Forecasting Carbon Emissions in Seven Eastern States of the United States; The Effects of Coal Deregulations

Rahim Khoie[1], **and Antonio Calderon**[1]

[1]Department of Electrical and Computer Engineering
University of the Pacific
Stockton, CA 95211
rkhoie@pacific.edu

Abstract

The 2008 through 2016 were the years of implementation of increasingly restrictive regulatory policies on climate change, and particularly on carbon emissions by coal-burning power plants. Some of these regulations were imposed by states (in the form of Renewable Portfolio Standards, RPS) and majority of them were imposed by Obama Administration. These regulations, among other factors, resulted in a significant drop in the U.S. total emissions; 12% drop from 2007 to 2016. The current Administration has taken several actions in reversing, relaxing, or repealing many of these regulations, and particularly regulations on use of coal in electricity generation. In this paper we present Two ARIMA models to forecast the potential effects of these deregulations on future carbon emissions of states of Ohio, Pennsylvania, North Carolina, Tennessee, Kentucky, Virginia, and West Virginia. These states were chosen in part because they rely heavily on electricity generated from coal and their RPS targets are among the lowest in the nation.

The results of our simulations over a large number of scenarios, based on a series of emission data in the years 1980 through 2014 clearly shows the significant role that the regulatory policies of the 2008-2014 era plays in significantly lowering these states' emissions by the year 2025. In particular, our results show that the continued implementation of the regulatory policies of Obama Administration could lower the states' emissions from coal generation from 2007-level of 588 million metric ton (MMT) to 189 MMT in 2025, a 68% drop. And conversely, reversal and or repeal of these regulations by the current Administration could result in the emissions of states to reach 713 MMT in 2025, an increase of 21% over the 2007-level.

Keywords: *Carbon Emissions, Coal Deregulations, Autoregressive Integrated Moving Average Model, Renewable Portfolio Standards*

---

1. Introduction

Taking the United States out of the historic 2016 International Paris Agreement is only one among a long list of actions taken by the current Administration in reversing many years of climate policies, especially those implemented by the Obama Administration (Adler, 2011) and (McCarthy and Copeland, 2016). The list of the deregulatory actions taken by the current Administration in coal industry include: (Brookings Institution, 2019) and (National Geographic, 2020):

- Relaxing the rules on emission of greenhouse gases in new coal-fuel power plants.
- Relaxing the rules on producing mercury and other air-toxins by coal-burning power plants.
- Repealing Clean Power Plan, and

doi:10.18086/solar.2020.01.13 Available at http://proceedings.ises.org

- Postponing enforcement of many Environmental Protection Agency (EPA) regulations.

The National Oceanic and Atmospheric Administration in its 2018 Report on "Climate Change: Current and Projected Impacts on the U.S." called for the need for removal of existing carbon from the atmosphere to prevent the projected climate disasters by 2050 (NOAA, Fahey 2018). In light of this warning, it is imperative that we investigate the effects of coal deregulations on carbon emissions, especially in those states in the United States who rely heavily on electricity generation from coal.

The total U.S. carbon emissions had been on a declining trend in the past several years, as shown in Fig. 1 (Energy In Depth, 2017).

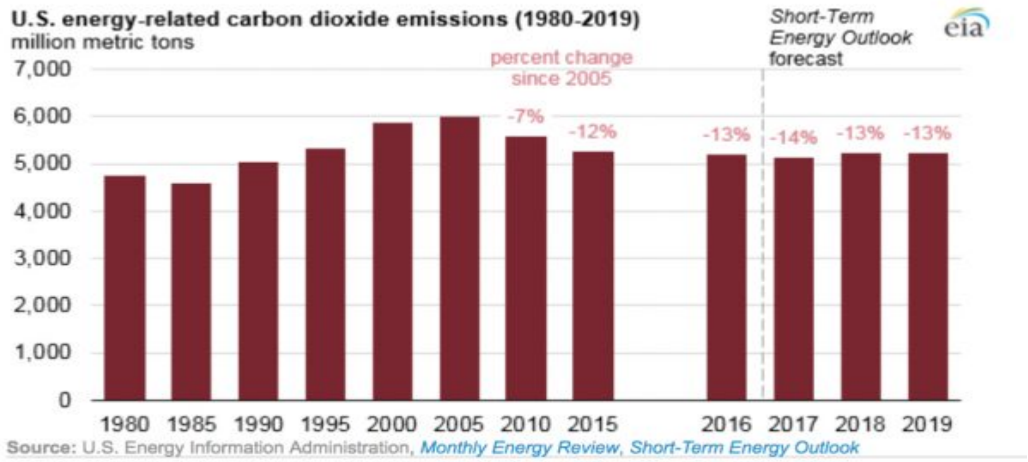

Fig. 1. The U.S. total carbon emissions from 1990 to 2016 (Energy in Depth, 2017)

After peaking at 5983 Million Metric Tons (MMT) in 2007, the total U.S. carbon emissions reached a trough of 5171 MMT in 2016. In fact compared to 2005-levels, the total U.S. emissions dropped by 7% and 13% in 2010 and 2016, respectively. The drop continued in 2017 at 14% below 2005 levels. This is a significant decline by any measure. Various researchers have cited reasons for this decline, including:

- decline in the U.S. economy output in the years following the financial crisis of 2008-2009 (Peters, et. al. 2012) (Guardian, 2010), and (Murray and Maniloff, 2015).
- increase in use of natural gas (Feng, et. al., 2015) and (De Gouw, et. al., 2014)
- federal regulations imposed by Obama Administration (Adler, 2011) (McCarthy and Copeland, 2016),
- and state-mandated regulations, and in particular, the Renewable Portfolio Standards (LBL, 2016).

