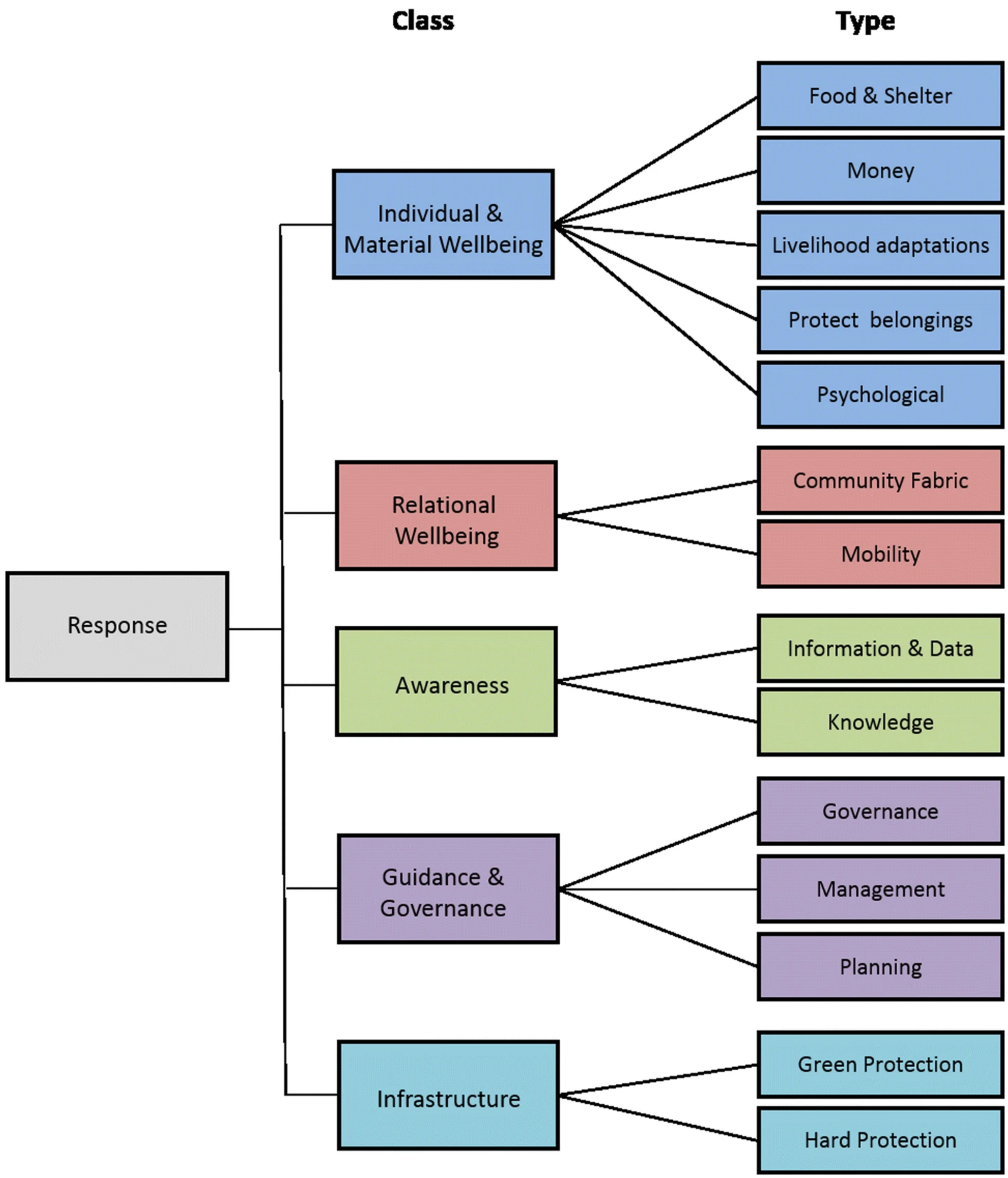

Figure 2.2: A categorization schema for various responses to climate risks. Reproduced from Paterson et al. (2019) [12].

CO_{2eq} in some cases) emissions is the primary focus for most of these policies [14]–[16], which includes the following broad strategies [15]:

1. Reducing greenhouse gas (GHG) emissions by transitioning from fossil-fueled to clean energy.
2. Removing CO_2 from the atmosphere using carbon capture and storage (CCS) and other sequestration techniques.
3. Altering the Earth's energy balance by increasing its albedo and other geoengineering concepts.

Despite this, only around five percent of these policies are considered robust according to their consistency with the United Nations (UN) "Race to Zero" campaign [16]. Further, even the full implementation of national climate policies leaves approximately a 28 $GtCO_{2eq}$ gap in GHG emissions [14]. This gap and the fundamental assumptions about carbon sequestration from the 2016 Paris Agreement suggest that the world is on track to overshoot these emissions targets [14], [17]. Carley et al. (2018) developed a quantitative framework for assessing the vulnerabilities associated with energy policies or responses [18].

Risk analysis is the first step to a complete understanding of the climate crisis. The literature on disproportionality further distinguishes *risks* and *impacts* [2]. Consistent with previous work, a risk is the aggregate of hazards, exposures, vulnerabilities, and responses. Impacts, then, are the realizations of risk in terms of loss and damages. This distinction is essential. Responses to *impacts* are always made *ex post facto*. Differences in vulnerability to a hazard, often arbitrated by socio-economic status, manifest as differential impacts. Access to resources conditions an individual's or community's ability to respond to the impacts of a hazard. Since losses from impacts disproportionately affect those with the fewest resources, their vulnerability to future hazards increases in a "vicious cycle" [2], [8]. In purely economic terms, studies estimate the loss of ecosystem services from land use change associated with climate change and other human activities at $4 - $20 trillion per year (in 2011 $US) globally, [19] and the poorest third of U.S. counties will experience financial damages between 2 and 20 percent of their annual income [20]. However, impacts also have cultural and psychological dimensions [2] that cannot be captured by accounting for "externalities."

Dorkenoo et al. [2] establish *burdens*, injustices arising from social, political, or economic power imbalances, as a third theme paramount for a holistic understanding of disproportionality. Burdens influence all aspects of risk and affect access to resources which condition impacts. Dorkenoo et al. wrote, "[p]rocesses of marginalization and exclusion influenced by power struggles [...] influence the distribution of burdens and consequently responsibilities, in addition to the different dimensions of climate risk (hazard, exposure, vulnerability [, response])" [2]. Figure 2.3 demonstrates the mutually reinforcing relationships among risks, impacts, and burdens. A particularly relevant example of burden is the persistence of energy burden, where low-income households pay the highest percentage of their income on energy bills relative to other income groups [21], [22]. Energy burden interferes with electricity access, thereby increasing vulnerability to extreme heat events [22], [23]. The risk assessment literature and the energy system modeling literature typically adopt an apolitical framing of vulnerabilities. However, inequities do not arise in a vacuum but through processes of marginalization and exclusion [24]. Often the distribution of burdens falls along class, race, and gendered lines [24], [25]. Research on siting patterns of polluting facilities indicates these projects frequently developed in areas with people of color and low-income populations [25]. Pollution from these facilities creates additional burdens for nearby communities. The energy justice and environmental justice literature offer insights to contrast this neutral framing and facilitate normative questions about alternative distributions [2], [24].

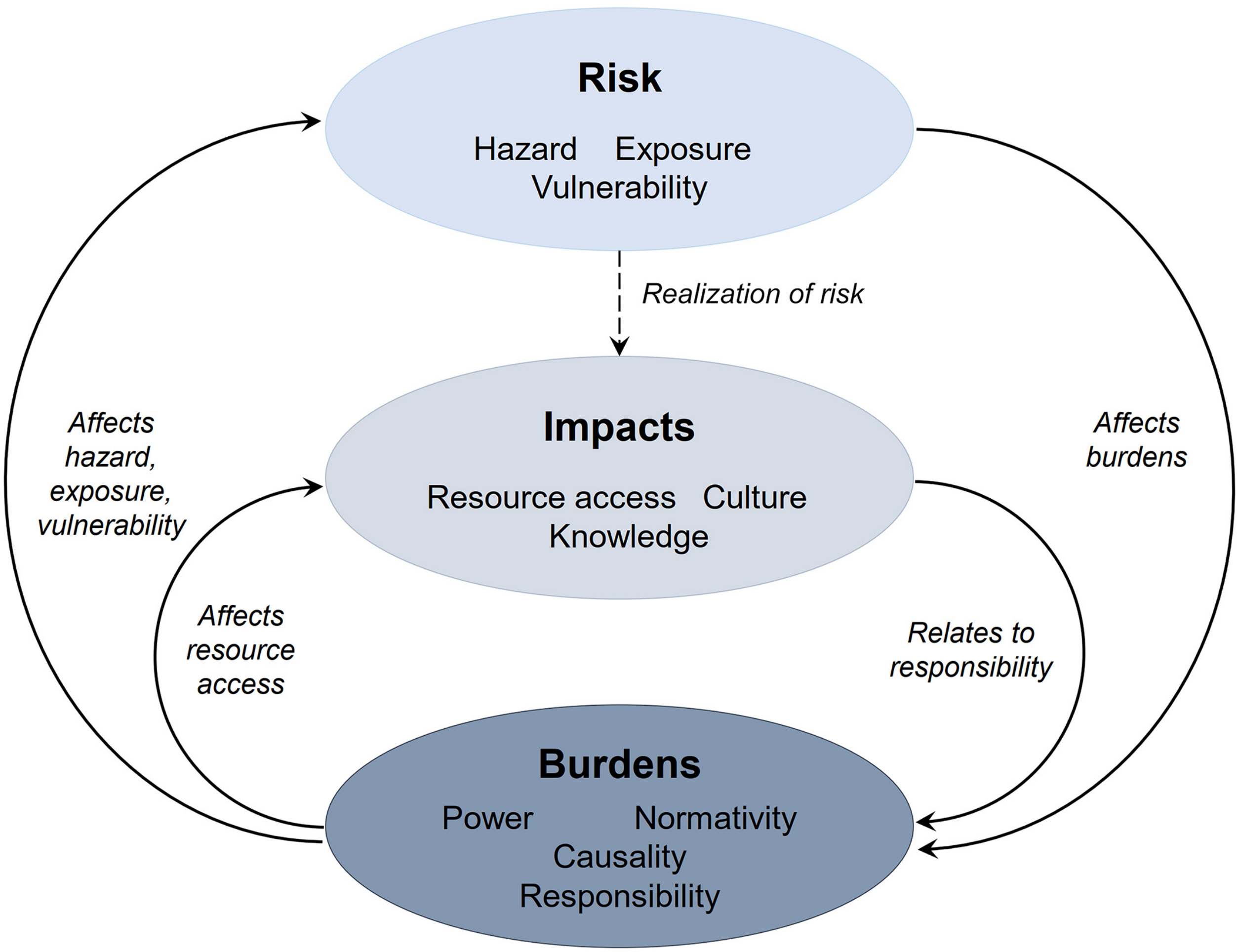

Figure 2.3: The relationships among risks, impacts, and burdens. Reproduced from Dorkenoo et al. (2022) [2].

2.2 Climate and Energy Systems

Climate change is driven by GHGs, a significant byproduct of the infrastructure that creates, delivers, and consumes energy (i.e., energy infrastructure). Specifically due to the fraction of carbon emissions already coming from electricity generation (25 percent in the United States [26]) and the total decarbonization of the global economy requiring electrification of other sectors, such as transportation and heat, thereby increasing the electricity demand, even when accounting for efficiency improvements [27], [28], decarbonizing our electricity production is one of the most critical issues to resolve climate change. Therefore, producing electricity with zero GHGs will initiate a cascade of deeper decarbonization throughout the economy but will require expanded electrical infrastructure. Accelerating the adoption of clean energy technology is essential for achieving a stable climate [14], [17].

2.2.1 Technical Solutions to Energy Decarbonization

Many studies show that global and local economies can be supported by 100% variable renewable energy (VRE), such as wind, hydro, and solar power [29]–[41]. Yet some countries that transition to majority VRE observe higher carbon emissions or a slower-than-expected reduction due to greater dependence on natural gas [42]. Other studies demonstrate that firm baseload power, such as nuclear power, is necessary for the deep decarbonization of our energy systems [42]–[54]. While some countries are building new nuclear reactors, and the Nuclear Regulatory Commission (NRC) just approved the first small modular reactor design from NuScale [55], other places are shutting down their operating nuclear plants [56]. Further, the only examples of highly decarbonized electrical grids are places with a high penetration of hydro or nuclear power and the former is widely considered exhausted. There is nearly universal agreement that decarbonizing electricity requires phasing out fossil-fueled power plants and a significant expansion of clean electricity generators. Although many studies show the *feasibility* of a variety of energy mixes, the following is strongly debated in the literature.

1. Whether energy systems should be 100% renewable or if nuclear power and CCS should be included [13], [35], [43], [57].

2. What the role of distributed and decentralized energy sources in expanding our energy infrastructure should be [10], [58]–[64].

The strength of the technical arguments on both sides of these discussions combined with the distinct lack of sufficient policy agendas pursuing any of them [14], [16], suggests the existence of poorly articulated trade-offs and that technical solutions cannot be assessed from an engineering perspective, alone. Some researchers and policymakers disagree on technical grounds, while others disagree on the basis of institutional or systemic injustices. There are also differences in values. Indeed, the cultural theory of risk argues that our social constructions, rather than risks themselves, dictate what threats are recognized and their corresponding liabilities and benefits [65], [66]. Clean technologies like nuclear power and renewables, such as solar or wind power, are not only different in how they produce electricity but also in the values and paradigms they represent. Sometimes, communication fails because the question being discussed is not agreed upon either. Often, feasibility studies address the positivist question, "what is the least-cost pathway to the energy transition," while others consider more normative questions, such as "how should we proceed equitably?" Normative questions are qualitative and, therefore, inherently challenging to answer and require the application of ethics. Indeed there are many more normative questions than positive ones. Is perfect the enemy of good? How do we balance stakeholder preferences, upstream and downstream effects, and the necessity to respond quickly to climate change? Will this mix of influences lead to paralysis or inaction? Given climate change's complex, interacting, and disproportionate nature, engineering alone is ill-equipped to resolve the problem. Ideas from the environmental and energy justice literature offer a social perspective for addressing the risks and impacts of climate change hazards.

2.2.2 Energy Justice

Energy justice is a conceptual and analytical tool regarding the ethical or normative dimensions of energy systems and addresses the systemic causes of burdens, and inequities [67].

There are many conceptions of justice; however, the most popular framework for understanding justice is a three-faceted approach originating from David Schlosberg: distributional, recognitional, and procedural justice [68]. Distributional justice relates to the fair distribution of resources, burdens, and responsibilities. Studies on distributional justice seek to address the normative question: how should a just society distribute the benefits it produces and *the burdens required to maintain it* [69]. Additionally, distributional justice considers *how* poor distributions are created [68]. Procedural (in)justice is defined as the presence of (un)fair and (in)equitable institutional processes of the state [68]. In other words, how decisions of societal import are made and who is involved in those decisions. Sovacool and Dworkin (2015) outline four elements of procedural justice: transparency, meaningful participation, impartiality, and avenues for redress [67]. Justice of recognition is the vaguest of the three tenets of justice and is frequently reduced to a component of either distribution or procedural justice [68], [70]. A common argument for this consolidation is that recognition is a precondition for achieving distributional justice or that achieving procedural justice necessarily includes recognition [68]. However, recognition is unique from distributive and procedural justices because it is concerned with a different family of injustice, namely, *misrecognition* [70]. van Uffelen (2022) suggests a nuanced definition of recognition justice as "the adequate recognition of all actors through love, law, and the status order" [70]. Sovacool and Dworkin (2015) offer a framework for assessing energy policies from a justice perspective. Table 2.1 map the relationships between justice-as-a-decision-making-tool from Sovacool & Dworkin, Paterson's hazard response characterization, and Schlosberg's triumvirate of justice.

Table 2.1: Different ways to operationalize justice concepts.

Schlosberg [68]	Sovacool & Dworkin [67]	Paterson et al. [12]
Distribution	Intragenerational Equity Intergenerational Equity Responsibility	Material Well-being Infrastructure
Procedure	Due Process Good Governance	Awareness Governance
Recognition	Availability[1] Affordability[1] Sustainability[1]	Relational Well-being

[1] van Uffelen [70] argues for this categorization.

Although Sovacool & Dworkin do not explicitly discuss recognition justice, it is a unique aspect of justice that can still be useful for contextualizing their recommendations. For example, due to the psychological pressures introduced by a lack of access to energy, either due to infrastructure or cost, interrupts relational well-being and is an injustice [70]. Further, (un)sustainable policies may be considered a misrecognition of the humanity of future generations.

Next, I examine the specific ways the social science literature understands how energy systems and their infrastructure (artifacts) contribute to the distribution of burdens.

2.2.3 Boundaries of Energy Systems

Previous work defined energy systems in purely technical terms as spatially, temporally, and topologically complex machines that coordinate the supply and demand of energy, especially electricity [48]. However, this definition neglects the ways energy systems may be used to construct and maintain power relations that contribute to inequitable distributions of burdens. Energy access is necessary to support complex modern economies and therefore possesses political power [71], [72]. The literature on the political economy of energy infrastructure locates this political influence in five distinct ways [72]. First, energy infrastructure affects competition and collaboration among nation-states in the geo-political sphere. The current situation in Ukraine makes this especially salient [73].

The second subset of the literature focuses on the process of energy infrastructure development and how these processes create social inequities. For example, energy policies that subsidize residential solar panels have not led to more equitable adoption of solar energy, with greater adoption in areas with higher income, among other social indicators [74]. Other popular arguments in favor of renewable energy assert that these energy sources are necessarily more egalitarian because the Sun and the wind cannot be (or have not yet been) privatized. Another is the urgency of climate change. While true, ignores or minimizes the potential environmental and social consequences of energy planning that does not consider energy justice [71]. Large-scale energy projects in the Global South have already led to the dispossession of nearby indigenous communities and other key actors [75], [76].

Third, the development of energy infrastructure is not simply conducted via policy measures, but also in the manner governments activate the public imagination in favor of these policies [72], [77]. Jasanoff and Kim (2009) articulate this concept as 'socio-technical imaginaries,' which are simultaneously descriptive and prescriptive of possible energy futures established by governments in the national zeitgeist [77]. This concept is demonstrated by the discourse surrounding nuclear energy in the United States and South Korea [77] as well as in Japan [78]. Governments can employ 'grand narratives' related to national security, climate change, or modernization to enhance public support while minimizing genuine participation [72].

Fourth, the political power of energy infrastructure can be traced further to the cultural values and policy choices embedded in the design and operation of seemingly technical systems [72]. In other words, the design and implementation of energy infrastructure may be used as a vehicle for apparently unrelated agendas, a form of "policy-making by other means" [72], [79]. Edwards and Hecht (2010) refer to the co-constitution of technological and political order as '*technopolitics*,' demonstrating the tangible material and political outcomes of technological systems [80].

Finally, energy systems and their infrastructure possess a unifying quality through which new political identities may evolve [72].

From these various perspectives, we can observe that confining an energy system to its technical characteristics is woefully incomplete. I propose that an energy system is a spatially, temporally, and topologically complex machine that coordinates the supply and demand of energy and acts as an important mediator of burdens that influence climate change risk. This thesis takes the important step of analyzing energy system planning and policy with this expanded definition.

The next section reviews current attempts to model energy systems and identifies gaps in conventional methods.

2.3 Modeling Energy Systems

ESOMs have several possible purposes such as forecasting future quantities, generating insight for policy development, or energy system planning for scheduling and acquisition [81], [82]. However, analyses using currently available ESOMs seldom consider the role of energy systems in creating and maintaining inequitable distributions of burdens. Table 2.2 summarizes the capabilities for a comprehensive list of energy system analysis tools. These tools are approximately sorted by mathematical formulation, e.g. explicit optimization or simulation. The "mixed-integer linear programming (MILP)" column indicates whether the framework uses a linear-programming approach to optimize an objective function. The "objective" column specifies the nature of the objective function if one exists. "Cost" objectives minimize total or annual energy costs, while "welfare" maximizes social welfare. Some entries have more than one objective listed. This means users may choose which objective to optimize. None of the tools in Table 2.2 are designed to handle simultaneous optimization (i.e., multi-objective optimization (MOO)). For those modeling frameworks that have an "objective" in Table 2.2, virtually all of them optimize system costs. EnergyScope is the only exception to this, which allows users to optimize GHG emissions. [83]. The "uncertainty" column indicates a feature to algorithmically generate model runs for testing either parametric or structural uncertainties. For example, EnergyScope is *suitable* for uncertainty analysis (i.e., many runs are computationally tractable) but does not have any built- in capabilities [83]. Some tools, such as NEMS [84], incorporate uncertainty into their calculations via learning curves. However, these learning curves require assumptions about learning factors and technological "optimism" – which are themselves uncertain [84]. Table 2.2 also indicates whether the tool is a "public code." This simply means users can download and inspect the source code. Other considerations for openness, such as licensing and development, vary among the listed frameworks. The other columns simply indicate the existence of particular features rather than the relative maturity or sophistication of each feature.

Frameworks, such as MEDEAS [85], and MultiMod [86], are general equilibrium models which embed energy systems within the macro-economy and facilitate the modeling of strategic behavior. The latter formulates a non-linear problem with the Karush-Kuhn-Tucker optimality condition [86], as opposed to more traditional linear programming methods. Models of this type are helpful for analyzing the economy-wide influence of policies but lack sufficient operational detail to be prescriptive for energy system planning.

Agent-based models are useful for modeling the market behaviors of different actors, such as firms (which produce power), transmission operators, and consumers. The latter category is typically aggregated for tractability. Modeled behaviors include technology preferences [87], [88], risk aversion [87], financial characteristics [87], [89], and information asymmetry among agents [87], [89]. Due to agent heterogeneity, agent-based models are considered useful for capturing social phenomena [82], [90].

A further set of tools focus on simulating power flow and demand fluctuations. CAPOW [91] generates synthetic data with statistical methods to explore uncertainties in energy dispatch and extreme demand events, but does not include any investment optimization based on these uncertainties. CESAR-P, SAM, Demod, and DESSTinEE focus on modeling demand profiles [92]–[94]. CESAR-P models individual building demand for energy based on the physical parameters of the building. However, it has no dispatch or investment optimization capabilities. Other tools such as Pandapower, GridCal, and SciGRID power model the infrastructure aspects of electricity systems – transmission and distribution – rather than the optimal dispatch of electricity producers [95]–[97].

2.3.1 Economic Dispatch and Social Welfare

Linear programming (LP) or MILP are the dominant optimization approaches among the frameworks in Table 2.2. Economic dispatch models optimize the power output of *dispatchable* generators in a model system [33], [152]. They all share the same fundamental formulation.

