Optimization of the Low-Carbon Energy Transition Under Static and Adaptive Carbon Taxes via Markov Decision Processes

Alaisha Sharma, **Jackson A. Killian**, **Andrew Perrault**
Center for Research on Computation and Society, Harvard University
alaisha_sharma@college.harvard.edu, jkillian@g.harvard.edu, aperrault@g.harvard.edu

Abstract

Many economists argue that a national carbon tax would be the most effective policy for incentivizing the development of low-carbon energy technologies. Yet existing models that measure the effects of a carbon tax only consider carbon taxes with fixed schedules. We propose a simple energy system transition model based on a finite-horizon Markov Decision Process (MDP) and use it to compare the carbon emissions reductions achieved by static versus adaptive carbon taxes. We find that in most cases, adaptive taxes achieve equivalent if not lower emissions trajectories while reducing the cost burden imposed by the carbon tax. However, the MDP optimization in our model adapted optimal policies to take advantage of the expected carbon tax adjustment, which sometimes resulted in the simulation missing its emissions targets.

1 Introduction

Modeling the transition to majority renewable energy systems is critical as countries race to meet ambitious decarbonization targets set for 2030, 2050, and even 2100. A growing coalition of economists around the world contend that market-based tools like a Pigouvian carbon tax [Rubio and Escriche, 2001] are critical in incentivizing the low-carbon energy transition because they internalize the social and environmental costs of carbon. A 2019 statement supporting carbon taxation with dividends, endorsed by over 3500 economists in the U.S. including all four former Chairs of the Federal Reserve, indicates strong support for carbon taxes in theory [Akerlof *et al.*, 2019]. Yet when it comes to designing the most effective and least burdensome carbon tax, both economists and policymakers are split.

In this paper, we use Markov Decision Processes (MDPs) to study the effects of carbon taxes on electricity generation. The carbon tax is embedded in the environment model of the MDP; the agent represents the combination of electricity generators and public financing, who must decide when to replace fossil fuel generation with low carbon (renewable) generation. Since the capital costs of power plants take several years to pay off, these decisions can be difficult in the face of uncertainty, especially with respect to technological advancements. For instance, postponing the construction of renewable generation may seem appealing if technology costs will decrease at some point in the future. Using an MDP-based model allows us to capture strategic decision-making by those responsible for building electricity generation. As we will demonstrate, strategic decision-making will give rise to interesting new purchasing behaviors under adaptive carbon taxes.

Our main contributions are as follows. We construct an MDP model of investment in renewable generation under a carbon tax and uncertain technological advancement. This model is able to stochastically match technological projections for 2030 and 2050, and captures the need for exponentially increasing carbon taxes to drive higher renewable penetration. This model allows us to study the effects of adaptive carbon taxes as proposed by Aldy [2017]. *We find that adaptive carbon taxes, which are adjusted at regular time intervals, can yield carbon emissions reductions closer to desired targets than static ones, even if a multi-year delay is imposed on tax adjustments.* However, we also find that this simple class of adaptive tax policies are sometimes "manipulated" by a strategic agent, which can cause the MDP optimal policy to miss its target carbon emissions reduction.

Background. The energy system modeled in this paper represents an isolated electric grid. The *load* on the grid refers to the energy (in kWh) required by consumers, which is equal to the power required over some period of time. The *reliability* of a grid system is often measured as how promptly it supplies the required load.

There are several costs associated with an electricity generating power plant. The first type is *capital cost*, or the one-time, initial cost of construction. Capital costs depend on the size or *nameplate capacity* of the power plant (in kW or MW). The second type is *operation and maintenance (O&M)* cost, or the continual cost of keeping the plant running. O&M costs are further broken down into *fixed* costs, which depend on the size of the power plant, and *variable* costs, which depend on how much power is actually produced.

One benefit of fossil fuel generation is its ability to provide a stable *base load*, or minimum power output, for long periods of time. Renewable energy suffers from *intermittency*, which refers to the inherently unpredictable nature of renewable resources such as wind and solar radiation. As *renewable penetration* of the grid, or the percentage of electricity generated by renewable energy plants, increases, the power supply becomes increasingly unreliable [Initiative and others, 2012; Wang *et al.*, 2012].