In the absence of any federal mandate on reducing the U.S. carbon emissions, and in light of recent federal energy deregulations by present administration, and in particular, deregulation of coal industry, the role of states in mandating emission reduction is now more essential. A large number of states in the U.S. have enacted legislations mandating Renewable Portfolio Standard (RPS) requiring utility companies to produce a certain percentage of their electricity from renewable resources (U.S. EIA, 2012). While the state of Hawaii has the most ambitious target of 100% renewable electricity by 2045 (Hawaii State Energy Office, 2018), the state of California has set a goal of 50% renewable power production by the year 2030 (California Public Utility Commission, 2018). The state of Colorado requires production of 30% renewable electricity by 2020 (Colorado Energy Office, 2018). Overall, 29 states and the District of Colombia have adopted mandatory RPS along with 7 states that have voluntary goals (See Fig. 2) (LBL, 2016). The remaining states have no clear renewable energy policy including, ironically, the State of Florida, which has one of the most abundant supply of renewable resources, especially in solar energy (Khoie and Yee, 2015). Among other states without RPS laws are the states of Kentucky, Tennessee, and West Virginia which are among the seven eastern states that are studied in this work.

A number of researchers have developed forecasting models for investigating possible future trends in carbon emissions of the U.S. and other countries. Using state-level data on carbon emissions, Auffhammer and Steinhauser (2012) compared a large number of models for forecasting the U.S. CO_2 emissions. Other researchers have used ARIMA models for forecasting long-term trends in carbon emissions. Silva (2013) used a combination of various models, including Autoregressive Integrated Moving Average (ARIMA) model for short-term projection

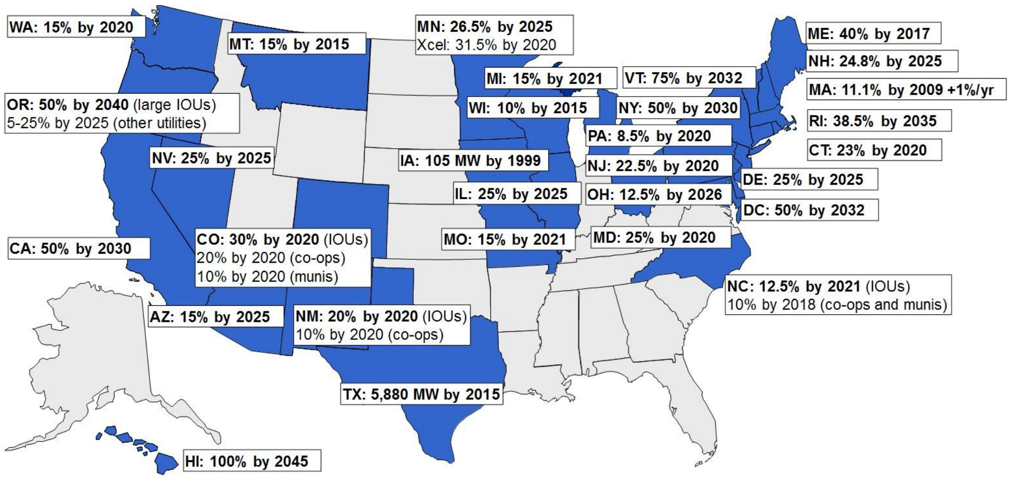

Fig. 2. Renewable Portfolio Standards of United States (LBL, 2016).

of the U.S. carbon emissions. Yuan, et. al., (2016) developed an ARIMA model for forecasting China's energy consumption while comparing the results to those of Grey Model (GM) and concluded that the results of ARIMA model are less sensitive to temporary fluctuations in the past data. A similar comparative study was performed by Pao and Tsai (2011) for carbon emissions in Brazil. Other researchers have used ARIMA models for forecasting carbon emissions in countries such as Indonesia (Prananda et. al., 2015), Iran (Lotfalipour, et. al., 2013) , and India (Sen, et. al., 2016). ARIMA models have also been used for forecasting near-term trends in stochastic processes such as wind power generation (Chen, et. al., 2010).

We (Khoie and Calderon, 2019) previously presented four ARIMA models for forecasting the future trends in carbon emissions of the three states of Hawaii, California, and Colorado whose RPS laws set the most ambitious renewable targets, and the State of Florida, which has no RPS laws. In this paper, we present ARIMA models for forecasting the future trends in carbon emissions of seven neighboring eastern states. These states are: Ohio, Pennsylvania, North Carolina, Tennessee, Kentucky, Virginia, and West Virginia. These states were chosen for two reasons: (a) they either do not have any RPS laws (KY, TN, and WV) or their RPS targets are among the lowest in the nation (see Table 1), and (b) they rely heavily on electricity generated from coal (U.S. EIA, 2018).

Table 1: The RPS and target year of the seven states (NCSL, 2019)

State	Year of RPS Enactment	RPS Target	RPS Target Year
Ohio	2008	12.5%	2026
Pennsylvania	2004	8.5%	2020
North Carolina	2007	12.5	2021
Tennessee	-	-	-
Kentucky	-	-	-
Virginia	2007	15%	2025

West Virginia	2007 (Repealed 2015)	-	-

2. Recent Emissions Trends

In the first eight years of 2000's, the seven states of NC, OH, PA, KY, TN, VA, and WV, individually and collectively relied heavily on electricity generation from coal. Fig. 3 shows the total electricity generation of the seven states in the years 2001 thru 2016. While hovering around 850 million MWHr a year, the total electricity generation of the seven states reached a peak of 875 million MWHr in 2007 after which it declined by about 9% to 794 million MWHr in 2016. During this period, the electricity generation from coal peaked at 614 million MWHr in 2007 after which it declined by about 56% to 347 million MWHr in 2016, as shown in Fig. 4.

