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How to cite this publication

Please cite the final published version:

Gilbert, A. Q., & Sovacool, B. K. (2016). Looking the wrong way: Bias, renewable electricity, and energy modelling in the united states. Energy, 94, 533-541.
doi:<http://dx.doi.org/10.1016/j.energy.2015.10.135>

Publication metadata

Title:	<i>Looking the wrong way: Bias, renewable electricity, and energy modelling in the united states</i>
Author(s):	<i>Gilbert, A. Q., & Sovacool, B. K.</i>
Journal:	<i>Energy</i>
DOI/Link:	<i>10.1016/j.energy.2015.10.135</i>
Publication date:	<i>January 2016</i>
Document version:	Accepted manuscript (post-print)

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Looking the Wrong Way: Bias, Renewable Electricity, and Energy Modeling in the United States

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Abstract: The United States Energy Information Administration releases an Annual Energy Outlook (AEO) projecting future supply, demand, and resources for energy and electricity in the U.S. It is widely relied upon for policymaking. This study assesses twelve years of these projections of generation and capacity for six classes of renewable technologies. It finds consistent under projections for most renewable energy types in the mid- and long- term, due to inaccuracies, limitations, and inconsistencies in the underlying model. It identifies and evaluates five hypotheses that may explain such inaccuracy: inaccurate modelling of state renewable energy mandates, expiration of renewable tax credits, flaws in modelling structure, a biomass co-firing assumption, and capital cost projections. Unless AEO's projections of renewable energy are greatly improved, the reliability of its sector-wide electricity projections is inherently low. Key modifications suggested by this study include: fully valuing financial and non-financial benefits of renewables, improving cost innovation expectations for renewable energy, and, perhaps most importantly, properly modelling state renewable energy mandates.

Keywords: Renewable energy, energy modelling, energy forecasts

Acknowledgments: The authors appreciate the generous feedback from two anonymous peer reviewers. The authors are also grateful to the Research Councils United Kingdom (RCUK) Energy Program Grant EP/K011790/1 "Center on Innovation and Energy Demand," which has supported elements of the work reported here. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of RCUK Energy Program.

Looking the Wrong Way: Bias, Renewable Electricity, and Energy Modeling in the United States

1. Introduction

Historian Peter Novick once joked that the process of compiling data amounted to trying to “nail jelly to the wall.” [1] By the time you’ve completed the process, untidy to begin with, reality has changed sufficiently to force you to start your research all over again, and clean up the mess that resulted. When applied to projections of renewable electricity, where innovation rates are high, adoption is growing, wholesale and retail prices are falling, and regulatory environments are changing quickly, Novick’s musing takes on a starker dimension: how reliable are even the best estimates of renewable energy growth? And how can potential flaws, if they exist, be corrected?

Techniques to model and forecast energy scenarios were initially developed at the end of the twentieth century to provide insights into the operations of the energy sector.[2] Energy forecasts and models are used to project and assess future electricity demand, natural gas consumption, dispatch decisions, technological change, and energy prices, among other important metrics.[3–5] In recent years, with the electric grid in a state of change, the effectiveness of models to forecast the impacts of growing renewable energy has been increasingly important. However, several studies have found that existing energy models, designed for traditional energy sources, are ill-suited to addressing renewable energy.[6] Most notably, Connolly et. al. assessed the ability of 37 major models to analyze integration renewable energy, finding that no energy tool addressed all issues related to integrating renewable energy.[7]

To more fully explore these questions and determine the reliability of renewable forecasts, we develop a case study based on one of the tools surveyed by Connolly et. al.: the National Energy Modelling System (NEMS).[7] NEMS is especially important as it is the energy economic model underlying the U.S. Energy Information Administration’s (EIA) *Annual Energy Outlook* (AEO), the chief energy forecast of the U.S. Federal Government. Released annually, AEO contains long-term projections of energy supply, demand, and prices in the U.S. [8] AEO projections are relied upon by industry, government, academia, and the public sector for regulatory proceedings, rulemakings, environmental projections, financial decisions, creating other energy models, and more. As the Executive Summary of the most recent edition states:

Projections in the Annual Energy Outlook ... focus on the factors expected to shape U.S. energy markets through 2040. The projections provide a basis for examination and discussion of energy market trends and serve as a starting point for analysis of potential changes in U.S. energy policies, rules, and regulations, as well as the potential role of advanced technologies.

