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A Cost Analysis Of Carbon Dioxide Emission Reduction Strategies For New Plants In Michigan's Electric Power Sector

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A Cost Analysis Of Carbon Dioxide Emission Reduction Strategies For New Plants In Michigan's Electric Power Sector

By

Fei Li

A THESIS

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This thesis has been approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE in Applied Natural Resource Economics.

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Any error that may remain in this work is entirely my own responsibility.

List of Abbreviations

ACF Autocorrelation Function

AEO Annual Energy Outlook

AIC Akaike's Information Criterion

AR Autoregressive

ARIMA Autoregressive Integrated Moving Average

BAU Business-as-usual

BIC Bayesian Information Criterion

BJ Box–Jenkins

BTU British Thermal Unit

CCS CO_2 Capture and Storage

CO_2 Carbon Dioxide

EACF Extended Autocorrelation Function

EIA U.S. Energy Information Administration

EOP Executive Office of the President

EPA U.S. Environmental Protection Agency

GDP Gross Domestic Product

GHG Greenhouse Gas

I Integration

IPCC Intergovernmental Panel on Climate Change

ITC Investment Tax Credit

kWh Killiowatt Hour

lb Pound

LCE Levelized Cost of Energy

LOS Least of Square

MA Moving Average

MWh Megawatt Hour

PACF Partial Autocorrelation Function

PTC Production Tax Credit

R&D Research and Development

RPS Renewable Portfolio Standard

Abstract

This thesis attempts to find the least-cost strategy to reduce CO_2 emission by replacing coal by other energy sources for electricity generation in the context of the proposed EPA's regulation on CO_2 emissions from existing coal-fired power plants. An ARIMA model is built to forecast coal consumption for electricity generation and its CO_2 emissions in Michigan from 2016 to 2020. CO_2 emission reduction costs are calculated under three emission reduction scenarios- reduction to 17%, 30% and 50% below the 2005 emission level. The impacts of Production Tax Credit (PTC) and the intermittency of renewable energy are also discussed. The results indicate that in most cases natural gas will be the best alternative to coal for electricity generation to realize CO_2 reduction goals; if the PTC for wind power will continue after 2015, a natural gas and wind combination approach could be the best strategy based on the least-cost criterion.

Chapter: 1 Introduction

1.1 Background

According to the Intergovernmental Panel on Climate Change (IPCC 2013), the increase in atmospheric concentrations of carbon dioxide (CO_2) and other greenhouse gases (GHGs) has resulted from human activity since 1750. The scientists also declare that it is extremely likely that the observed warming since 1950 is mainly influenced by human activities (IPCC 2013). Global warming causes changes in water cycles, sea level rise, climate extremes, etc. (IPCC 2007; IPCC 2013). To reduce the negative impacts from global warming, it is necessary to control the emissions of CO_2 and other GHGs from human activities.

In 2009, President Obama pledge to reduce American GHGs emission by 17 % below 2005 emission level by 2020. To achieve this goal, the Obama Administration wants to double electricity generation from renewable energy resources and update new fuel economy standards (EOP 2013). The total amount of GHGs emission in 2005 and 2011 are 7,195 and 6,702 million metric tons (CO_2 equivalent), respectively (EPA 2013). The total GHG emissions in 2011 decreases by 6.9 percent below the 2005 emission level. However, it is uncertain that whether or not Obama's 17% Goal will be achieved by 2020.

According to U.S. Environmental Protection Agency (EPA)'s Inventory of U.S. Greenhouse Gases and Sinks, in 2011, 33% of GHGs was emitted from electricity production, which was the single largest GHGs emissions source in the U.S. (EPA 2013). Also, about 67% of the electricity was generated from coal and natural gas in 2011[1].

[1] See Table 1.1 on http://www.eia.gov/electricity/annual/, retrieved on Jan 10th, 2014.

To reduce the carbon pollution from the electric industry, in September 2013 the EPA proposed carbon dioxide emission standards for coal-fired and natural gas power plants which will be built in the future[2]. This was EPA's first strong action under President Obama's Climate Action Plan. However, these strict standards only regulate new coal-fired and natural gas power plants. The program to reduce carbon emission from existing power plants is still under consideration[3].

However, existing power plants emit large quantities of GHGs. According to the EIA, electricity in the U.S. declined in the four of years from 2008 to 2012; and it continued to decline continuingly in 2013[4]. It is possible that, with the current trend, there would be no need to expand the current electricity generation capacity. Thus, in the electric industry, the major contributor of carbon emission is still the existing power plants. If the Obama Administration wants to achieve the ambitious goals of the Climate Change Plan, the regulation to reduce carbon emission from existing power plants needs to be worked out.

Michigan depends heavily on fossil fuels to generate electricity. For example, in 2010 the primary resource for electricity generation is coal, which accounted for 58.81% of total electricity generation[5]. A large amount of CO_2 is emitted from the Michigan electric power sector. According to the U.S. Energy Information Administration (EIA), in

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[2] More details about the proposed separate standards for new coal and natural gas based power plants can be found at http://www.gpo.gov/fdsys/pkg/FR-2014-01-08/pdf/2013-28668.pdf , retrieved on April 11th, 2014.

[3] See http://www2.epa.gov/sites/production/files/2013-09/documents/20130923statequestions.pdf, retrieved on Jan 11th, 2014.

[4] See http://www.eia.gov/todayinenergy/detail.cfm?id=14291, retrieved on Jan 11th, 2014.

[5] See Table 5 on http://www.eia.gov/electricity/state/michigan/, retrieved on Jan 8th, 2014.

2010, Michigan's total amount of CO_2 emissions from electricity generation was 74, 480 thousand metric tons, which ranked 11th among all the states in the U.S[5]. Thus, reducing the carbon emission from the existing power plants will be a great challenge to Michigan.

1.2 Study Purpose and Thesis Structure

Various technologies are available to avoid carbon emissions in the electric power sector, such as CO_2 capture and storage (CCS), improving energy efficiency and replacing fossil fuels by low or non-emission energy resources. The ultimate goal of this thesis is to estimate the cost of reducing CO_2 emission by different technologies in the Michigan electric power industry under different CO_2 emission reduction targets. Also, by comparing the costs of available low-carbon technologies, this thesis attempts to help Michigan electricity providers to find the most cost-effective strategy to avoid releasing CO_2 from electricity production.

Coal is the primary energy resource to generate electricity, and nearly 90% of total CO_2 in the Michigan electric power industry is emitted from coal-fired power plants[6]. Therefore, this thesis only estimates the cost of CO_2 emission reduction strategies for existing coal-fired power plants.

The rest of this thesis is organized as follows: the literature review and the methodologies for analysis are presented in Chapter 2. Chapter 3 mainly focuses on building statistical models to project future CO_2 emissions in Michigan coal-fired power

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[6] See Table 7 on http://www.eia.gov/electricity/state/michigan/, retrieved on Feb 4th, 2014.

plants. Based on the results in Chapter 3, Chapter 4 will conduct cost analysis of CO_2 emission reductions. At the end of this chapter, the cost ranges and least cost strategies under different emission reduction scenarios will be provided. Some uncertain factors, like the intermittency feature of renewable energy and the production tax credit for renewable power plants, may influence the results of the cost analysis. In Chapter 6, the impacts of these factors will be discussed. The conclusions and limitations of this thesis, and the implications for future studies will be presented in Chapter 7.