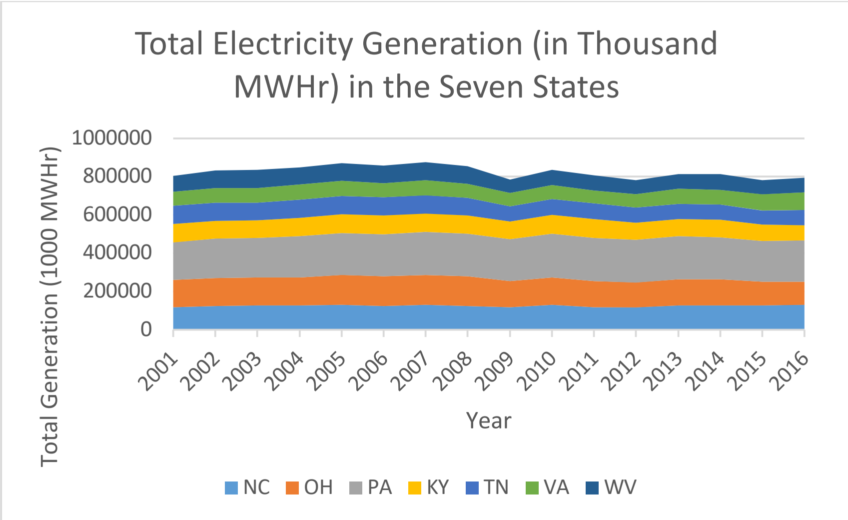

Fig. 3. Total electricity generation in each of the seven states between 2001 and 2016 (U.S. EIA, 2018).

Therefore, in the 8 years between 2001 and 2008, the percentage of electricity generation from coal in all seven states hovered around 70% (See Figs. 5 and 6). In the next 8 years (2008 to 2016) the percentage of electricity generation from coal in all seven states dropped from 70% in 2008 to 44% in 2016. This was a substantial drop in coal generation over the 8 years of the Obama Administration. In the meanwhile, the total emissions of the electricity generation from coal in all of the seven states (shown in Fig. 7) peaked at 588 MMT in 2007 after which it declined to 421 MMT in 2014 which is a 29% drop in emissions. This drop is significantly higher than the national average drop of about 11% during the same period.

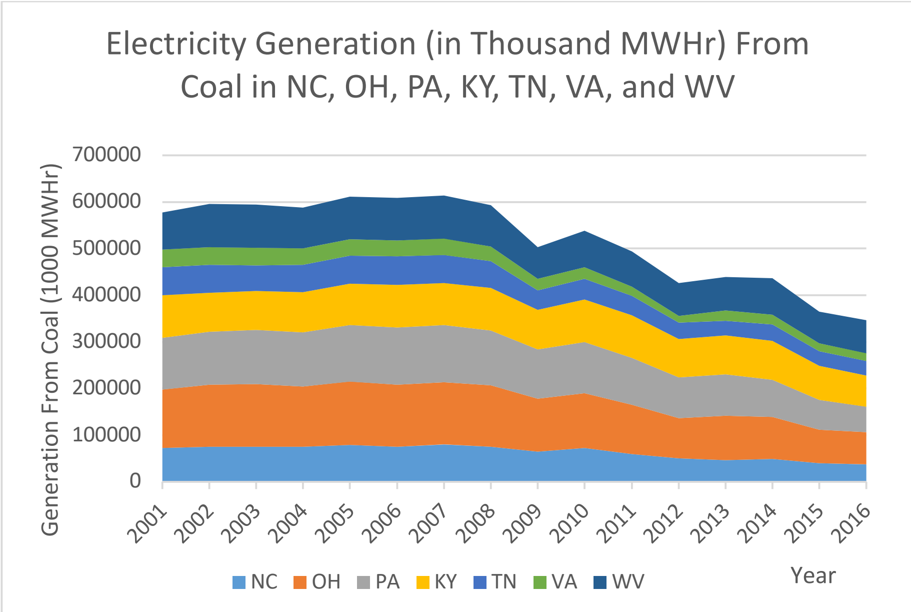

Fig. 4. Electricity generation from coal in each of the seven states between 2001 and 2016 (U.S. EIA, 2018).

The declining trends in coal generation and carbon emissions in these states in the years 2008 to 2016 correlate to four possible factors mentioned in the Introduction. These factors are downturn in the U.S. economy in 2008-2010, increase in use of natural gas, enactment of RPS laws in the prior years in most of these states, and increasing coal and emission regulations by the Obama Administration. To investigate the possible effects of coal regulations on carbon emissions by coal power plants we developed two different ARIMA models described below. We then used these models to forecast carbon emissions through 2025 with 8 different scenarios.

- In scenario 1, we use the combined emission data for all seven states in the years 1980 to 2007 and predict the combined emissions of all seven states in the years 2008 to 2025.