One colleague of ours even refers to it colloquially as “The Bible of energy information.”

Indeed, many high-profile regulatory proceedings in the U.S. rely on AEO or NEMS to assess the costs and benefits of regulatory policies. Notably, these include EPA’s proposed greenhouse gas regulations for the power sector and regulatory approvals for liquefied natural gas exports. [9][10] One of the major challenges with energy economic models is a lack of transparency: it is

usually difficult or impossible for third parties to be able to “independently verify published results.”[11] Unlike other energy models, AEO projections have been published for many years and are well documented, making them a prime candidate to test the effectiveness of energy model projections. Accordingly, multiple studies have assessed the accuracy of EIA’s projections for energy demand and generation.[12—14] Of these, only Fischer et. al. considered the accuracy of renewable energy projections, finding that electricity utility renewables were consistently over-projected.[14] However, Fischer et. al. did not differentiate between renewable energy types, did not examine issues underlying model errors, and was published before large increases in renewable energy began in 2009. [14]

And so in this paper, we ask: is the AEO biased against renewable energy and what might account for the errors? To provide an answer, we compare the historical performance of twelve AEO Reference Case projections made between 2004 and 2014. We expand on previous work by examining technology specific assessments and providing analysis of more recent time frames. We find large technology specific biases as well as an overall under-prediction trend for total non-hydro utility renewables.

We propose, develop and test five hypotheses about the inaccuracy of AEO’s projections: challenges modelling state renewable energy mandates, expiration of renewable tax credits are hard to capture, NEMS modelling structure undervalues renewable benefits, inaccurate cost assumptions, and an unjustified biomass co-firing assumption. By exploring these issues in depth in NEMS, we build on previous work by identifying specific errors in one of the most widely used energy models. Our findings have major implications for the reliability of using AEO in regulatory and policymaking in the United States. Finally, we explore potential challenges in renewable energy forecasting that are likely present in the broader energy modelling field.

2. Background and Methodology

While the AEO contains multiple scenarios that model the impacts of different economic, technological, and policy assumptions, we only examine projections from the reference case. Other cases are more or less favorable to renewable energy through different technology or policy assumptions. However, AEO’s reference case is the most important and widely used – the projections from the reference case have the most influence on policy.

Since 2004, each edition of the AEO has contained reference case projections for generation and capacity for individual renewable technologies for each year until at least 2025. To evaluate the accuracy of these projections, we compare the annual projections against the last year for which actual data is available from the AEO. Due to the time frame of projections chosen for the study, capacity and generation verifications range from 1 to 10 years out. In total, this led to 330 generation verifications and 300 capacity verifications.¹ Notably, AEO output only separates out

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¹ AEO output only separates out dedicated and co-firing generation for AEOs 2004-2010 – hence generation verifications for biomass co-firing are only for these years.

dedicated and co-firing generation for AEOs 2004-2010 – hence generation verifications for biomass co-firing are only for these years.

After we analyze the projection errors for each technology class, we test five hypotheses about the causes of errors. To test these hypotheses we review the extensive methodology and assumptions documentation provided by EIA for each edition of the AEO.

Finally, it should be noted that there are two editions of the Annual Energy Outlook 2009. The passage of the American Recovery and Reinvestment Act (ARRA) contained a significant number of energy-related policies. This led to EIA re-running NEMS with the effects of the new policies. We measure the projection ability of both: the original outlook is designated as AEO 2009 (pre-ARRA) while the second outlook is labeled as AEO 2009 (post-ARRA).

3. Selecting renewable energy classifications and analyzing projections

We selected six distinct renewable technology classifications to evaluate within the AEO:

- Electric power sector wind
- Electric power sector solar photovoltaics
- End-use solar photovoltaics
- Electric power sector biomass
- Biomass co-firing in coal power plants
- Total non-hydro renewables (Total non-hydro RE)

Figure 1 illustrates individual generation and capacity verifications for five of the six technology classes (biomass co-firing is excluded due to significant over predictions and only a limited number of predictions). Table 1 illustrates average errors for generation and capacity for each technology type during the following periods: 1-3 years, 4-7 years, and 8-10 years.