Chapter 2: Literature Review and Methodology

Most current studies focus on estimating the CO_2 mitigation cost for a global or a national level. For example, Sim et al. (2003) compares the mitigation costs of technologies, which can contribute to reducing carbon emission from electricity generation. They found that except for solar energy power plants and carbon dioxide sequestration technologies, other carbon emission-reducing technologies (like nuclear and other renewable energy power plants) have the potential to reduce both the cost of electricity generation and carbon emissions by 2020 from a global level.

Crane et al. (2011) estimate the cost of a national 25 percent Renewable Portfolio Standard (RPS) in the U.S. by 2025. In their study, it is assumed that a 25% RPS only replaces coal by renewable energy resources to generate electricity. A national 25% RPS can reduce about 670 million metric tons of GHG emissions per year. However, this study only discusses the role of renewable energy resources to reduce carbon emissions from coal-fired power plants.

Fischer and Newell (2007) assess the CO_2 emission reduction polices and the ones aimed at renewable energy technology diffusion and innovation. It is found that emission price is the most effective single carbon emission reduction policy. It works well except for small emissions reduction targets. Also, a portfolio of policies, rather than one single policy, can lower the cost considerably, especially if emissions price and R&D and learning subsidies are included.

Few studies have analyzed the issue from a state level. Also, there remains a need to incorporate all the alternative energy sources (renewable energy, nuclear energy, low-carbon emission fossil fuels) into consideration, and compare their individual behaviors and costs of carbon emission reductions.

The methodology of this thesis is presented as follows: First, the thesis projects the future CO_2 emissions from coal-fired plants in Michigan. A time series model based on Box–Jenkins (BJ) methodology can be built to predict coal demand for electricity generation. Then, future CO_2 emissions can be estimated by multiplying the annual coal consumption by the CO_2 emission factor[7].

Next, the CO_2 reduction targets will be determined. Reduction to 17% below 2005 CO_2 emission level by 2020 (proposed by the Obama Administration) is regarded as one scenario. Also, a progressive target- reduction to 30% below 2005 level by 2020, and an even more challenging target-reduction to 50% below 2005 level by 2020- are used to estimate the potential cost under more stringent regulations.

Based on the annual emission reduction target, which is decomposed from the ultimate target of the different scenarios, the required avoided electricity generation from coal and avoided coal consumption for electricity generation can be calculated. The cost can be approximated by multiplying the avoided electricity generation from coal by the electricity generation cost of the alternative energy resource. One can find the cost of electricity produced from different energy sources from other studies, governmental and

[7] See http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11

industry reports. In this thesis, the information is gathered from EIA's Levelized Cost of Energy in the Annual Energy Outlook (AEO) (EIA 2011b, 2012b, 2013b, 2014b).

Finally, the total cost of all the alternative technologies proposed to reduce CO_2 emission for coal-fire power plants can be estimated and compared. The least cost one will be recommended as the most promising energy resource to replace coal to generate electricity under the CO_2 emission reduction requirement.

Chapter 3: Projecting Future CO_2 Emission from Coal-Fired Power Plants in Michigan

Before estimating the cost of replacing coal by other energy sources, the CO_2 emission reduction target should be determined. In other words, the cost estimation for each alternative energy technology in this study is mainly based on how much CO_2 emissions should be avoided. Thus, it is necessary to estimate the total CO_2 emitted from the existing coal-fired power plants in Michigan currently. The rest of this chapter will discuss how to build a time series model to project future CO_2 emissions.

3.1 Literature Reviews of Forecast Models

Many methods are available for forecasting electricity demand. For example, Mohamed and Bodger (2005) built a multiple linear regression model to forecast the electricity consumption in New Zealand. They found that gross domestic product (GDP), the average price of electricity and the population of New Zealand are highly related to New Zealand's electricity demand. A simulation approach based on artificial neural network can be used to forecast monthly electricity consumption (Azadesh et al. 2008). Also, some scholars applied the Grey Prediction method to forecast electricity demand (Yao et al. 2003; Zhou et al. 2006).

Another popular approach is building an Autoregressive Integrated Moving Average (ARIMA) models to project electricity demand (Hagan and Behr 1987; Abdel-Aal and Al-Garni 1997; Pappas et al. 2008). The ARIMA (p,d,q) model includes three parts: the autoregressive (AR), integration (I) and moving average (MA) terms. In the AR (*p*) and

MA (q) model, the dependent variable is linearly regressed on its own previous values and its past forecast errors, respectively. Both p and q indicate the time lag in the model or the order of model. I (d) serves as the integration part of the model. The time series data becomes stationary after differencing d times.

Here are the reasons why this thesis uses ARIMA model for forecasting rather than other approaches. First, the forecast of ARIMA model is only based on analyzing the historical data. It is assumed that the past data includes the influences of all the possible explanatory variables and the pattern of those influences will continue in the future. To build an ARIMA model, there is no need to find the exact influential factors and analyze their impacts on the dependent variable like multiple linear regression approach. Second, the model applied in this thesis only needs forecasting the data a few years ahead and ARIMA models do well in this case. However, the long-term predictions of ARIMA model can have very wide prediction intervals. Last but not the least, the ARIMA model has the advantage of responding quickly to changes in underlying trends. Thus, the ARIMA model is selected as the forecasting model in this thesis. The methodology of establishing ARIMA models for time series analysis in this study is mainly based on the Box and Jenkins (2013) study. With the help of the R statistical software package, one can build ARIMA models for projection. In this study, most of the R codes for analyzing the time series data, building the appropriate ARIMA model and predicting the future trend is based on the study by Cryer and Chan (2008).

The goal of this section focuses on forecasting annual CO_2 emissions. However, in this study the ARIMA model based on Box-Jenkins (B-J) methodology is only applied to the time series data of coal consumption, rather than CO_2 emission, to project future coal demand for electricity generation in Michigan. Ultimately, one can estimate the annual quantity of CO_2 emission by multiplying the total coal consumption for electricity generation by CO_2 emission per unit of coal used in power plants. There are 3 major steps to find an appropriate ARIMA models for precise prediction: model identification, parameter estimation, and model diagnosis. Based on these steps, the rest of this chapter will present how to find an appropriate ARIMA model to forecast future coal use for electricity generation and thus CO_2 emission from coal-fired power plants in Michigan.

3.2 Building the ARIMA Model

3.2.1 Model Identification

Michigan's annual coal consumption for electricity generation from 1960 to 2011 is available from *EIA's State Profile and Energy Estimates* website[8]. First, one can plot the data of annual coal consumption for electricity generation against time to check the trend of the data. Figure 1 shows the results of the plot. The original data are presented in Appendix A of this thesis. Based on the plot of the raw data, the coal consumption for electricity generation is apparently decreasing after 2007 in Michigan.

Linear Approach

If a simple model can summarize all the information in the data, there is no need to build a complex one. Thus, before applying an ARIMA model to fit the data, one simple liner regression model is checked to see if it fits the data well or not. According to Figure

[8]Seehttp://www.eia.gov/state/seds/data.cfm?incfile=/state/seds/sep_use/eu/use_eu_MI.html&sid=MI, retrieved on March 16, 2014.