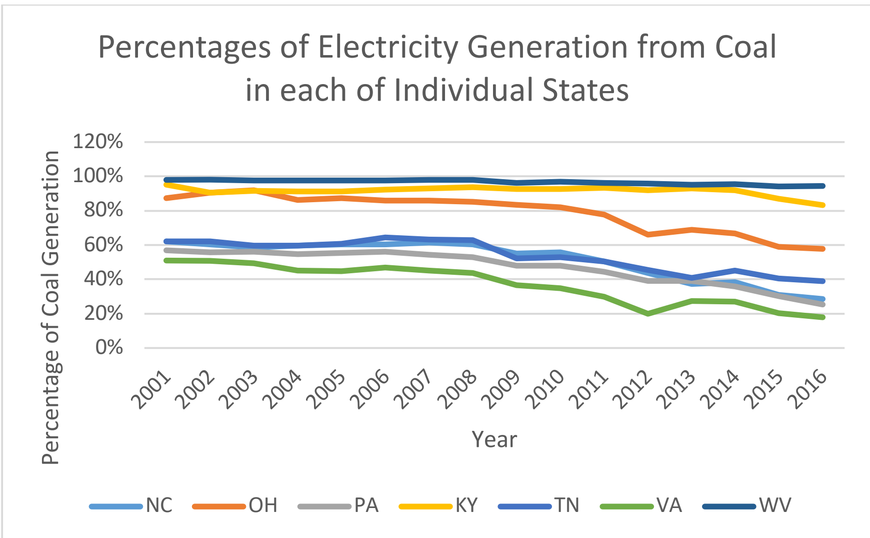

Fig. 5. Percentages of electricity generation from coal in each of the seven states between 2001 and 2016 (U.S. EIA, 2018). West Virginia and Virginia are the two extremes in percentage of coal generation.

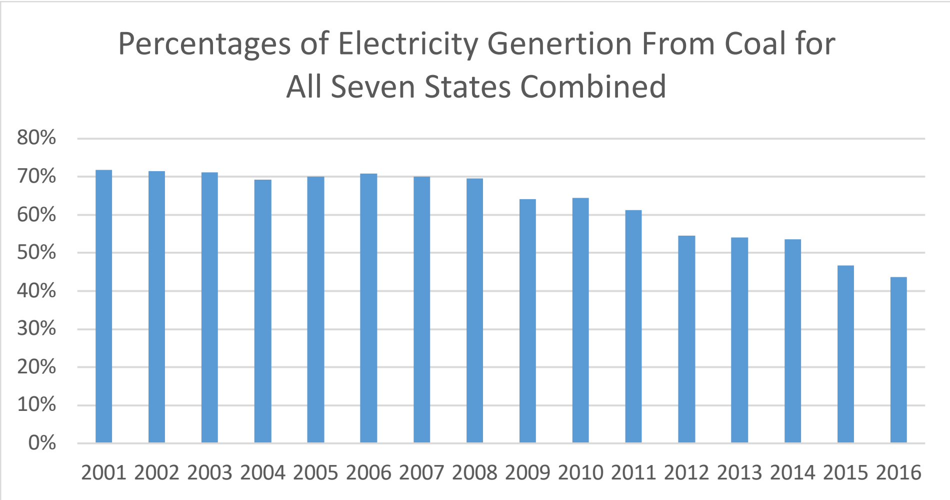

Fig. 6. Percentages of electricity generation from coal for all the seven states combined between 2001 and 2016 (U.S. EIA, 2018).

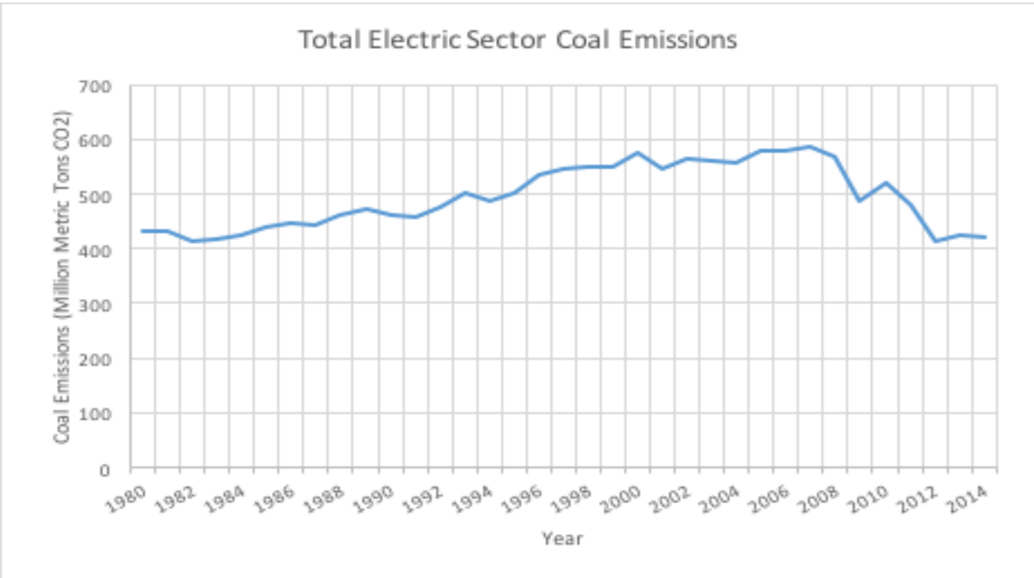

Fig. 7. Total carbon emissions of electricity generation from coal for all the seven states combined from 1980 to 2014 (U.S. EIA, 2018).

- In scenario 2, we use the combined emission data for all seven states in the years 1980 to 2008 and predict the combined emissions of all seven states in the years 2009 to 2025.
- …..
- In scenario 7, we use the combined emission data for all seven states in the years 1980 to 2013 and predict the combined emissions of all seven states in the years 2014 to 2025.
- In scenario 8, we use the combined emission data for all seven states in the years 1980 to 2014 and predict the combined emissions of all seven states in the years 2015 to 2025.