Energy storage is often hailed as the holy grail solution to intermittency. However, the main downside of storage technologies, especially batteries, is their prohibitive cost. A 2018 study published in *Energy & Environmental Science* found that meeting 80% of electricity demand in the U.S. with wind and solar power would require either a nationwide high-speed transmission system to balance excess supply and demand over hundreds of miles, or 12 hours of electricity storage for the entire system [Shaner *et al.*, 2018]. The *MIT Tech Review* estimates the cost of the latter option at 2.5 trillion USD [Temple, 2018].

One strategy for incentivizing renewable energy development is redirecting funds from a carbon tax into R&D. Designing a carbon tax is a complex process, involving 1) the base price or tax rate, 2) the annual change in price, 3) to which materials the tax applies, 4) at what point in the supply chain the tax is applied, and 5) how tax revenues are spent [Larsen *et al.*, 2018]. The carbon tax schedule that we use as a baseline in this paper starts at $41.84 per ton (2020-USD) and increases by 5% annually. This schedule was proposed in 2017 by the Climate Leadership Council (CLC) [Baker *et al.*, 2019]. A sensitivity analysis using the E3 CGE model [Goulder and Hafstead, 2013] of the U.S. showed that this CLC proposed carbon tax would lead to 50% fewer carbon emissions relative to 2005 levels by 2035 [Hafstead, 2019].

Related Work. Several studies have explored the feasibility of 100% renewable energy systems by 2050. The widely used LUT Energy System Transition Model incorporates power, heat, and transportation sectors, as well as carbon removal and desalination. Child et al. [2019] demonstrated the feasibility of achieving 100% renewable energy in Europe by 2050 using this model. The TIMES economic model generator is another popular family of models—given primary energy sources, energy end usage, and availability of future technology, the TIMES model aims to supply energy services at minimum global cost [Loulou, 2016]. Krakowski et al. applied a TIMES model to analyze transitions to 40–100% renewable penetration in France by 2050 [2016].

As a major tool in driving renewable energy development, carbon taxes have been analyzed in many case studies, including those on Sweden [Andersson, 2019], Canada [Liu *et al.*, 2018], and China [Ding *et al.*, 2019]; findings widely agree on the efficacy of carbon taxes in reducing projected emissions curves. However, most carbon tax scenarios are modeled with respect to specific geographic areas. In addition, the models used to measure emissions reductions and optimize carbon prices only consider carbon taxes with a flat rate or a static (deterministic) schedule.

Yet carbon taxes must be able to adapt to an uncertain world [Aldy, 2017]. Aldy proposes a policy approach to adjusting a carbon tax at five year intervals based on carbon emission levels, climate predictions, tax schemes of other countries, and the economic burden imposed by the tax. Beyond just testing different starting prices for a static carbon tax, current models lack the capacity to test taxes that adapt based on these conditions.

2 Problem Formulation

The guiding question underlying our model is: given a carbon tax incentive, how does a 100% fossil fuel energy system transition to a lower-carbon renewable energy system over time?

We consider an energy system observed over a fixed time span, in which each power plant begins as fossil fuel and can be converted into renewable energy. As renewable penetration increases, energy storage required to address intermittency also increases. To account for technological advancement, the cost of building renewable plants and storage stochastically decreases with time.

Formally, we model the conversion of fossil fuel (FF) plants into renewable energy (RES) plants given the following parameters: 1) a finite time horizon, 2) an initial number of fossil fuel plants, 3) stochastically decreasing costs of technology, 4) storage requirements based on renewable penetration, and 5) carbon tax schedule. The problem is formulated as a finite-horizon Markov Decision Process (MDP) [Puterman, 2014].

Tech Stage. To capture decreasing costs of technology over time, we consider discrete "tech stages" calibrated to technological projections. We assign some probability p_v of moving on to tech stage $v+1$ given that v is the current tech stage.

$$p_v = \frac{1}{n_v} \tag{1}$$

where n_v is the expected number of years in tech stage v.

Energy Storage. A 2019 survey of E.U. countries aggregated estimates for the energy storage required to support different levels of renewable penetration [Zsiborács *et al.*, 2019]. We used the U.K. data points from this survey to fit an exponentially increasing function that calculates the required energy storage as a percentage of total system load:

$$S(r) = c_0 \cdot \exp(c_1 \cdot 100r) + c_2 \tag{2}$$

where $S(r)$ is the total storage required to support r percent renewable penetration.