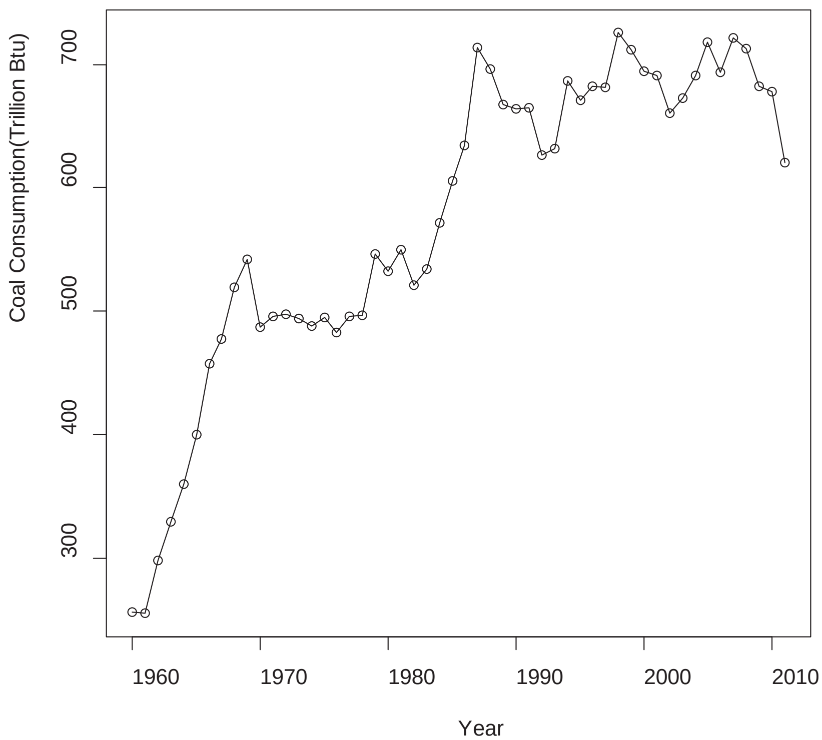

Figure 1: Coal consumption for electricity generation from 1960 to 2011 in Michigan.

1, it is not easy to find a perfect function to describe the relationship between the annual coal consumption and year. Thus, a linear regression model is built by using coal consumption (C) as the dependent variable and Year (t) as the independent variable. The regression results from R are shown in the Appendix B of the thesis.

Based on the results, one can conclude that at a 95% confidence level, the coefficient of Year (t) is statistically significant from the t-test. The Multiple R-squared indicate the model can explain the 80.21% of the data by using Least of Square (LOS) method. Also, the whole model is significant based on the F-statistic.

However, when plotting the residuals against the independent variable, the residuals are not evenly distributed on both sides of the zero line, and a possible increasing trend exists (See Appendix C). Also, one can check the normality of the residuals by Q-Q plot. A Q–Q plot is a plot of the percentiles of distributions of the observed data against the percentiles of a standard normal distribution. If the observed data are close to a normal distribution, the plot looks like a straight line. For a good fitting model, it is assumed that the residuals follow a normal distribution if the model is a proper to fit the data. However, based on the Q-Q plot shown in Appendix D, the distribution of the residuals is not a straight line, which means that it contradicts the assumption of normality of the residuals.

Also, it is assumed that the residuals are independent and have no correlations. The Durbin-Watson test can be is applied to check whether or not the residuals are correlated (Durbin and Watson 1971). The results of the Durbin-Watson test are shown in Appendix E. At a 95% significance level, from lag 5, we cannot reject the null hypothesis that autocorrelation of the residuals is 0, which means the residuals before lag 5 are highly correlated. Also the sample autocorrelation function (ACF) for the standardized residuals in Appendix F provides similar conclusion: before lag 4, the residuals are highly related. Based on the above findings, the linear regression model cannot be applied to fit the data. As this statistical work confirms, Figure 1 is not a linear plot.

ARIMA Approach

The ARIMA model should be built from stationary time series data with constant mean and variances. The first step of model identification is checking whether or not

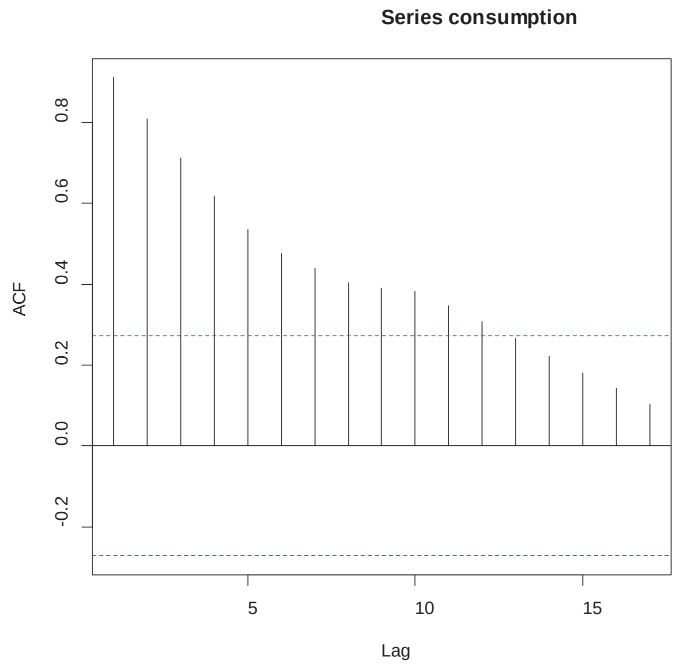

Figure 2: Sample ACF for Time Series Data of Coal Consumption in Michigan

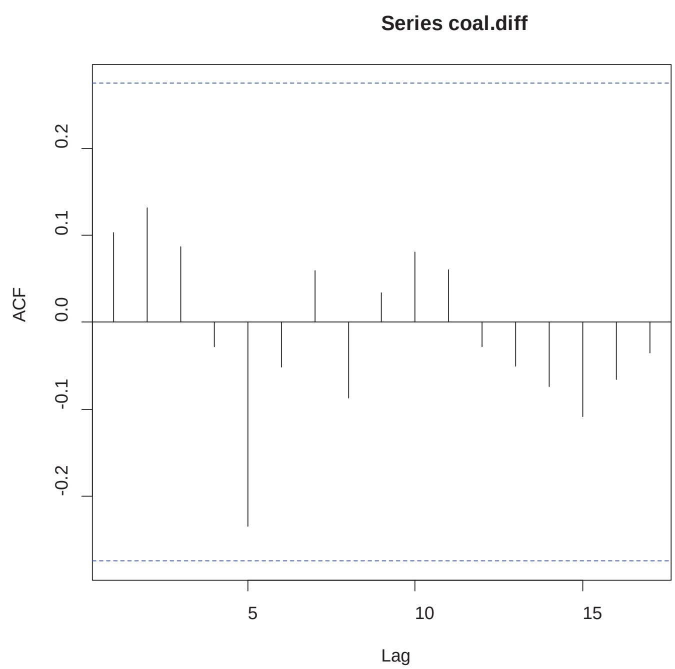

Figure 3: Sample ACF Computed on the First Difference of Time Series Data of Coal Consumption in Michigan

transformation is needed to make the time series data stationary. Differencing can remove the non-stationarity of the data. The purpose of differencing is to attain a more homogeneous mean and more stable variance. The order of differencing can be determined by checking the ACF of the time series data. Figure 2 shows the results of computing the sample ACF for the raw data. Apparently, there is a decreasing trend in the sample ACF of the data. The sample ACF drifts slowly and does not disappear rapidly when the lag is increasing. Thus, the data needs differencing. Figure 3 presents the sample ACF of the differencing data. Obviously, after the differencing, the slowly decreasing trend of the sample ACF disappears, and it seems that no certain trend exists.

The Dickey Fuller Unit Root test can be applied to test whether or not the first difference of the original time series data is stationary (David and Fuller 1979). The null hypothesis of the test is that a unit root exists, which means that the time series data is not stationary. The alternative hypothesis is that there is no unit root. The results of the test are shown in Appendix G. In this case, the p-value is greater than α of 0.05 (5%), thus we cannot reject the null hypothesis of a unit root. Thus, the first difference of the data is still not stationary, and further differencing may be needed. Appendix H shows the results of the Dickey Fuller Unit Root test for the second difference of the data. Since the p-value is less than 5%, we can reject the null hypothesis and conclude that the data after the second differencing is now stationary.