Figure 1. Annual Generation and Capacity Projection Errors by Technology Type²

a. Generation Errors

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² Positive percentage indicates AEO over-projected technology class while negative percentage indicates under-prediction. Some utility solar results are not plotted in figures due to significant over-prediction (200%-1796%).

b. Capacity Errors

Source: Authors, AEOs 2004-2014

Table 1. Average AEO Generation and Capacity Errors by Technology Class³

Power Source	Generation			Capacity		
	1-3 Years	4-7 Years	8-10 Years	1-3 Years	4-7 Years	8-10 Years
Wind	1%	-45%	-79%	-17%	-55%	-82%
Utility Solar PV	291%	71%	-85%	-15%	-63%	-93%

³ Biomass generation refers to total generation while capacity is for dedicated biomass plants only. AEO does not provide capacity levels of coal plants that co-fire biomass.

End-Use Solar PV	-15%	-60%	-88%	-22%	-67%	-91%
Biomass	30%	72%	70%	-1%	0%	-2%
Biomass Co-Firing	453%	879%	N/A	N/A		
Total Non-Hydro RE	13%	-8%	-36%	-10%	-41%	-66%

Source: Authors, AEOs 2004-2014

These results indicate that AEO projections of renewable energy generation and capacity significantly miss actual levels by large amounts in many cases.

3.1 Generation Errors

In the short term (1-3 years), on average, AEO reference cases over predict generation from utility solar, biomass, and total renewables. However, average errors for this time frame for utility solar and total renewables are influenced by larger than projected short term generation during AEOs 2004 – 2007. Very large relative projections for solar PV occurred during these periods due to an EIA assumption for a minimum level of solar deployment as solar was not economically viable at that time.

After AEO 2007, short term errors for these categories decline greatly – utility solar has an average -45% generation under prediction 1-3 years out while total renewables over predictions decrease from an average of 13% to 4%. The post-2008 time frame is especially important as total non-hydro renewable generation more than doubled during these years and generation levels more fully reflected growth rates of maturing renewable industries.

Over the long term (4-10 years), AEO projections under predict generation from all renewable technology classes except biomass. Notably, the average utility solar 4-7 year error of a 71% over prediction is due to the same relatively large over predictions in AEOs 2004-2007 mentioned earlier. The 8 long term generation predictions for utility solar PV after AEO 2007 have an average -93% under projection, indicating the AEO missed the solar boom that began in 2011.

Projections for 8 years out and beyond greatly under estimate the levels of renewable energy that were actually built for all technologies classes except biomass. In the next several years, a similar verification for AEOs 2004-2008 will indicate that longer term projections (10 years out or longer) have an even greater tendency to underestimate wind, solar, and total non-hydro renewables.

Electric power sector biomass was the only renewable technology class whose generation was consistently over predicted. Of the sixty verifications for total biomass, only one had an under prediction (of only -2%). This consistent directional error was due to an over prediction of biomass from both existing dedicated plants and biomass co-firing at existing coal plants.

3.2 Capacity Errors

AEO's short and long term capacity projections also have consistent, major errors. Wind, solar, and total non-hydro capacity levels are under projected during all time frames and particularly over longer time frames. When compared with errors in generation projections, lower capacity errors for these categories indicate that AEO has overestimated future wind and solar capacity factors. For example, implied capacity factors for wind in assessed AEO projections are 33-38% while actual capacity factors have ranged from 23-31%. Over time, AEO implied capacity factors for both wind and solar have declined and are now closer to actual annual levels – future generation and capacity projection errors are therefore likely to be more closely related.

Projections of dedicated biomass capacity are very accurate, with an average error of less than 1%. This is due to relatively small changes in dedicated biomass capacity over the projection periods.

Uncertainty and inaccuracy are inherent in projections of the future. However, the consistent inaccuracy in AEO reference case projections for renewable generation and capacity suggests that specific factors may be influencing AEO's results. Under prediction errors for wind, solar, and total renewables are particularly bad beyond 4 years.

Specifically, AEO 2014 projects that both wind and utility solar will not increase greatly after 2016 for a decade or longer with a significant slowdown in the rate of growth for distributed solar. Accordingly, if AEO's history of renewable energy under projections continues, AEO's 2014 broader projections for the electricity sector are likely to be inaccurate. The following section reviews our hypotheses for why these consistent errors occur and, more importantly, how to fix them so that AEO's projection for the broader energy system improve.

