

## **EPA Public Access**

Author manuscript

Energy Econ. Author manuscript; available in PMC 2019 May 29.

About author manuscripts

Submit a manuscript

Published in final edited form as:

Energy Econ. 2018; 73: 286–289. doi:10.1016/j.eneco.2018.03.007.

# The EMF 32 study on technology and climate policy strategies for greenhouse gas reductions in the U.S. electric power sector: An overview

Brian C. Murray,

Duke University, United States

John Bistline.

Electric Power Research Institute, United States

Jared Creason,

United States Environmental Protection Agency, United States

Evelyn Wright,

Sustainable Energy Economics, United States

Amit Kanudia, and KanORS-EMR, India

Francisco de la Chesnaye

Electric Power Research Institute, United States

## 1. Introduction

This special issue of *Energy Economics* presents the key findings of Energy Modeling Forum Model Inter-comparison Project Number 32 (EMF 32) entitled "The EMF 32 Study on Technology and Climate Policy Strategies for Greenhouse Gas Reductions in the U.S. Electric Power Sector." This study focused on the development and cross model comparison of results from an array of comprehensive United States climate policy intervention scenarios focusing on policy strategies for achieving greenhouse gas (GHG) emission reductions in the electric power sector and the sensitivity of emissions and economic results to changes in technology and market assumptions. The special issue includes articles that synthesize the results of common policy and technology scenarios produced by the study's modeling teams as well as several companion articles that each focus on a particular topic that the authors have modeled and mined for deeper insights.

This overview article is organized to address these four objectives in sequence: (1) describe the motivation for the EMF 32 study, (2) identify the models used in the study and their main features, (3) describe the study's scope and design, and (4) give a brief review of the insights developed in the articles included in the special issue.

## 2. Motivation for the study

Mounting scientific evidence that the accumulation of anthropogenic greenhouse gases in Earth's atmosphere could change our climate system in potentially harmful ways has induced a collective international response to address climate change risks (IPCC, 1990, 2014; Wuebbles et al., 2017). In 1994, the United Nations Framework Convention on Climate Change (UNFCCC) was formed with the goal to "(stabilize) greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" ... (UNFCCC, 1992, Article 2). With 197 signatory nations, the UNFCCC now has nearly universal sanction by the world's countries.

The United States is a signatory to the UNFCCC and to the 2015 Paris Accord that was formed under its auspices. As part of its nationally determined contribution (NDC) to the Paris Accord, the U.S. pledged to reduce GHG emissions 26–28% below 2005 levels by 2025 (USA, 2015). As the largest sector source of GHG emissions in the U.S. economy at the time of the Paris Accord, the electric power sector was placed front and center in U.S. efforts to pursue its NDC pledge. In the final year of the Barack Obama administration (2016), the U.S. Environmental Protection Agency (EPA) advanced the *Clean Power Plan* a regulation to reduce the GHG emissions from the electric power sector by an estimated 32% below 2005 levels, which would go a substantial way toward meeting the U.S. NDC (US EPA, 2015).

Donald Trump assumed the U.S. presidency in January 2017 and made both the withdrawal of the United States from the Paris Accord and the withdrawal of the Clean Power Plan early priorities for his administration. As of this writing, the Trump Administration is moving forward with plans for both withdrawals, but there remains significant uncertainty about what the U.S will do in their place. Even if the U.S. removes itself from the Paris Accord, the country remains a signatory to the UNFCCC and thus is committed in principle to its goals. Moreover, under current law, the Trump administration is required to develop controls for GHGs in the power sector due to its previously determined status (by EPA) as a dangerous pollutant (US EPA, 2009). Thus, the issue of how best the U.S. can reduce GHGs from the electric power sector remains an important policy issue worthy of the deep exploration conducted in the EMF 32 study.

## 3. Models contributing to the study

Table 1 lists the models used in the EMF 32 study, the research institutions where they were developed, their sectoral coverage, intertemporal dynamism, and level of detail in which they cover the electric power sector.

The study included 16 distinct models, though some were variations on a single core model (e.g., NEMS and NewERA) and another was a joint effort between two models (ReEDS and USREP). Some models have the electricity sector modeled in isolation either as a partial equilibrium (PE) market model or a linear programming (LP) systems optimization model and others have the sector directly linked to an economy wide computable general equilibrium (CGE) model. There is variation in the way that decisions with intertemporal

effects are modeled. Some are dynamic optimization models that assume perfect foresight about future outcomes in determining today's optimal decisions, others are recursive models that solve for the optimal decision under present conditions and roll those decisions forward to affect future decisions, and others are a variation on the two. The models all have varying degrees of electricity sector detail, meaning the technologies and regions covered.