Carbon Tax. To incentivize building RES plants, our model uses a per-ton carbon tax, which applies a growth rate of 5% per year on top of a base price. The base price may be one of three values, allowing the carbon tax to be adjusted up or down. We implemented a simple version of the update mechanism proposed by Aldy [2017]: if in year t carbon emission levels are above/below the target for that year by some delta, c_{init} will move up/down one level starting in year $t+D$, where D is the interval length in years. This delay ensures that the tax recipients have some time to plan ahead for the change in carbon prices.

MDP Setup. In the finite horizon case, the MDP is defined by a controlled, dynamic system and a cost or reward structure; this becomes the objective function in the optimization. Starting from some initial state, the "agent" in the model must choose a sequence of actions that minimizes its cost over the finite horizon. In our case, the optimal policy defines a schedule for converting FF plants into RES plants that incurs the lowest total cost.

States and Actions. We define state as a combination of valid values for the variables listed in Table 1. A policy can take action a from state (t,v,r,l,e) to convert a FF plants into RES plants where $a \in \{i \in \mathbb{Z} : 0 \leq i \leq n_{\text{plants}}\}$ and n_{plants} is the total number of power plants in the system. Converting a FF plant into a RES plant involves building a new RES plant as well as the required amount of energy storage. No action can convert a RES plant back into a FF plant, or shut down any existing plants.

Transition Probabilities. Let E_i refer to the carbon tax in state i and p_{v_i} to the probability of moving into tech stage v_i+1. Given an action a, the transition probability of some state (t_i,v_i,r_i,l_i,e_i) to any state (t_j,v_j,r_j,l_j,e_j) obeys the following rules:

States pairs where $p_{ij}=0$ always:

i) $t_j < t_i$ (cannot go backwards in time)

ii) $v_j < v_i$ (cannot revert to a previous tech stage)

Variable	Name	Description	Range
t	Time	Timestep in MDP	$[0, n_{\text{years}})$
v	Tech Stage	Stage of technological development	[0, 2]
r	RES Plants	Number of renewable plants existing at beginning of year	$[0, n_{\text{years}}]$
l	Tax Level	Base value used in calculating price per ton of carbon	$[0.8c_{\text{base}}, 1.2c_{\text{base}}]$
e	Tax Adjustment	How to adjust tax level in the next tax cycle	[-1, 1]

Table 1: MDP model state variables, where n_{years} is the length of the time horizon, n_{plants} is the total number power plants in the system, and c_{base} is the default base price of carbon.

iii) $r_j \neq r_i + a$ (must build exactly a RES plants)

All other state pairs:

i) $p_{ij} = p_{v_i}$ if $v_j = v_i + 1$

ii) $p_{ij} = 1 - p_{v_i}$ if $v_j = v_i$

iii) $p_{ij} = 0$ otherwise

If D is the tax adjustment interval length, then e and l are ignored unless $t \mod D$ is 0. In these years (when a tax adjustment may be made) transition probabilities are split amongst states in which the tax level, l, increases, decreases, or remains the same.

Cost Function. Given a state (t,v,r) and an action a taken in that state, the cost can be calculated as follows:

$$\begin{aligned} C(t,v,r,a) = &\sum_f (C_{\text{co2}}(t) + C_{\text{ff}})) \\ &+ \sum_r C_{\text{old-res}}(v) + \sum_a C_{\text{new-res}}(v) \\ &+ C_{\text{old-stor}}(r,a) + C_{\text{new-stor}}(v,r,a) \end{aligned} \tag{3}$$

where $f = n_{\text{plants}} - r$ is the remaining FF plants at the end of time step t, C_{FF} is the cost paid for FF plants, $C_{\text{old-RES}}$ is the cost paid for existing RES plants, $C_{\text{new-RES}}$ the cost paid for RES plants built in the time step t, $C_{\text{old-stor}}$ is the cost paid for existing storage, and $C_{\text{new-stor}}$ is the cost paid for building storage required to support a new RES plants. See Appendix B for the full calculation of each cost component.

3 Results and Discussion

In our simulations, increasing the base price of the carbon tax has diminishing returns in terms of decreasing carbon emissions. For instance, taxes in the 40 USD/ton range achieve about 30% renewable penetration by 2050, while in the 100 USD/ton range achieve about 60% and above 120 USD/ton achieve about 70%. The costs of building RES plants are severely dominated by energy storage requirements, indicating that, especially towards higher renewable penetration levels, decreased costs of wind/solar have a negligible effect on incentivizing further building since storage costs remain exponentially high.[1]

We find that adaptive carbon taxes (AT) may reduce uncertainty in renewable penetration compared to static carbon taxes (ST). For these experiments, we fixed the cycle of adjustment at five years to align with the proposal by Aldy [2017].