Obviously, the known values of emission data for the years 2008-2014, and especially emission data for the years 2015, 2016, and 2017 are used to validate our projections and adjust the ARIMA models' parameters for the minimum error between the predicted values and actual known emission data.

3. The ARIMA Models

The general form of the ARIMA model is given by (Chen, et. al, 2010):

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

Where:
y_t is the predicted value for year t,
y_{t-1} is the predicted value for year $t-1$,
μ is a constant term for a non-zero average trend,
φ_p terms are autoregressive term (AR),
p is the order of autoregressive process,
θ_q terms are moving average parameters (MA),
q is number of lagged forecast errors in prediction model,
ε_q terms are forecast errors.

In order to stationarize the predicted trends and mask seasonal variations, the order of differencing parameter, d was determined to be:

$$d = 2 \quad then \quad y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$$

In the above equations, y_t is the predicted value for the year t and Y_t is the value of original data at year t.

The parameters p, and q represent the number of AR and MA terms, respectively. In other words, p represents the tendency of the data to return to the mean value, and q represents the shock response of the data to a sudden change. The higher the order of these terms, the more past data is used to calculate the predicted value. The parameters p, and q are determined based on a Box-Jenkins (Chen, et. al., 2010) method using series of simulations resulting in least prediction error of known years. The adaptive nature of the model ensures that historical trends associated to policy changes are reflected in future trends. For more details of our ARIMA models see (Khoie and Calderon, 2018).

Using the total emissions data of all seven states, and testing various ARIMA models for various scenarios described in the above section, we determined the following two models:

- ARIMA (p= 0, d= 2, q= 1) and
- ARIMA (p= 4, d= 2, q= 0)

to have the best fit based on Akaike Information Criterion (AIC). The fitting process was done with the R package *forecast* which provides functions for AIC which is an integral step in model fitting (Yamaoka, et. al., 1978). The order of the fit was adjusted as appropriate to achieve a minimum absolute error between the predicted data and the known emissions data in the years 2008 through 2016 (as appropriate). The open-source statistical software R was used to facilitate the model fitting process and prediction to year 2025. For each of the eight scenarios described in the above section, we ran the two ARIMA models and produced prediction results which are described below.

4. Results

The two ARIMA models described above are simulated for the 8 scenarios producing 16 sets of forecasts. The results of the two ARIMA models for the two extreme scenarios, namely scenarios 1 and 8 (four sets of forecasts) are presented and discussed in this paper. The results of the other 6 scenarios fall somewhere in between these two extremes and are not presented here.

Fig. 8 Shows the forecast results of ARIMA (0,2,1) model for emissions of electricity generation from coal in all seven states through 2025. These results are based on emission data from1980 through 2007 which exclude the emission data of the 2008-2014 era. These results show continued increase in emissions if the regulatory policy changes of 2008-2014 had not taken effect. The range of data for 80% and 90% confidence levels are also shown.

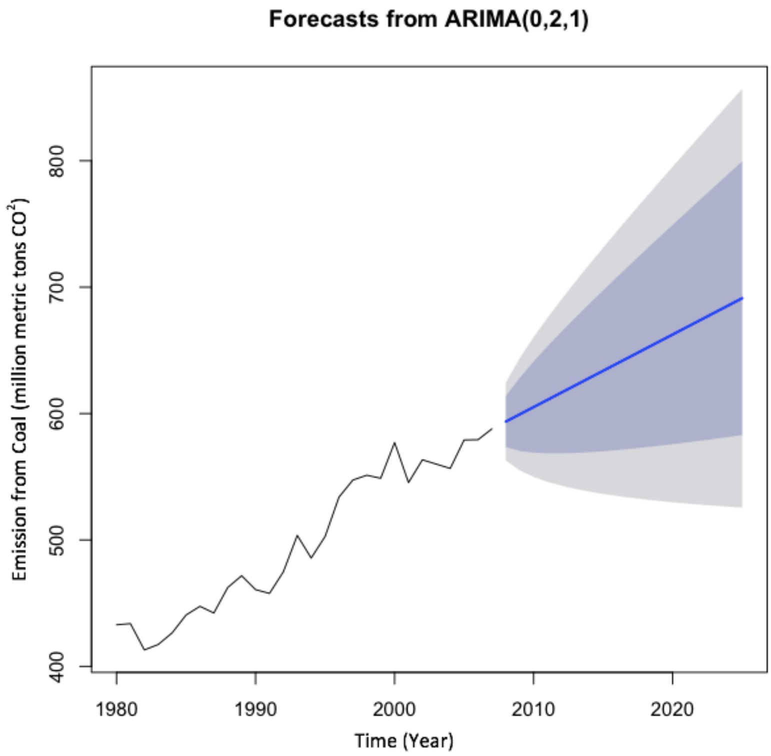

Fig. 8. Forecast of ARIMA (0,2,1) model for emissions of electricity generation from coal in all seven states through 2025. The results are based on emission data of 1980 through 2007 and show continued increase in emissions if the regulatory policy changes of 2008-2014 had not taken place. The range of data for 80% and 90% confidence levels are also shown.

Fig. 9 Shows the forecast results of ARIMA (0,2,1) model for emissions of electricity generation from coal in all seven states through 2025. These results are based on emission data of 1980 through 2014 and include the data for the 2008-2014 years in which increasingly more restrictive federal regulations and especially on coal power generation were implemented. These results show declining trends in emissions in years 2015-2025 in response to the regulatory policy changes of 2008-2014.