The variations in model features provide a wider perspective on projected outcomes than if all models were of one type which is, of course, the point of an intermodel comparison exercise. Those that model the interaction between the electric power sector and the rest of the economy will capture macroeconomic feedback such as total economic output and investment that can affect outcomes within the sector, but may lose some of the detail within the power sector. Dynamic optimization models will have the advantage of identifying the most efficient intertemporal pathways but will do so under the strong assumption that economic agents have perfect foresight many decades ahead. And some models may trade off greater specificity in the electricity technologies deployed at the cost of less specificity in which regions the deployments are occurring.

## 4. Study design

Table 2 outlines the modeling scenarios across the primary dimensions of the EMF 32 study – "technology" and policy, reporting the number of models that ran each scenario. We introduce "technology" in quotes here because those assumptions vary across both technological and economic lines but are more succinctly conveyed with one word.

The technology scenarios are represented from the second column onward, starting with the identification of the U.S. Annual Energy Outlook 2016 (AEO 2016) reference case scenario as the "baseline" case for this study – the primary point of reference and the one to which all other scenarios are compared. Moving rightward along columns introduces low and high variations in key baseline parameters for natural gas prices, end use efficiency costs, the lifetime of nuclear plants, the cost of newly installed renewable energy sources (such as wind and solar), and one scenario that captures a higher level of electricity demand than assumed in the baseline. More detail on the variation in technology assumptions is provided in the article by *Creason et al.* in this special issue.

The policy scenarios are listed in the first column and vary by row. The first case is the reference case, indicating that only the policies that were on the books in the formation of the AEO 2016 baseline are captured – no new GHG reduction policies are considered. Moving down rows from there, the first policy scenario captures the imposition of a mass-based GHG cap for the electric power sector, wherein sources are allowed to trade GHG emission allowances to meet the cap and thereby form a market for these tradable permits (also known as "cap and trade"). The subsequent four rows capture variations on a carbon tax policy that would be imposed on the electricity sector only, examining the combinations of two tax rates (\$25 and \$50 per ton of CO2) and two levels of annual rate escalation (1% and 5% per year).

A companion study to the one reported in this special issue explored similar tax rates, but applied to the entire U.S. economy (Fawcett et al., 2018). More detail on the policy scenarios can be found in the article by *Bistline et al.* in this special issue.

One will note that most models focused on variations in the reference case. Of the 16 models that ran the reference case scenarios, the alternative technology scenarios drew anywhere from 6 to 15 models, with fewer exploring the energy efficiency cost assumptions (fewer models had this capability) and more exploring the natural gas price variations. On the policy scenario front, the "cap and trade" and carbon tax scenarios were explored by most (10–13) of the models.

### 5. Overview of the special issue articles' findings

The special issue continues with the article by Creason *et al.* that evaluates the effects of different technology and economic assumptions (see columns of Table 2) on U.S. power sector capacity, generation and emissions projections out to 2050 across all 16 models used in the EMF 32 study. The article finds fairly broad agreement across models that the reference case scenario will likely lead to less coal capacity and generation, more natural gas (though at lower rates of growth than recent history), continued growth in renewables, little to no growth in nuclear power, and competition between natural gas and renewables to serve load growth. Reference case emissions are projected to be flat over this time period, as the coal to gas and renewables transition lowers emissions rates but this is effectively offset by modest load growth. Compared to the reference case, lower natural gas prices, lower renewable costs, and lower energy efficiency costs all would reduce future emissions, while limits on nuclear power and higher demand growth would raise emissions.

An article by Bistline *et al.* explores the various climate policy measures identified in the rows of Table 2. The article demonstrates robust model agreement that climate policy can amplify the capacity, generation and emissions trends highlighted in the Creason *et al.* article. Many climate policy scenarios strengthen and accelerate the transition from coal to natural gas and renewables and make these trends some-what less susceptible to future market changes. They also identify the need to focus future research on understanding cross-sector market linkages (e.g., model representations of electrification under deep decarbonization) and the impact of technologies such as energy storage and bioenergy with carbon capture and storage (BECCS) to more robustly estimate the effects of climate policies on future market outcomes.

The Creason *et al.* and Bistline *et al.* papers each synthesize the results across all models for the reference case, technology and climate policy scenarios. The remaining papers in the special issue are written by authors from individual modeling teams on specific topics of relevance to the broader study. Fischer, Mao and Shawhan's article explores potential tradeoffs associated with taking a rate-based approach to emissions reduction rather than a mass-based cap-and-trade system – both types of approaches were allowable in the U.S.' *Clean Power Plan.* Their analysis uses theoretical exposition and numerical modeling to find that shifting of generation from mass-based regions to rate-based regions can increase

emissions, as feared, but market feedback effects, transmission constraints and other factors can lead to a net emissions reduction relative to a pure mass-based system.