Figure 4 shows the second difference of the original data. The new series of data looks evenly distributed around the zero line, and no specific pattern or trend exists

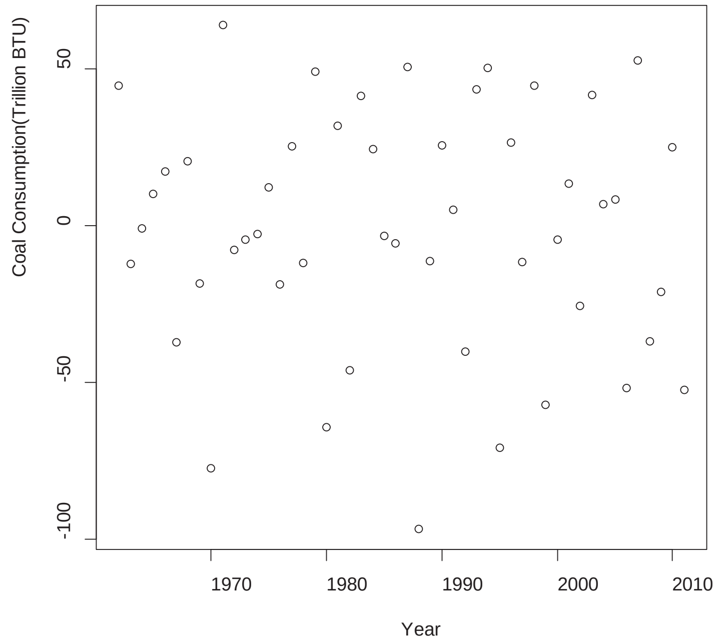

Figure 4: The Second Difference of Time Series Data of Coal Consumption in Michigan

comparing with the plot of original data in Figure 1. Here, it should be mentioned that after differencing twice, two observations are lost in Figure 4.

However, one should be cautious about the disadvantages of differencing. First, differencing causes the loss of one observation each time. Also, overdifferencing can introduce unnecessary correlations into a series and make the modeling process more complicated (Cryer and Chan 2008). To check whether or not the second difference of the data causes unexpected correlations of the time series data, one can calculate the ACF of the second differences. The results are shown in Figure 5. Compared with Figure 3, which shows the sample ACF for the first difference of data, lag 1 has a strong correlation and the correlation at lag 5 is significant. However, usually, at most two differences and some transformations can stabilize the data (Cryer and Chan 2008). Thus, differencing the data twice is accepted in this study in spite of the unexpected correlations introduced by differencing the data.

The next step is specifying the model. The model identification procedures are mainly due to Cryer and Chan (2008). In this study, the ARIMA model is selected based on the ACF, partial (PACF) and extended ACF (EACF). According to Figure 5, which represents the ACF of the second difference of data, the ACF cuts off at lag 1. The dashed lines in Figure 5 shows the critical values for checking whether the coefficients of the ACF are significantly different from zero or not. The behavior of ACF indicates that the MA (1) model is appropriate to fit the data. The PACF of the second difference of the data is shown in Figure 6. The PACF cuts off at lag 2, which means that AR (2) should be considered. To further check which ARIMA model is appropriate to fit the data, EACF will be applied next. The R outputs of EACF are shown in Figure 7.

The first appearance of zero can indicate the orders of AR and MA terms of the ARIMA model. The above EACF results supports the previous assumption that MA (1) model is worthy of consideration. However, there is uncertainty about whether or not the model should incorporate the autoregressive part, ARMA (2,1), which is based on the ACF and PACF of the differenced data. It is tested to check how well it fits the data. Finally, the two possible models ARIMA (0,2,1) and ARIMA (2,2,1) are selected when considering the second difference of data.

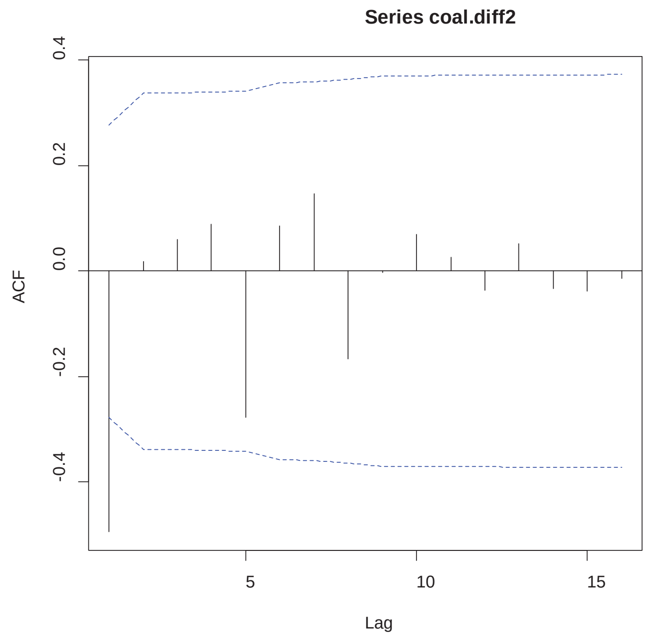

Figure 5: Sample ACF Computed on the Second Difference of Time Series Data of Coal Consumption in Michigan

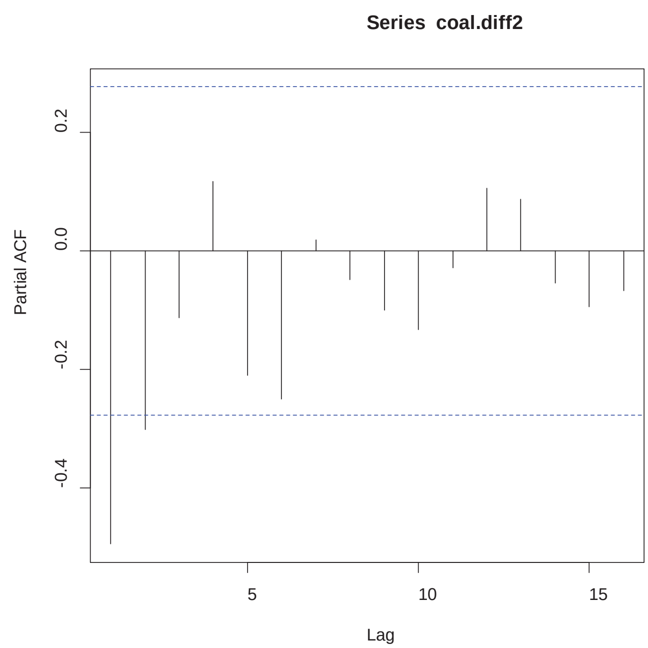

Figure 6: Sample PACF Computed on the Second Difference of Time Series Data of Coal Consumption in Michigan

AR/MA	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	x	o	o	o	o	o	o	o	o	o	o	o	o	o
1	x	o	o	o	o	o	o	o	o	o	o	o	o	o
2	x	o	o	o	o	o	o	o	o	o	o	o	o	o
3	x	o	o	o	o	o	o	o	o	o	o	o	o	o
4	o	o	x	o	x	o	o	o	o	o	o	o	o	o
5	x	o	x	o	x	o	o	o	o	o	o	o	o	o
6	o	x	o	o	o	x	o	o	o	o	o	o	o	o
7	x	o	o	o	o	o	o	o	o	o	o	o	o	o

Figure 7: R output of EACF of the Second Difference of Time Series Data of Coal Consumption in Michigan

Normally, the following step is used to answer the question: which model is more appropriate and can be adopted for predicting future coal consumption for electricity generation in Michigan. Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC) and residual analysis will be tested for final model selection. The R software provides the results of AIC, BIC and the parameter estimates. The model selection will be discussed together with parameter estimation in the next section.