Fig 10 shows the results of ARIMA (4,2,0) model for emissions of electricity generation from coal in all seven states through 2025. Similar to the results shown in Fig. 8, these results which are based on emission data of 1980 through 2007 show continued increase in emissions in the years 2008 through 2025 had it not been for the regulatory policy changes of 2008-2014 period. And finally, Fig. 11 depicts the forecast results from the ARIMA (4,2,0) model based on emission data of 1980 through 2014 which includes the years of increasing regulatory actions by the federal government in electricity generation from coal. And again similar to the results shown in Fig. 9, this model also projects continued declined in emissions in response to the policy changes and regulations imposed by the Obama Administration in the years 2008 through 2014.

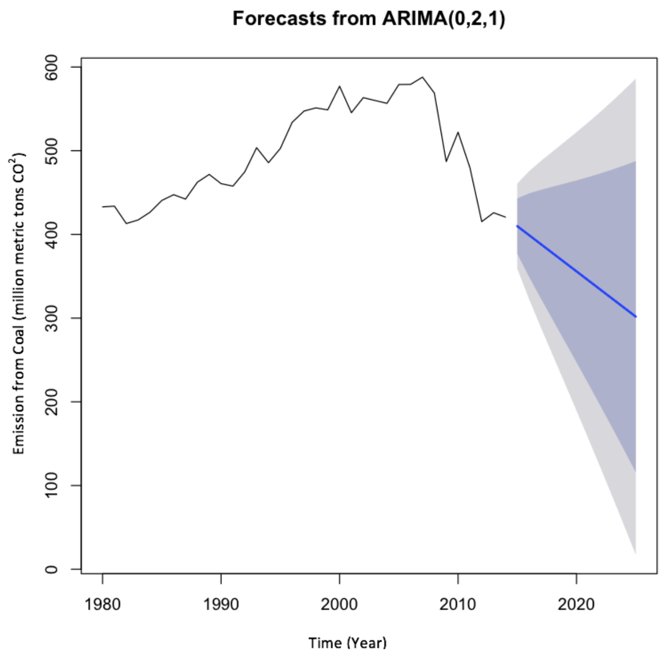

Fig. 9. Forecast of ARIMA (0,2,1) model for emissions of electricity generation from coal in all seven states through 2025. The results are based on emission data of 1980 through 2014 and show continued declined in emissions in response to the regulatory policy changes of 2008-2014.

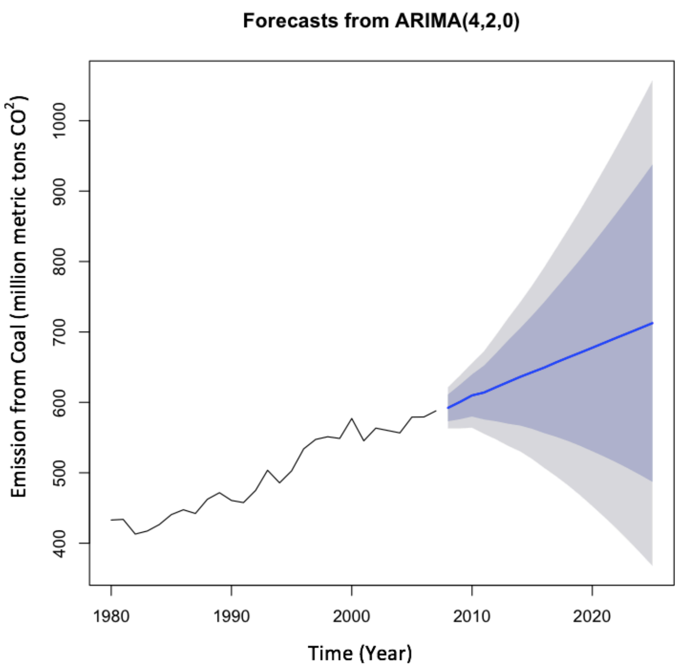

Fig. 10. Forecast of ARIMA (4,2,0) model for emissions of electricity generation from coal in all seven states through 2025. The results are based on emission data of 1980 through 2007 and show continued increase in emissions if the regulatory policy changes of 2008-2014 had not taken place. The range of data for 80% and 90% confidence levels are also shown.

The highlights of the four sets of data described above are summarized in Table 2 where we list the predicted values of the combined emissions of electricity generation from coal in all the seven states over the years 2008 through 2025. Also listed in this table are the actual known emission values in the years 2008 through 2016. As can be seen, in both models, the errors between the predicted value and the known value for the year 2008 in scenario 1 are about 4%. However, in Scenario 8, the errors between the predicted value and known value for the year 2015 is about 15% in ARIMA (0,2,1) and about 6% for ARIMA (4,2,0), which is to be expected.