Minimize

$$F(x) = \sum_i C_i x_i \tag{2.1}$$

subject to,

$$g(x,p) \leq 0.$$
$$x \in \vec{X}$$

where

$\vec{X}$ is the set of decision variables,

C_i is the *i-th* cost,

g is some linear inequality constraint.

The exact formulation of Equation 2.1 may vary slightly across models, but the objective for most economic dispatch models is to minimize total cost. The near universality of a cost-based objective function comes from the concept of *social welfare maximization*. This concept is illustrated in Figure 2.4.

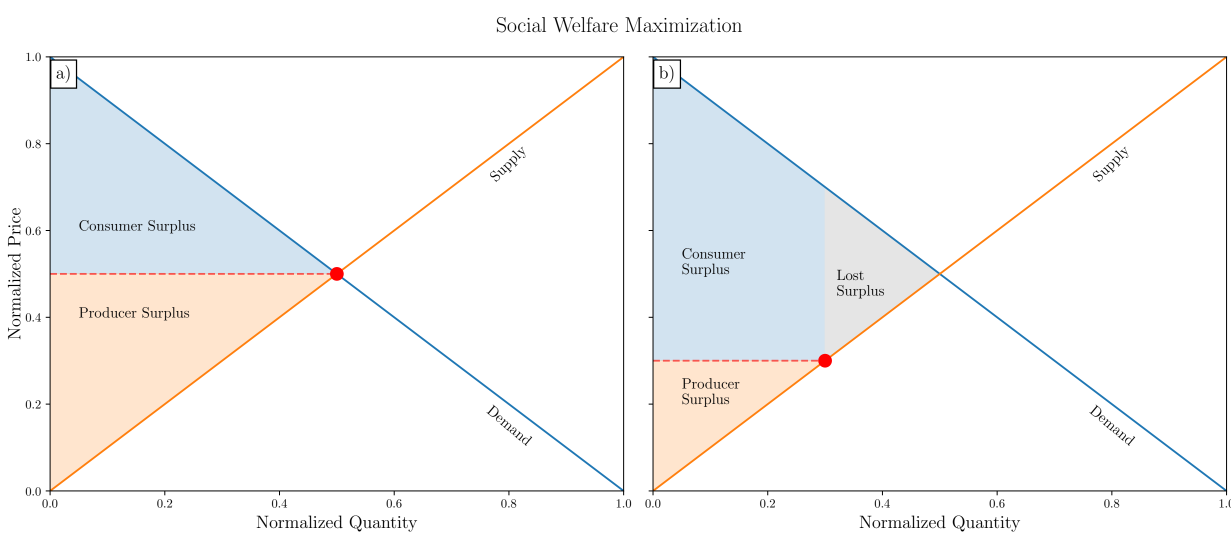

Figure 2.4: Demonstration of "social welfare maximization." Plot a) shows the total surplus when the price is at equilibrium. Plot b) shows the total surplus when the price is artificially depressed.

Table 2.2: Summary of ESOM frameworks.

Model	Citation	math model type	MILP	Objective	Transmission	Sector			Investment	Physical	Forecasting	Agent	Uncertainty	Public
						Heat	Electric	Transport	Optimization	Models		Based	Analysis	Code
AnyMOD	[98]	Optimization	✓	Cost		✓	✓		✓					✓
Backbone	[99]	Optimization	✓	Cost	✓	✓	✓	✓	✓		✓		SP	✓
Balmorel	[100]	Optimization	✓	Cost	✓		✓		✓					✓
Calliope	[101]	Optimization	✓	Cost		✓	✓	✓	✓					✓
CapacityExpansion	[102]	Optimization	✓	Cost	✓		✓		✓					✓
DIETER	[103]	Optimization	✓	Cost		✓	✓		✓					✓
Dispa-SET	[104]	Optimization	✓	Cost	✓		✓		✓					✓
ELMOD	[105]	Optimization	✓	Welfare	✓		✓		✓					✓
ELTRAMOD	[106]	Optimization	✓	Cost			✓		✓					
EMMA	[107]	Optimization	✓	Cost			✓		✓					✓
EOLES elec	[108]	Optimization	✓	Cost			✓		✓					✓
ESME	[109]	Optimization	✓	Cost		✓	✓	✓	✓				MC	
ESO-X	[110]	Optimization	✓	Cost			✓		✓					✓
EnergyRt	[111]	Optimization	✓	Cost			✓		✓					✓
EnergyScope	[83]	Optimization	✓	Cost, GHG		✓	✓	✓	✓					✓
Ficus	[112]	Optimization	✓	Cost			✓		✓					✓
FlexiGIS	[113]	Optimization	✓	Cost		✓	✓	✓						✓
GAMAMOD-DE	[114]	Optimization	✓	Cost			✓		✓					
GenX	[115]	Optimization	✓	Cost	✓		✓		✓				MGA	✓
GRIMSEL-FLEX	[10]	Optimization	✓	Cost		✓	✓		✓	✓				✓
HighRES	[116]	Optimization	✓	Cost		✓	✓		✓					
MARKAL	[117]	Optimization	✓	Cost		✓	✓	✓	✓				MC, SP	✓
METIS	[118]	Optimization	✓	Cost	✓	✓	✓		✓				MC	✓
Medea	[119]	Optimization	✓	Cost			✓		✓					✓
Oemof	[120]	Optimization	✓	Cost		✓	✓	✓	✓					✓
OPERA	[121]	Optimization	✓	Cost	✓	✓	✓		✓					✓
OSeMOSYS	[122]	Optimization	✓	Cost		✓	✓	✓	✓					✓
OnSSET	[123]	Optimization	✓	Cost	✓		✓		✓					✓
PLEXOS	[124]	Optimization	✓	Cost			✓		✓				MC	
POLES	[125]	Optimization	✓	Cost			✓		✓					
POMATO	[126]	Optimization	✓	Cost	✓	✓	✓							✓
PRIMES	[127]	Optimization	✓	Cost	✓	✓	✓	✓	✓					
PyPSA	[128]	Optimization	✓	Cost	✓	✓	✓	✓	✓	✓			MGA	✓
REMix	[129]	Optimization	✓	Cost	✓	✓	✓	✓	✓					✓
REopt	[130]	Optimization	✓	Cost		✓	✓		✓					✓
StELMOD	[131]	Optimization	✓	Cost	✓		✓		✓					✓
Switch	[132]	Optimization	✓	Cost	✓	✓	✓	✓	✓					✓
TIMES	[133]	Optimization	✓	Cost, Welfare		✓	✓		✓				SP	✓
Temoa	[134]	Optimization	✓	Cost		✓	✓	✓	✓				MGA, MC, SP	✓
TransiEnt	[135]	Simulation	✓	Cost	✓	✓	✓							✓
URBS	[136]	Optimization	✓	Cost	✓	✓	✓	✓	✓					✓
Genesys	[34]	Optimization and Simulation		Cost			✓		✓					
OpenTUMFlex	[88]	Optimization and Simulation	✓	Cost		✓	✓	✓			✓			✓
PowNet	[137]	Optimization and Simulation	✓	Cost	✓		✓			✓				✓
Renpass	[138]	Optimization and Simulation		Cost			✓							✓
SimSEE	[139]	Optimization and Simulation		Cost			✓			✓				✓
MEDEAS	[85]	Other				✓	✓	✓		✓			MC	✓
MultiMod	[86]	Other		Welfare	✓	✓	✓	✓	✓					
NEMS	[84]	Other	✓	Cost	✓	✓	✓	✓	✓		✓			
Breakthrough Energy Model	[140]	Simulation			✓		✓		✓					✓
CAPOW	[91]	Simulation	✓	Cost	✓		✓				✓		✓	✓
CESAR-P	[92]	Simulation					✓			✓	✓			✓
DESSTinEE	[93]	Simulation	✓	Cost	✓	✓	✓			✓				✓
Demod	[94]	Simulation				✓	✓			✓	✓		MC	✓
EMLab-Generation	[141]	Simulation		Cost			✓		✓				MC	✓
EnergyPLAN	[142]	Simulation		Cost	✓	✓	✓	✓	✓					
Energy Transition Model	[143]	Simulation					✓							✓
GridCal	[96]	Simulation			✓					✓				✓
LoadProfileGenerator	[144]	Simulation				✓	✓			✓	✓	✓		✓
Pandapower	[95]	Simulation			✓					✓				✓
Pvlib	[145]	Simulation				✓				✓	✓			✓
PyLESA	[146]	Simulation		Cost	✓		✓	✓		✓				✓
SAM	[147]	Simulation								✓	✓		PA	✓
SciGRID power	[97]	Simulation			✓		✓							✓
SimSES	[148]	Simulation					✓			✓				✓
AMIRIS	[89]	Simulation and Agent-based					✓		✓			✓		✓
ASAM	[149]	Simulation and Agent-based			✓		✓					✓		✓
EMIS-AS	[87]	Simulation and Agent-based	✓	Welfare	✓		✓					✓	✓	✓
Lemlab	[150]	Simulation and Agent-based	✓	Welfare			✓					✓		✓
MOCES	[151]	Simulation and Agent-based		Cost			✓			✓		✓		

In microeconomics, social welfare is identical to the sum of consumer and producer surplus. Therefore social welfare is maximized when the sum of these two quantities is maximized. Figure 2.4 shows this case on the left panel. However, suppose an economic policy capped the price of some product at a price lower than the equilibrium price. In that case, the consumer surplus expands, and the producer surplus contracts, as shown in the right panel of Figure 2.4. Nobody receives the "lost surplus" because suppliers do not produce more despite unmet demand for the product because the price is capped. Typically, modeling tools consolidate the demand curve to a single value. In this case, social welfare maximization is approximated by minimizing the total cost of energy [141]. This simplification is valid because demand for energy is highly inelastic [110], [153]–[155]. Figure 2.5 shows the impact of highly inelastic demand.

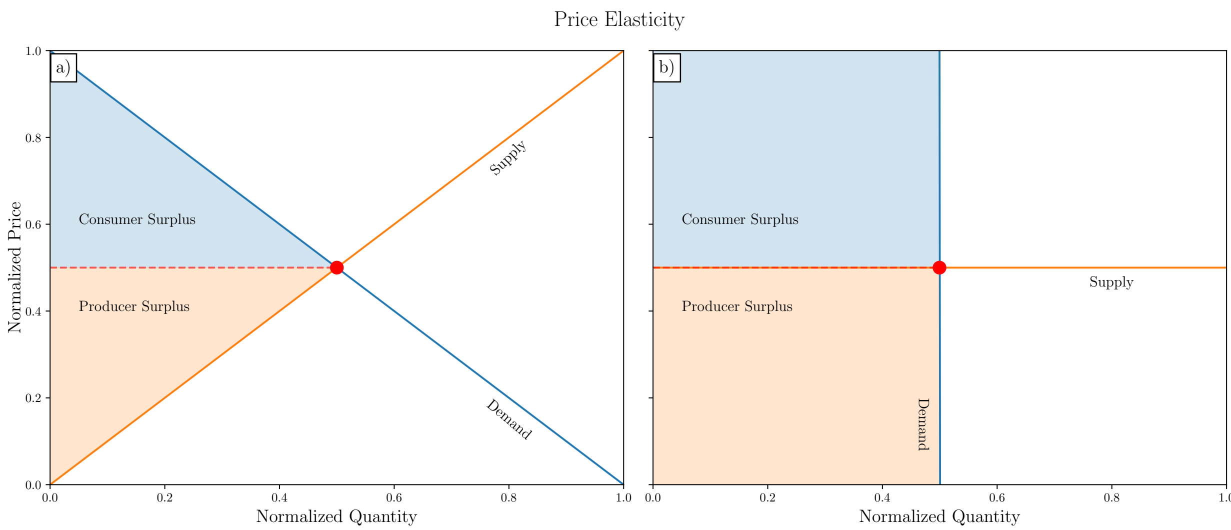

Figure 2.5: Demonstration of "price elasticity." Plot a) shows a typical supply-demand curve where changes in price lead to proportional changes in demand. Plot b) shows an inelastic demand where consumption does not change proportionally with price.

For an elastic good supply and demand are in proportion with each other. An increase in the supply leads to a proportional increase in demand via a reduced price, eventually returning to an equilibrium price (shown in Figure 2.5a). However, as Figure 2.5b demonstrates, an inelastic demand does not respond proportionally to changes in price, such that consumers become "price- takers," paying the price set by producers. Importantly, in the latter case consumer surplus is infinite and minimizing the energy cost through policy mechanisms does not create a lost surplus as shown in Figure 2.4b. Since electricity demand is highly inelastic, economic dispatch models minimize the cost of generating electricity. Although optimizing welfare, rather than the total cost, is useful for disaggregating multiple demands for the same commodity [105], this thesis adopts the former, simplified, approach to economic dispatch.

2.3.2 Accounting for Uncertainty

Due to the complexity of our energy system, handling uncertainty is one of the most important features for ESOMs [81], [82]. There are broadly two types of uncertainties: parametric and structural. The former method refers to uncertainty around the value of some empirical quantity (e.g. price of fuel or the discount rate). In many cases, these quantities are better represented by *distributions* which may be sampled using formal methods like Monte Carlo (MC) or parametric analysis (PA) [82], [156]. Deterministic codes such as

TEMOA, TIMES, or ESME use these techniques to generate many model runs. Another method for handling parametric uncertainty is stochastic programming (SP), where parameters are replaced with non-linear risk functions [82], [157]. Although parametric uncertainty is important the analysis of uncertain values is not a focus of this thesis.

Structural uncertainty relates to *unmodeled objectives* [81], [82], [158]. There are few formal methods to address structural uncertainty due to its qualitative nature. The most common approach to handling this type of uncertainty is using Modeling-to-Generate-Alternatives (MGA) to probe the near-optimal decision space [33], [81], [115], [156], [159]. DeCarolis wrote, "[p]olicy-makers often have strong concerns outside the scope of most models (e.g., political feasibility, permitting and regulation, and timing of action), which implies that feasible, sub-optimal solutions may be preferable for reasons that are difficult to quantify in energy economy optimization models" [81]. Therefore, an "optimal solution" may lie in the model's inferior space [81]. Section 3.5.1 details the implementation of MGA. However, this approach still requires an objective function, and the sub-optimal space is still within some tolerance of the optimal value. Further, the solutions generated by MGA still admit bias from policy-makers and does not require users to consider the equity implications of these alternative solutions.

Another strategy to handle structural uncertainty is optimizing multiple objectives simultaneously. However, some researchers dismissed this approach for the following reasons [81]:

1. structural uncertainty will always exist, regardless of the number of modeled objectives;
2. traditional MOO enables the exploration of the Pareto-front, but not the near-optimal space;
3. analyzing tradeoffs for problems with many objectives is tedious.

These critiques may explain the distinct lack of frameworks that apply MOO for energy system problems. However, there are important benefits to MOO, and the lack of an energy system *framework* to apply this technique is one of the gaps this thesis fulfills.

2.4 Multi-objective optimization

A multi-objective problem may be formulated as

$$\min \quad \{F_1(x), F_2(x), ..., F_i(x)\}, \tag{2.2}$$

subject to

$$g(x,p) \leq 0.$$
$$x \in \vec{X}$$

Where Equation 2.1 had a single objective $F(x)$ to minimize, Equation 2.2 has a *set* of objectives, $\{F_i(x)\}$. Rather than identifying a global minimum point, the solution to Equation 2.2 is a *set* of non-dominated points along a non-inferior region called a Pareto-front. Each point on this frontier cannot improve one objective without making another objective worse, hence "non-dominated." Generally, for competing objectives, there will be an infeasible space that is not attainable by the given combination of objectives. For a minimization problem, the space above the Pareto-front is the sub-optimal feasible space. This is the space that MGA promises to search for a corresponding single-objective problem. Figure 2.6 illustrates a set of solutions along a Pareto-front for an example problem from Multi-Objective Optimization in Python (`Pymoo`) [160], [161].

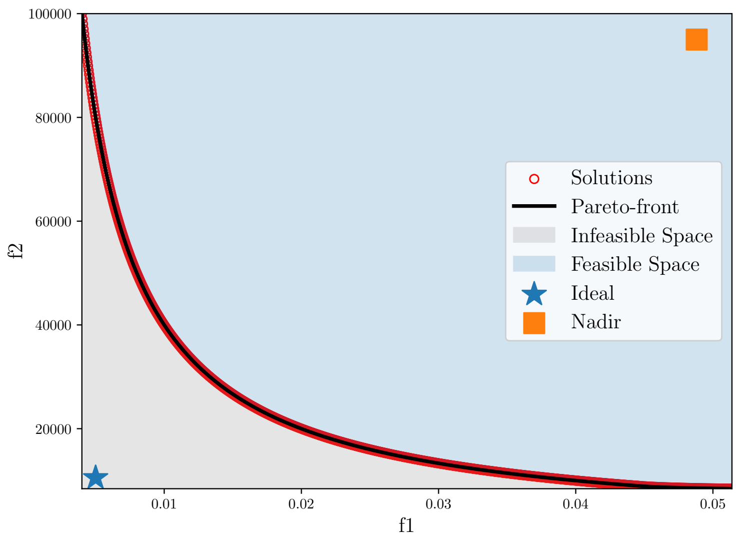

Figure 2.6: An example *convex* Pareto-front from `Pymoo` [160], [161].

There are broadly two classes of MOO algorithms for solving Equation 2.2, *scalarization* and *population-based* [162], [163]. Scalarization approaches map the multi-objective problem onto a set of single-objective problems using variation of parameters. In the weighted-sum (WS) algorithm, the objectives are assigned weights, w_i, and the aggregated objective becomes

$$\min \quad J(x) = \sum_i w_i F_i(x) \tag{2.3}$$

subject to the same constraints as Equation 2.1 [162], [163]. These weights are varied in order to sample points along the Pareto-front. Alternatively, the ϵ-constraint (EC) algorithm chooses one objective from $\{F_n\}$ to solve and converts the others into constraints, whose bounds are denoted by ϵ. These bounds are varied until the desired number of points on the Pareto-front is reached [162], [163]. This problem can be written as

$$\min \quad F_1(x), \tag{2.4}$$

subject to,

$$\begin{aligned} &F_2(x) - \epsilon_1 \leq 0 \\ &\vdots \\ &F_i(x) - \epsilon_1 \leq 0 \\ &g(x, p) \leq 0, \\ &x \in \vec{X}. \end{aligned}$$

The sub-problem, Equation 2.4, must be repeated for each ϵ_i.

Scalarization is attractive due to its simplicity. However, this approach is sensitive to problem convexity. WS will never be able to sample points in a concave region of the Pareto-front, and EC will have poorly spaced samples along a concave region. Further, these algorithms can only sample points on the frontier, not the sub-optimal feasible space. Thus supporting the critique of using MOO for handling structural uncertainty [81]. Fortunately, population-based algorithms, also called *genetic algorithm (GA)* or *evolutionary algorithms*, resolve some of these issues by solving Equation 2.2 directly. GAs are based on the principle of natural selection. In a GA, such as Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), an initial population is randomly generated using the problem's decision variables, the 'fitness' of this population (i.e., performance on each objective) is calculated, then a new population is selected from the 'fittest' (most optimal) individuals. This process continues until a convergence criterion is reached. The advantages of this method are

1. a guaranteed solution, regardless of convexity,
2. no prior knowledge is required to initialize the problem, as with EC,
3. greater diversity of solutions (i.e., spacing of points along the Pareto-front),
4. the sub-optimal space is sampled through the iterative process (though not uniformly).

Specifically, point four address one of the primary criticisms of using MOO to reduce structural uncertainty by obtaining points in the inferior region [164]–[166]. An additional advantage of GAs is the ability to incorporate more physics and simulations into the optimization procedure than LP, MILP, or scalarization allow [164].

Previous work handled structural uncertainty using MGA which samples unique solutions from the sub-optimal space in a neighborhood around the global minimum for a single objective [81]. Researchers argue that this approach is valid because there will always be structural uncertainty and sampling the inferior region may offer insight for decision-makers. While structural uncertainty may persist it is not *irreducible*. By increasing the number of modeled objectives MOO reduces structural uncertainty. Further, ideas from MGA can be applied to MOO by efficiently sampling the near-optimal space [164]–[167]. The goal of MGA is to find a *reduced* set of maximally different alternatives to provide insight, where analyzing the full set of alternatives would be overwhelming [81], [167]. Figure 2.7 shows the near-optimal space around the Pareto-front from Figure 2.6.

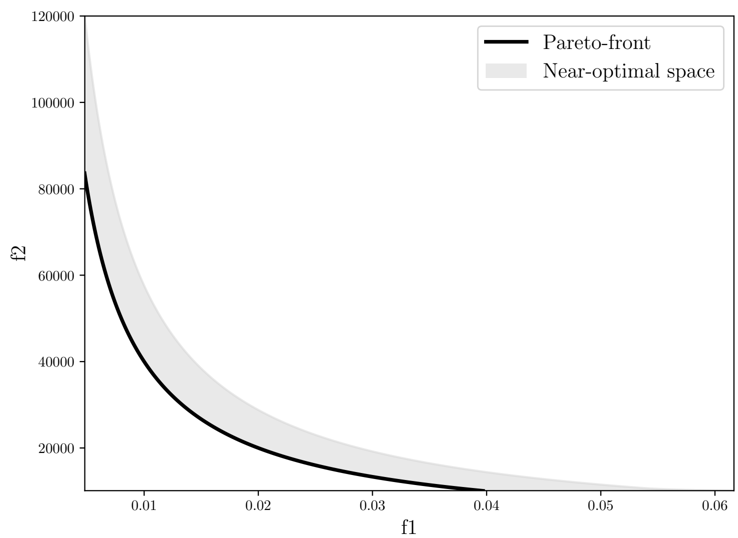

Figure 2.7: The near-optimal space around the Pareto-front.

For these reasons, this thesis explores energy systems optimization and the handling of structural uncertainty through MOO and GAs. Section 3.3 reviews the details of the GA used in this thesis.

2.4.1 Energy System Applications

It is well understood that engineering and policy problems, which include energy systems optimization, often require satisfying multiple antagonistic objectives [164]–[166], [168]. However, the application of MOO to energy systems in the literature is limited. Table 2.3 summarizes the current body of work. As before, the "public code" column only indicates if the source code is accessible. Additionally, the "sector" columns only indicate the presence of a feature, not the relative maturity or sophistication of the modeling. There are six "objective columns," indicating which objectives are considered the in the model or study. A "technology" objective might optimize a specific technology or set of technologies. For example, maximizing the percentage of renewable energy in a system. The "reliability" metric varies among studies, but generally refers to the potential for load loss. For all of the studies in Table 2.3, the "environmental" objective refers to GHG or "global warming potential" [169]. Although it could refer to other environmental impacts such as land use, water use, or thermal pollution.