3.2.2 Parameter Estimation and Model selection

Box et al. (2013) discuss how to select the optimal model by using AIC and BIC, and how to estimate the parameters of an ARIMA model by maximizing the likelihood function. The maximum likelihood method uses all the information in the data and it can generate "many large-sample results which are known under very general conditions" (Cryer and Chan 2008). The R parameter estimates of the ARIMA (2,2,1) and ARIMA

(0,2,1) models by using maximum likelihood method, and AIC and BIC for each model are shown in Appendix I and Appendix J, respectively. Among all the candidate models for the same data set, the promising model should have the minimum AIC and BIC values. In other words, the lower the values of AIC and BIC are, the better the model fits the data. Comparing the fitting results of two candidate models, ARIMA (0,2,1) has the lower AIC, and BIC values. Thus, it is regarded as the better model.

The “forecast” package in R has an *auto.arima* function, which can help to inspect the best the ARIMA (p,d,q) model based on AIC and BIC criterion. By default, this function limits the value of p and q from 0 to 5. According to the results, which are present in Appendix K, the most appropriate model is ARIMA (0,2,1). This confirms that the reasoning processes in the previous section to find the best model are correct. Although the *auto.arima* function does not consider the intercept of the model, this does not impact the results of finding the most appropriate ARIMA model the data. However, it is too early to conclude that ARIMA (0,2,1) is the ultimate model before a residual analysis is done. Residual analysis is an important model diagnostics method which is necessary to further check the goodness of the model.

3.2.3 Model Diagnosis

A diagnosis check is mainly conducted on the residuals. Residuals should follow a white noise process, which means it must fulfill the following requirements: normal distribution, zero mean, constant variance, and the residuals are uncorrelated to each other.

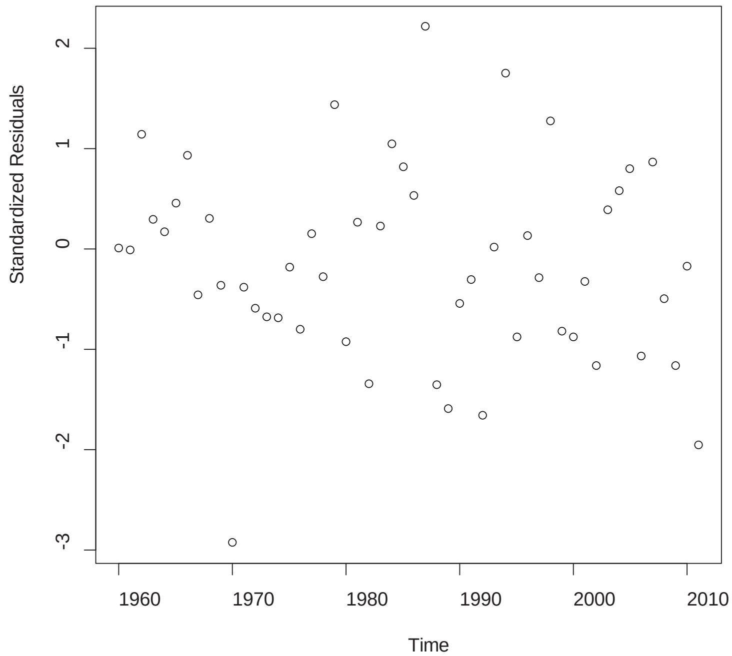

Figure 8: The Residuals of ARIMA (0,2,1) Model

First, the residuals of the model are plotted over time to check whether or not the results have any pattern. Figure 8 shows the residuals from the ARIMA (0,2,1) model of coal consumption. The plot suggests most of the residuals randomly scatter around a zero and weak heteroskedasticity exists.

Next, the normality of residuals will be checked. It is assumed that the residuals follow a normal distribution. The Q-Q plot is shown in Figure 9. Most of the residuals seem to be on a straight line except in the extreme tails. Although several points are wondering off around the upper right tail of the plot, overall, we can concluded that residuals are normally distributed.

The last but not the least step is to examine whether or not the residuals are correlated. It is expected that the residuals are not correlated to each other. Figure 10

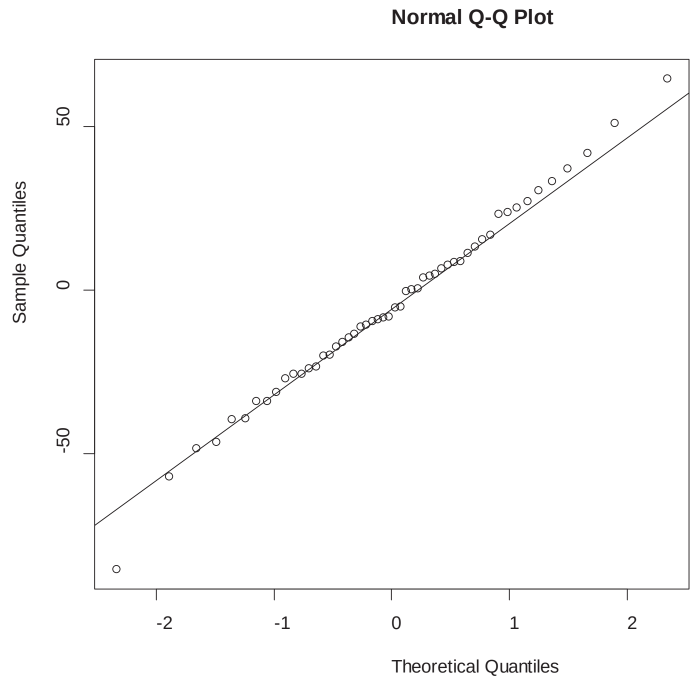

Figure 9: Q-Q Plot of the Residuals of ARIMA (0,2,1) Model

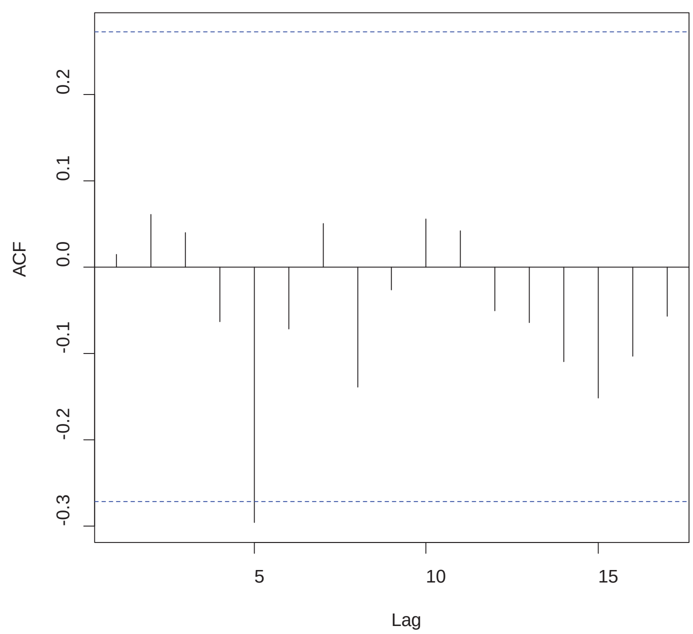

Figure 10: Sample ACF for the Residuals of ARIMA (0,2,1) Model

presents the ACF of residuals. It is obvious that only at lag 5 is there a slightly significant autocorrelation. However, considering no strong autocorrelations exist at other lags, one can still conclude that there is no statistically powerful autocorrelation in the residuals.