[1]Considering a mixture of storage, transmission and extra generation could reduce costs below what is required with storage alone [Williams *et al.*, 2012], but we would expect similar high-level trends.

Table 2: A subset of the national carbon taxes implemented in 2020. We selected countries to show an even spread of starting carbon prices.

Country	2020-USD/ton
United Kingdom	23.63
United States	41.84
Finland	68.52
Switzerland	99.11
Sweden	123.18

We used starting prices of carbon based on national carbon taxes currently implemented in various countries [The World Bank, 2020]—see Table 2. We set a 20% difference in price between each level for each country. For instance, the tax levels for the U.S. are [33.47,41.84,50.21], which are the possible base prices of carbon in 2020-USD. The AT uses the mean emissions of 200 ST simulation runs as a target emissions trajectory.

Emissions under Adaptive vs. Static Carbon Taxes. Figure 1 compares the annual carbon emissions under ST and AT carbon taxes based on the countries in Table 2. The emissions trajectories of all AT simulations except the U.S. appear to reach the same or lower levels compared to their ST counterparts. Since carbon emissions are directly proportional to the number of fossil fuel plants in the system, these curves also indicate the level of renewable penetration under AT and ST simulations.

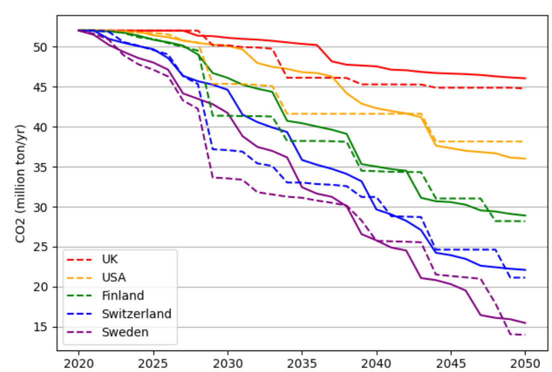

Figure 1: Annual carbon emissions under adaptive (dashed) and static (solid) carbon taxes. Each curve represents the average of 200 independent runs of the MDP.

Effects of Adaptive Carbon Tax on Cost. Figures 2 and 3 compare the effectiveness of the ST and AT tax schedules under the Sweden-based carbon tax. The black dots represent the points along this trajectory when the AT simulation checked (but not necessarily adjusted) the carbon tax level against the target trajectory.

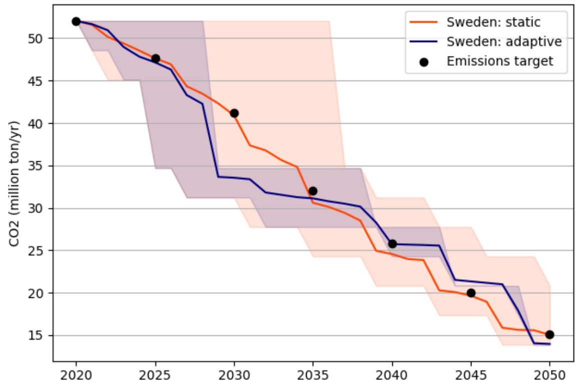

Figure 2: Annual carbon emissions for the Sweden-based carbon tax with uncertainty bounds at 90th and 10th percentiles.

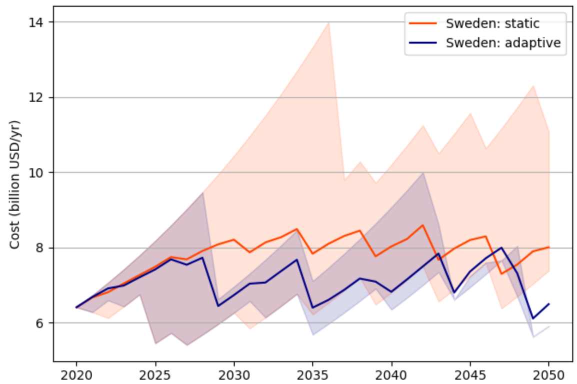

Figure 3: Annual carbon tax collected for the Sweden-based carbon tax with uncertainty bounds at 90th and 10th percentiles.