Most of the studies in Table 2.3 used NSGA-II to identify the Pareto-front with a few using scalarization. Consistent with the trend shown in Table 2.2, every study in Table 2.3 uses some economic or "cost" metric as one of the objectives. Also consistent, is that none of these studies identified a metric to optimize over social concerns. Laha et al. [171] used fatalities per GWh and employment per GWh as criteria for social sustainability, but these were not objectives in their model, rather they were calculated *ex post facto* with scenario analysis. Riou et al. [170] investigated the tradeoffs among renewable share, reliability, and total cost. Their findings were consistent with single objective scenario analysis [53], that greater renewable penetration leads to greater costs and less reliable energy with a 100% renewable energy system being the least reliable or incurring the greatest costs [170].

Although previous work demonstrated the applicability of MOO to energy systems optimization, there are significant limitations.

Table 2.3: MOO used with energy systems.

Citation	Model	Algorithm	Objectives						Sector			
			Economic	Social	Environment	Reliability	Technology	User-defined	Heat	Electricity	Transport	Public Code
[170]		NSGA-II	✓			✓	✓			✓		
[171]		NSGA-II	✓				✓			✓		
[172]		NSGA-II	✓		✓				✓	✓		
[173]	Oemof-moea	NSGA-II	✓		✓				✓	✓	✓	✓
[174]	HYRES	GAToolbox	✓			✓				✓		
[175]		NSGA-II	✓		✓				✓	✓		
[176]		WS	✓		✓				✓	✓	✓	
[64]		NSGA-II	✓		✓				✓	✓		
[177]		NSGA-II	✓		✓				✓	✓		
[178]	SIREN	WS	✓		✓	✓				✓		✓
[169]		EC	✓		✓	✓			✓	✓		
[179]		NSGA-II	✓			✓				✓		
[180]		NSGA-II	✓			✓				✓		
[181]		NSGA-II	✓		✓				✓	✓		
[182]		EC	✓		✓	✓			✓		✓	
[183]		NSGA-II	✓		✓					✓		

- There are at most three modeled objectives [169], [170], [182].
- Where traditional ESOMs have many mature frameworks (as shown in Table 2.2, there are no frameworks that use MOO. Simultaneously, none of the studies in Table 2.3 developed a framework. Prina et al. developed a bespoke and unlicensed model called "Oemof-moea," however this does not constitute a framework.
- None of the studies in Table 2.3 allow user-defined objectives, because none of them have *users*.
- None of the studies incorporate social metrics into the modeled objectives.

This thesis develops, Open source multi-objective energy system framework (`Osier`), a novel energy systems framework using MOO that fills these gaps by using GAs that allows for efficient modeling of many objectives, enabling user-defined objectives, providing the option to make metrics of interest either objectives or constraints, and incorporating ideas from MGA to provide insight from the sub-optimal objective space.

The next section outlines attempts to incorporate social justice concerns with energy system models.

2.5 Modeling and Quantifying Energy Justice

We have already seen that incorporating energy justice into ESOMs is challenging and seldom attempted. The literature on energy justice and socio-technical transitions tend to derogate modeling efforts as cold and calculating [67], [184], and most models do not account for energy justice in either equations or analysis. However, there have been some notable attempts to bridge this gap. The first $\mathcal{N}$ papers explicitly use ESOMs in their analysis.

Patrizio et al. (2020) conducted a technology-agnostic 'social equity' scenario that maximized the gross value added (GVA) of several countries' energy systems rather than minimizing the total cost [46]. GVA is also distinct from social welfare because it measures contributions to gross domestic product (GDP) from individual producers rather than maximizing surplus. This metric enables sector-specific analysis of the impacts of energy infrastructure on employment and sales. Equity, in this context, is identical to socioeconomic development as measured by GDP. The researchers looked at a socio-technical transition for three countries: Spain, the United Kingdom, and Poland. They found that a 100% renewable energy system would reduce labor compensation by 50-60% in the UK and Poland but could increase benefits in Spain. They argue this is due to the outsourcing of manufacturing and mining jobs in the former cases, while Spain has enough domestic resources to accommodate the transition. The researchers did not analyze possible shifts in power dynamics related to the energy systems, but they did identify that there is no one-size-fits-all solution to achieving net-zero carbon emissions.

Neumann & Brown (2021) performed a detailed analysis of the European energy system considering the expansion of transmission networks and energy producers for a 100% renewable energy system under cost minimization [33]. They also used a novel formulation of MGA to identify the boundaries of the feasible space for each technology within different levels of tolerance. This study uses Lorenz curves and Gini coefficients to measure the uniformity of the distribution of energy production and consumption. In other words, the most equitable distribution of energy resources would accord with energy consumption [33]. The researchers conclude that wind power and greater transmission capacity are associated with less regional equity, while solar power and storage technologies lead to a more even distribution of the power supply. This is useful for measuring the distribution of energy benefits from the energy system but does not consider the distribution of costs nor consider regional preferences.

Chapman et al. (2018) looked at the energy justice implications of transitioning coal plants to renewable energy projects for the nearby communities [185]. They measure distributional justice with "relative equity" and "policy burden." Relative equity accounts for factors such as GHG reduction, employment, electricity cost, and health impacts. Policy burden is a weighted value according to the income level of each community. These two quantities were plotted together to identify a retirement schedule that maximizes equity outcomes and ensures that burdens are borne by the ablest communities [185]. Additionally, the researchers argue that by using equity measures to inform policy choices, those policy decisions are more procedurally just. However, this neglects meaningful participation and may or may not address decision-making transparency [67]. Further, this study does not consider how replacing dispatchable suppliers with VRE will affect the availability and affordability of electricity [67].

Mayfield et al. (2019) quantified the social equity implications for the expansion of natural gas infrastructure in Appalachia using spatial and temporal metrics such as job-years generated by greater gas development, premature deaths caused by air pollution, changes in poverty and income, and the distribution of these various benefits along regional, racial, and economic lines. Additionally, they identified some of the intergenerational equity impacts of climate change and expanded gas infrastructure.

2.5.1 Enabling Procedural Justice Through Energy Models

Traditionally, ESOMs are used to inform policy-makers [186] in order to infuse policy choices with an appearance of objectivity. Indeed, some of the studies reviewed in the previous section argue that this infusion will lead to greater procedural and recognitional justice outcomes as long as the policies maximize some measure of energy justice [185], [187]. However, these types of detailed analyses may also be used to dismiss concerns or opposition from the public due to insufficient 'technical expertise' [188]. Further, without meaningful participation from the affected public, this approach is further entrenches procedural injustices. To credit the energy modeling community, there is significant awareness of the importance of transparency and repeatability in the space [120], [156], [189]–[191]. Yet these two goals are challenged by the computational resources required to run the more complex and detailed models, as well as the learning curve necessary to understand and modify the model inputs themselves. There has been some effort to reduce this learning curve and make modeling itself more accessible. Frameworks such as METIS, EnergyRT, and Python for Generating Energy Systems (`PyGenesys`) all emphasize reproducibility, user-friendliness, and a shallower learning curve [111], [118], [192]. The creators of METIS state their goal is to "close the gap between modelers and policy-makers, enabling policy-makers to become modelers" [118]. However, these frameworks do not offer computational resources to run their models. The Tools for Energy Model Optimization and Analysis (`Temoa`) project offers limited cloud computing capabilities, free of charge [193]. However, the responsibility for creating an input file still falls to the user, which can be overwhelming even for experienced modelers. Finally, it's not clear that perfectly accessible and transparent modeling tools will translate to more procedurally just policy-making. The next section outlines one method used to address this challenge.

2.5.2 Participatory value evaluation

Even if the public could use modeling tools, their testimony may still be dismissed due to a 'lack of expertise.' However, the public has preferences that should be incorporated into decision-making. Additionally, community members are frequently able to assess trade-offs when presented with them. Participatory value evaluation (PVE) is one method for translating community preferences into just policy outcomes. Researchers in the Netherlands developed this method to enhance democratic participation and infuse policies with genuine feedback from constituents [194]. They observed that a common method of assessing social impacts is willingness to pay (WTP), which is the maximum price an individual is willing to pay for a good or service, yet individual purchasing habits do not necessarily reflect their views on public policy due to the relative salience of moral considerations [194]. With PVE, participants can allocate a specific amount of the public budget for certain policies, including levying or reducing taxes for greater or lesser government spending [194]. Researchers applied PVE in three different settings, mobility and transportation [195], flood risk projects (i.e., a climate hazard *infrastructure* response) [196], and with a phaseout of natural gas [197]. Importantly, the studies also measured the impact of these interventions and found that PVE enables participation from people that do not typically participate (recognition), the results were useful for decision-making and participation was meaningful for the majority of subjects [197]. Although previous applications of PVE focused on economic policy levers, this approach offers a promising pathway toward identifying equitable and just energy mixes for the future.

In summary, climate change is a multi-dimensional existential threat to society. Transitioning to a zero-carbon economy by decarbonizing our energy systems may prevent the worst outcomes of climate change. However, energy systems do not only transport electrons and gas but also mediate socio-political power. Therefore this transition must be done equitably in order to avoid entrenching further injustices. The existing energy system modeling tools and literature routinely ignore the social dimensions of these systems and forego true trade-off analysis. Additionally, it's unclear whether improving these modeling practices will correspond to just energy policy outcomes. This thesis attempts to bridge the gap between energy system modeling and energy justice by developing a novel framework that allows multiple, and perhaps non-economic, objectives and is designed for transparency and usability by non-modelers to inform energy policy decisions. A framework such as the one developed in this thesis may be used in conjunction with a policy process like PVE to fully enclose the triumvirate of energy justice tenets: distribution, procedure, and recognition.

Chapter 3

Methods and Data

This chapter is split into two broad sections, which describe the technical and qualitative methods used in this thesis. The first section covers the technical details of `Osier`, the novel framework developed by this thesis, and discusses the capacity expansion model `Temoa` used as a benchmark for `Osier`. Second, the qualitative section discusses the interview questions and the analysis methods.

3.1 Open source multi-objective energy system framework

Open source multi-objective energy system framework (`Osier`) is a novel open-source energy system modeling framework for multi-objective optimization. There are currently no ESOMs that enable MOO and `Osier` fills that gap. Figure 3.1 illustrates the flow of data into and within `Osier`.

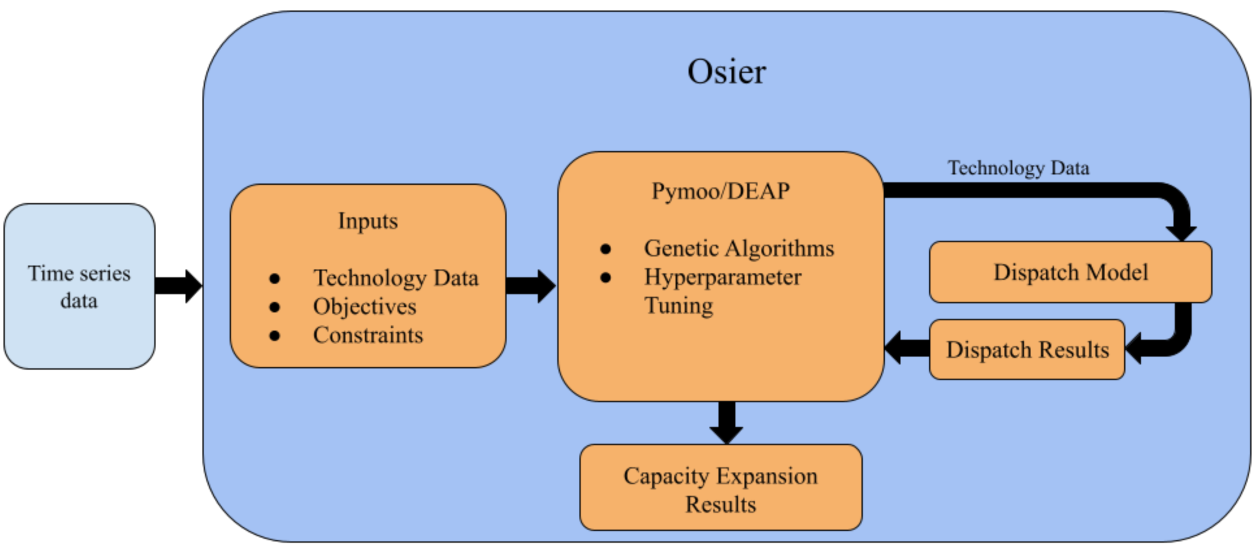

Figure 3.1: The flow of data into and within `Osier`

Technology data, objectives, constraints, and a dispatch model are all features within `Osier`, while `Pymoo` drives the optimization of these objectives. The dispatch model is independently executable for inspecting specific test cases and mapping solutions from other solvers onto `Osier`'s objective space. The next section elaborates on the dispatch model's formulation.

3.2 Economic Dispatch

The economic dispatch model minimizes the generation cost subject to physical constraints but does not optimize capacity investments. The complete set of equations for the model is detailed below.

Minimize:

$$\left(\sum_{t}^{T}\sum_{g}^{G}\left[C_{g,t}^{fuel}+C_{g,t}^{vom}\right]x_{g,t}\right)+\left(\sum_{t}^{T}\sum_{g}^{S}x_{g,t}c_{g,t}\pi\right) \tag{3.1}$$

such that,

1. The generation meets demand, less the amount of energy stored or curtailed, within a user-specified tolerance (undersupply and oversupply),

$$\left[\sum_{g}^{G}x_{g,t}-\sum_{g}^{S}c_{g,t}\right]\geq(1-\text{undersupply})\,\mathrm{D}_t \quad \forall \quad t\in T,S, \tag{3.2}$$

$$\left[\sum_{g}^{G}x_{g,t}-\sum_{g}^{S}c_{g,t}\right]\leq(1+\text{oversupply})\,\mathrm{D}_t \quad \forall \quad t\in T,S, \tag{3.3}$$

2. A generator's production, x_g does not exceed its capacity at any time, t

$$x_{g,t}\leq\mathbf{CAP}_g\Delta\tau \quad \forall \quad g,t\in G,T \tag{3.4}$$

3. A generator's ramping rate is never exceeded,

$$\frac{x_{r,t}-x_{r,t-1}}{\Delta\tau}=\Delta P_{r,t}\leq\rho_g^{up}\mathbf{CAP}_g\Delta\tau \quad \forall \quad r,t\in R,T, \tag{3.5}$$

$$\frac{x_{r,t}-x_{r,t-1}}{\Delta\tau}=\Delta P_{r,t}\leq-\rho_g^{down}\mathbf{CAP}_g\Delta\tau \quad \forall \quad r,t\in R,T, \tag{3.6}$$

4. Storage capacity for each storage technology is never exceeded

$$\mathbf{SOC}_{s,t}\leq\mathbf{CAP}_s^S \quad \forall \quad s,t\in S,T, \tag{3.7}$$

5. Storage discharge cannot exceed stored energy.

$$x_{s,t}\leq\mathbf{SOC}_{s,t} \quad \forall \quad s,t\in S,T, \tag{3.8}$$

6. Storage charge rate cannot exceed unit capacity

$$c_{s,t}\leq\mathbf{CAP}_s\Delta\tau \quad \forall \quad s,t\in S,T. \tag{3.9}$$

Where,

$$
\begin{aligned}
G &= \text{ the set of all generating technologies,} \\
R &= \text{ the set of all ramping technologies,} \quad R \subset G, \\
S &= \text{ the set of all storage technologies,} \quad S \subset G, \\
T &= \text{ the set of all time periods in the model,} \\
D_t &= \text{ the demand at each time period, } t, \\
\mathbf{CAP}_g &= \text{ the capacity of the } g\text{-}th \text{ technology} \quad [MW]\,, \\
\mathbf{CAP}_g^S &= \text{ the storage capacity of the } g\text{-}th \text{ technology} \quad [MWh]\,, \\
\mathbf{SOC}_{s,t} &= \text{ the state of charge of the } g\text{-}th \text{ technology at time } t \quad [MWh]\,, \\
\Delta\tau &= t_{i+1} - t_i \quad \forall \quad t_i \in T \quad [h]\,, \\
x_{g,t} &= \text{ the energy produced by generator, } g, \text{ at time, } t \quad [MWh]\,, \\
c_{s,t} &= \text{ the energy stored by storage technology, } s, \text{ at time, } t \quad [MWh]\,, \\
\rho_g &= \text{ the up/down ramp rate for technology, } g \quad [-]\,, \\
\pi &= \text{ A small penalty for simultaneous charging and discharging.}
\end{aligned}
$$

The second term in the objective function, Equation 3.1, represents a minor penalty to prevent the unphysical behavior of simultaneous charging and discharging from storage technologies. I used this approach because constraining this behavior requires a binary variable that makes the problem non-convex and therefore requires a more sophisticated solver. A small but sufficiently large π will always nullify the penalty term. This dispatch model reflects the minimum physical constraints for an energy system without considering fine-scale operational details such as frequency control. Equation 3.1 assumes that the retail cost for generating electricity is identical to the marginal cost of producing electricity.

3.3 Genetic Algorithms

Rather than rely on LP to model future capacity requirements, in this thesis, GAs assume the role of investment optimizer. GAs share a fundamental algorithmic structure, which is [160]

1. **Initialize** a starting population of N_p individuals, where each individual has a set of "genes" that are randomly chosen from the bounds of the decision variables.
2. Each individual in the population is **evaluated** for "fitness."
3. The **fittest**, N_f individuals "survive" and persist in the next generation.
4. A "selection" operator **chooses** among the surviving individuals to mate.
5. The parents are **combined** using a "crossover" operator, thereby filling the remaining $N_p - N_f$ individuals for the next generation.
6. The offspring are finally **mutated** with some probability, μ, to improve genetic diversity.

Figure 3.2 illustrates the flow of these steps applied to an energy systems model.

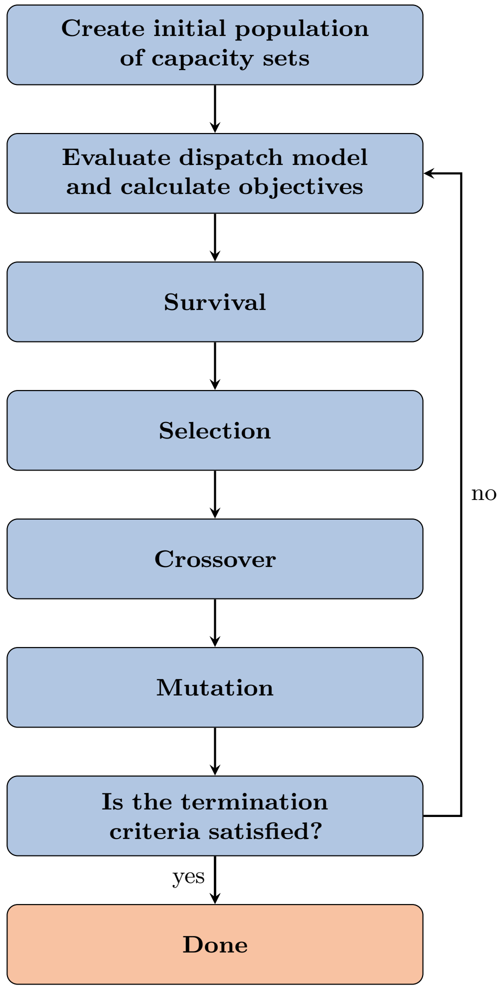

Figure 3.2: The basic flow of the GA used in this thesis.

3.3.1 Specific genetic algorithms

The variety of GAs comes from different types of operators being applied to the selection, crossover, and mutation steps. Section 2.4 showed that NSGA-II is a popular genetic algorithm choice. However, this algorithm performs poorly with greater than three objectives [198], [199]. In this thesis, I use a more modern algorithm, Unified Non-Dominated Sorting Genetic Algorithm (UNSGA-III). UNSGA-III builds on its predecessors NSGA-II and Non-Dominated Sorting Genetic Algorithm-III (NSGA-III) by unifying efficient solutions of mono-, multi-, and many-objective problems in a single algorithm.

NSGA-II improves on the basic GA by introducing a more sophisticated mating and selection algorithms. Instead of random selection, the individuals are sorted by rank (i.e. fitness) and crowding distance in binary tournament mating selection. The crowding distance is simply the Manhattan distance between individuals. A greater crowding distance is desirable to preserve diversity and since the extreme points are maximally diverse they should always persist and are therefore assigned a crowding distance of infinity [198].

The successor to NSGA-II, NSGA-III, enhances the many-objective capabilities of the former by introducing reference directions. Reference directions are used for initialization and the survival steps. In addition to fitness, individuals are chosen based on their proximity to a reference line, thus ensuring population diversity which greatly important for many-objective problems. Since diversity is handled by reference directions, individuals are selected randomly for mating. References directions are rays passing through uniformly spaced points on the unit simplex [199], [200]. In this thesis, I use the Riesz s- Energy method described by Blank et al. to calculate these points for a problem with an arbitrary number of objectives [200]. Figure 3.3 illustrates a set of initialized reference directions.

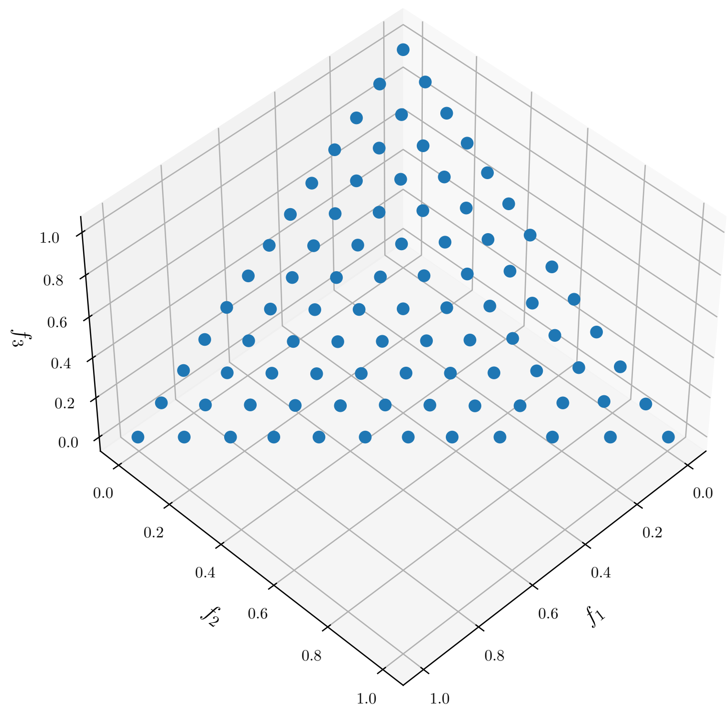

Figure 3.3: A set of reference directions for a three-objective problem.