Young and Bistline's article also explores alternatives to a mass-based cap-and-trade program for achieving emissions reductions by focusing on renewable portfolio standards (RPS) that require a certain percentage of electricity to be generated by renewable sources. They estimate that an RPS would be a more expensive way to achieve a given level of CO<sub>2</sub> emissions reduction because it displaces less coal generation on the margin than technologyneutral, least-cost actions to achieve reductions. The analysis quantifies this cost premium and its variation under different policy stringencies and market conditions.

The Hodson et al. article explores the interaction between federal research and development technology goals and national electric-sector climate  $(CO_2)$  policy, comparing outputs from four energy-economic models through the year 2050. Overall, Hodson et al. find that achieving the high technology goals achieved  $CO_2$  similar emissions reductions to the representative  $CO_2$  policy, but at lower costs. Moreover, the authors present a detailed comparison of modeling methods and find that much of the variation in their results is explained by how the models determine generating capacity requirements, retirements, and additions, as well as the models' ability to include demand and price responses.

The Palmer, Paul and Keyes article provides a useful reminder that should increase our humility as economists. They examine results of the EMF 32 energy policy scenarios alongside previous unpublished estimates of similarly scaled carbon price measures. Over time, they find the policy costs and benefits tend to be overestimated because technology change over and above baseline levels has had a large effect: emissions trended lower than expected, reducing both the benefits of prospective policy measures and their associated costs. The authors compare command-and-control policies with market-based measures and conclude that market-based policies are more robust to this type of uncertainty.

The Shawhan paper expands the EMF  $CO_2$  emissions results to include  $SO_2$ ,  $NO_x$ , and methane. The "co-emission" (i.e. non- $CO_2$  emission) type that causes the largest estimated damage, by far, is  $SO_2$ . The estimated damages from co-emissions together are in many cases similar in magnitude to the estimated damages from  $CO_2$ , and sometimes larger. Averaged across the results of all eight models, the estimated damage from  $SO_2$  in the reference scenario is \$1.2 trillion and the average from  $NO_X$  is \$0.16 trillion, while an additional \$0.2 trillion is attributable to methane emissions. The average estimated damage from  $CO_2$  is \$1.9 trillion.

An article by Ross examines how market trends and technological costs impact the electric sector under various carbon pricing policies. Using the DIEM model, the analysis indicates that emissions reductions are more similar across technological and market sensitivities under carbon pricing relative to the no-policy scenario due to a combination of low natural gas prices and declines in forecasted renewables costs. Under the carbon tax scenarios, technological change impacts policy costs more than emissions.

The Victor, Nichols, and Zelek article examines the impacts of climate policies and innovation on power sector decarbonization and electrification using an economy-wide

MARKAL model. Model results incorporate sensitivities involving additional cost reductions from technological change and demonstrate how innovation for low-carbon options like carbon capture and storage (CCS) can shift the generation portfolio, reduce emissions, and reduce policy costs. Economy-wide CO<sub>2</sub> targets stimulate substantial end-use electrification, and electricity demand growth is highest with more stringent policies and economy-wide coverage.

#### References

- Fawcett AA, McFarland J, Morris A, Weyant J (Eds.), 2018 EMF 32 study on U.S. Carbon Tax scenarios. Clim. Chang. Econ 9 (1), 1840001–18400015.
- IPCC, 1990 In: Houghton JT, Jenkins GJ, Ephraums JJ (Eds.), Report Prepared for Intergovernmental Panel on Climate Change by Working Group I Cambridge University Press, Cambridge, Great Britain, New York, NY, USA and Melbourne, Australia (410 pp.).
- IPCC, 2014 Climate change 2014: synthesis report. In: Core Writing Team, Pachauri RK, Meyer LA (Eds.), Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change IPCC, Geneva, Switzerland (151 pp.).
- UNFCCC, 1992 United Nations Framework Convention on Climate Change. Article 2. United Nations http://unfccc.int/files/essential\_background/background\_publications\_htmlpdf/application/pdf/conveng.pdf.
- US EPA, 2009 Endangerment and cause or contribute findings for greenhouse gases under section 202(a) of the Clean Air Act. Code of Federal Regulations: 74 FR 66495, pp. 66495–66546 (Docket number: EPA-HQ-OAR-2009–0171, FRL-9091–8).
- US EPA, 2015 Regulatory Impact Analysis for the Clean Power Plan Final Rule. U.S. Environmental Protection Agency, Office of Air and Radiation Office of Air Quality Planning and Standards, Research Triangle Park, NC.
- US EIA, 2016 Annual Energy Outlook 2016: With Projections to 2040. US Energy Information Administration, Office of Energy Analysis, US Department of Energy, Washington, DC www.eia.gov/forecasts/aeo.
- USA, 2015 Intended nationally determined contribution (to the Paris Agreement): United States of America http://www4.unfccc.int/Submissions/INDC/Published%20Documents/United%20States%20of%20America/1/U.S.%20Cover%20Note%20INDC%20and%20Accompanying%20Information.pdf.
- Wuebbles DJ, Fahey DW, Hibbard KA, DeAngelo B, Doherty S, Hayhoe K, Horton R, Kossin JP, Taylor PC, Waple AM, Weaver CP, 2017 Executive summary. In: Wuebbles DJ, Fahey DW, Hibbard KA, Dokken DJ, Stewart BC, Maycock TK (Eds.), Climate Science Special Report: Fourth National Climate Assessment, Volume U.S. Global Change Research Program, Washington, DC, USA:pp. 12–34 10.7930/J0DJ5CTG.