As shown in Figure 2, the AT simulation is able to adhere to the target emissions emissions trajectory, even reaching a slightly lower annual emissions level by 2050. Figure 3 shows that in addition to achieving this emissions trajectory, the AT also incurs a lower carbon tax than the ST from 2020 to 2050. Furthermore, under the AT there is less uncertainty around the extreme bounds of tax collected. This indicates that applying an adaptive carbon tax scheme that gets updated at regular intervals is an effective way of reducing the carbon tax burden while still fulfilling a target reduction in carbon emissions.

Strategic Response to Adaptive Carbon Tax. The MDP may adopt strategic behavior in response to adaptive carbon tax schemes, forming an S-shaped trajectory of annual carbon emissions trajectory. This is particularly prominent for the U.S.-based carbon tax; results show the AT (blue) missing the ST (orange) emissions trajectory by a large margin in 2050, as seen in Figure 4.

The sharp drop right before 2030 in the AT curve followed by the leveling out in 2045 indicates how the strategic MDP agent is optimizing differently under the adaptive carbon tax. The first few renewable plants are relatively cheap to build since storage costs increase exponentially, so the agent overbuilds early to induce a downward adjustment in carbon tax. For the U.S.-based carbon tax, it appears that this early cost reduction is enough to make up for the higher cost incurred later when the agent is taxed more for operating more fossil fuel plants. Perhaps this could be avoided by extending the time horizon so carbon taxes on fossil fuel plants accumulate further.

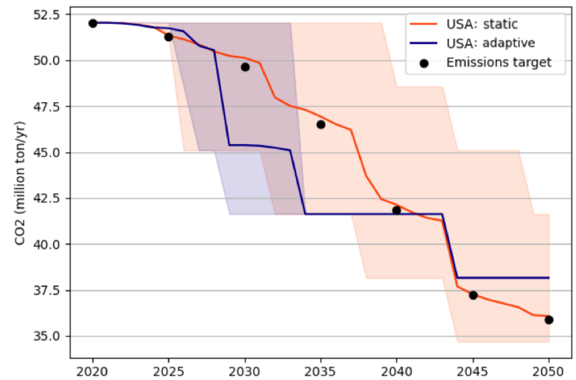

Figure 4: Annual carbon emissions for the USA-based carbon tax with uncertainty bounds at 90th and 10th percentiles.

Out of all the countries, this behavior seems to cause a significant difference in annual emission levels in 2050 only for U.S.-based carbon tax. However, Figure 1 reveals early overbuilding behavior for all of the countries except the U.K. The AT curves for the Finland, Switzerland, and Sweden-based taxes all have an inflection point around 2040 past which the AT simulation seems to build renewable plants on average later than its ST counterpart. This indicates that because the MDP overbuilt early, it could tolerate being taxed on more fossil fuel plants for longer. Yet the AT simulations in Finland, Switzerland, and Sweden end up playing catch-up to build renewable plants because the carbon prices are higher. The advantage of this is lower average costs of renewable technology, especially storage; the drawback is that several years worth of carbon tax was paid unnecessarily.

4 Limitations and Future Work

MDPs are well-suited to modeling the effect of carbon taxes on energy transition scenarios because they naturally accommodate strategic decision-making in the face of uncertainty and long planning horizons. The former highlights potential weaknesses of adaptive carbon taxes; the latter provides a natural lens to study the effect of uncertain technological progress. MDPs reveal that, despite the increase in uncertainty caused by adaptive carbon taxes, implementing an adaptive carbon tax can substantially reduce the role of *technological* uncertainty, resulting in a more stable tax and investment environment.

MDPs make the inaccurate assumption that agents are rational actors. Nonetheless, studying the robustness of regulation to manipulation is important. See, for example, the self-interested manipulation of LIBOR rates by banks [Duffie and Stein, 2015].

Important questions remain with respect to the S-shaped behavior that arises in response to adaptive carbon taxes. First, does this behavior occur under more realistic models, for example when there is political uncertainty in whether a rate will be adjusted, or if the tax is only ever adjusted upwards? Second, can we design taxes more intelligently to mitagate the impact of manipulation?

References

[Akerlof *et al.*, 2019] G Akerlof, R Aumann, A Deaton, P Diamond, R Engle, E Fama, LP Hansen, O Hart, B Holmström, D Kahneman, et al. Economists' statement on carbon dividends. *Bipartisan agreement on how to combat climate change. Wall Street J*, 2019.