Figure 2. AEO Projections by Renewable Energy Technology Class, 2004-2020

a. Total Non-Hydro Renewables

b. Wind (Electric Power Sector)

c. Solar PV (Electric Power Sector)

d. Biomass (Electric Power Sector)

Source: Authors, AEOs 2004-2014

4. Testing Five Hypotheses about Bias, Error, and Inaccuracy

To better explain the specific dynamics which may contribute to such inaccurate renewable energy projections, this section of the paper proposes and tests five core hypotheses: poor modelling of state renewable energy mandates, expiration of renewable tax credits, flaws in modelling structure, assumptions of biomass co-firing, and assumptions of capital cost.

4.1 Hypothesis 1: Poor modelling of state renewable energy mandates

In the United States, state renewable portfolio standards (RPSs) have been essential in driving renewable energy growth. [15][16][17] Such standards generally require that a certain percentage of total electricity demand in state come from renewable energy. Although requirements vary widely, eligible resources for renewable standards typically include most non-hydro renewable sources and usually exclude conventional hydroelectric power.⁴ Our first hypothesis is that AEOs tend to under project renewable energy generation (excluding biomass) in the short term after 2008 and in the long-term because NEMS does not properly account for RPS mandates.

Importantly, renewable mandates are one of the few state policies that are explicitly modeled by NEMS when developing scenarios for the AEO. To assess the impacts of renewable standards, NEMS converts RPS requirements into renewable percentage requirements for its 22 electric power regions.

There are two major ways in which renewable portfolio standards could impact AEO results:

1. New or enhanced state policies could be implemented that did not previously exist.
2. NEMS may not properly account for the effects of existing renewable standards.

We find that both likely influence poor projections of non-hydro renewables.

Firstly, during the time frame of the AEO projections we assessed, the number of state RPS policies grew while the stringency of several existing policies were increased. Since 2004, at least 16 states in the lower 48 have implemented mandatory renewable energy standards. [18] Multiple states also increased the level of their RPS requirements; notably, California increased its renewable standards three times, in 2006, 2011, and 2015. Combined, these changes in policy can be significant – we find that the minimum level of renewables required by the NEMS methodology in 2030 almost doubled between AEO 2007 and AEO 2014 (from 231 TWh to 417 TWh). Due to a dynamic policy environment, it is prohibitively difficult for EIA to model such changes in state policy frameworks.

Secondly, there could also be issues in how NEMS models the level of renewable generation induced from existing renewable standards. [19] The assumptions included with the AEO reference cases from 2007 to 2014 include the minimum renewable energy percentage for specific years used by NEMS to model RPS policies by region. These minimum generation

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⁴ The major exceptions are New York and Michigan, which allow conventional hydro to count for RPS mandates. Our assessment of NEMS' treatment of RPSs accounts for this inclusion.

levels are used in the following equation for each region in NEMS to determine the model's output for that region's renewable generation:

$$\begin{aligned} & (\text{Generation from existing and new intermittent generation sources (i.e. wind and solar)} + \\ & \text{generation from dispatchable renewable capacity} + \text{generation from co-firing biomass} \\ & \text{with coal} + \text{renewable exports from region} - \text{renewable imports to that region} - \text{regional} \\ & \text{renewable generation requirement}) \geq 0 \end{aligned}$$

Essentially this equation is ensuring that total renewable generation in a region, modified by net exports, is equal to or greater than the minimum renewable energy requirement for that region. However, there are several methodological issues with this equation.

First, cofiring biomass with coal only counts as an eligible resource for some state RPS mandates; assuming that it can be used to meet renewable requirements does not match with the policy reality in many states. Further, as explained in section 4.4 (below), cofiring biomass with coal generation has not occurred at significant levels in the United States.

Second, the renewable constraints equation implies the potential for unlimited renewable credit trading between all regions in the country, regardless of whether states in regions even have their own RPS mandates or credit system. Although some states allow renewable energy credits from out of state to meet their own mandates, many states have in-state generation requirements that limit interstate trading. Further, although some credits are traded between states for RPS compliance, these trades happen primarily at a regional level and with states that have their own RPS mandates. Accordingly, the unrestricted trading assumption implied by the NEMS equation does not reflect the actual policy environment.

To test the potential effect of the unlimited trading assumptions on NEMS' output, we conducted an analysis that assumed no trading between regions.⁵ For AEOs 2007-2014, we multiplied the assumed percentages for renewables by modelled regional load levels and compared them to the modelled eligible renewable output for each region for 2015-2040. Essentially, we tested whether NEMS actually models renewable energy mandates the way that it claims it does.