The last but not the least step is to examine whether or not the residuals are correlated. It is expected that the residuals are not correlated to each other. Figure 10 presents the ACF of residuals. It is obvious that only at lag 5 is there a slightly significant autocorrelation. However, considering no strong autocorrelations exist at other lags, one can still conclude that there is no statistically powerful autocorrelation in the residuals.

Also, the Ljung-Box test can be used to check whether or not the residuals are autocorrelated when considering their group magnitude instead of individual lags (Ljung and Box 1978). The null hypothesis is that the residuals are uncorrelated. The results of test are shown in Appendix L. At a 95% significance level, one cannot reject the null hypothesis: thus considering all the residuals as a group, the residuals are uncorrelated.

Thus, the final model ARIMA (0,2,1) is defined as :

$$\boldsymbol{\nabla^2 Y_t = \theta_0 + e_t - \theta_1 e_{t-1}}$$

where $\nabla^2 Y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$

Based on the R outputs in Appendix J, $\theta_0 = 18.2447$, $\theta_1 = 0.8906$. Thus, the model can be written as follows:

$$\boldsymbol{\nabla^2 Y_t = 18.2447 + e_t - 0.8906\, e_{t-1}} \quad \textbf{(1)}$$

Ultimately, model (1) is appropriate to fit the data and can be applied to make a prediction of the future coal consumption for electricity generation in Michigan.

3.3 Projecting Future CO_2 Emissions from Coal-fired Power Plant in Michigan

Model (1) is now used to predict the future coal consumption needed for electricity generation in Michigan from 2012 to 2020. The results are shown in Figure 11. In Figure 11, the solid circles represent the predicted values from 2012 to 2020. The predicted values describe a continuously decreasing trend in coal consumption after 2007. The upper and lower dashed lines around the predicted values are the 95% prediction bounds. The output of the predicted values, 95% prediction intervals, and standard errors of prediction are shown in Appendix M. One limitation of the prediction is that the standard errors, lower and upper predicted intervals for the years after 2012 become greater and greater. Other limitations of applying an ARIMA model for forecasting will be discussed in Chapter 6.

Figure 11: The Projection of Coal Consumption for Electricity Generation in Michigan

The CO_2 emission factors for coal can be found from EIA's FREQUENTLY ASKED QUESTIONS website[9]. This website provides the information of CO_2 carbon emission factors for bituminous, sub-bituminous and lignite coal. The types and the total amount of coal consumed for electricity generation in Michigan in 2010 are available from American Lung Association (2011). Only Subbituminous and Bituminous coal are used for electricity generation in Michigan. Based on the proportion of individual coal needed for electricity production, the weighted CO_2 emission factor can be calculated[10]. Multiplying the projected coal consumption by the weighted CO_2 emission factor, the annual CO_2 emission generated from coal-fired power plants from 2012 to 2020 can be calculated. The results are shown in Table 1.

Table 1: The Predicted CO_2 Emission from Coal-fired Power Plant under the Business as Usual Scenario

Year	Coal Consumption (Trillion BTU)	CO_2 Emission (Billion lbs)
2012	613.88	126.52
2013	607.36	125.18
2014	600.84	123.83
2015	594.32	122.49
2016	587.80	121.15
2017	581.28	119.80
2018	574.76	118.46
2019	568.24	117.11
2020	561.72	115.77

Source: Author's calculation.

[9] See http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11, retrieved on March 30th, 2014.
[10] After the calculation, the total consumptions of subbituminous and bituminous coal are 29,201,133 and 3,484,589 tons, respectively. The CO_2 emissions per million Btu of these two kinds of coal are 205.30 and 212.70 lbs. Thus, the weighted CO_2 emission factor is 206.10 lbs per million Btu of coal consumed for electricity production.

Chapter 4: Calculating CO_2 Emission Reduction Cost

4.1 CO_2 Emission Reductions under Different Scenarios

Before estimating the cost of reducing CO_2 emission in the existing coal-fired power plants in Michigan, it is necessary to determine the emission reduction targets. In this thesis, the mitigation costs of carbon emission reduction will be discussed under 3 scenarios. Reduction to 17% below 2005 CO_2 emission level by 2020 (17% scenario), which is proposed by the Obama Administration, is regarded as the first scenario. Also, a progressive reduction target-30% below 2005 level by 2020 (30% scenario), and an even more challenging reduction target- 50% below 2005 level by 2020 (50% scenario) are used to estimate the potential cost under more stringent regulations. In April 2014, the EPA proposed a new CO_2 emission standard for new coal and natural gas power plants. However, for the existing power plants, according to the timetable in the "Presidential Memorandum-Power Sector Carbon Pollution Standards", the final CO_2 emission standards should be issued by June 1, 2015[11]. It is uncertain whether the standards for existing power plants will be finally approved and when it will be implemented. This thesis assumes that it will be approved and implemented after 2015. The relevant time frame for this study is from 2016 to 2020.

The future CO_2 emissions in Michigan coal-fired power plants have been estimated in Chapter 3. The total amount of CO_2 in Michigan's coal plants in the base

[11] See http://www.whitehouse.gov/the-press-office/2013/06/25/presidential-memorandum-power-sector-carbon-pollution-standards , retrieved on Jan 8th, 2014.

year (2005) can be calculated by multiplying the coal consumption for electricity production in that year (see Appendix A) by the CO_2 emission factor (which is calculated in Chapter 3). From this calculation, the total CO_2 emission generated from coal plants is about 148.02 billion lbs in 2005. To achieve the emission reduction goal, the CO_2 emission generated from coal plants should be 122.86, 103.61 and 74.01 million lbs under 17%, 30% and 50% scenario by 2020, respectively. In this thesis, it is assumed that the emission reduction targets would be achieved in 2020 under all the scenarios. Also, the annual emission target increases with the same growth rate in the individual scenario. The annual CO_2 emission reduction targets in different scenarios are shown in the Table 2.

The annual amount of CO_2 emission from coal-fired plants is presented in Table 1. Also, the CO_2 emission level in 2005 is known. Thus, the actual annual emission compared with 2005 level under the business-as-usual (BAU) scenario can be calculated. The results are also presented in Table 2.

Table 2: Annual CO_2 Emission Reduction Target and Actual Emission Reduction Compared with 2005 Level

Year	17% Scenario	30% Scenario	50% Scenario	BAU Scenario
2015	17.25%	17.25%	17.25%	17.25%
2016	17.20%	19.80%	23.80%	18.16%
2017	17.15%	22.35%	30.35%	19.06%
2018	17.10%	24.90%	36.90%	19.97%
2019	17.05%	27.45%	43.45%	20.88%
2020	17.00%	30.00%	50.00%	21.79%

Source: Author's calculation.

Here are some explanations about the figure in Table 2. The annual increase in the emission reduction target under 17%, 30% and 50% scenarios can be calculated by the following equation:

$$\frac{\text{Final Emission Target in 2020} - \text{Emission Reduction Level in 2015}}{\text{Year Period}}$$

For example, the annual increase of emission reduction target under the 17% scenario equals to $\frac{17\% - 11.4\%}{5}$ = 1.11%.