[Aldy, 2017] Joseph E Aldy. Designing and updating a US carbon tax in an uncertain world. *Harv. Envtl. L. Rev. F.*, 41:28, 2017.

[Andersson, 2019] Julius J Andersson. Carbon taxes and co 2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy*, 11(4):1–30, 2019.

[Baker *et al.*, 2019] James A. Baker, Henry M. Paulson, Martin Feldstein, Ted Halstead, George P. Schlutz, Thomas Stephenson, Gregory N. Mankiw, and Rob Walton. The four pillars of our carbon dividends plan. Climate Leadership Council, at: https://clcouncil.org/our-plan/, 2019.

[Child *et al.*, 2019] Michael Child, Claudia Kemfert, Dmitrii Bogdanov, and Christian Breyer. Flexible electricity generation, grid exchange and storage for the transition to a 100% renewable energy system in Europe. *Renewable energy*, 139:80–101, 2019.

[Ding *et al.*, 2019] Suiting Ding, Ming Zhang, and Yan Song. Exploring China's carbon emissions peak for different carbon tax scenarios. *Energy Policy*, 129:1245–1252, 2019.

[Duffie and Stein, 2015] Darrell Duffie and Jeremy C Stein. Reforming libor and other financial market benchmarks. *Journal of Economic Perspectives*, 29(2):191–212, 2015.

[Goulder and Hafstead, 2013] Lawrence H. Goulder Goulder and Marc Hafstead. A numerical general equilibrium model for evaluating U.S. energy and environmental policies. Resources for the Future, at: https://media.rff.org/archive/files/sharepoint/Documents/WP-Numerical-General-Equilibrium-Model.pdf, 2013.

[Hafstead, 2019] Marc Hafstead. Analysis of alternative carbon tax price paths for the Climate Leadership Council (CLC) carbon dividends plan. Climate Leadership Council, at: https://clcouncil.org/reports/RFF-IB-18-07-rev_mar19.pdf, 2019.

[Initiative and others, 2012] MIT Energy Initiative et al. Managing large-scale penetration of intermittent renewables.". 2012.

[Krakowski *et al.*, 2016] Vincent Krakowski, Edi Assoumou, Vincent Mazauric, and Nadia Maïzi. Feasible path toward 40–100% renewable energy shares for power supply in France by 2050: A prospective analysis. *Applied Energy*, 171:501–522, 2016.

[Larsen *et al.*, 2018] John Larsen, Shashank Mohan, Whitney Herndon, and Peter Marsters. Energy and environmental implications of a carbon tax in the United States. Prepared by Rhodium Group for Columbia SIPA Center on Global Energy Policy. http://energypolicy.columbia.edu/ourwork/topics/climate-change-environment/carbon-tax-research-initiative/carbon-taxinitiativeresearch, 2018.

[Liu *et al.*, 2018] Lirong Liu, Charley Z Huang, Guohe Huang, Brian Baetz, and Scott M Pittendrigh. How a carbon tax will affect an emission-intensive economy: A case study of the province of Saskatchewan, Canada. *Energy*, 159:817–826, 2018.

[Loulou, 2016] Richard Loulou. Documentation for the TIMES model part i. International Energy Agency, at: https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-I_July-2016.pdf, 2016.

[Puterman, 2014] Martin L Puterman. *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, 2014.

[Rubio and Escriche, 2001] Santiago J Rubio and Luisa Escriche. Strategic Pigouvian taxation, stock externalities and polluting non-renewable resources. *Journal of Public Economics*, 79(2):297–313, 2001.

[Shaner *et al.*, 2018] Matthew R Shaner, Steven J Davis, Nathan S Lewis, and Ken Caldeira. Geophysical constraints on the reliability of solar and wind power in the United States. *Energy & Environmental Science*, 11(4):914–925, 2018.

[Temple, 2018] James Temple. The $2.5 trillion reason we can't rely on batteries to clean up the grid, 2018.

[The World Bank, 2020] The World Bank. Carbon pricing dashboard: Up-to-date overview of carbon pricing initiatives. World Bank, at: https://carbonpricingdashboard.worldbank.org/map_data, 2020.

[Wang *et al.*, 2012] W Maria Wang, Jianhui Wang, and Dan Ton. Prospects for renewable energy: Meeting the challenges of integration with storage. In *Smart Grid*, pages 103–126. Elsevier, 2012.