**EPA Author Manuscript** 

Table 1

Models used in the EMF 32 power sector study and their key features.

Model name	Research institution where developed	Coverage/equilibrium approach	Intertemporal approach for electricity	Electric sector detail
AMIGA	Argonne National Lab	CGE with least cost electricity	Perfect foresight	32 technologies, 6 US regions
DIEM	Duke University	CGE with electricity LP	Perfect foresight	29 technologies, 48 US regions
E4ST	Resources for the Future, Cornell U, Arizona State U	Electricity LP	Recursive	6670 US regions, includes transmission
Energy 2020	Systematic Solutions Inc	PE w/ electricity LP	Perfect foresight	22 technologies, 24 US regions
FACETS	Sustainable Energy Economics and KanORS-EMR	PE w/ electricity LP	Limited foresight	9 technologies, 41 US regions
GCAM-USA	US Dept of Energy Joint Global Change Research Institute	PE with electricity logistic shares	Recursive	17 technologies, 51 US regions
Haiku	Resources for the Future	Electricity	Perfect foresight	24 technologies, 26 US regions
MARKAL	International Energy Agency US Dept of Energy National Energy Technology Lab	PE w/ electricity LP	Perfect foresight	30 technologies, 9 US regions
NEMS	US Energy Information Administration (US EIA)	PE w/ electricity LP	Perfect foresight	16 technologies, 22 US regions
EPSA-NEMS	US Dept of Energy Office of Policy and US EIA	PE w/ electricity LP	Perfect foresight	16 technologies, 22 US regions
RHG-NEMS	Rhodium Group and US EIA	PE w/ electricity LP	Perfect foresight	16 technologies, 22 US regions
NewERA	NERA Consulting	CGE with electricity LP	Perfect foresight	20 technologies, 61 US Regions
NewERA-Elec	NERA Consulting	Electricity LP	Perfect foresight	20 technologies, 61 US Regions
ReEDS	US Dept of Energy National Renewable Energy Lab	PE, electricity LP	Recursive	20 technologies, 134 US regions
ReEDS-USREP	US Dept of Energy National Renewable Energy Lab and MIT	CGE w/ electricity LP	Recursive	20 technologies, 134 US regions
USREGEN	Electric Power Research Institute	Electricity LP	Perfect foresight	100+ technologies, 48 US regions

Notes: CGE: Computable General Equilibrium model of the entire economy; PE: Partial Equilibrium model of the electricity sector only; LP: Linear Programming. Perfect foresight models solve simultaneously for all time periods. Recursive models solve sequentially.

Murray et al.

Table 2

Technology and policy scenarios and the number of models participating in each.

Policy dimension	AEO16 Reference Assumptions	Technolo	gy sensitivi	ties (number	Technology sensitivities (number of models participating)	ipating)		
		Natural	Natural gas prices	End use ene	End use energy efficiency costs	Nuclea lifetimes	Renewable energy costs	Higher electricity demand
		Low	High	Low	High	Low	Low	
Reference	16	14	15	9	9	12	10	12
Power Sector National Mass Based Cap	13	7	6	3	ю	9	7	7
Power sector carbon tax \$25@5%	11	4	v.	2	2	3	4	4
Power sector carbon tax \$50@5%	11	4	S.	2	2	8	4	4
Power sector carbon tax \$25@1%	10	4	4	2	2	8	4	3
Power sector carbon tax \$50@1%	11	4	4	2	2	3	4	3

Notes: Carbon tax \$X@R% refers to a carbon price on per (metric) ton of CO2 emitted that begins at \$X in 2020 and rises at R% per year annually. AEO16 refers to the 2016 Annual Energy Outlook (US EIA, 2016). Page 8