NSGA-II is useful for mono- and multi-objective functions while NSGA-III is better for many-objective problems. UNSGA-III can handle any number of objectives by introducing the binary tournament from NSGA-II and reducing to the most efficient algorithm for the problem at hand [199]. Chapter 4 demonstrates these three algorithms in

3.3.2 Hyperparameter Tuning

Similar to other machine learning models, GAs have several hyperparameters that must be tuned for optimal behavior. These hyperparameters include probabilities for mutation, crossover, and selection, as well as the number of parents, number of offspring, and population size. Determining ideal hyperparameters is often performed using either a grid search or random sampling [201]. This thesis adopts the approach from Blank and Deb [160] using a genetic algorithm to identify the ideal hyperparameters. A problem is converted into a single objective problem using the desired algorithm, then a second genetic algorithm drives the problem where the decision variables are hyperparameters of the desired algorithm.

3.3.3 Convergence

There are several ways to stop a simulation in `Pymoo`. A simulation may end after reaching

1. a specified end time (e.g., 100 minutes),
2. a specified number of evaluations or iterations (e.g., 500 individual evaluations or 20 generations),
3. a tolerance value in the design space,
4. a tolerance value in the objective space.

It is possible that criteria 3 and 4 will never be met; therefore, they are often combined with either of the first two criteria. The fourth convergence criterion is the most interesting due to the challenge of calculating an appropriate metric. This thesis uses the weakly Pareto-compliant algorithm inverted generational distance plus (IGD+) over the more common hypervolume calculation due to its reduced computational requirements [202].

3.3.4 `Pymoo` and `DEAP`

The ESOM framework developed in this thesis is built on top of `Pymoo` and Deep Evolutionary Algorithms in Python (`DEAP`). `Pymoo` is an open-source library for GAs developed by the creators of NSGA-II and UNSGA-III [160]. This package implements several GAs out-of-the-box and offers a set of visualization tools and hyperparameter tuning. `DEAP` is another open-source library offering a toolkit for constructing GAs and therefore has fewer prepackaged algorithms than `Pymoo`. There are robust reasons to use both libraries, so `Osier` facilitates both.

3.4 Objectives

There are many possible objectives to optimize. This section summarizes a few of them and how they may be calculated in `Osier`. Due to `Pymoo`'s structure, all objectives are minimized. Therefore, if users wish to maximize some quantity, it must be negated first.

3.4.1 Per-unit-capacity

Some quantities of interest depend on the *capacity* of each technology. For example, land use of different energy producers is often reported as a power density MW/km^2. A general power density may be MW/unit. The objective function for these quantities reads

$$\mathcal{K} = \sum_g^G \mathbf{CAP}_g \kappa_g, \tag{3.10}$$

Where

$$\kappa = \text{the power density of the } g\text{-}th \text{ technology} \quad \left[\frac{-}{MW}\right]. \tag{3.11}$$

Table 3.1 lists some example objectives could be minimized or maximized.

Table 3.1: Example objectives on a per-unit-capacity basis.

Quantity	Units (per MW)
Land Use	[km^2]
Employment	[jobs]
Capital Cost	[$]
Fixed O&M Cost	[$ / year]

3.4.2 Per-unit-energy

Some quantities of interest depend on the *amount of energy produced* by each technology. For example, carbon emissions only occur when a coal or natural gas plant burns fuel. A general energy density may be in MWh/unit. The objective function for these quantities reads

$$\mathcal{E} = \sum_{g}^{G} \xi_g \sum_{t}^{T} x_{g,t}, \tag{3.12}$$

where

$$\xi_g = \text{the energy density of the } g\text{-}th \text{ technology} \quad \left[\frac{-}{MWh}\right]. \tag{3.13}$$

Table 3.2: Example objectives on a per-unit-energy basis.

Quantity	Units (per MWh)
GHG Emissions	[kg]
Water Use	[L]
"Safety"	[deaths]
Fuel Cost	[$]
Variable O&M Cost	[$]

3.4.3 Reliability and Predictability

Reliability has many definitions in the literature and it also depends heavily on the dispatch method. A hierarchical flow, which dispatches energy based on a set of rules (as opposed to true cost minimization), may simply report the fraction of hours when electricity demand was not met by the model [170], [174], [179], [180]. In an LP or MILP problem, electricity demand must be satisfied at all times. Thus reliability may be translated into a cost by determining consumers' WTP for electricity [203], [204]. However, this thesis relates system reliability to price volatility and net demand predictability. Since the price of electricity is determined by matching supply and demand, the price will spike when supply and demand are out of phase. For instance, geopolitics may cause the supply of natural gas to drop, increasing the spot price of electricity. Or, more commonly, the availability of solar and wind resources may fall unexpectedly, leading to a greater demand for backup energy. Both of those examples are difficult to predict; otherwise, fuel reserves could be deployed, avoiding the price shock. Thus, I propose that measuring the predictability and volatility of an energy system is an appropriate proxy for reliability. Additionally, minimal price volatility is considered an aspect of energy justice [67], [70].

In this thesis, I measure the predictability of hourly electricity prices and net demand using a measure from complexity science, weighted permutation entropy (WPE) [205]. Permutation entropy, the precursor to WPE, is essentially the Shannon entropy for particular sequences of values called 'motifs' [206]. WPE expands on this concept by weighting each instance of a motif by its variance [205], [207]. WPE is defined as

$$H_w(m) = -\sum_{\pi \in \Pi} P_w(\pi) \log_2(P_w(\pi)) \tag{3.14}$$

where

$$\begin{aligned}
\pi &= \text{a particular motif,} \\
P_w &= \text{the probability of a given motif, } \pi, \\
&= \frac{\sum_{j \leq N} w\left(x_j^{(m,\tau)}\right) \cdot \delta\left(\phi\left(x_j^{(m,\tau)}\right), \pi_i\right)}{\sum_{j \leq N} w\left(x_j^{(m,\tau)}\right)}
\end{aligned} \tag{3.15}$$

and

$$\begin{aligned}
w\left(x_j^{(m,\tau)}\right) &= \text{the weight of a particular vector} \\
&= \frac{1}{m}\sum_{j}^{m}\left(x_j^{(m,\tau)} - \bar{x}\right)^2,
\end{aligned} \tag{3.16}$$

$$\begin{aligned}
\phi(\cdot) &= \text{the ordinal pattern of a vector,} \\
\delta(\cdot) &= \text{Kronecker delta,} \\
m &= \text{the embedding dimension,} \\
\tau &= \text{the time delay.}
\end{aligned}$$

There are other reliability metrics in the literature, frequently employing some variation on the "spread" of data through standard deviation or mean squared error [208]–[210]. However, these metrics are unbounded and do not contain any information about the underlying dynamics that produce a certain distribution. Whereas WPE can indicate a theoretical ceiling on predictability [207]. Importantly, WPE works for systems where the underlying dynamics are unknown. The Hurst exponent is another measure of predictability, but it too has drawbacks, such as computational expense and a stationarity requirement [211], [212]. This thesis uses the WPE implementation I contributed to the open source package `PyEntropy` [213].

3.4.4 User-defined Objectives

A key feature of `Osier` is the ability for users to define their own objectives and make it relatively easy to do so. This feature is required because modelers cannot know *a priori* every objective that users might be interested in optimizing. While `Osier` ships with some standard objective functions, allowing users to create their own objectives makes every model bespoke. *Any quantitative metric may be used as an objective in* ***`Osier`****.* Every objective function has at least two arguments, the list of technologies used in the model and the solved dispatch model. Users will never have to pass these arguments manually since `Osier` will automatically call the function during a simulation. One example of a user-defined objective might be technology readiness. This objective is independent from the energy produced and could be weighted by the capacity but is not a per-unit-capacity objective. The values of the readiness parameter must be passed to each `Technology` object, which can be accessed at run-time. Code listing 1 shows the basic approach to creating a new objective. Appendix **??** lists the default accessible attributes for the technology list and the solved dispatch model.

```python

nuclear.readiness = 9
fusion.readiness = 3

technology_list = [nuclear, fusion]

def osier_objective(technology_list, solved_dispatch_model):
    """
        Calculate the capacity-weighted technology readiness
        score for this energy mix.
    """

    total_capacity = np.array([t.capacity for t in technology_list]).sum()
                               objective_value =
                               np.array([t.readiness*t.capacity for t in
                               technology_list]).sum()

    return objective_value / total_capacity
```

Listing 1: The fundamental way to create a novel objective in `Osier`.

Importantly, because all technologies in `Osier` are Python objects, users can add attributes at will. Such as the technology readiness level as shown in Code listing 1.

3.4.5 Constraints

Besides the physical constraints defined in Section 3.2, `Osier` does not have any default constraints. This is because each additional constraint corresponds to an additional assumption and will affect the trade-off analysis that makes MOO so powerful. However, there are some circumstances where the *optimal* solutions are still *infeasible*. For instance, if a community wants to determine the best energy mix according to their unique objectives, this community might not have the budget for even a least-cost solution because the capital requirements are too high. Therefore, they must constrain the capital cost for their modeling problem. Thus, `Osier` enables the following:

1. Users may define their own constraints.
2. Any objective function may be transformed into a constraint.

This feature makes `Osier` absolutely unique among ESOMs. Single-objective ESOMs can never account for unique situations such as the one suggested above, nor any other bespoke considerations. In the case above, the capital cost may constrain the problem while still minimizing the total cost. The solutions under these conditions will have a higher total cost but could be achievable in the near term due to meeting capital cost requirements.

3.5 Temoa and PyGenesys

This thesis uses the tools Temoa and PyGenesys to establish benchmark results for a typical ESOM. Temoa is an open-source ESOM developed at North Carolina State University that uses MILP to develop capacity-expansion scenarios [214]. The key benefits of Temoa are its open-source code, open data, and built-in uncertainty analysis capabilities. These features address the need for greater transparency in ESOM modeling and robust assessment of future uncertainties [90], [134]. PyGenesys is another open-source code that facilitates rapid development of Temoa models and enables sensitivity analyses using a templated approach [48], [192]. These features of PyGenesys reduce the learning curve and the cost of producing unique models in Temoa [48].

A single Temoa run minimizes total system cost [214],

$$C_{total} = C_{loans} + C_{fixed} + C_{variable} \tag{3.17}$$

where

$$\begin{aligned} C_{loans} &= \text{the sum of all investment loan costs,} \\ C_{fixed} &= \text{the sum of all fixed operating costs,} \\ C_{variable} &= \text{the sum of all variable operating costs.} \end{aligned}$$

Each of these terms is amortized over the model time horizon. The decision variables include the generation from each technology at time, t, and the capacity of each technology in year, y. The dispatch model deviates slightly from the model described in Section 3.2 by making the initial storage level for energy storage technologies a decision variable, whereas the dispatch model used in this thesis does not optimize initial storage and assumes energy storage starts at zero. The detailed formulation of Temoa's constraints and equations are available online [214] (maybe in an appendix?).

3.5.1 Modeling-to-Generate-Alternatives

Temoa's built-in method for uncertainty analysis is the Hop-Skip-Jump algorithm (HSJ) formulation of MGA. This algorithm is designed to handle *structural* uncertainty, which presumes to account for unmodeled objectives. The steps for HSJ are [48], [81]:

1. obtain an optimal solution by any method,
2. add a user-specified amount of slack to the objective function value from the first step,
3. use the adjusted objective function value as an upper bound constraint,
4. generate a new objective function that minimizes the sum of all decision variables,
5. iterate the procedure,
6. stop the MGA when no significant changes are observed.

The mathematical formulation of this algorithm is

Minimize:

$$p = \sum_{k \in K} x_k, \tag{3.18}$$

Subject to:

$$f_j(\vec{x}) \leq T_j \quad \forall \quad j, \tag{3.19}$$

$$\vec{x} \in X, \tag{3.20}$$

where

$$\begin{aligned} p &= \text{the new objective function,} \\ x_k &= \text{the } k^{th} \text{ decision variable with a nonzero value in previous solutions,} \\ f_j(\vec{x}) &= \text{the } j^{th} \text{ original objective function,} \\ T_j &= \text{the slack-adjusted target value,} \\ X &= \text{the set of all feasible solutions.} \end{aligned}$$

This procedure results in a small set of maximally different solutions for modelers to interpret. In this way, MGA efficiently proposes alternatives that may capture unmodeled objectives, such as political expediency or social acceptance. However, this method depends on a single objective function which does not guarantee that these alternative solutions will be close to any other measurable objective.

3.6 MGA with multi-objective optimization

This thesis applies some ideas from MGA to the analysis of the sub-optimal space from a multi-objective optimization problem. Due to their iterative process, GAs naturally generate many samples in a problem's feasible space. However, this does not lead to a "limited set" of solutions but rather a potentially infinite set. Some literature developed GAs that directly use MGA in the iterative process [165], [166]. However, existing Python libraries such as `Pymoo` and `DEAP` do not implement these methods, and the challenge is not an inability to sample the sub-optimal space, but rather to provide a comprehensible subset of solutions. The algorithm I developed in this thesis to search the near-feasible space is the following:

1. Identify a slack value (e.g., 10% or 0.1).
2. Create a "near-feasible front" where the coordinates of each point are multiplied by unity plus the slack value.
3. Every individual is checked if all of its coordinates are
   - below all of the coordinates for at least one point on the near-feasible front and
   - above all of the coordinates for at least one point on the Pareto front.
4. Lastly, a subset of points may be randomly sampled from the interior points for analysis.

Figure 3.4 and Figure 3.5 demonstrate this algorithm with 10 percent slack for a 2-D and 3-D Pareto front, respectively. Figure 3.4 shows clearly that only points within the near-optimal space (gray) are considered. Illustrating this behavior in three dimensions (and above) is considerably more difficult. The 3-D interior points should be covered by both surfaces, obstructing their view. Figure 3.5 shows that this is the case in three panels. First, a top view of an opaque Pareto front (green) where no interior points can be observed. Second, the same view with a translucent Pareto front, revealing interior points and the near-optimal front (blue). Finally, the view from underneath the near-optimal front once again obscures the interior points, except for two near the edges of the sub-optimal space. The tested points are omitted for clarity.

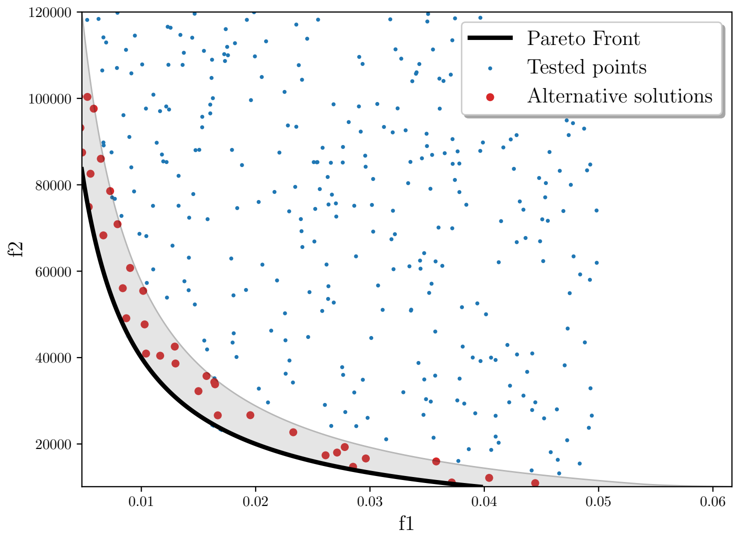

Figure 3.4: All of the alternative points inside the near-feasible space selected using the algorithm described in Section 3.6.

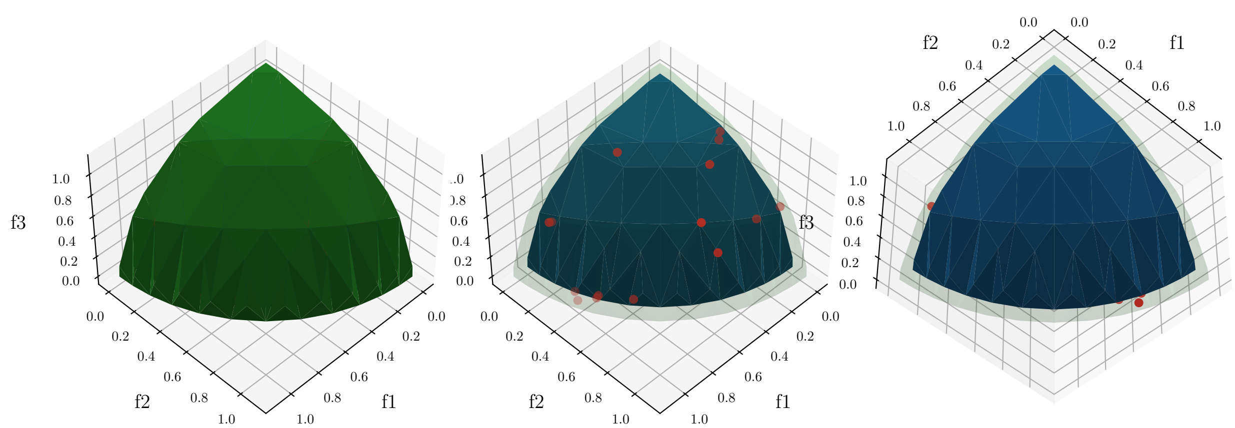

Figure 3.5: From left to right: An opaque Pareto front; a translucent Pareto front showing the interior points above a sub-optimal front; and the sub-optimal front hiding the interior points from a different angle.

3.7 Model Data

Chapter 4 demonstrates `Osier` on a series of problems. The basic inputs for `Osier` are

1. Demand time series data,
2. VRE time series data (e.g., solar or wind),
3. and technology data.

The time series data for electricity demand, wind energy, and solar energy, come from University of Illinois Urbana-Champaign (UIUC). All of the time series are averaged across several years to simulate a "typical" year. I re-scaled the demand data by the total energy demand for Illinois in order for the hourly demand to be on the same scale as the default power units (MW) for `Osier` technologies. However, this choice is somewhat arbitrary. `Osier` automatically normalizes the VRE time series because VRE capacity is a decision variable. Figure 3.6 shows the normalized demand and load duration curves.

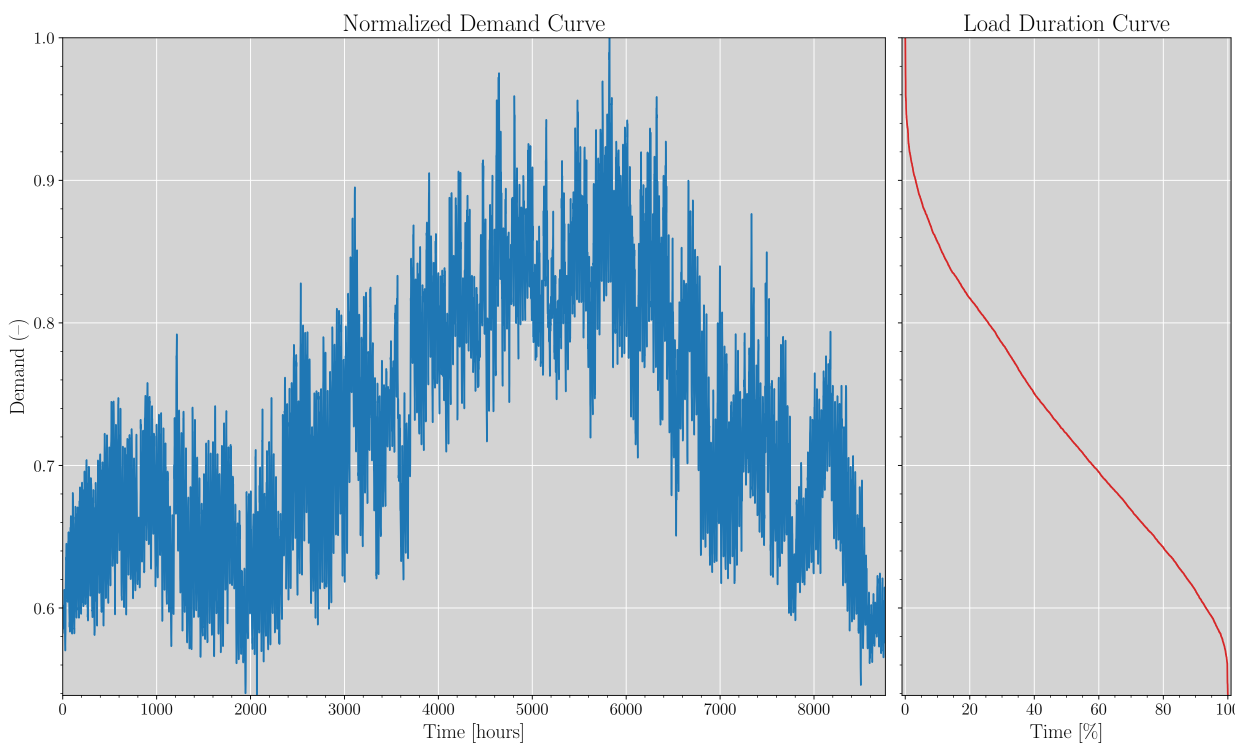

Figure 3.6: The normalized demand and load duration curves that are used in this thesis.

Another feature of `Osier` is automatically exporting technology data to a `pandas` dataframe or a LaTeXtable. Table 3.3 summarizes the technology data used in this thesis and was generated by `Osier`.

Table 3.3: Summary of Technologies and Parameters available in `Osier`.

technology_name	Battery	Biomass	Coal_Conv	Coal_Adv	NaturalGas_Conv	NaturalGas_Adv	Nuclear	Nuclear_Adv	SolarPanel	WindTurbine
technology_category	base	thermal	thermal	thermal	thermal	thermal	thermal	thermal	base	base
technology_type	storage	production	production	production	production	production	production	production	production	production
dispatchable	True	True	True	True	True	True	True	True	False	False
renewable	False	True	False	False	False	False	False	False	True	True
fuel_type	None	None	None	None	None	None	None	None	solar	wind
lifetime	25	25	25	25	25	25	25	25	25	25
capacity (MW)	815	0	0	0	8.38e+03	0	1.86e+04	0	2.81e+03	0
capacity_factor	1	1	1	1	1	1	1	1	1	1
capacity_credit	0.5	1	1	1	1	1	1	1	0.19	0.35
efficiency	0.85	1	1	1	1	1	1	1	1	1
capital_cost (1/kW)	0.000613	0.00344	0.001	0.00492	0.00096	0.00189	5e-05	0.00492	0.000673	0.00118
om_cost_fixed (1/kW)	1.53e-05	0.000123	4.07e-05	5.82e-05	1.12e-05	2.7e-05	0.000178	0.000119	8.05e-06	3.31e-05
om_cost_variable (1/(MW*hr))	0	0	0	0	0	0	0	0	0	0
fuel_cost (1/(MW*hr))	0	4.7e-05	2.14e-05	3.66e-05	2.24e-05	2.75e-05	5.81e-06	9.16e-06	0	0
co2_rate (megatonnes/(MW*hr))	0	0	0	0	0	0	0	0	0	0
lifecycle_co2_rate (megatonnes/(GW*hr))	2.32e-05	0.00023	0.00082	0.00022	0.00049	4.9e-05	1.2e-05	1.2e-05	4.8e-05	1.1e-05
land_intensity (km/MW**2)	0	0	0	0	0	0	0	0	0	0
storage_duration (hr)	4	nan	nan	nan	nan	nan	nan	nan	nan	nan
initial_storage (MW*hr)	0	nan	nan	nan	nan	nan	nan	nan	nan	nan
land_use (km**2/GW)	0.006	0.006	0.0051	0.0051	0.0032	0.0032	0.0044	0.0044	4.4	12.3
ramp_up_rate (1/hr)	nan	1	0.5	0.5	1	1	0	0.25	nan	nan
ramp_down_rate (1/hr)	nan	1	0.5	0.5	1	1	0	0.25	nan	nan
heat_rate	nan	None	None	None	None	None	None	None	nan	nan

Chapter 4

Benchmark Results

This chapter shows that solutions calculated by `Osier` agree with a more established ESOM, `Temoa`, and demonstrates some `Osier`'s advanced features, such as many-objective objective problems and combining MOO with MGA.