[Williams *et al.*, 2012] James H. Williams, Andrew DeBenedictis, Rebecca Ghanadan, Amber Mahone, Jack Moore, William R. Morrow, Snuller Price, and Margaret S. Torn. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *Science*, 335(6064):53–59, 2012.

[Zsiborács *et al.*, 2019] Henrik Zsiborács, Nóra Hegedűsné Baranyai, András Vincze, László Zentkó, Zoltán Birkner, Kinga Máté, and Gábor Pintér. Intermittent renewable energy sources: The role of energy storage in the European power system of 2040. *Electronics*, 8(7):729, 2019.

A Abbreviations

In order of appearance in this paper:

- **FF** : fossil fuel
- **RES** : renewable energy source
- **ST** : static (carbon) tax
- **AT** : adaptive (carbon) tax

B Cost Function Components

The cost for a given state state (t,v,r,l,e) and some action a taken in that state can be calculated as follows:

$$\begin{aligned} C(t,v,r,l,e,a) = & \sum_f (C_{\text{co2}}(t) + C_{\text{ff}})) \\ & + \sum_r C_{\text{old-res}}(v) + \sum_a C_{\text{new-res}}(v) \\ & + C_{\text{old-stor}}(r,a) + C_{\text{new-stor}}(v,r,a) \end{aligned} \tag{4}$$

B.1 Carbon Tax

$$C_{\text{co2}}(t,l,e) = E(t,l,e) \cdot e_{\text{ff}} \tag{5}$$

where e_{ff} is the per kWh emissions of a FF plant and $E(t)$ is the carbon tax calculated at time t. If *e* is 1, then the carbon price at *MIN*(one level above *l*, highest level) is used; if *e* is -1, then the carbon price at *MAX*(one level below *l*, lowest level) is used.

B.2 FF Plant Costs

$$C_{\text{ff}} = \frac{c_{\text{ff-cap}}}{l_{\text{ff}}} + c_{\text{ff-fix}} \cdot z_{\text{ff}} + c_{\text{ff-var}} \cdot (z_{\text{ff}} \cdot y_{\text{ff}} \cdot 8760) \tag{6}$$

where $c_{\text{ff-cap}}$ is the capital cost of building a FF plant, l_{ff} is the plant lifetime, $c_{\text{ff-fix}}$ is the fixed O&M cost, $c_{\text{ff-var}}$ is the variable O&M cost, z_{ff} is the plant size or nameplate capacity, y_{ff} is the capacity factor, and 8760 is the number of hours in 1 year.

B.3 RES Plant Costs

$$C_{\text{old-RES}}(v) = \frac{c_{\text{res-cap},v}}{l_{\text{res}}} \tag{7}$$

$$C_{\text{new-RES}}(v) = c_{\text{res-cap},v} \tag{8}$$

where $c_{\text{res-cap},v}$ is the capital cost of building a renewable energy plant in tech stage v, and l_{res} is the plant lifetime. We assume that there are no O&M costs for RES plants.

B.4 Storage Costs

$$c_{\text{stor-cap},v} = b c_{\text{bss-cap},v} + h c_{\text{phs-cap},v} \tag{9}$$

$$c_{\text{stor-fix}} = b c_{\text{bss-fix}} + h c_{\text{phs-fix}} \tag{10}$$

$$c_{\text{stor-var}} = b c_{\text{bss-var}} + h c_{\text{phs-var}} \tag{11}$$

$$C_{\text{old-stor}}(r,a) = S(r+a) \cdot \left(\frac{c_{\text{stor-fix}}}{8760} + c_{\text{stor-var}} \right) \tag{12}$$

$$C_{\text{new-stor}}(v,r,a) = (S(r+a) - S(r)) \cdot (c_{\text{stor-cap},v}) \tag{13}$$

where $c_{\text{bss-cap},v}$ and $c_{\text{phs-cap},v}$ are the capital costs of building battery system and pumped hydro energy storage in tech stage v, $c_{\text{bss-fix}}$ and $c_{\text{phs-fix}}$ are the fixed O&M costs of battery systems and pumped hydro, and $c_{\text{bss-var}}$ and $c_{\text{phs-var}}$ are the fixed O&M costs of battery systems and pumped hydro, respectively. We assume that fixed and variable O&M costs do not depend on tech stage, mainly because they are negligible compared to the capital costs.