We determine that, adjusting for these factors, NEMS does not properly model the renewable energy induced by existing renewable standards at a regional level. While some regions have more than enough renewables to be in compliance, others do not. In **Figure 3** we aggregate the regional renewable "misses."

Figure 3. AEO 2007-2014 Under-Projections of Regional Renewable Energy Induced by State RPS Mandates

⁵ Due to a lack of information availability, we were unable to test a second case where generation from biomass cofiring with coal was not treated as eligible resources for RPS compliance. This analysis thus includes biomass cofiring – if biomass cofiring was excluded, the "missing" renewable energy explained later would be higher.

Source: Authors, AEOs 2007-2014

For all editions of the AEO examined, the results of the AEO did not equal the amount of renewables that should have been induced by state requirements when calculated without unlimited trading. These misses grow especially large for AEO's 2011-2014, when the modelled output for future years was a massive 47-134 terawatt hours (TWh) lower than what would be needed to meet state requirements. Only for AEO 2009 (post-ARRA) and AEO 2010 was the modelled output close to what renewable mandates would have required.

In particular, renewable mandates in specific regions were consistently missed. Interestingly, the most consistently missed state was California, which has one of the most stable and consistent state policies for renewable electricity. AEO output did not meet what was necessary for compliance with California's RPS in 20 of 27 timeframes examined. Nine of these misses were due to a specific assumption made by EIA for AEOs 2007-2009: EIA assumed that California would not have sufficient funding to meet required RPS levels. [20] However, even beyond AEO 2009, renewable projections for California were still less than required for compliance. Modelled renewables for other regions also show a tendency for consistently missing required levels, particularly for states in the Reliability First Corporation and New York.

These findings confirm our hypothesis that methodological errors in EIA's modelling of Renewable Portfolio Standards influence the demonstrated tendency to under project most non-hydro renewables in most time frames.

4.2 Hypothesis 2: Expiration of renewable tax credits

Federal renewable energy tax credits play a central role in encouraging renewable energy development in the United States. [21] Our second hypothesis is that the periodic expirations of these renewable tax credits leads to a tendency for AEO forecasts to underestimate generation from renewable energy. Federal renewable energy tax credits can be broadly broken down into two categories: the wind production tax credit (PTC) and other tax credits for renewable energy.

Of the two credits, the wind PTC is especially remarkable due to periodic expiration and renewals. Congress repeatedly passes the tax credit with a specific sunset date (i.e. the policy will end after a set time frame, usually 1-3 years). However, Congress frequently renews the tax credit immediately before or following its expiration, extending it for one or more years. In total, the wind tax credit has been renewed at least ten times since the credit was initially passed and has expired or almost expired six times. [22] This has resulted in a boom-bust cycle that causes wind installations to drop up significantly when the tax credit expires ever several years. [23] The industry “busts” that occur in years immediately following tax credit expirations imply that the wind industry is dependent on the PTC and may not survive its expiration, a perspective potentially taken by the EIA when projecting wind generation into the future.

An examination of projections from AEO 2004-2014 indicate that the expiration of the PTC greatly impacts the demonstrated error in wind generation projections (see **Figure 2.B.** above). When the PTC is expected to expire in an edition of the AEO, modelled wind capacity installations and additional generation halt immediately. Subsequently, projected wind generation and capacity additions in individual projections are near zero for a decade or more. At least eleven of the twelve AEOs examined in this study have wind capacity installations drop off due to an expected expiration of tax credits. Wind generation in AEO 2014 (the most recent AEO reviewed for this study) is projected to stop growing in 2015, likely due to the expiration of wind PTC eligibility at the end of the year. Critically, the wind tax credit’s political fate remains uncertain as the cycle of expire and renew could continue further.

This consistent AEO result of a virtual halt in wind installations after PTC expiration is not likely reflective of how a long-term expiration would actually play out due to two reasons.

First, the expiring nature of the credit itself may drive up wind capital costs compared to a non-PTC scenario. In the short term, a rush to install turbines before the tax credit expires creates momentary demand which “unnecessarily drives up already high prices” for many completed projects. [24] So short-term risks of PTC expiration can lead to accelerated deployment. Then, if the PTC were to actually expire, the wind industry would likely innovate and reduce costs to ensure continued development of wind energy. A modelled result of wind dropping off is unlikely in either case.