4.1 Exercise 1: Exploring objective space

In the first benchmark exercise, I used `Temoa` to calculate the least-cost solution. Then I generated 30 alternative solutions with MGA as described in Section 3.5.1 with a 10% slack variable added to `Temoa`'s objective function. Figure 4.1 shows the points from `Temoa` in red and `Osier`'s Pareto-front for the same problem in blue. The red- and blue-shaded regions are the sub-optimal spaces (i.e., within 10% of any objective) for `Temoa` and `Osier`, respectively.

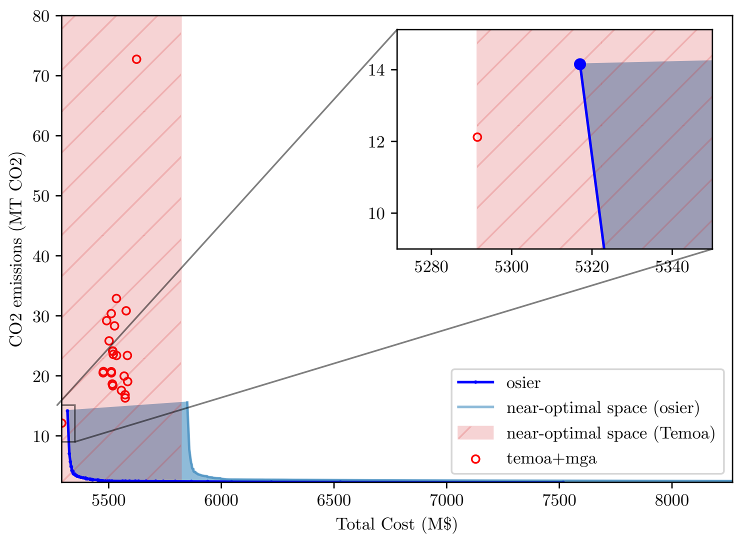

Figure 4.1: Compares the least-cost solutions between `Temoa` and `Osier` as well as their sub-optimal spaces. The least-cost solutions for `Osier` and `Temoa` are within 0.5% of each other.

First, `Temoa`'s least-cost solution is slightly better (within 0.5%) than `Osier`'s in terms of both cost and emissions. This happens because `Temoa` optimizes energy dispatch slightly differently than `Osier`. In particular, the initial storage value for energy storage technologies is a decision variable in Temoa and not in Osier. A second reason for this discrepancy has to do with convergence. Osier's Pareto-front could likely be improved with a lower convergence tolerance, but this would use additional computational resources.

Next, the sub-optimal spaces partially overlap, indicating that Temoa could find a solution with lower carbon emissions after sufficient iterations. However, none of Temoa's MGA solutions fall within Osier's sub-optimal space. This point highlights the necessity for multi-objective optimization. The objective of MGA is to produce a *diverse subset* of points in the sub-optimal region. MGA may capture appealing alternatives for some unmodeled objective in the original problem, but it cannot guarantee that those solutions will be an improvement along any other objective axis. This is especially apparent here, where the least-cost solution happens also to be the lowest carbon solution. Even though MOO reduces structural uncertainty, it will always exist, as discussed in Section 2.3.2. Therefore, identifying alternative solutions by sampling points in the inferior region is still useful. Figure 4.2 shows a set of solutions in Osier's inferior region and some randomly selected points.

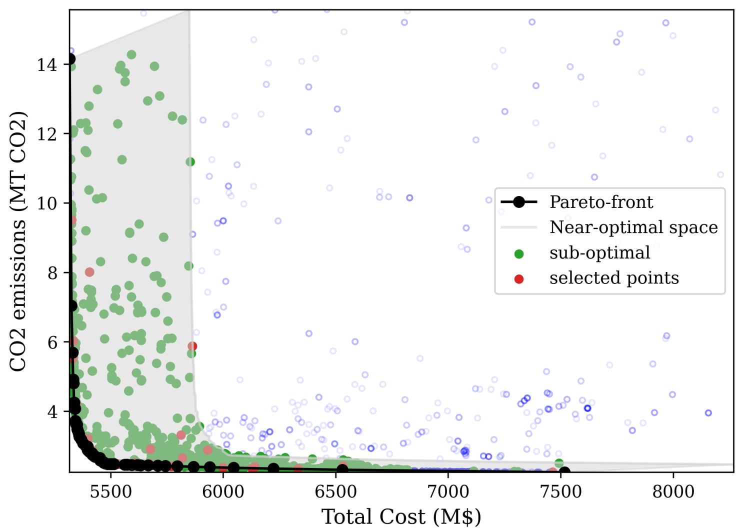

Figure 4.2: Points within Osier's sub-optimal space.

Natural gas with CCS shows up in the randomly selected points in Osier's sub-optimal region. A geo-political locus for energy infrastructure, described in Section 2.2.3 offers one possible explanation for this technology since states with significant natural gas resources might seek to maintain their influence by developing low-carbon technology that still uses natural gas.

4.2 Exercise 2: Four Simultaneous Objectives

This exercise optimized four objectives simultaneously.

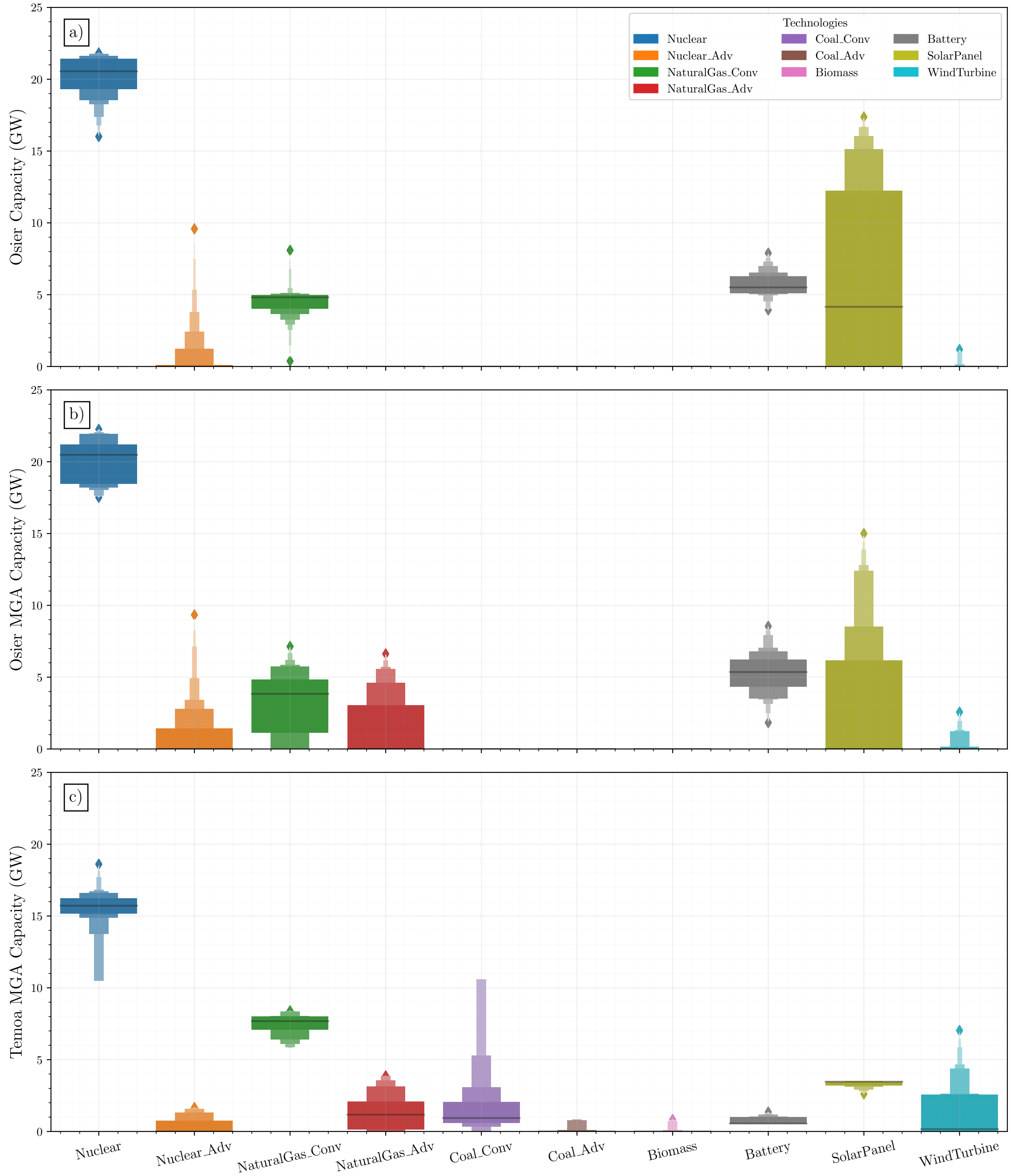

Figure 4.3: The design spaces for a) points on the Pareto-front in Figure 4.1, b) selected points in `Osier`'s sub-optimal space, identified in Figure 4.2, and c) points generated by `Temoa`'s MGA algorithm shown in Figure 4.1.

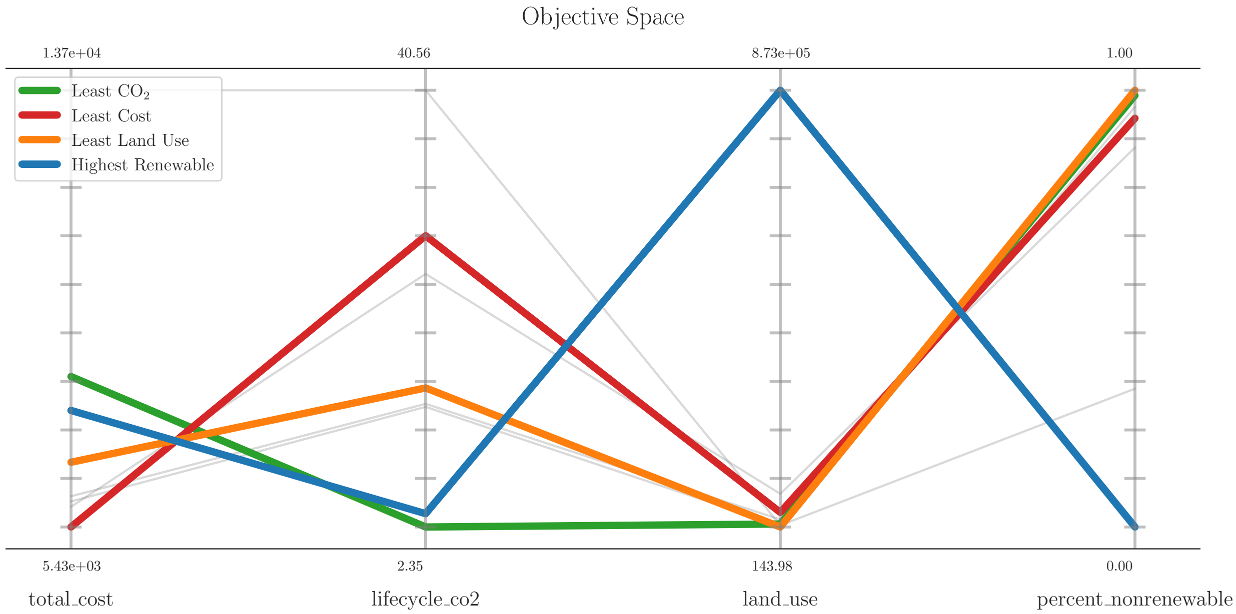

Figure 4.4: The design spaces for a four objective problem.

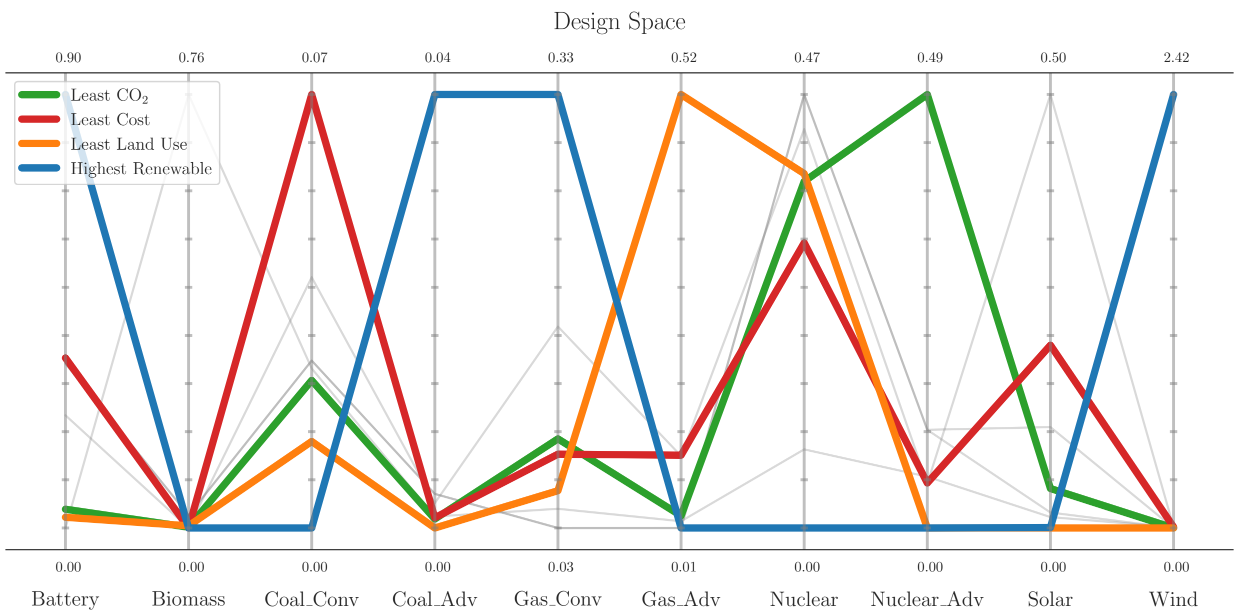

Figure 4.5: The design spaces for a four objective problem.

Chapter 5

Conclusions

We conclude that graduate students like coffee.

References

[1] A. Reisinger, M. Howden, C. Vera, and et al., "The concept of risk in the IPCC sixth assessment report: A summary of cross-working group discussions.," International Panel on Climate Change, Geneva, Switzerland, Sep. 4, 2020, p. 15. [Online]. Available: https://www.ipcc.ch/site/assets/uploads/2021/02/Risk-guidance-FINAL_15Feb2021.pdf (visited on 02/01/2023).

[2] K. Dorkenoo, M. Scown, and E. Boyd, "A critical review of disproportionality in loss and damage from climate change," *WIREs Climate Change*, vol. 13, no. 4, e770, 2022, _eprint: https://wires.onlinelibrary.wiley.com/doi/pdf ISSN: 1757-7799. DOI: 10.1002/wcc.770. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcc.770 (visited on 02/01/2023).

[3] N. P. Simpson, K. J. Mach, A. Constable, *et al.*, "A framework for complex climate change risk assessment," *One Earth*, vol. 4, no. 4, pp. 489–501, Apr. 23, 2021, ISSN: 2590-3322. DOI: 10.1016/j.oneear.2021.03.005. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2590332221001792 (visited on 02/23/2022).

[4] D. Reidmiller, C. Avery, D. Easterling, *et al.*, "Fourth national climate assessment," U.S. Global Change Research Program, United States, Volume II, 2018, p. 1526.

[5] I. P. on Climate Change, "Climate change 2021: Summary for all," Intergovernmental Panel on Climate Change, Dec. 12, 2021. [Online]. Available: https://www.ipcc.ch/report/ar6/wg1/downloads/outreach/IPCC_AR6_WGI_SummaryForAll.pdf (visited on 01/27/2023).

[6] K. Dahl, E. Spanger-Siegfried, R. Licker, *et al.*, "Killer heat in the united states," Union of Concerned Scientists, Jul. 2019. [Online]. Available: https://www.ucsusa.org/sites/default/files/2020-12/UCS_extreme_heat_report_190712b_low-res_corrected12-20.pdf (visited on 02/01/2022).

[7] H.-M. LI, X.-C. WANG, X.-F. ZHAO, and Y. QI, "Understanding systemic risk induced by climate change," *Advances in Climate Change Research*, vol. 12, no. 3, pp. 384–394, Jun. 2021, ISSN: 1674-9278. DOI: 10.1016/j.accre.2021.05.006. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9188644/ (visited on 02/01/2023).

[8] S. N. Islam and J. Winkel, "Climate change and social inequality," Department of Economic & Social Affairs, United Nations, New York, NY, Working Paper 152, Oct. 2017, p. 32.

[9] G. S. Seck, V. Krakowski, E. Assoumou, N. Maïzi, and V. Mazauric, "Embedding power system's reliability within a long-term energy system optimization model: Linking high renewable energy integration and future grid stability for france by 2050," *Applied Energy*, vol. 257, p. 114 037, Jan. 1, 2020, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.114037. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919317246 (visited on 03/03/2021).

[10] A. Rinaldi, S. Yilmaz, M. K. Patel, and D. Parra, "What adds more flexibility? an energy system analysis of storage, demand-side response, heating electrification, and distribution reinforcement," *Renewable and Sustainable Energy Reviews*, vol. 167, p. 112 696, Oct. 1, 2022, ISSN: 1364-0321. DOI: 10.1016/j.rser.2022.112696. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032122005858 (visited on 12/13/2022).

[11] K. Dehghanpour, M. H. Nehrir, J. W. Sheppard, and N. C. Kelly, "Agent-based modeling of retail electrical energy markets with demand response," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3465–3475, Jul. 2018, Conference Name: IEEE Transactions on Smart Grid, ISSN: 1949-3061. DOI: 10.1109/TSG.2016.2631453.

[12] B. Paterson and A. Charles, "Community-based responses to climate hazards: Typology and global analysis," *Climatic Change*, vol. 152, no. 3, pp. 327–343, Mar. 1, 2019, ISSN: 1573-1480. DOI: 10.1007/s10584-018-2345-5. [Online]. Available: https://doi.org/10.1007/s10584-018-2345-5 (visited on 02/02/2023).

[13] S. Elmallah, T. G. Reames, and C. A. Spurlock, "Frontlining energy justice: Visioning principles for energy transitions from community-based organizations in the united states," *Energy Research & Social Science*, vol. 94, p. 102 855, Dec. 1, 2022, ISSN: 2214-6296. DOI: 10.1016/j.erss.2022.102855. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629622003589 (visited on 01/12/2023).

[14] M. Roelfsema, H. L. van Soest, M. Harmsen, *et al.*, "Taking stock of national climate policies to evaluate implementation of the paris agreement," *Nat Commun*, vol. 11, p. 2096, Apr. 29, 2020, ISSN: 2041-1723. DOI: 10.1038/s41467-020-15414-6. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7190619/ (visited on 01/30/2023).

[15] S. Fawzy, A. I. Osman, J. Doran, and D. W. Rooney, "Strategies for mitigation of climate change: A review," *Environ Chem Lett*, vol. 18, no. 6, pp. 2069–2094, Nov. 1, 2020, ISSN: 1610-3661. DOI: 10.1007/s10311-020-01059-w. [Online]. Available: https://doi.org/10.1007/s10311-020-01059-w (visited on 10/29/2021).

[16] T. Hale, S. M. Smith, R. Black, *et al.*, "Assessing the rapidly-emerging landscape of net zero targets," *Climate Policy*, vol. 22, no. 1, pp. 18–29, Jan. 14, 2022, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2021.2013155, ISSN: 1469-3062. DOI: 10.1080/14693062.2021.2013155. [Online]. Available: https://doi.org/10.1080/14693062.2021.2013155 (visited on 01/30/2023).

[17] G. Taylor and S. Vink, "Managing the risks of missing international climate targets," *Climate Risk Management*, vol. 34, p. 100 379, Jan. 1, 2021, ISSN: 2212-0963. DOI: 10.1016/j.crm.2021.100379. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221209632100108X (visited on 01/30/2023).

[18] S. Carley, T. P. Evans, M. Graff, and D. M. Konisky, "A framework for evaluating geographic disparities in energy transition vulnerability," *Nat Energy*, vol. 3, no. 8, pp. 621–627, Aug. 2018, Number: 8 Publisher: Nature Publishing Group, ISSN: 2058-7546. DOI: 10.1038/s41560-018-0142-z. [Online]. Available: https://www.nature.com/articles/s41560-018-0142-z (visited on 01/12/2023).

[19] R. Costanza, R. de Groot, P. Sutton, *et al.*, "Changes in the global value of ecosystem services," *Global Environmental Change*, vol. 26, pp. 152–158, May 2014, ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2014.04.002. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0959378014000685 (visited on 10/29/2021).

[20] S. Hsiang, R. Kopp, A. Jina, *et al.*, "Estimating economic damage from climate change in the united states," *Science*, vol. 356, no. 6345, pp. 1362–1369, Jun. 30, 2017, Publisher: American Association for the Advancement of Science. DOI: 10.1126/science.aal4369. [Online]. Available: https://www.science.org/doi/10.1126/science.aal4369 (visited on 01/30/2023).

[21] M. A. Brown, A. Soni, M. V. Lapsa, K. Southworth, and M. Cox, "High energy burden and low-income energy affordability: Conclusions from a literature review," vol. 2, no. 4, p. 042 003, Oct. 2020, Publisher: IOP Publishing, ISSN: 2516-1083. DOI: 10.1088/2516-1083/abb954. [Online]. Available: https://doi.org/10.1088/2516-1083/abb954 (visited on 11/01/2021).