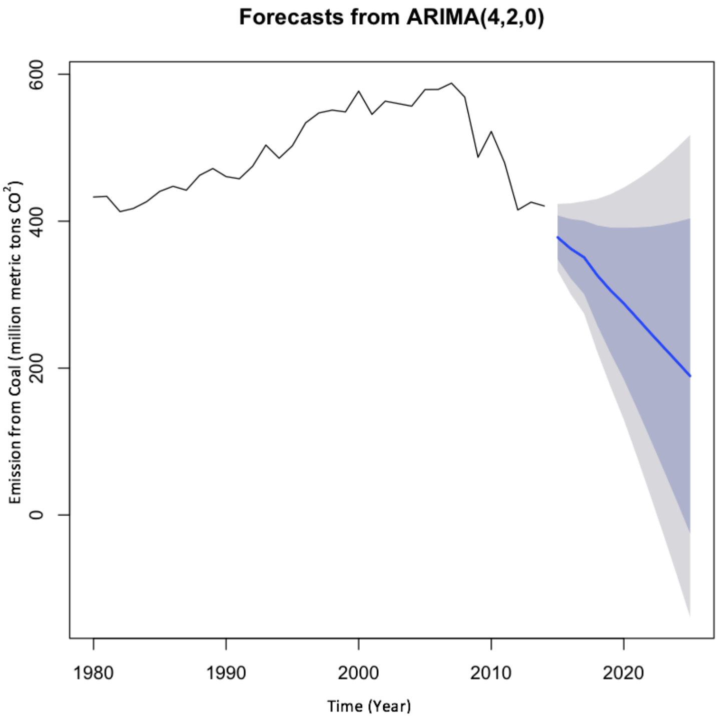

Fig. 11. Forecast of ARIMA (4,2,0) model for emissions of electricity generation from coal in all seven states through 2025. The results are based on emission data of 1980 through 2014 and show continued declined in emissions in response to the regulatory policy changes of 2008-2014.

5. Conclusions

In this study, we performed a series of simulations using two different ARIMA models to predict the impact of the Obama-era Environmental Protection Agency regulations on reducing CO_2 emissions from coal. To investigate the effect of federal policy changes on emissions from coal power generation, we created a large number of scenarios each using emission data of a specific period starting in 1980 and ending in the years 2007, 2008, 2009, and so on through 2014, resulting in 8 different scenarios. All these scenarios were tested with two somewhat of extreme ARIMA models, one almost a linear predictor, ARIMA (0,2,1) and another more nonlinear, ARIMA (4, 2, 0).

Both ARIMA models predicted similar trends, although with different precision and different confidence level. The forecast results of both ARIMA models for scenario 1 were based on data from 1980 to 2007, which were pre-Obama years. Both ARIMA models predicted that if the policies in effect in those years had continued in 2008 through 2014, the emissions from coal power generation in the seven states of NC, OH, PA, KY, TN, VA, and WV would have continued rising to extremely high levels (nearly 713 MMT in 2025). On the other hand, when we ran both ARIMA models with emission data in the Obama years included (scenario 8), the results showed sharp decline in emissions. Under the extreme scenario 8 which uses emission data from 1980 to 2014, the ARIMA(4,2,0) model predicted an emission level of 189 MMT in 2025 which would be 73% less than 713 MMT in 2025 predicted under scenario 1. These results support the conclusion that undoing, reversing, repealing, and or not enforcing the Obama-era coal regulations would result in reversing the recent declining trends in combined emissions of not only the seven states of NC, OH, PA, KY, TN, VA, and WV studied here, but also the of the entire United States.

Table 2: Emission results (in MMT) predicted by the two ARIMA forecast models for the two extreme scenarios 1 and 8. Both ARIMA models predict declining trends in emissions should regulatory policies of 2008 to 2016 continue.

Year	Forecast Scenario 1 ARIMA (0,2,1)	Forecast Scenario 8 ARIMA (0,2,1)	Forecast Scenario 1 ARIMA (4,2,0)	Forecast Scenario 8 ARIMA (4,2,0)	Actual (MMT)
2008	594		592		569
2009	599		601		487
2010	605		610		522
2011	611		614		480
2012	616		622		415
2013	622		629		425
2014	628		636		421
2015	634	410	643	378	355
2016	639	399	650	362	340
2017	645	388	657	351	
2018	651	377	664	326	
2019	657	367	671	306	
2020	663	356	678	288	
2021	668	345	685	268	
2022	674	334	692	248	
2023	680	323	699	229	
2024	685	312	705	209	
2025	691	301	713	189	

The short-term energy outlook forecast by Energy Information Administration (shown in Fig. 1 (Energy In Depth, 2017)) indicates that the total U.S. carbon emissions in the years 2018 and 2019 are on the rise. This trend, and potential acceleration of such trend as result of continuation of the deregulatory environment created by current Administration are in sharp contrast to the warning issued by the current National Oceanic and Atmospheric Administration. To prevent projected climate disasters by 2050 (NOAA, Fahey 2018), we need to remove existing carbon from the atmosphere. With that as our goal, even the 189 MMT projected emission in 2025 (under our best scenario 8 with ARIMA (4,2,0) would still too much emission to have to be removed from the atmosphere.

6. References

Adler, J. 2011. Heat expands all things: The proliferation of greenhouse gas regulation under the Obama administration. Harvard Journal of Law and Public Policy, 421. http://heinonline.org/, Accessed March 2018.

Auffhammer, M., and Steinhauser, R., 2012. “Forecasting The Path of US CO_2 Emissions Using State-Level Information,” Review of Economics and Statistics, MIT Press, Volume 94, Issue 1, February 2012, p.172-185.
Brookings Institution, 2019. “Tracking deregulation in the Trump era,” Friday, April 12, 2019, https://www.brookings.edu/interactives/tracking-deregulation-in-the-trump-era/ Accessed: April 2019

California Public Utility Commission, 2018. California Renewables Portfolio Standard, http://www.cpuc.ca.gov/RPS_Homepage/ Accessed: March 2018.

Chen, P., Pedersen,T., Bak-Jensen, B. 2010. ARIMA-based time series model of stochastic wind power generation. IEEE Transactions on Power Systems. vol. 25, pp. 667-676.