Second, the boom and bust cycle that results from the expiration and renewal of the PTC may not actually indicate the wind industry’s dependence on the PTC. Rather, the possibility of the PTC ending may influence contract negotiations for wind projects more than actual construction timetables. [23] If the PTC were to end, many wind projects would still be economic and eventually built, contrary to EIA’s modelling.

As a last supporting argument for this hypothesis, the tax credit dependency that is embedded in AEO for wind power is also present for solar projections. The solar investment tax credits for residential installations are scheduled to expire in 2017 while commercial and utility-scale credits fall from 30% to 10% of the project installation costs. AEO projections for utility and distributed solar PV generally fall off in 2016/2017 when current tax credits expire (See **Figure 2.C.** and **Figure 2.E** above.).

Similarly, it is unclear whether solar installations would drop off in the face of tax credit expirations. Unlike wind, solar tax credits have not been subject to periodic expiration and thus there is no evidence of installations dropping off when a credit expires. Considering the rapid cost reductions that are ongoing in solar (which we elaborate on in Hypothesis 5) the solar industry may be able to survive the tax credits' expirations and continue to grow, even if at a reduced pace.

4.3 Hypothesis 3: Flaws in modelling structure that do not monetize full benefits

Our third hypothesis is that the very modelling structure of NEMS itself causes under projections of renewable energy by not accounting for their full benefits. NEMS is a “computer-based, energy-economic modeling system” for the U.S. energy system. [25] Accordingly, the model decides to build or dispatch energy sources based on a least-cost analysis, either on a levelized or operating cost basis.

Energy decision making is considerably more complex than as currently modelled in NEMS. We identify several financial and non-financial factors that affect the rate of renewable energy deployment: natural gas price volatility, perfect knowledge of future prices, the energy-water nexus, and air pollution issues.

One of the most important financial aspects that is not modelled by NEMS is natural gas price volatility. Although coal and oil prices also experience volatility, the price volatility for natural gas is more persistent and is especially important for electricity markets. Between 2012 and 2014, natural gas contracts at Henry Hub (the trading benchmark for U.S. natural gas) varied between \$1.91/MMBtu and \$6.15/MMBtu. [26] This volatility can bring significant negative impacts on natural gas consumers, especially for those in the power sector. Notably, editions of the AEO often come with different scenarios, some of which have different natural gas prices. While these scenarios are examining the market impacts from different natural gas supply curves, they are still examining average annual prices. As such, the different price assumptions in these alternative scenarios do not account for intra- or inter-annual price volatility that impacts energy consumers and decision makers.

NEMS' decision to overlook price volatility is further complicated by a key modelling assumption: energy decisions within NEMS are based on perfect knowledge of future prices. Electric utilities and power providers do not have this knowledge when making actual energy decisions and are rather faced with uncertainty, making the overall reliability of such models low. [27]

In light of this volatility, fixed cost renewable energy sources can provide key hedges to protect electric utilities against price swings. [28] Critically, NEMS does not assign a value to the ability of renewables to price hedge. Solar and wind power are high capital cost, low operating cost technologies. They offer a supply of consistently priced energy that provides an attractive hedge against volatile natural gas and electricity prices. Renewable energy, therefore, provides a direct risk mitigation benefit against uncertain future prices that is not accounted for in typical levelized cost assessments.[29][30] By not accounting for this significant financial benefit of renewable energy, NEMS is likely to under count the financial incentives of using renewable energy.

Renewable energy also provides significant environmental benefits that are not accounted for during decision making in NEMS. For instance, renewable energy provides significant benefits when it comes to water usage. The amount of water used for generation from solar, geothermal, and wind is much lower than what is needed for thermoelectric generation (nuclear, natural gas, and coal). [31] Water is a critical component to ensuring reliable generation from thermoelectric generation. [32] With growing demand for water resources and effects from climate change, renewable energy's relatively lower water use is a major benefit, particularly in drought prone areas like California and Texas. NEMS does not model water consumption, water withdrawals, or water limitations, meaning it is unable to incorporate this benefit.