Based on the results in Table 2, one can calculate the annual additional reduction requirements compared with the BAU scenario. The additional required amount of CO_2 emission reduction can be estimated as well. The results are shown in Table 3 and Table 4, respectively. The figures in the column of "17% Scenario" in Table 3 are negative. That means the CO_2 emission in coal-fired power plants from 2016 is lower than annual 17% emission reduction target. In other words, the 17% scenario target is achieved in 2016 instead of 2020. The absolute values of the negative figures in this column represent the addition emission reductions compared with emission reduction target in 17% scenario. According to the results in Table 4, from 2016 to 2020, a target of 30% and 50% below 2005 CO_2 emission level can contribute to 36.47 and 125.28 billion lbs of CO_2 emission reductions, respectively. Also, in the BAU scenario, 21.26 billion more lbs of CO_2 are reduced when compared with target of 17% below 2005 emission level.

Table 3: The Annual Additional Required CO_2 Emission Reduction Compared with 2005 Level

Year	17% Scenario	30% Scenario	50% Scenario
2016	-0.96%	1.64%	5.64%
2017	-1.92%	3.28%	11.28%
2018	-2.87%	4.93%	16.93%
2019	-3.83%	6.57%	22.57%
2020	-4.79%	8.21%	28.21%

Source: Author's calculation.

Table 4: The Additional Amount of CO_2 Emission Reductions (Billion lbs)

Year	17% Scenario	30% Scenario	50% Scenario
2016	-1.42	2.43	8.35
2017	-2.83	4.86	16.70
2018	-4.25	7.29	25.06
2019	-5.67	9.72	33.41
2020	-7.09	12.16	41.76
Total	-21.26	36.47	125.28

Source: Author's calculation.

4.2 Cost Calculation of CO_2 Emission Reduction

This section will calculate the cost of replacing coal by other energy sources for electricity production. Initially, the replaced amount of electricity generated from coal should be known. Dividing the additional required amount of CO_2 emission reduction in Table 4 by the CO_2 emission factor for coal, the avoided amount of coal used for electricity generation is presented in Table 5. Based on the information in Table 3, no additional required CO_2 emission reduction is needed under the 17% reduction target and

Table 5: The Avoided Coal Consumption for Electricity Production (Trillions BTU)

Year	30% Scenario	50% Scenario
2016	11.80	40.52
2017	23.59	81.05
2018	35.39	121.57
2019	47.18	162.10
2020	58.98	202.62

Source: Author's calculation.

no cost is need for CO_2 reductions. Thus, this scenario will not be discussed in the following sections. The heat rate refers to the actual amount of fuel used for 1 kWh electricity production. According to EIA's FREQUENTLY ASKED QUESTIONS website[12], the heat rate of coal is 10,498 Btu/kwh. Thus, the avoided amount of electricity generation in the coal-fired power plants can be estimated by dividing the figures in Table 5 by the heat rate of coal. The results are shown in Table 6.

Table 6: The Avoided Electricity Generation in the Coal Plants (10^6 MWh)

Year	30% Scenario	50% Scenario
2016	1.12	3.86
2017	2.25	7.72
2018	3.37	11.58
2019	4.49	15.44
2020	5.62	19.30

Source: Author's calculation.

Various technologies are available to avoid carbon emissions in the electric power

[12] See http://www.eia.gov/tools/faqs/faq.cfm?id=667&t=6, retrieved on April 10th, 2014.

sector. For example, CO_2 capture and storage (CCS) technology can reduce large quantities of GHGs emission in fossil fuel power plants (IPCC 2005). However, there are some concerns about applying CCS. Despite of the critical requirements for geological storage, some other factors, such as the development of relevant laws and regulations, public acceptance, and CO_2 transporting infrastructure, can influence the implement of CCS (Gibbins and Chalmers 2008). Currently, no power plant, which is over 100MW capability, has been put into practice (Rubin et al. 2007). In the industrial sector, increasing energy efficiency is regarded as one of the most important technologies to reduce GHG emissions in the short- to mid-term (Worrell et al. 2009).

Also, utilities can choose alternative energy resources, rather than fossil fuels, which have less or even no GHGs emissions. Renewable energy technology, such as solar energy and wind power, generates no GHGs during electricity production. Even considering the full life cycle of renewable energy technology, CO_2 and other GHGs emissions per unit electricity generation are much lower than those from fossil fuel based power plants (Roth and Ambs 2004). According to the U.S. National Renewable Energy Laboratory (Lopez et al. 2012), Michigan is abundant in renewable energy, especially solar and wind energy. However, most of the potential of hydropower has been tapped.

Like some renewable energy technologies, no air pollutants are emitted during electricity generation in nuclear power plants. Thus, replacing fossil fuels by nuclear energy can also contribute to reducing large quantities of GHGs emissions in the electric industry. However, despite the high capital cost of construction of a nuclear power plant, some other issues, including nuclear reactor safety, nuclear waste disposal, nuclear proliferation, should also be fully considered (Sailor et al. 2000).

Burning natural gas for electricity generation cannot avoid GHGs emission. However, burning coal can generate two times the CO_2 emissions from burning natural gas when generating an equal amount of electricity (Epstein et al. 2011). Thus, replacing coal by natural gas for electricity production is one effective way to cut CO_2 emissions considerably. Inevitably, generating electricity by burning biomass emits CO_2. However, if biomass is managed properly, net emissions of CO_2 can be neglected because the carbon is sequested by photosynthesis and returned to the atmosphere by combution (Gustavsson et al. 2007).

Although the CO_2 emissions from burning oil is less than burning coal to produce electricity (Epstein et al. 2011), according to IEA's electricity Michigan profile, from 2006 to 2010 the annual share of electricity generated from petroleum is less than 0.1% of the total[13].

This thesis only focuses on replacing coal by alternative energy resources to reduce CO_2 emissions. Also, it is assumed that electricity providers will apply new power capacity to achieve annual CO_2 reduction goals. Based on the above discussions, natural gas, nuclear energy, wind power, biomass and solar energy are selected as promising candidates to replace coal for electric generation to achieve the CO_2 emission reduction targets under different scenarios. The rest of this chapter will estimate the total costs of generating electricity from these low-carbon emission energy sources instead of coal. By comparing costs, the most cost-effective technology is regarded as the best CO_2

[13] See Table 5 on http://www.eia.gov/electricity/state/michigan/, retrieved on Jan 8th, 2014.

mitigation strategy for coal-fired power plants.

Levelized cost of energy (LCE) approach attempts to incorporate all the aspects of electricity generation. Besides the utilization rate, it also considers all the following costs: the overnight capital cost, fuel cost, fixed and variable operation and maintenance cost, financing cost for different types of power plants (EIA 2011b; EIA 2012b; EIA 2013b; EIA 2014b). LCEs of different technologies under one plant type are available in EIA's "Levelized Cost of New Generation Resources" of the Annual Energy Outlook (AEO). The final decision of which technology in an individual plant would be applied for generating electricity is based on the "least cost" criteria. In other words, the electricity providers are always looking for the least-cost technology to produce electricity.

Subsidies for energy should be included to reflect the real cost of electricity production. Investment tax credit (ITC) can be regarded as a type of subsidy, which reduces the cost of electricity generation. ITC reduces 30% of capital expenditures for new solar PV power plant by the end of 2016. After 2016, it only covers 10 % of the capital cost[14]. Production tax credit (PTC) works in the similar way. According to The Energy Policy Act of 2005, an advanced nuclear plant can receive $18.0/MWh production tax credit[15]. The PTC for wind power and closed-loop biomass power plants is 2.3¢/kWh if they start construction before the end of 2013[16]. Moreover, it is assumed

[14] See "Note 1" under Table 1 in "Levelized Cost of New Generation Resources in the Annual Energy Outlook 2014" (EIA 2014b). Retrieved from http://www.eia.gov/forecasts/aeo/pdf/electricity_generation.pdf on April 20th, 2014.
[15] "ENERGY POLICY ACT (EPACT) OF 2005". Retrieved from http://energy.gov/sites/prod/files/2013/10/f3/epact_2005.pdf on April 15th, 2014.
[16] "Renewable Electricity Production Tax Credit (PTC)" Retrieved from http://dsireusa.org/incentives/incentive.cfm?Incentive_Code=US13F on April 15th, 2014.

that generating electricity from biomass by close-loop technology will be used so that the biomass will be CO_2 neutral.