Colorado Energy Office, 2018. https://www.colorado.gov/pacific/energyoffice/renewable-energy-standard, Accessed March 2018.

De Gouw, J. A.,Parrish, D.D., Frost, G. J., and Trainer, M., 2014. “Reduced emissions of CO_2, NOx, and SO2 from US power plants owing to switch from coal to natural gas with combined cycle technology." Earth's Future 2, no. 2 (2014): 75-82.

Energy In Depth, 2017. “EIA: U.S. Carbon Emissions Fall Again in 2017, ‘Mainly’ Because of Natural Gas,” Energy In Depth: Climate and Environment, https://eidclimate.org/eia-u-s-carbon-emissions-fall-2017-mainly-natural-gas/ Accessed April 2019.

Feng, K., Davis, S., Sun, L., and Hubacek, K. 2015. Drivers of the U.S. CO_2 emissions 1997–2013. Nature Communications, 21 July 2015, Open Source. https://www.nature.com/articles/ncomms8714.pdf.
Guardian, The, 2010. Global emissions of carbon dioxide drop 1.3%, say international Scientists. https://www.theguardian.com/environment/2010/nov/21/carbon-emissions-fall-report, Accessed March 2018.

Hawaii State Energy Office. 2018. http://energy.hawaii.gov/renewable-energy , Accessed March 2018.

Khoie, R. and Yee, V., 2015. A forecast model for deep penetration of renewables in the Southwest, South Central, and Southeast regions of the United States. Clean Technologies and Environmental Policy, Volume 17, pp 957–971.

Khoie, R. and Calderon, A., 2018. “Forecasting Carbon Emissions in States of Hawaii, California, Colorado, and Florida; The Effects of States’ Renewable Portfolio Standards,” Published in Proceedings of SOLAR 2018, *American Solar Energy Society 47th National Solar Conference and Summit,* Boulder, Colorado, August 5-8, 2018.

LBL, 2016. Electricity Markets and Policy Group. Renewable Portfolio Standards Resources. Lawrence Berkeley National Laboratory. 2016. Available: https://emp.lbl.gov/projects/renewables-portfolio. Accessed March 2018.

Lotfalipour, M., Falahi , M., and Bastam, M., 2013. “Prediction of CO2 emissions in Iran using Grey and ARIMA models, International Journal of Energy Economics and Policy; Vol. 3, pp. 229.

McCarthy, J. and Copeland C. 2016. EPA Regulations: Too Much, Too Little, or On Track? Congressional Research Service, Library of Congress, December 30, 2016 https://fas.org/sgp/crs/misc/R41561.pdf, Accessed March 2018.

Murray, Brian C., and Maniloff, P., 2015. "Why have greenhouse emissions in RGGI states declined? An econometric attribution to economic, energy market, and policy factors." Energy Economics 51 pp. 581-589.

National Geographic, 2020. https://news.nationalgeographic.com/2017/03/how-trump-is-changing-science-environment/. Accessed June 2020.

National Oceanic and Atmospheric Administration, 2018. David Fahey, “Climate Change: Current and Projected Impacts on the U.S.,” ASES SOLAR 2018, Pathways to the Renewable Energy Transformation, August 5-8, 2018, Boulder, CO. See: https://www.noaa.gov/climate-data-and-reports.

NCSL, 2019, National Conference of State Legislators, “State Renewable Portfolio Standards and Goals,”http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx , Accessed April 2019.

Pao, H., and Tsai, C., 2011. “Modeling and forecasting the CO2 emissions, energy consumption, and economic growth in Brazil,” Energy, Volume 36, Issue 5, May 2011, Pages 2450-2458.

Peters, G. Marland, G., Le Quéré,C., and Boden, T. 2012. Rapid growth in CO_2 emissions after the 2008–2009 global financial crisis. Nature Climate Change, 2012, https://www.nature.com/articles/nclimate1332, Accessed March 2018.

Prananda, J., Hantoro,R., Nugroho, G., 2015. "The Prediction of Carbon Dioxide Emission Using ARIMA for Support Green Energy Development in Surabaya Municipality, Knowledge E, Vol. 2, pp. 106-110.

Sen, P., Roy, M., Pal, P., 2016, "Application of ARIMA for forecasting energy consumption and GHG emission: A case study of an Indian pig iron manufacturing organization,” Energy, Volume 116, Part 1, 1 December 2016, Pages 1031-1038.

Silva , E., 2013. “A COMBINATION FORECAST FOR ENERGY-RELATED CO_2 EMISSIONS IN THE UNITED STATES,” International Journal of Energy and Statistics, Vol. 1, Issue 4, December 2013.

U.S. Energy Information Administration, 2012. Most States Have Renewable Portfolio Standards. February 2012. https://www.eia.gov/todayinenergy/. Accessed: March 2018.

U.S. Energy Information Administration, 2016. Environment, U.S. Energy-Related Carbon Dioxide Emissions. https://www.eia.gov/environment/emissions/carbon/. Accessed: August 2018.

U.S. Energy Information Administration, 2018. “State Carbon Dioxide Emissions Data, https://www.eia.gov/environment/emissions/state/ , Accessed April 2019

Yamaoka, K., Nakagawa, T., and Uno, T., 1978. “Application of Akaike's information criterion (AIC) in the evaluation of linear pharmacokinetic equations,” Journal of Pharmacokinetics and Biopharmaceutics, April 1978, Volume 6, Issue 2, pp 165–175.

Yuan, C. , S Liu, S. Fang, Z, 2016. ” Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model,” Energy, Volume 100, 1 April 2016, Pages 384-390.