[22] S. Cong, D. Nock, Y. L. Qiu, and B. Xing, "Unveiling hidden energy poverty using the energy equity gap," *Nat Commun*, vol. 13, no. 1, p. 2456, May 4, 2022, Number: 1 Publisher: Nature Publishing Group, ISSN: 2041-1723. DOI: 10.1038/s41467-022-30146-5. [Online]. Available: https://www.nature.com/articles/s41467-022-30146-5 (visited on 07/18/2022).

[23] E. Klinenberg, *Heat Wave: A Social Autopsy of Disaster in Chicago*. Chicago: University of Chicago Press, Jul. 15, 2003, 324 pp., ISBN: 978-0-226-44322-5.

[24] K. Thomas, R. D. Hardy, H. Lazrus, *et al.*, "Explaining differential vulnerability to climate change: A social science review," *WIREs Climate Change*, vol. 10, no. 2, e565, 2019, _eprint: https://wires.onlinelibrary.wiley.com/doi/ ISSN: 1757-7799. DOI: 10.1002/wcc.565. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcc.565 (visited on 02/03/2023).

[25] P. Mohai and R. Saha, "Which came first, people or pollution? assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice," *Environ. Res. Lett.*, vol. 10, no. 11, p. 115 008, Nov. 2015, Publisher: IOP Publishing, ISSN: 1748-9326. DOI: 10.1088/1748-9326/10/11/115008. [Online]. Available: https://dx.doi.org/10.1088/1748-9326/10/11/115008 (visited on 01/12/2023).

[26] U. EPA. "Sources of greenhouse gas emissions," Sources of Greenhouse Gas Emissions. (Jan. 14, 2020), [Online]. Available: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions#main-content.

[27] National Academies of Sciences, Engineering, and Medicine, *Accelerating Decarbonization of the U.S. Energy System*. Washington, DC: The National Academies Press, 2021, 268 pp., ISBN: 978-0-309-68292-3. DOI: 10.17226/25932. [Online]. Available: https://www.nap.edu/catalog/25932/accelerating-decarbonization-of-the-us-energy-system (visited on 10/22/2021).

[28] T. T. Mai, P. Jadun, J. S. Logan, *et al.*, "Electrification futures study: Scenarios of electric technology adoption and power consumption for the united states," NREL/TP–6A20-71500, 1459351, Jun. 29, 2018, NREL/TP–6A20–71 500, 1 459 351. DOI: 10.2172/1459351. [Online]. Available: http://www.osti.gov/servlets/purl/1459351/ (visited on 10/12/2021).

[29] M. Z. Jacobson, M. A. Delucchi, G. Bazouin, *et al.*, "100% clean and renewable wind, water, and sunlight (WWS) all-sector energy roadmaps for the 50 united states," *Energy Environ. Sci.*, vol. 8, no. 7, pp. 2093–2117, Jul. 3, 2015, Publisher: The Royal Society of Chemistry, ISSN: 1754-5706. DOI: 10.1039/C5EE01283J. [Online]. Available: http://pubs.rsc.org/en/content/articlelanding/2015/ee/c5ee01283j (visited on 02/02/2022).

[30] D. Bogdanov and C. Breyer, "North-east asian super grid for 100% renewable energy supply: Optimal mix of energy technologies for electricity, gas and heat supply options," *Energy Conversion and Management*, vol. 112, pp. 176–190, Mar. 15, 2016, ISSN: 0196-8904. DOI: 10.1016/j.enconman.2016.01.019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0196890416000364 (visited on 02/02/2022).

[31] M. Esteban, J. Portugal-Pereira, B. C. Mclellan, *et al.*, "100% renewable energy system in japan: Smoothening and ancillary services," *Applied Energy*, vol. 224, pp. 698–707, Aug. 15, 2018, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.04.067. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918306299 (visited on 10/26/2021).

[32] X. Yue, N. Patankar, J. Decarolis, *et al.*, "Least cost energy system pathways towards 100% renewable energy in ireland by 2050," *Energy*, vol. 207, p. 118 264, Sep. 15, 2020, ISSN: 0360-5442. DOI: 10.1016/j.energy.2020.118264. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544220313712 (visited on 01/30/2023).

[33] F. Neumann and T. Brown, "The near-optimal feasible space of a renewable power system model," *Electric Power Systems Research*, vol. 190, p. 106 690, Jan. 1, 2021, ISSN: 0378-7796. DOI: 10.1016/j.epsr.2020.106690. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779620304934 (visited on 10/19/2021).

[34] C. Bussar, M. Moos, R. Alvarez, *et al.*, "Optimal allocation and capacity of energy storage systems in a future european power system with 100% renewable energy generation," *Energy Procedia*, 8th International Renewable Energy Storage Conference and Exhibition (IRES 2013), vol. 46, pp. 40–47, Jan. 1, 2014, ISSN: 1876-6102. DOI: 10.1016/j.egypro.2014.01.156. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1876610214001726 (visited on 12/13/2022).

[35] T. W. Brown, T. Bischof-Niemz, K. Blok, C. Breyer, H. Lund, and B. V. Mathiesen, "Response to 'burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems'," *Renewable and Sustainable Energy Reviews*, vol. 92, pp. 834–847, Sep. 1, 2018, ISSN: 1364-0321. DOI: 10.1016/j.rser.2018.04.113. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032118303307 (visited on 12/01/2022).

[36] H. Dorotić, B. Doračić, V. Dobravec, T. Pukšec, G. Krajačić, and N. Duić, "Integration of transport and energy sectors in island communities with 100% intermittent renewable energy sources," *Renewable and Sustainable Energy Reviews*, vol. 99, pp. 109–124, Jan. 2019, ISSN: 13640321. DOI: 10.1016/j.rser.2018.09.033. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032118306816 (visited on 08/09/2022).

[37] R. Wallsgrove, J. Woo, J.-H. Lee, and L. Akiba, "The emerging potential of microgrids in the transition to 100% renewable energy systems," *Energies*, vol. 14, no. 6, p. 1687, Jan. 2021, Number: 6 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en14061687. [Online]. Available: https://www.mdpi.com/1996-1073/14/6/1687 (visited on 09/15/2022).

[38] J. Cochran, P. Denholm, M. Mooney, *et al.*, "LA100: The los angeles 100% renewable energy study executive summary," National Renewable Energy Laboratory, Golden, CO, United States, NREL/TP-6A20-79444, Mar. 2021, p. 67.

[39] B. Ćosić, G. Krajačić, and N. Duić, "A 100% renewable energy system in the year 2050: The case of macedonia," *Energy*, 6th Dubrovnik Conference on Sustainable Development of Energy Water and Environmental Systems, SDEWES 2011, vol. 48, no. 1, pp. 80–87, Dec. 1, 2012, ISSN: 0360-5442. DOI: 10.1016/j.energy.2012.06.078. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544212005300 (visited on 02/02/2022).

[40] T. Traber, F. S. Hegner, and H.-J. Fell, "An economically viable 100% renewable energy system for all energy sectors of germany in 2030," *Energies*, vol. 14, no. 17, p. 5230, Jan. 2021, Number: 17 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en14175230. [Online]. Available: https://www.mdpi.com/1996-1073/14/17/5230 (visited on 02/02/2022).

[41] D. Bogdanov, A. Gulagi, M. Fasihi, and C. Breyer, "Full energy sector transition towards 100% renewable energy supply: Integrating power, heat, transport and industry sectors including desalination," *Applied Energy*, vol. 283, p. 116 273, Feb. 1, 2021, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2020.116273. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261920316639 (visited on 02/02/2022).

[42] F. Wagner, "CO2 emissions of nuclear power and renewable energies: A statistical analysis of european and global data," *Eur. Phys. J. Plus*, vol. 136, no. 5, p. 562, May 20, 2021, ISSN: 2190-5444. DOI: 10.1140/epjp/s13360-021-01508-7. [Online]. Available: https://doi.org/10.1140/epjp/s13360-021-01508-7 (visited on 01/27/2023).

[43] B. W. Brook, A. Alonso, D. A. Meneley, J. Misak, T. Blees, and J. B. van Erp, "Why nuclear energy is sustainable and has to be part of the energy mix," *Sustainable Materials and Technologies*, vol. 1-2, pp. 8–16, Dec. 1, 2014, ISSN: 2214-9937. DOI: 10.1016/j.susmat.2014.11.001. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214993714000050 (visited on 02/15/2021).

[44] A. Epiney, C. Rabiti, P. Talbot, and A. Alfonsi, "Economic analysis of a nuclear hybrid energy system in a stochastic environment including wind turbines in an electricity grid," *Applied Energy*, vol. 260, p. 114 227, Feb. 15, 2020, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.114227. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261919319142 (visited on 12/15/2019).

[45] D. Petti, "The future of nuclear energy in a carbon-constrained world," *Massachusetts Institute of Technology Energy Initiative (MITEI)*, p. 272, 2018.

[46] P. Patrizio, Y. W. Pratama, and N. M. Dowell, "Socially equitable energy system transitions," *Joule*, vol. 4, no. 8, pp. 1700–1713, Aug. 19, 2020, ISSN: 2542-4351. DOI: 10.1016/j.joule.2020.07.010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2542435120303287 (visited on 07/14/2022).

[47] M. R. Shaner, S. J. Davis, N. S. Lewis, and K. Caldeira, "Geophysical constraints on the reliability of solar and wind power in the united states," *Energy Environ. Sci.*, vol. 11, no. 4, pp. 914–925, Apr. 18, 2018, Publisher: The Royal Society of Chemistry, ISSN: 1754-5706. DOI: 10.1039/C7EE03029K. [Online].

Available: http://pubs.rsc.org/en/content/articlelanding/2018/ee/c7ee03029k (visited on 03/17/2021).

[48] S. G. Dotson, "The influence of temporal detail and inter-annual resource variability on energy planning models," Thesis, University of Illinois Urbana-Champaign, Urbana, IL, 2022, 99 pp. [Online]. Available: https://hdl.handle.net/2142/115793 (visited on 11/14/2022).

[49] S. R. Greene, "Enhancing electric grid, critical infrastructure, and societal resilience with resilient nuclear power plants (rNPPs)," *Nuclear Technology*, vol. 205, no. 3, pp. 397–414, Mar. 4, 2019, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00295450.2018.1505357, ISSN: 0029-5450. DOI: 10.1080/00295450.2018.1505357. [Online]. Available: https://doi.org/10.1080/00295450.2018.1505357 (visited on 07/13/2022).

[50] S. H. Kim, T. A. Taiwo, and B. W. Dixon, "The carbon value of nuclear power plant lifetime extensions in the united states," *Nuclear Technology*, vol. 0, no. 0, pp. 1–19, Oct. 13, 2021, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00295450.2021.1951554, ISSN: 0029-5450. DOI: 10.1080/00295450.2021.1951554. [Online]. Available: https://doi.org/10.1080/00295450.2021.1951554 (visited on 11/02/2021).

[51] M. Lehtveer and F. Hedenus, "How much can nuclear power reduce climate mitigation cost? – critical parameters and sensitivity," *Energy Strategy Reviews*, vol. 6, pp. 12–19, Jan. 1, 2015, ISSN: 2211-467X. DOI: 10.1016/j.esr.2014.11.003. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2211467X14000601 (visited on 10/27/2021).

[52] K. Vaillancourt, M. Labriet, R. Loulou, and J.-P. Waaub, "The role of nuclear energy in long-term climate scenarios: An analysis with the world-TIMES model," *Energy Policy*, vol. 36, no. 7, pp. 2296–2307, Jul. 1, 2008, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2008.01.015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421508000153 (visited on 03/23/2021).

[53] F. J. de Sisternes, J. D. Jenkins, and A. Botterud, "The value of energy storage in decarbonizing the electricity sector," *Applied Energy*, vol. 175, pp. 368–379, Aug. 1, 2016, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2016.05.014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261916305967 (visited on 10/28/2021).

[54] R. Alzbutas and E. Norvaisa, "Uncertainty and sensitivity analysis for economic optimisation of new energy source in lithuania," *Progress in Nuclear Energy*, vol. 61, pp. 17–25, Nov. 2012, ISSN: 01491970. DOI: 10.1016/j.pnucene.2012.06.006. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0149197012000844 (visited on 10/19/2021).

[55] S.
bibinitperiod T. Office of Nuclear Energy. "NRC certifies first u.s. small modular reactor design," Energy.gov. (Jan. 20, 2023), [Online]. Available: https://www.energy.gov/ne/articles/nrc-certifies-first-us-small-modular-reactor-design (visited on 02/08/2023).

[56] S. Johnson. "New york's indian point nuclear power plant closes after 59 years of operation," EIA.gov. (Apr. 30, 2021), [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=47776 (visited on 02/08/2023).

[57] B. P. Heard, B. W. Brook, T. M. L. Wigley, and C. J. A. Bradshaw, "Burden of proof: A comprehensive review of the feasibility of 100% renewable-electricity systems," *Renewable and Sustainable Energy Reviews*, vol. 76, pp. 1122–1133, Sep. 1, 2017, ISSN: 1364-0321. DOI: 10.1016/j.rser.2017.03.114. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032117304495 (visited on 02/08/2023).

[58] D. Pitt and G. Michaud, "Assessing the value of distributed solar energy generation," *Curr Sustainable Renewable Energy Rep*, vol. 2, no. 3, pp. 105–113, Sep. 1, 2015, ISSN: 2196-3010. DOI: 10.1007/s40518-015-0030-0. [Online]. Available: https://doi.org/10.1007/s40518-015-0030-0 (visited on 03/01/2022).

[59] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nat Energy*, vol. 1, no. 4, pp. 1–6, Mar. 21, 2016, Number: 4 Publisher: Nature Publishing Group, ISSN: 2058-7546. DOI: 10.1038/nenergy.2016.32. [Online]. Available: http://www.nature.com/articles/nenergy201632 (visited on 07/11/2022).

[60] N. Wang, R. Verzijlbergh, P. Heijnen, and P. Herder, "Modeling the decentralized energy investment and operation in the prosumer era: A systematic review," in *2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, Oct. 2020, pp. 1079–1083. DOI: 10.1109/ISGT-Europe47291.2020.9248838.

[61] B. Morvaj, R. Evins, and J. Carmeliet, "Decarbonizing the electricity grid: The impact on urban energy systems, distribution grids and district heating potential," *Applied Energy*, vol. 191, pp. 125–140, Apr. 2017, ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.01.058. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261917300661 (visited on 08/09/2022).

[62] A. Q. Gilbert and M. D. Bazilian, "Can distributed nuclear power address energy resilience and energy poverty?" *Joule*, vol. 4, no. 9, pp. 1839–1843, Sep. 16, 2020, ISSN: 2542-4351. DOI: 10.1016/j.joule.2020.08.005. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2542435120303512 (visited on 07/11/2022).

[63] L. Li, H. Mu, N. Li, and M. Li, "Economic and environmental optimization for distributed energy resource systems coupled with district energy networks," *Energy*, vol. 109, pp. 947–960, Aug. 2016, ISSN: 03605442. DOI: 10.1016/j.energy.2016.05.026. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0360544216305783 (visited on 08/09/2022).

[64] T. Falke, S. Krengel, A.-K. Meinerzhagen, and A. Schnettler, "Multi-objective optimization and simulation model for the design of distributed energy systems," *Applied Energy*, vol. 184, pp. 1508–1516, Dec. 2016, ISSN: 03062619. DOI: 10.1016/j.apenergy.2016.03.044. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261916303646 (visited on 08/09/2022).

[65] S. M. McNeeley and H. Lazrus, "The cultural theory of risk for climate change adaptation," *Weather, Climate, and Society*, vol. 6, no. 4, pp. 506–519, Oct. 1, 2014, Publisher: American Meteorological Society Section: Weather, Climate, and Society, ISSN: 1948-8327, 1948-8335. DOI: 10.1175/WCAS-D-13-00027.1. [Online]. Available: https://journals.ametsoc.org/view/journals/wcas/6/4/wcas-d-13-00027_1.xml (visited on 01/30/2023).

[66] S. van de Graaff, "Understanding the nuclear controversy: An application of cultural theory," *Energy Policy*, vol. 97, pp. 50–59, Oct. 1, 2016, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2016.07.007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421516303597 (visited on 08/18/2021).

[67] B. K. Sovacool and M. H. Dworkin, "Energy justice: Conceptual insights and practical applications," *Applied Energy*, vol. 142, pp. 435–444, Mar. 15, 2015, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2015.01.002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261915000082 (visited on 01/12/2023).

[68] D. Schlosberg, "2 distribution and beyond: Conceptions of justice in contemporary theory and practice," in *Defining Environmental Justice: Theories, Movements, and Nature*, D. Schlosberg, Ed., Oxford University Press, May 1, 2007, p. 0, ISBN: 978-0-19-928629-4. DOI: 10.1093/acprof:oso/9780199286294.003.0002. [Online]. Available: https://doi.org/10.1093/acprof:oso/9780199286294.003.0002 (visited on 01/12/2023).

[69] H. Brighouse, *Justice*. Polity, 2004, 188 pp., Google-Books-ID: 8XrVJJlQvEUC, ISBN: 978-0-7456-2595-9.

[70] N. van Uffelen, "Revisiting recognition in energy justice," *Energy Research & Social Science*, vol. 92, p. 102 764, Oct. 1, 2022, ISSN: 2214-6296. DOI: 10.1016/j.erss.2022.102764. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629622002675 (visited on 02/06/2023).

[71] C. F. Jones, "Building more just energy infrastructure: Lessons from the past," *Science as Culture*, vol. 22, no. 2, pp. 157–163, Jun. 1, 2013, Publisher: Routledge _eprint: https://doi.org/10.1080/09505431.2013.786991, ISSN: 0950-5431. DOI: 10.1080/09505431.2013.786991. [Online]. Available: https://doi.org/10.1080/09505431.2013.786991 (visited on 02/07/2023).

[72] G. Bridge, B. Özkaynak, and E. Turhan, "Energy infrastructure and the fate of the nation: Introduction to special issue," *Energy Research & Social Science*, Energy Infrastructure and the Fate of the Nation, vol. 41, pp. 1–11, Jul. 1, 2018, ISSN: 2214-6296. DOI: 10.1016/j.erss.2018.04.029. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629618302251 (visited on 01/12/2023).

[73] R. Figueiredo, M. Soliman, A. N. Al-Alawi, and M. J. Sousa, "The impacts of geopolitical risks on the energy sector: Micro-level operative analysis in the european union," *Economies*, vol. 10, no. 12, p. 299, Dec. 2022, Number: 12 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 2227-7099. DOI: 10.3390/economies10120299. [Online]. Available: https://www.mdpi.com/2227-7099/10/12/299 (visited on 02/07/2023).

[74] T. G. Reames, "Distributional disparities in residential rooftop solar potential and penetration in four cities in the united states," *Energy Research & Social Science*, vol. 69, p. 101 612, Nov. 1, 2020, ISSN: 2214-6296. DOI: 10.1016/j.erss.2020.101612. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629620301870 (visited on 04/25/2022).

[75] K. Yenneti, R. Day, and O. Golubchikov, "Spatial justice and the land politics of renewables: Dispossessing vulnerable communities through solar energy mega-projects," *Geoforum*, vol. 76, pp. 90–99, Nov. 1, 2016, ISSN: 0016-7185. DOI: 10.1016/j.geoforum.2016.09.004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0016718515303249 (visited on 07/21/2022).

[76] S. J. Barragan-Contreras, "Procedural injustices in large-scale solar energy: A case study in the mayan region of yucatan, mexico," *Journal of Environmental Policy & Planning*, vol. 24, no. 4, pp. 375–390, Jul. 4, 2022, Publisher: Routledge _eprint: https://doi.org/10.1080/1523908X.2021.2000378, ISSN: 1523-908X. DOI: 10.1080/1523908X.2021.2000378. [Online]. Available: https://doi.org/10.1080/1523908X.2021.2000378 (visited on 11/23/2022).

[77] S. Jasanoff and S.-H. Kim, "Containing the atom: Sociotechnical imaginaries and nuclear power in the united states and south korea," *Minerva*, vol. 47, no. 2, pp. 119–146, Jun. 1, 2009, ISSN: 1573-1871. DOI: 10.1007/s11024-009-9124-4. [Online]. Available: https://doi.org/10.1007/s11024-009-9124-4 (visited on 02/07/2023).

[78] S. V. Valentine and B. K. Sovacool, "Energy transitions and mass publics: Manipulating public perception and ideological entrenchment in japanese nuclear power policy," *Renewable and Sustainable Energy Reviews*, vol. 101, pp. 295–304, Mar. 2019, ISSN: 13640321. DOI: 10.1016/j.rser.2018.11.008. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032118307408 (visited on 07/27/2022).

[79] C. v. Clausewitz, "Chapter i: What is war?" In *On War*, trans. by J. Graham, New and Revised, vol. 1, 3 vols., Google-Books-ID: q4dZyNl0EukC, London: Kegan Paul, Trench, Trübner & Company, 1918, p. 23.

[80] P. N. Edwards and G. Hecht, "History and the technopolitics of identity: The case of apartheid south africa," *Journal of Southern African Studies*, vol. 36, no. 3, pp. 619–639, Sep. 1, 2010, Publisher: Routledge _eprint: https://doi.org/10.1080/03057070.2010.507568, ISSN: 0305-7070. DOI: 10.1080/03057070.2010.507568. [Online]. Available: https://doi.org/10.1080/03057070.2010.507568 (visited on 02/07/2023).

[81] J. F. DeCarolis, "Using modeling to generate alternatives (MGA) to expand our thinking on energy futures," *Energy Economics*, vol. 33, no. 2, pp. 145–152, Mar. 1, 2011, Publisher: Elsevier, ISSN: 0140-9883. DOI: 10.1016/j.eneco.2010.05.002. [Online]. Available: https://ideas.repec.org/a/eee/eneeco/v33y2011i2p145-152.html (visited on 05/22/2020).

[82] X. Yue, S. Pye, J. DeCarolis, F. G. Li, F. Rogan, and B. Gallachóir, "A review of approaches to uncertainty assessment in energy system optimization models," *Energy Strategy Reviews*, vol. 21, pp. 204–217, Aug. 2018, ISSN: 2211467X. DOI: 10.1016/j.esr.2018.06.003. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2211467X18300543 (visited on 10/27/2021).

[83] G. Limpens, S. Moret, H. Jeanmart, and F. Maréchal, "EnergyScope TD: A novel open-source model for regional energy systems," *Applied Energy*, vol. 255, p. 113 729, Dec. 1, 2019, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2019.113729. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919314163 (visited on 12/14/2022).