Moreover, renewable energy provides significant benefits in terms of displaced air pollution. Coal, natural gas, and oil generation all lead to the emission of significant levels of air pollutants. All emit significant levels of carbon dioxide and NO_x while coal and oil also emit high levels of SO₂, mercury, particulate emissions, and other pollutants. Many of these pollutants are controlled by specific regulations under the Clean Air Act, which are usually modelled within NEMS once they have been finalized. However, the current structure of NEMS is limited in its ability to determine how decisions to build renewable energy may be driven by decisions to limit emissions that are not currently controlled by regulations.

Thus, in each case, investors, electric utilities, state regulators, and even consumers may be embracing renewable electricity for reasons—reduced natural gas volatility, hedging, water withdrawals, and air pollution—not monetized or appreciated by the AEO.

4.4 Hypothesis 4: Assumptions of biomass co-firing

One of NEMS' key assumptions is that coal-fired power plants have the ability to co-fire with biomass. Our fourth hypothesis is that this co-firing assumption is the primary driver behind AEO's consistent over projection of biomass generation. Between AEO 2004 and AEO 2010, the AEO reference case indicated the amount of generation that specifically came from biomass co-firing at coal-fired power plants. We use these disaggregated projections to test our hypothesis.

AEOs 2004-2010 continually projected that biomass co-firing will boom. From a base of less than 2 TWh, co-firing of biomass at coal-fired power plants grew rapidly in AEOs 2004-2010. For example, AEO 2006 and AEO 2007 projected co-firing biomass to grow to 32-34 TWh by 2010 (despite actual levels of less than 2 TWh).

Short term projections of biomass co-firing (i.e. 1-2 years out), similarly demonstrate rapid increases in co-firing generation that are not subsequently realized. The biomass co-firing assumption, therefore, is a principal factor in AEO's over projecting biomass generation in the short-term.

The co-firing assumption also influences errors in projections of biomass generation over the long-term. AEO projections for 2006-2010 indicate significant, continued growth in co-firing generation. AEO 2009 (pre-ARRA) projected biomass co-firing generation would reach 97.7 TWh in 2024, more than 2% of US electricity generation. AEO 2009 (post-ARRA) and AEO 2010 similarly projected biomass co-firing would reach around 80 TWh by the mid-2020s. As

AEO's model structure restricts the amount of generation that come from biomass co-firing to 15% of a plant's output, up to 40% of coal-fired capacity in the United States would need to co-fire biomass for these projections to be realized.

Figure 4. AEO 2010 Reference Case Projections of Biomass Co-Firing Generation versus Other Renewables

Source: Authors, AEOs 2004-2014

These massive increases in co-firing biomass are likely influenced by including biomass cofiring as a way to meet RPS goals, as explained in section 4.1 (above). This is indicated by the rapid ramp up in biomass co-firing generation that occurs in AEO 2008-2010 projections for the late 2010's (to nominally meet 2020 regional standards). For example, AEO 2008 projects that biomass co-firing would almost quadruple between 2015 and 2020. This is likely due to AEO assumptions that lead to biomass being the most cost effective way for regions to meet renewable requirements – financially, NEMS assumes that converting to allow biomass would only cost \$280/kW as opposed to much larger capital expenditures for other renewable sources.

The assumption of biomass co-firing, therefore, is critical to EIA's future over projections of biomass generation and, due to its influence on RPS projections, its general projections for overall non-hydro renewables. The assumption that coal plants will cofire biomass, however, is not justified. Biomass co-firing in the United States has primarily been limited to demonstration projected and has not achieved significant commercial penetrations. [33] This is likely due to a number of technical, economic, and regulatory barriers to co-firing. [34] To achieve AEO's current projected levels for biomass generation, a significant portion of the coal-fired fleet would need to co-fired biomass. However, as far as we could tell, there are no major plans to co-fire power plants in the US with biomass, especially at the scale implied by the AEO.

4.5 Hypothesis 5: Wrong assumptions of capital cost

Our final hypothesis is that inaccurate capital cost assumptions used by NEMS result in errors in AEO projections. To test this hypothesis, we examine specific cost projections based on data available in several editions of the AEO. We examine costs for utility-scale wind and solar in AEOs 2004-2011 and for end-use solar in AEOs 2004-2014. These projections are compared against actual installation costs, as reported by Lawrence Berkeley National Laboratory. [35—37]

The decision to build specific renewable technologies in NEMS occurs when it is a least cost option to meet electricity demand or capacity needs. As a result, the modelled cost of renewable energy technologies is a critical factor impacting the level of renewable energy that AEOs project. Total costs for solar and wind are primarily based on capital costs due to low fuel costs.

Each edition of the AEO has different assumptions about capital costs for solar and wind technologies. For electric power sector (utility-scale) wind and solar, capital costs are set at a base level and then, like all power technologies in the AEO, are reduced on the basis of technological learning factors as new capacity is built. Over time, this make capital costs, and the attractiveness of renewables within AEO, dependent on the level of renewable energy that is projected.

We find that AEO costs projections rarely match actual costs (See **Figure 5**). The rapid decline in solar capital costs that occurred between 2009 and 2014 was steeper than projected for electric power sector solar in AEOs 2008-2011 and for end-use solar in all AEO projections. Capital costs in 2013 for both categories were usually at or below projected cost levels 2-10 years out. Under projections for solar generation line up closely with under projections for cost, implying a close relationship.

Figure 5. AEO Projected Installation Costs for Select Renewable Technologies versus Actuals⁶

a. Utility-Scale Solar PV Installation Costs AEO Projections versus Actuals

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⁶ Cost data from each AEO is given in specific 5 or 10 year intervals. Linear or polynomial trend lines are used to visualize implied cost trends.

b. Utility-Scale Wind Installation Costs AEO Projections versus Actual

c. Residential End-Use (Distributed) Solar Installation Costs AEO Projections versus Actual

Source: Authors, AEOs 2004-2014, LBNL [35--37]

We also find that capital cost errors are not limited to a technology like solar PV with rapidly falling prices. Unlike solar, wind generation has neither had projections of falling costs nor a consistent actual cost direction. Capital costs for wind rose from 2005 to 2009 before falling from 2010 to 2013. However, differences between these cost trends and AEO generation errors do not indicate any relationship.

5. Conclusions and policy implications

We find that EIA's AEO publications between 2004 and 2014 consistently erred in projecting renewable energy. Capacity projections regularly under projected solar, wind, and total non-hydro renewables, particularly over longer time frames. Conversely, biomass generation is consistently over projected due to biomass co-firing assumptions that fail to materialize. Given this record, continued AEO projections for an imminent halt in renewable energy growth, and the methodological challenges we identify, the current reliability of AEO's electricity projections for use by government and industry is inherently low.

With this in mind, we present three conclusions. First, AEO's errors in projecting renewable energy, both by technology class and a whole, are influenced by two policy factors that are hard or impossible to predict. The continuous expiration and renewal of the federal wind production tax credit is notable for its likely effect on limiting projected wind generation growth. Until the expire-renewal policy cycle is broken, wind projection accuracy is likely to remain low. Similarly, state level renewable portfolio standards pose a significant modelling challenge due to changing state policies. New and improved RPS mandates generally increase the amount of renewable energy that will be built but cannot be modelled until they become law. The inverse holds true as well: RPS mandates that are rolled back are also difficult to account for. Considering the dynamic nature of tax credits and policies, EIA should consider an alternative AEO scenario specifically examining a more 'aggressive' renewable policy environment.

486 Second, however, we find that there are critical errors in EIA's methodology that can be
487 corrected or improved immediately. Perhaps most worryingly, our analysis indicates that the
488 AEO is likely not modelling existing renewable energy mandates correctly. EIA can improve
489 modelling of these standards by removing assumptions regarding unlimited renewable credit
490 trading and cofiring biomass with coal. Further, beyond these immediate fixes, EIA can likely
491 improve its modelling of renewable standards by coordinating with other federal agencies, such
492 as Lawrence Berkeley National Laboratory. Similarly, considering consistent inaccurate cost
493 projections, EIA should consider alternative methods of forecasting solar PV prices. , .

494 Third, and lastly, if these errors persist, the EIA and AEO in particular will likely continue to
495 systematically distort future projections of renewable electricity. Unfortunately, the
496 inaccuracies, biases, and errors within the EIA's AEO are systemic. That is, they are
497 independent of any analyst or even administrator. For instance, we found persistent errors during
498 both Republican and Democratic administrations, and over the tenure of four very different
499 Secretaries of Energy and three heads of the EIA. This is because EIA's errors in assessment are
500 built into the NEMS. Even as analysts and managers come and go, bias against renewables will
501 continue because it is predetermined as part of the model itself. And so the EIA is left not only
502 doing a poor job of nailing the jelly to the wall, as Nozick put it, they're also using improper
503 ingredients and an incomplete recipe.

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