[84] S. Nalley, A. LaRose, J. Diefenderfer, J. Staub, J. Turnure, and L. Westfall, "The national energy modeling system: An overview 2018," Energy Information Administration, Washington D.C. United States, Apr. 2019, p. 75. [Online]. Available: https://www.eia.gov/outlooks/aeo/nems/overview/pdf/0581(2018).pdf.

[85] I. Capellán-Pérez, I. d. Blas, J. Nieto, *et al.*, "MEDEAS: A new modeling framework integrating global biophysical and socioeconomic constraints," *Energy Environ. Sci.*, vol. 13, no. 3, pp. 986–1017, Mar. 18, 2020, Publisher: The Royal Society of Chemistry, ISSN: 1754-5706. DOI: 10.1039/C9EE02627D. [Online]. Available: https://pubs.rsc.org/en/content/articlelanding/2020/ee/c9ee02627d (visited on 12/13/2022).

[86] D. Huppmann and R. Egging, "Market power, fuel substitution and infrastructure: A large-scale equilibrium model of global energy markets," German Institute for Economic Research (DIW Berlin), Berlin, Germany, 1370, 2014, p. 35. [Online]. Available: http://www.diw.de/discussionpapers.

[87] M. B. Anwar, G. Stephen, S. Dalvi, *et al.*, "Modeling investment decisions from heterogeneous firms under imperfect information and risk in wholesale electricity markets," *Applied Energy*, vol. 306, p. 117 908, Jan. 2022, ISSN: 03062619. DOI: 10.1016/j.apenergy.2021.117908. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261921012198 (visited on 06/21/2022).

[88] M. Zade, Z. You, B. Kumaran Nalini, P. Tzscheutschler, and U. Wagner, "Quantifying the flexibility of electric vehicles in germany and california—a case study," *Energies*, vol. 13, no. 21, p. 5617, Jan. 2020, Number: 21 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en13215617. [Online]. Available: https://www.mdpi.com/1996-1073/13/21/5617 (visited on 12/12/2022).

[89] F. Nitsch, M. Deissenroth-Uhrig, C. Schimeczek, and V. Bertsch, "Economic evaluation of battery storage systems bidding on day-ahead and automatic frequency restoration reserves markets," *Applied Energy*, vol. 298, p. 117 267, Sep. 15, 2021, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.117267. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921006851 (visited on 01/11/2023).

[90] A. Fattahi, J. Sijm, and A. Faaij, "A systemic approach to analyze integrated energy system modeling tools: A review of national models," *Renewable and Sustainable Energy Reviews*, vol. 133, p. 110 195, Nov. 2020, ISSN: 1364-0321. DOI: 10.1016/j.rser.2020.110195. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7452863/ (visited on 10/19/2021).

[91] Y. Su, J. D. Kern, S. Denaro, *et al.*, "An open source model for quantifying risks in bulk electric power systems from spatially and temporally correlated hydrometeorological processes," *Environmental Modelling & Software*, vol. 126, p. 104 667, Apr. 1, 2020, ISSN: 1364-8152. DOI: 10.1016/j.envsoft.2020.104667. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364815219309739 (visited on 12/12/2022).

[92] LeonieFierz, *Hues-platform/cesar-p-core: CESAR-p-v2.0.1*, Jul. 30, 2021. DOI: 10.5281/zenodo.5148531. [Online]. Available: https://zenodo.org/record/5148531 (visited on 12/13/2022).

[93] T. Boßmann and I. Staffell, "The shape of future electricity demand: Exploring load curves in 2050s germany and britain," *Energy*, vol. 90, pp. 1317–1333, Oct. 1, 2015, ISSN: 0360-5442. DOI: 10.1016/j.energy.2015.06.082. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544215008385 (visited on 12/12/2022).

[94] M. Barsanti, J. S. Schwarz, L. G. Gérard Constantin, P. Kasturi, C. R. Binder, and S. Lehnhoff, "Socio-technical modeling of smart energy systems: A co-simulation design for domestic energy demand," *Energy Informatics*, vol. 4, no. 3, p. 12, Sep. 13, 2021, ISSN: 2520-8942. DOI: 10.1186/s42162-

021-00180-6. [Online]. Available: https://doi.org/10.1186/s42162-021-00180-6 (visited on 12/12/2022).

[95] L. Thurner, A. Scheidler, F. Schäfer, *et al.*, "Pandapower - an open source python tool for convenient modeling, analysis and optimization of electric power systems," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6510–6521, Nov. 2018, ISSN: 0885-8950, 1558-0679. DOI: 10.1109/TPWRS.2018.2829021. arXiv: 1709.06743[cs]. [Online]. Available: http://arxiv.org/abs/1709.06743 (visited on 12/13/2022).

[96] S. P. Vera, *GridCal*, version 4.5.5, original-date: 2016-01-13T15:40:10Z, Dec. 7, 2022. [Online]. Available: https://github.com/SanPen/GridCal (visited on 12/13/2022).

[97] C. Matke, W. Medjroubi, D. Kleinhans, and S. Sager, "Structure analysis of the german transmission network using the open source model SciGRID," in *Advances in Energy System Optimization*, V. Bertsch, W. Fichtner, V. Heuveline, and T. Leibfried, Eds., ser. Trends in Mathematics, Cham: Springer International Publishing, 2017, pp. 177–188, ISBN: 978-3-319-51795-7. DOI: 10.1007/978-3-319-51795-7_11.

[98] L. Göke, "A graph-based formulation for modeling macro-energy systems," *Applied Energy*, vol. 301, p. 117 377, Nov. 2021, ISSN: 03062619. DOI: 10.1016/j.apenergy.2021.117377. arXiv: 2004.10184[physics]. [Online]. Available: http://arxiv.org/abs/2004.10184 (visited on 12/13/2022).

[99] N. Helistö, J. Kiviluoma, J. Ikäheimo, *et al.*, "Backbone—an adaptable energy systems modelling framework," *Energies*, vol. 12, no. 17, p. 3388, Jan. 2019, Number: 17 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en12173388. [Online]. Available: https://www.mdpi.com/1996-1073/12/17/3388 (visited on 12/12/2022).

[100] L. Göransson and F. Johnsson, "Cost-optimized allocation of wind power investments: A nordic–german perspective," *Wind Energy*, vol. 16, no. 4, pp. 587–604, 2013, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/we ISSN: 1099-1824. DOI: 10.1002/we.1517. [Online]. Available: http://onlinelibrary.wiley.com/doi/abs/10.1002/we.1517 (visited on 12/12/2022).

[101] S. Pfenninger and B. Pickering, "Calliope: A multi-scale energy systems modelling framework," *Journal of Open Source Software*, vol. 3, no. 29, p. 825, Sep. 12, 2018, ISSN: 2475-9066. DOI: 10.21105/joss.00825. [Online]. Available: https://joss.theoj.org/papers/10.21105/joss.00825 (visited on 12/12/2022).

[102] L. E. Kuepper, H. Teichgraeber, and A. R. Brandt, "CapacityExpansion: A capacity expansion modeling framework in julia," *Journal of Open Source Software*, vol. 5, no. 52, p. 2034, Aug. 31, 2020, ISSN: 2475-9066. DOI: 10.21105/joss.02034. [Online]. Available: https://joss.theoj.org/papers/10.21105/joss.02034 (visited on 12/12/2022).

[103] A. Zerrahn and W.-P. Schill, "Long-run power storage requirements for high shares of renewables: Review and a new model," *Renewable and Sustainable Energy Reviews*, vol. 79, pp. 1518–1534, Nov. 1, 2017, ISSN: 1364-0321. DOI: 10.1016/j.rser.2016.11.098. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032116308619 (visited on 12/13/2022).

[104] S. Quoilin, I. Hidalgo, and A. Zucker, *Modelling Future EU Power Systems Under High Shares of Renewables: The Dispa-SET 2.1 open-source model*. Jan. 1, 2017. DOI: 10.2760/25400.

[105] F. Leuthold, H. Weigt, and C. von Hirschhausen, *ELMOD - a model of the european electricity market*, Rochester, NY, Jul. 22, 2008. DOI: 10.2139/ssrn.1169082. [Online]. Available: http://papers.ssrn.com/abstract=1169082 (visited on 12/13/2022).

[106] T. Ladwig, *Demand Side Management in Deutschland zur Systemintegration erneuerbarer Energien* (Schriften des Lehrstuhls für Energiewirtschaft, TU Dresden Band 14), Stand: 05/2018, in collab. with T. U. Dresden. Dresden: Technische Universität Dresden, Fakultät der Wirtschaftswissenschaften, Lehrstuhl für Energiewirtschaft, 2018, 224 pp., ISBN: 978-3-86780-569-8.

[107] L. Hirth, O. Ruhnau, and R. Sgarlato, "The european electricity market model EMMA - model description," Kiel, Hamburg: ZBW - Leibniz Information Centre for Economics, Working Paper, 2021. [Online]. Available: https://www.econstor.eu/handle/10419/244592 (visited on 12/13/2022).

[108] B. Shirizadeh, Q. Perrier, and
bibinitperiod P. Quirion, "How sensitive are optimal fully renewable power systems to technology cost uncertainty?" *The Energy Journal*, vol. Volume 43, Number 1 2022, Publisher: International Association for Energy Economics. [Online]. Available: https://ideas.repec.org/a/aen/journl/ej43-1-quirion.html (visited on 12/12/2022).

[109] C. Heaton, "Modelling low-carbon energy system designs with the ETI ESME model," Energy Technologies Institute, Apr. 2014, p. 28.

[110] C. F. Heuberger, E. S. Rubin, I. Staffell, N. Shah, and N. Mac Dowell, "Power capacity expansion planning considering endogenous technology cost learning," *Applied Energy*, vol. 204, pp. 831–845, Oct. 15, 2017, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.07.075. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261917309479 (visited on 12/13/2022).

[111] O. Lugovoy and V. Potashnikov, *energyRt: Energy systems modeling toolbox in r, development version*, version 0.01.21.9003, original-date: 2016-03-17T16:08:29Z, Sep. 2, 2022. [Online]. Available: https://github.com/energyRt/energyRt (visited on 12/13/2022).

[112] D. Atabay, "An open-source model for optimal design and operation of industrial energy systems," *Energy*, vol. 121, pp. 803–821, Feb. 15, 2017, ISSN: 0360-5442. DOI: 10.1016/j.energy.2017.01.030. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544217300300 (visited on 12/13/2022).

[113] A. Alhamwi, W. Medjroubi, T. Vogt, and C. Agert, "GIS-based urban energy systems models and tools: Introducing a model for the optimisation of flexibilisation technologies in urban areas," *Applied Energy*, vol. 191, pp. 1–9, Apr. 1, 2017, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2017.01.048. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261917300569 (visited on 12/12/2022).

[114] P. Hauser, "A modelling approach for the german gas grid using highly resolved spatial, temporal and sectoral data (GAMAMOD-DE)," Leibniz Information Centre for Economics, Kiel, Hamburg, Dresden, Germany, 2019, p. 63. [Online]. Available: http://hdl.handle.net/10419/197000.

[115] J. Jenkins, N. Sepulveda, D. Mallapragada, *et al.*, *GenX*, version 0.3.0, Apr. 2022. DOI: 10.5281/zenodo.6229425. [Online]. Available: https://github.com/GenXProject/GenX (visited on 12/12/2022).

[116] M. Zeyringer, J. Price, B. Fais, P.-H. Li, and E. Sharp, "Designing low-carbon power systems for great britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather," *Nat Energy*, vol. 3, no. 5, pp. 395–403, May 2018, Number: 5 Publisher: Nature Publishing Group, ISSN: 2058-7546. DOI: 10.1038/s41560-018-0128-x. [Online]. Available: https://www.nature.com/articles/s41560-018-0128-x (visited on 12/13/2022).

[117] R. Loulou, G. Goldstein, and K. Noble, "Documentation for the MARKAL family of models," Internation Energy Agency, Oct. 2004, p. 389.

[118] K. Sakellaris, J. Canton, E. Zafeiratou, and L. Fournié, "METIS – an energy modelling tool to support transparent policy making," *Energy Strategy Reviews*, vol. 22, pp. 127–135, Nov. 1, 2018, ISSN: 2211-467X. DOI: 10.1016/j.esr.2018.08.013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2211467X18300816 (visited on 12/13/2022).

[119] S. Wehrle, J. Schmidt, and C. Mikovits, "The cost of undisturbed landscapes," *Energy Policy*, vol. 159, p. 112 617, Dec. 2021, ISSN: 03014215. DOI: 10.1016/j.enpol.2021.112617. arXiv: 2006.08009[cs,econ,eess,q-fin]. [Online]. Available: http://arxiv.org/abs/2006.08009 (visited on 12/12/2022).

[120] S. Hilpert, C. Kaldemeyer, U. Krien, S. Günther, C. Wingenbach, and G. Plessmann, "The open energy modelling framework (oemof) - a new approach to facilitate open science in energy system modelling," *Energy Strategy Reviews*, vol. 22, pp. 16–25, Nov. 2018, ISSN: 2211467X. DOI: 10.1016/j.esr.2018.07.001. arXiv: 1808.08070[cs]. [Online]. Available: http://arxiv.org/abs/1808.08070 (visited on 12/13/2022).

[121] J. N. P. van Stralen, F. Dalla Longa, B. W. Daniëls, K. E. L. Smekens, and B. van der Zwaan, "OPERA: A new high-resolution energy system model for sector integration research," *Environ Model Assess*, vol. 26, no. 6, pp. 873–889, Dec. 1, 2021, ISSN: 1573-2967. DOI: 10.1007/s10666-020-09741-7. [Online]. Available: https://doi.org/10.1007/s10666-020-09741-7 (visited on 12/13/2022).

[122] M. Howells, H. Rogner, N. Strachan, *et al.*, "OSeMOSYS: The open source energy modeling system: An introduction to its ethos, structure and development," *Energy Policy*, Sustainability of biofuels, vol. 39, no. 10, pp. 5850–5870, Oct. 1, 2011, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2011.06.033. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421511004897 (visited on 12/13/2022).

[123] D. Mentis, M. Welsch, F. Fuso Nerini, *et al.*, "A GIS-based approach for electrification planning—a case study on nigeria," *Energy for Sustainable Development*, vol. 29, pp. 142–150, Dec. 2015, ISSN: 09730826. DOI: 10.1016/j.esd.2015.09.007. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0973082615000952 (visited on 12/12/2022).

[124] J. P. Deane, Á. Driscoll, and B. P. Ó. Gallachóir, "Quantifying the impacts of national renewable electricity ambitions using a north–west european electricity market model," *Renewable Energy*, vol. 80, pp. 604–609, Aug. 1, 2015, ISSN: 0960-1481. DOI: 10.1016/j.renene.2015.02.048. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148115001640 (visited on 12/13/2022).

[125] T. Vandyck, K. Keramidas, B. Saveyn, A. Kitous, and Z. Vrontisi, "A global stocktake of the paris pledges: Implications for energy systems and economy," *Global Environmental Change*, vol. 41, pp. 46–63, Nov. 1, 2016, ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2016.08.006. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S095937801630142X (visited on 12/13/2022).

[126] R. Weinhold and R. Mieth, "Power market tool (POMATO) for the analysis of zonal electricity markets," *SoftwareX*, vol. 16, p. 100 870, Dec. 1, 2021, ISSN: 2352-7110. DOI: 10.1016/j.softx.2021.100870. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352711021001394 (visited on 12/12/2022).

[127] Y. Antoniou and P. Capros, "Decision support system framework of the PRIMES energy model of the european commission," *International Journal of Global Energy Issues*, vol. 12, Jan. 1, 1999. DOI: 10.1504/IJGEI.1999.000823.

[128] T. Brown, J. Hörsch, and D. Schlachtberger, "PyPSA: Python for power system analysis," *Journal of Open Research Software*, vol. 6, no. 1, p. 4, Jan. 16, 2018, Number: 1 Publisher: Ubiquity Press, ISSN: 2049-9647. DOI: 10.5334/jors.188. [Online]. Available: http://openresearchsoftware.metajnl.com/articles/10.5334/jors.188/ (visited on 12/12/2022).

[129] H. C. Gils, Y. Scholz, T. Pregger, D. Luca de Tena, and D. Heide, "Integrated modelling of variable renewable energy-based power supply in europe," *Energy*, vol. 123, pp. 173–188, Mar. 15, 2017, ISSN: 0360-5442. DOI: 10.1016/j.energy.2017.01.115. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544217301238 (visited on 12/13/2022).

[130] T. Simpkins, D. Cutler, K. Anderson, *et al.*, "REopt: A platform for energy system integration and optimization: Preprint,"

[131] J. Abrell and F. Kunz, "Integrating intermittent renewable wind generation - a stochastic multi-market electricity model for the european electricity market," *Netw Spat Econ*, vol. 15, no. 1, pp. 117–147, Mar. 1, 2015, ISSN: 1572-9427. DOI: 10.1007/s11067-014-9272-4. [Online]. Available: https://doi.org/10.1007/s11067-014-9272-4 (visited on 12/12/2022).

[132] J. Johnston, R. Henríquez, B. Maluenda, and M. Fripp, "Switch 2.0: A modern platform for planning high-renewable power systems," *SoftwareX*, vol. 10, p. 100 251, Jul. 2019, ISSN: 23527110. DOI: 10.1016/j.softx.2019.100251. arXiv: 1804.05481[physics]. [Online]. Available: http://arxiv.org/abs/1804.05481 (visited on 12/12/2022).

[133] R. Loulou, G. Goldstein, A. Kanudia, A. Lettila, and U. Remme, "Documentation for the TIMES model part i," International Energy Agency, Jul. 2016, p. 151. [Online]. Available: https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-I_July-2016.pdf (visited on 12/12/2022).

[134] K. Hunter, S. Sreepathi, and J. F. DeCarolis, "Modeling for insight using tools for energy model optimization and analysis (temoa)," North Carolina State University, Raleigh, NC, Apr. 8, 2013. [Online]. Available: https://temoacloud.com/wp-content/uploads/2019/12/Hunter_etal_2013.pdf.

[135] L. Andresen, P. Dubucq, R. Peniche Garcia, G. Ackermann, A. Kather, and G. Schmitz, "Status of the TransiEnt library: Transient simulation of coupled energy networks with high share of renewable energy," presented at the The 11th International Modelica Conference, Sep. 18, 2015, pp. 695–705. DOI: 10.3384/ecp15118695. [Online]. Available: https://ep.liu.se/en/conference-article.aspx?series=ecp&issue=118&Article_No=75 (visited on 01/11/2023).

[136] J. Dorfner, "Open Source Modelling and Optimisation of Energy Infrastructure at Urban Scale," Doctoral, Technical University of Munich, Munich, Germany, 2015, 205 pp.

[137] A. F. M. K. Chowdhury, J. Kern, T. D. Dang, and S. Galelli, "PowNet: A network-constrained unit commitment/economic dispatch model for large-scale power systems analysis," *Journal of Open Research Software*, vol. 8, no. 1, p. 5, Mar. 12, 2020, Number: 1 Publisher: Ubiquity Press, ISSN: 2049-9647. DOI: 10.5334/jors.302. [Online]. Available: http://openresearchsoftware.metajnl.com/articles/10.5334/jors.302/ (visited on 12/12/2022).

[138] Frauke Wiese, "Renpass renewable energy pathways simulation system - open source as an approach to meet challenges in energy modeling," Doctoral Dissertation, University of Flensburg, Flensburg, Germany, Apr. 2015, 176 pp. [Online]. Available: https://www.reiner-lemoine-stiftung.de/pdf/dissertationen/Dissertation-Frauke_Wiese.pdf.

[139] I. R. Chaer, "SIMULACIÓN DE SISTEMAS DE ENERGÍA ELÉCTRICA.," M.S. Electrical Engineering, Instituto de Ingeniería Eléctrica, Montevideo, Uruguay, Aug. 2008, 137 pp. [Online]. Available: https://simsee.org/simsee/tesischaer.pdf.

[140] Y. Xu, N. Myhrvold, D. Sivam, *et al.*, *U.s. test system with high spatial and temporal resolution for renewable integration studies*, Feb. 14, 2020. arXiv: 2002.06155[physics]. [Online]. Available: http://arxiv.org/abs/2002.06155 (visited on 12/12/2022).

[141] J. C. Richstein, E. J. L. Chappin, and L. J. de Vries, "Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach," *Energy Policy*, vol. 71, pp. 139–158, Aug. 1, 2014, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2014.03.037. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421514002043 (visited on 12/13/2022).

[142] H. Lund, J. Z. Thellufsen, P. A. Østergaard, P. Sorknæs, I. R. Skov, and B. V. Mathiesen, "EnergyPLAN – advanced analysis of smart energy systems," *Smart Energy*, vol. 1, p. 100 007, Feb. 1, 2021, ISSN: 2666-9552. DOI: 10.1016/j.segy.2021.100007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666955221000071 (visited on 12/13/2022).

[143] Quintel, *ETM documentation*, original-date: 2013-01-07T15:34:17Z, Oct. 31, 2022. [Online]. Available: https://github.com/quintel/documentation (visited on 12/13/2022).

[144] N. D. Pflugradt, "Modelling of water and energy consumptionäuchen in households," Aug. 26, 2016.

[145] W. F. Holmgren, C. W. Hansen, and M. A. Mikofski, "Pvlib python: A python package for modeling solar energy systems," *Journal of Open Source Software*, vol. 3, no. 29, p. 884, Sep. 7, 2018, ISSN: 2475-9066. DOI: 10.21105/joss.00884. [Online]. Available: https://joss.theoj.org/papers/10.21105/joss.00884 (visited on 12/13/2022).

[146] A. Lyden, G. Flett, and P. G. Tuohy, "PyLESA: A python modelling tool for planning-level local, integrated, and smart energy systems analysis," *SoftwareX*, vol. 14, p. 100 699, Jun. 1, 2021, ISSN: 2352-7110. DOI: 10.1016/j.softx.2021.100699. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352711021000443 (visited on 12/13/2022).

[147] N. Blair, A. P. Dobos, J. Freeman, *et al.*, "System advisor model, SAM 2014.1.14: General description," *Renewable Energy*, 2014.

[148] M. Naumann, C. N. Truong, M. Schimpe, D. Kucevic, A. Jossen, and H. C. Hesse, "SimSES: Software for techno-economic simulation of stationary energy storage systems," in *International ETG Congress 2017*, Nov. 2017, pp. 1–6.

[149] S. Glismann, "Ancillary services acquisition model: Considering market interactions in policy design," *Applied Energy*, vol. 304, p. 117 697, Dec. 15, 2021, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.117697. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030626192101045X (visited on 12/13/2022).

[150] M. Zade, S. D. Lumpp, P. Tzscheutschler, and U. Wagner, "Satisfying user preferences in community-based local energy markets — auction-based clearing approaches," *Applied Energy*, vol. 306, p. 118 004, Jan. 15, 2022, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2021.118004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921013003 (visited on 12/13/2022).

[151] L. Exel, F. Felgner, and G. Frey, "Multi-domain modeling of distributed energy systems - the MOCES approach," in *2015 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov. 2015, pp. 774–779. DOI: 10.1109/SmartGridComm.2015.7436395.

[152] A. R. de Queiroz, D. Mulcahy, A. Sankarasubramanian, *et al.*, "Repurposing an energy system optimization model for seasonal power generation planning," *Energy*, vol. 181, pp. 1321–1330, Aug. 2019, ISSN: 03605442. DOI: 10.1016/j.energy.2019.05.126. arXiv: 1911.03780. [Online]. Available: http://arxiv.org/abs/1911.03780 (visited on 10/26/2021).

[153] EIA, "Price elasticity for energy use in buildings in the united states," U.S. Department of Energy, Washington D.C. United States, 2021, p. 23.

[154] X. Labandeira, J. M. Labeaga, and X. López-Otero, "A meta-analysis on the price elasticity of energy demand," *Energy Policy*, vol. 102, pp. 549–568, Mar. 1, 2017, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2017.01.002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421517300022 (visited on 12/08/2022).

[155] Z. Csereklyei, "Price and income elasticities of residential and industrial electricity demand in the european union," *Energy Policy*, vol. 137, p. 111 079, Feb. 1, 2020, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2019.111079. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0301421519306664 (visited on 12/08/2022).

[156] S. Pfenninger, A. Hawkes, and J. Keirstead, "Energy systems modeling for twenty-first century energy challenges," *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 74–86, May 1, 2014, ISSN: 1364-0321. DOI: 10.1016/j.rser.2014.02.003. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032114000872 (visited on 01/16/2023).

[157] J. DeCarolis, K. Hunter, and S. Sreepathi, "Multi-stage stochastic optimization of a simple energy system," p. 14, 2012.

[158] J. DeCarolis, S. Babaee, B. Li, and S. Kanungo, "Modelling to generate alternatives with an energy system optimization model," *Environmental Modelling & Software*, vol. 79, pp. 300–310, May 2016, ISSN: 13648152. DOI: 10.1016/j.envsoft.2015.11.019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364815215301080 (visited on 04/13/2020).

[159] E. Brill, J. Flach, L. Hopkins, and S. Ranjithan, "MGA: A decision support system for complex, incompletely defined problems," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 20, no. 4, pp. 745–757, Jul. 1990, Conference Name: IEEE Transactions on Systems, Man, and Cybernetics, ISSN: 2168-2909. DOI: 10.1109/21.105076.

[160] J. Blank and K. Deb, "Pymoo: Multi-objective optimization in python," *IEEE Access*, vol. 8, pp. 89 497–89 509, 2020, Conference Name: IEEE Access, ISSN: 2169-3536. DOI: 10.1109/ACCESS.2020.2990567.

[161] K. Deb and S. Tiwari, "Omni-optimizer: A generic evolutionary algorithm for single and multi-objective optimization," *European Journal of Operational Research*, vol. 185, no. 3, pp. 1062–1087, Mar. 16, 2008, ISSN: 0377-2217. DOI: 10.1016/j.ejor.2006.06.042. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0377221706006291 (visited on 01/19/2023).

[162] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Engineering*, vol. 5, no. 1, Q. Ai, Ed., p. 1 502 242, Jan. 1, 2018, Publisher: Cogent OA _eprint: https://doi.org/10.1080/23311916.2018.1502242, ISSN: null. DOI: 10.1080/23311916.2018.1502242. [Online]. Available: https://doi.org/10.1080/23311916.2018.1502242 (visited on 12/01/2022).

[163] M. T. M. Emmerich and A. H. Deutz, "A tutorial on multiobjective optimization: Fundamentals and evolutionary methods," *Nat Comput*, vol. 17, no. 3, pp. 585–609, Sep. 1, 2018, ISSN: 1572-9796. DOI: 10.1007/s11047-018-9685-y. [Online]. Available: https://doi.org/10.1007/s11047-018-9685-y (visited on 12/01/2022).

[164] D. H. LOUGHLIN, S. R. RANJITHAN, E. D. BRILL, and J. W. BAUGH, "Genetic algorithm approaches for addressing unmodeled objectives in optimization problems," *Engineering Optimization*, vol. 33, no. 5, pp. 549–569, Jun. 1, 2001, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/03052150108940933, ISSN: 0305-215X. DOI: 10.1080/03052150108940933. [Online]. Available: https://doi.org/10.1080/03052150108940933 (visited on 01/18/2023).

[165] E. M. Zechman and S. R. Ranjithan, "An evolutionary algorithm to generate alternatives (EAGA) for engineering optimization problems," *Engineering Optimization*, vol. 36, no. 5, pp. 539–553, Oct. 1, 2004, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/03052150410001704863, ISSN: 0305-215X. DOI: 10.1080/03052150410001704863. [Online]. Available: https://doi.org/10.1080/03052150410001704863 (visited on 01/18/2023).

[166] E. M. Zechman, M. H. Giacomoni, and M. E. Shafiee, "An evolutionary algorithm approach to generate distinct sets of non-dominated solutions for wicked problems," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 5, pp. 1442–1457, May 1, 2013, ISSN: 0952-1976. DOI: 10.1016/j.engappai.2013.03.004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0952197613000468 (visited on 01/17/2023).

[167] A. Pajares, X. Blasco, J. M. Herrero, and M. A. Martínez, "A comparison of archiving strategies for characterization of nearly optimal solutions under multi-objective optimization," *Mathematics*, vol. 9, no. 9, p. 999, Jan. 2021, Number: 9 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 2227-7390. DOI: 10.3390/math9090999. [Online]. Available: https://www.mdpi.com/2227-7390/9/9/999 (visited on 01/17/2023).

[168] A. Chattopadhyay, A.-P. Witmer, and P. W. Sauer, "The need for teaching place-based contextualization for sustainable power system infrastructure design," *IEEE Transactions on Power Systems*, vol. 36, no. 6, pp. 5846–5853, Nov. 2021, Conference Name: IEEE Transactions on Power Systems, ISSN: 1558-0679. DOI: 10.1109/TPWRS.2021.3072069.

[169] S. De-León Almaraz, C. Azzaro-Pantel, L. Montastruc, and M. Boix, "Deployment of a hydrogen supply chain by multi-objective/multi-period optimisation at regional and national scales," *Chemical Engineering Research and Design*, vol. 104, pp. 11–31, Dec. 2015, ISSN: 02638762. DOI: 10.1016/j.cherd.2015.07.005. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0263876215002506 (visited on 08/09/2022).

[170] M. Riou, F. Dupriez-Robin, D. Grondin, C. Le Loup, M. Benne, and Q. T. Tran, "Multi-objective optimization of autonomous microgrids with reliability consideration," *Energies*, vol. 14, no. 15, p. 4466, Jan. 2021, Number: 15 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en14154466. [Online]. Available: https://www.mdpi.com/1996-1073/14/15/4466 (visited on 07/18/2022).

[171] P. Laha and B. Chakraborty, "Low carbon electricity system for india in 2030 based on multi-objective multi-criteria assessment," *Renewable and Sustainable Energy Reviews*, vol. 135, p. 110 356, Jan. 2021, ISSN: 13640321. DOI: 10.1016/j.rser.2020.110356. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032120306444 (visited on 07/15/2022).

[172] M. J. Mayer, A. Szilágyi, and G. Gróf, "Environmental and economic multi-objective optimization of a household level hybrid renewable energy system by genetic algorithm," *Applied Energy*, vol. 269, p. 115 058, Jul. 2020, ISSN: 03062619. DOI: 10.1016/j.apenergy.2020.115058. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261920305705 (visited on 07/13/2022).

[173] M. G. Prina, V. Casalicchio, C. Kaldemeyer, *et al.*, "Multi-objective investment optimization for energy system models in high temporal and spatial resolution," *Applied Energy*, vol. 264, p. 114 728, Apr. 2020, ISSN: 03062619. DOI: 10.1016/j.apenergy.2020.114728. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261920302403 (visited on 07/14/2022).

[174] K. Donado, L. Navarro, C. G. Quintero M., and M. Pardo, "HYRES: A multi-objective optimization tool for proper configuration of renewable hybrid energy systems," *Energies*, vol. 13, no. 1, p. 26, Jan. 2020, Number: 1 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 1996-1073. DOI: 10.3390/en13010026. [Online]. Available: https://www.mdpi.com/1996-1073/13/1/26 (visited on 08/18/2022).

[175] M. G. Prina, M. Cozzini, G. Garegnani, *et al.*, "Multi-objective optimization algorithm coupled to EnergyPLAN software: The EPLANopt model," *Energy*, vol. 149, pp. 213–221, Apr. 15, 2018, ISSN: 0360-5442. DOI: 10.1016/j.energy.2018.02.050. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544218302780 (visited on 07/13/2022).

[176] S. Samsatli and N. J. Samsatli, "A multi-objective MILP model for the design and operation of future integrated multi-vector energy networks capturing detailed spatio-temporal dependencies," *Applied Energy*, vol. 220, pp. 893–920, Jun. 2018, ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.09.055. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261917313375 (visited on 08/09/2022).

[177] M. S. Mahbub, M. Cozzini, P. A. Østergaard, and F. Alberti, "Combining multi-objective evolutionary algorithms and descriptive analytical modelling in energy scenario design," *Applied Energy*, vol. 164, pp. 140–151, Feb. 2016, ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.11.042. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261915014920 (visited on 08/09/2022).

[178] S. E. Now, "RENEWABLE ENERGY SCENARIOS: PRELIMINARY MODELLING FOR WA's SWIS ELECTRICITY GRID, 2030," Sustainable Energy Now, West Perth, WA, Australia, Feb. 28, 2016, p. 4. [Online]. Available: https://d3n8a8pro7vhmx.cloudfront.net/sen/pages/132/attachments/original/1458114771/Modelling_Report_Summary_for_Launch_28-2-2016.pdf?1458114771 (visited on 12/13/2022).

[179] A. Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, "Multi-objective design under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 187–194, Jan. 1, 2016, ISSN: 0142-0615. DOI: 10.1016/j.ijepes.2015.07.007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0142061515002938 (visited on 07/20/2022).

[180] H. Bilil, G. Aniba, and M. Maaroufi, "Multiobjective optimization of renewable energy penetration rate in power systems," *Energy Procedia*, Technologies and Materials for Renewable Energy, Environment and Sustainability (TMREES14 – EUMISD), vol. 50, pp. 368–375, Jan. 1, 2014, ISSN: 1876-6102. DOI: 10.1016/j.egypro.2014.06.044. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1876610214007802 (visited on 07/13/2022).

[181] S. Fazlollahi, G. Becker, and F. Maréchal, "Multi-objectives, multi-period optimization of district energy systems: II—daily thermal storage," *Computers & Chemical Engineering*, vol. 71, pp. 648–662, Dec. 2014, ISSN: 00981354. DOI: 10.1016/j.compchemeng.2013.10.016. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0098135413003384 (visited on 08/09/2022).

[182] S. De-León Almaraz, C. Azzaro-Pantel, L. Montastruc, L. Pibouleau, and O. B. Senties, "Assessment of mono and multi-objective optimization to design a hydrogen supply chain," *International Journal of Hydrogen Energy*, vol. 38, no. 33, pp. 14 121–14 145, Nov. 2013, ISSN: 03603199. DOI: 10.1016/j.ijhydene.2013.07.059. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0360319913018065 (visited on 08/09/2022).

[183] Y. Katsigiannis, P. Georgilakis, and E. Karapidakis, "Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables," *IET Renew. Power Gener.*, vol. 4, no. 5, p. 404, 2010, ISSN: 17521416. DOI: 10.1049/iet-rpg.2009.0076. [Online]. Available: https://digital-library.theiet.org/content/journals/10.1049/iet-rpg.2009.0076 (visited on 07/20/2022).

[184] B. K. Sovacool, R. J. Heffron, D. McCauley, and A. Goldthau, "Energy decisions reframed as justice and ethical concerns," *Nat Energy*, vol. 1, no. 5, pp. 1–6, May 6, 2016, Number: 5 Publisher: Nature Publishing Group, ISSN: 2058-7546. DOI: 10.1038/nenergy.2016.24. [Online]. Available: https://www.nature.com/articles/nenergy201624 (visited on 01/27/2023).

[185] A. J. Chapman, B. C. McLellan, and T. Tezuka, "Prioritizing mitigation efforts considering co-benefits, equity and energy justice: Fossil fuel to renewable energy transition pathways," *Applied Energy*, vol. 219, pp. 187–198, Jun. 1, 2018, ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2018.03.054. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918303830 (visited on 07/15/2022).

[186] B. Li, J. Thomas, A. R. de Queiroz, and J. F. DeCarolis, "Open source energy system modeling using break-even costs to inform state-level policy: A north carolina case study," *Environ. Sci. Technol.*, vol. 54, no. 2, pp. 665–676, Jan. 21, 2020, ISSN: 0013-936X, 1520-5851. DOI: 10.1021/acs.est.9b04184. [Online]. Available: https://pubs.acs.org/doi/10.1021/acs.est.9b04184 (visited on 05/06/2020).

[187] R. J. Heffron, D. McCauley, and B. K. Sovacool, "Resolving society's energy trilemma through the energy justice metric," *Energy Policy*, vol. 87, pp. 168–176, Dec. 1, 2015, ISSN: 0301-4215. DOI: 10.1016/j.enpol.2015.08.033. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030142151530077X (visited on 02/15/2023).

[188] M. F. Johnson, A. G. Sveinsdóttir, and E. L. Guske, "The dakota access pipeline in illinois: Participation, power, and institutional design in united states critical energy infrastructure governance," *Energy Research & Social Science*, vol. 73, p. 101 908, Mar. 1, 2021, ISSN: 2214-6296. DOI: 10.1016/j.erss.2021.101908. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629621000013 (visited on 11/17/2022).

[189] J. F. DeCarolis, K. Hunter, and S. Sreepathi, "The case for repeatable analysis with energy economy optimization models," *Energy Economics*, vol. 34, no. 6, pp. 1845–1853, Nov. 1, 2012, ISSN: 0140-9883. DOI: 10.1016/j.eneco.2012.07.004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0140988312001405 (visited on 05/27/2021).

[190] S. Pfenninger, I. Schlect, T. Trondle, and T. Brown. "Openmod - open energy modelling initiative," openmod-initiative. (), [Online]. Available: https://www.openmod-initiative.org/ (visited on 12/13/2022).

[191] H. Forster and A. Siemons. "Open energy platform," openenergy-platform. (Feb. 24, 2022), [Online]. Available: https://openenergy-platform.org/ (visited on 12/13/2022).

[192] S. Dotson, *Python for generating energy systems (PyGenesys)*, version 0.1.0, original-date: 2021-05-27T18:28:46Z, Champaign, IL, Nov. 12, 2021. [Online]. Available: https://github.com/arfc/pygenesys (visited on 02/02/2022).

[193] T. Project. "Temoa – tools for energy model optimization and analysis," temoacloud.com. (Feb. 17, 2023), [Online]. Available: https://temoacloud.com/ (visited on 02/17/2023).

[194] N. Mouter, P. Koster, and T. Dekker, *An introduction to participatory value evaluation*, Rochester, NY, Dec. 15, 2019. DOI: 10.2139/ssrn.3358814. [Online]. Available: https://papers.ssrn.com/abstract=3358814 (visited on 01/27/2023).

[195] N. Mouter, P. Koster, and T. Dekker, "Contrasting the recommendations of participatory value evaluation and cost-benefit analysis in the context of urban mobility investments," *Transportation Research Part A: Policy and Practice*, vol. 144, pp. 54–73, Feb. 1, 2021, ISSN: 0965-8564. DOI: 10.1016/j.tra.2020.12.008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0965856420308016 (visited on 01/27/2023).

[196] T. Dekker, P. Koster, and N. Mouter, *The economics of participatory value evaluation*, Rochester, NY, Jan. 27, 2019. DOI: 10.2139/ssrn.3323645. [Online]. Available: https://papers.ssrn.com/abstract=3323645 (visited on 01/27/2023).

[197] N. Mouter, R. M. Shortall, S. L. Spruit, and A. V. Itten, "Including young people, cutting time and producing useful outcomes: Participatory value evaluation as a new practice of public participation in the dutch energy transition," *Energy Research & Social Science*, vol. 75, p. 101 965, May 1, 2021, ISSN: 2214-6296. DOI: 10.1016/j.erss.2021.101965. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S221462962100058X (visited on 01/27/2023).

[198] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002, ISBN: 1089-778X Publisher: IEEE.

[199] H. Seada and K. Deb, "A unified evolutionary optimization procedure for single, multiple, and many objectives," *IEEE Transactions on Evolutionary Computation*, vol. 20, no. 3, pp. 358–369, Jun. 2016, Conference Name: IEEE Transactions on Evolutionary Computation, ISSN: 1941-0026. DOI: 10.1109/TEVC.2015.2459718.

[200] J. Blank, K. Deb, Y. Dhebar, S. Bandaru, and H. Seada, "Generating well-spaced points on a unit simplex for evolutionary many-objective optimization," *IEEE Trans. Evol. Computat.*, vol. 25, no. 1, pp. 48–60, Feb. 2021, ISSN: 1089-778X, 1089-778X, 1941-0026. DOI: 10.1109/TEVC.2020.2992387. [Online]. Available: https://ieeexplore.ieee.org/document/9086772/ (visited on 01/23/2023).

[201] J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *J. Mach. Learn. Res.*, vol. 13, pp. 281–305, null Feb. 1, 2012, ISSN: 1532-4435.

[202] H. Ishibuchi, H. Masuda, Y. Tanigaki, and Y. Nojima, "Modified distance calculation in generational distance and inverted generational distance," in *Evolutionary Multi-Criterion Optimization*, A. Gaspar-Cunha, C. Henggeler Antunes, and C. C. Coello, Eds., ser. Lecture Notes in Computer Science, Cham: Springer International Publishing, 2015, pp. 110–125, ISBN: 978-3-319-15892-1. DOI: 10.1007/978-3-319-15892-1_8.

[203] W. Gorman, "The quest to quantify the value of lost load: A critical review of the economics of power outages," *The Electricity Journal*, vol. 35, no. 8, p. 107 187, Oct. 1, 2022, ISSN: 1040-6190. DOI: 10.1016/j.tej.2022.107187. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1040619022001130 (visited on 12/13/2022).

[204] M. Najafi, A. Akhavein, A. Akbari, and M. Dashtdar, "Value of the lost load with consideration of the failure probability," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 659–663, Mar. 1, 2021, ISSN: 2090-4479. DOI: 10.1016/j.asej.2020.05.012. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2090447920301167 (visited on 12/13/2022).

[205] B. Fadlallah, B. Chen, A. Keil, and J. Príncipe, "Weighted-permutation entropy: A complexity measure for time series incorporating amplitude information," *Phys. Rev. E*, vol. 87, no. 2, p. 022 911, Feb. 20, 2013, Publisher: American Physical Society. DOI: 10.1103/PhysRevE.87.022911. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevE.87.022911 (visited on 01/01/2021).

[206] C. Bandt and B. Pompe, "Permutation entropy: A natural complexity measure for time series," *Phys. Rev. Lett.*, vol. 88, no. 17, p. 174 102, Apr. 11, 2002, Publisher: American Physical Society. DOI: 10.1103/PhysRevLett.88.174102. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevLett.88.174102 (visited on 01/01/2021).

[207] J. Garland, R. James, and E. Bradley, "Model-free quantification of time-series predictability," *Phys. Rev. E*, vol. 90, no. 5, p. 052 910, Nov. 12, 2014, Publisher: American Physical Society. DOI: 10.1103/PhysRevE.90.052910. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevE.90.052910 (visited on 01/01/2021).

[208] S. Galvani, B. Mohammadi-Ivatloo, M. Nazari-Heris, and S. Rezaeian-Marjani, "Optimal allocation of static synchronous series compensator (SSSC) in wind-integrated power system considering predictability," *Electric Power Systems Research*, vol. 191, p. 106 871, Feb. 1, 2021, ISSN: 0378-7796. DOI: 10.1016/j.epsr.2020.106871. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779620306696 (visited on 03/03/2021).

[209] S. Galvani, M. T. Hagh, and M. B. B. Sharifian, "Unified power flow controller impact on power system predictability," *IET Generation, Transmission & Distribution*, vol. 8, no. 5, pp. 819–827, 2014, _eprint: https://ietresearch.onlinelibrary.wiley.com/doi/pdf/10.1049/iet-gtd.2013.0350, ISSN: 1751-8695. DOI: https://doi.org/10.1049/iet-gtd.2013.0350. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-gtd.2013.0350 (visited on 03/03/2021).

[210] T. DelSole, "Predictability and information theory. part i: Measures of predictability," *Journal of the Atmospheric Sciences*, vol. 61, no. 20, pp. 2425–2440, Oct. 1, 2004, Publisher: American Meteorological Society Section: Journal of the Atmospheric Sciences, ISSN: 0022-4928, 1520-0469. DOI: 10.1175/1520-0469(2004)061<2425:PAITPI>2.0.CO;2. [Online]. Available: https://journals.ametsoc.org/view/journals/atsc/61/20/1520-0469_2004_061_2425_paitpi_2.0.co_2.xml (visited on 03/09/2021).

[211] O. J. Mesa and G. Poveda, "The hurst effect: The scale of fluctuation approach," *Water Resources Research*, vol. 29, no. 12, pp. 3995–4002, 1993, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/93WR01686, ISSN: 1944-7973. DOI: https://doi.org/10.1029/93WR01686. [Online]. Available: http://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/93WR01686 (visited on 03/04/2021).

[212] S. Chandrasekaran, S. Poomalai, B. Saminathan, S. Suthanthiravel, K. Sundaram, and F. F. A. Hakkim, "An investigation on the relationship between the hurst exponent and the predictability of a rainfall time series," *Meteorological Applications*, vol. 26, no. 3, pp. 511–519, 2019, _eprint: https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/met.1784, ISSN: 1469-8080. DOI: https://doi.org/10.1002/met.1784. [Online]. Available: https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/met.1784 (visited on 03/04/2021).

[213] N. Donets, Dreyer, R. Vallat, C. Scholzel, and S. G. Dotson, *pyEntropy (pyEntrp)*, version 0.7.1, original-date: 2015-02-27T20:53:15Z, Feb. 8, 2023. [Online]. Available: https://github.com/nikdon/pyEntropy (visited on 02/17/2023).

[214] J. DeCarolis, K. Hunter, and S. Sreepathi, "The TEMOA project: Tools for energy model optimization and analysis," *Stockholm, Sweden*, 2010.