The amount of CO_2 emissions for natural gas combustion equals about half of the emissions of using coal to generate the same amount of electricity[17]. Undoubtedly, replacing coal by natural gas for electricity generation can help to reduce CO_2 emissions, however, compared with the zero-emission technology (like solar and nuclear energy), it still contributes to carbon emission. Also, the impacts of the proposed carbon emission regulation on new power plants should be taken into consideration.

According to the EPA's latest proposed standards of greenhouse gas emissions regulation for new stationary sources, the amount of CO_2 emission per MWh electricity generated from new larger natural gas power plants should be less than 1,000 lbs. The emission cap for a new smaller natural gas plant is 1,100 lbs /MWh (EPA 2013). It is uncertain whether or not the proposed the standard will be approved and when the standard will be enacted if it were approved. In this thesis, it is assumed that the new regulation will be implemented after 2015.

Based on the "least cost" criteria, an advanced-combined-cycle natural gas plant is selected to be the best among the all the natural gas electric generation technologies from all the AEO references. The possible impacts of the proposed CO_2 emission standard on the cost of generating electricity from new natural gas are not clear. To estimate the potential increase in the cost of electricity generated by natural gas, this thesis uses the following approaches. 2011, 2012, 2013 and 2014 Annual Energy Outlook

[17] See http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11, retrieved on March 30th, 2014.

references show a 3% increase in the capital cost considering the possible investments in greenhouse gas mitigation technologies adopted in coal power plants. Taking EPA's proposed CO_2 emission regulation on new natural gas power plants into account, similarly, a 3% point of capital cost is added to the LCE of natural gas power plant reflecting the new carbon emission regulation after 2015.

Based on the above discussion, the inflation adjusted LCEs of the selected electric generation technologies, including subsidies and CO_2 emission cost under the proposed regulation, are shown in Table 7. The LCEs of power plants entering service in 2020 are not available, so the increasing or decreasing percentage of LCE from 2018 to 2019 is applied to predict the LCEs in 2020 for the each technology.

Table 7: LCEs of Technologies Selected for Reducing CO_2 Emission in Michigan

Technology	Entering Service Year	Inflation Adjusted LCE (2009$/MWh)	LCE Before Inflation Adjusted ($/MWh)	Subsidies/ CO_2 Cost ($/MWh)	Cost Included Subsidies and CO_2 Cost ($/MWh)
Natural gas-Advanced Combined Cycle	2016	62.56	63.10	0.54	62.56
	2017	61.59	63.10	0.53	62.58
	2018	62.25	65.60	0.52	65.08
	2019	59.89	64.40	0.47	63.93
	2020	57.62	N/A	N/A	N/A
Advanced Nuclear	2016	95.90	113.90	18.00	95.90
	2017	91.93	111.40	18.00	93.40
	2018	86.47	108.40	18.00	90.40
	2019	73.17	96.10	18.00	78.10
	2020	61.92	N/A	18	N/A
Wind	2016	97.00	97.00	0	97.00
	2017	94.49	96.00	0	96.00
	2018	82.83	86.60	0	86.60
	2019	75.23	80.30	0	80.30
	2020	68.33	N/A	0	N/A
Solar PV	2016	152.32	210.70	58.38	152.32
	2017	136.45	152.70	14.07	138.63
	2018	125.55	144.30	13.04	131.26
	2019	111.06	130.00	11.45	118.55
	2020	98.24	N/A	0	N/A
Biomass	2016	112.50	112.50	0.00	112.50
	2017	113.58	115.40	0.00	115.40
	2018	106.17	111.00	0.00	111.00
	2019	96.12	102.60	0.00	96.12
	2020	87.02	N/A	0	N/A

Sources: EIA 2011b; EIA 2012b; EIA 2013b; EIA 2014b.
Note: The 2020 inflation adjusted LCEs are estimated by the author based on the trends from 2018 to 2019. Except for the PTCs for some power plants are known, other data are not available.

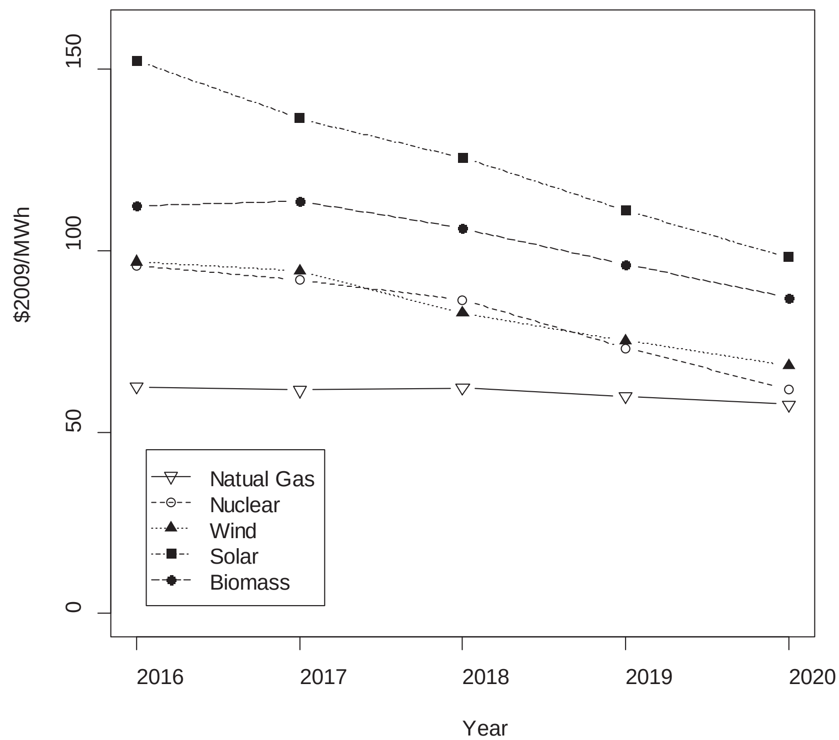

Figure 12: Annual LCEs for Different Types of Technology Applied for CO_2 Emission Reduction in Michigan

To compare the electricity generation costs per unit of electricity generation, the annual LCEs of different types of power plants are plotted in Figure 12. Here are some other findings in Figure 12: 1) The LCE of each energy power plant has a clearly decreasing trend; 2) Although the per unit electric production cost of solar energy decreases the fastest among all the technologies, its cost is not comparative with natural gas and nuclear energy based power plants; 3) The cost of wind power plant is the lowest among all the renewable technologies. In 2018, the LCE of a wind power plant is even lower than nuclear energy power plant. It is clear that the LCEs for nuclear and wind power plants are very close. The possible reason for nuclear energy having a relatively lower LCE is that it benefits from PTC annually. For wind power plants, whether or not the current PTC for it will exist after 2015 is uncertain.

Thus, based on the information in Table 6 and 7, the costs of reducing CO_2 emission by replacing coal by other energy sources can be easily calculated. The costs of using different kinds of energy under different scenarios are shown in Table 8. Figure 13 and 14 show the total costs of using alternative energy sources instead of coal to generate electricity to achieve CO_2 emission reduction.

Based on the results in Table 8, the cost ranges of reducing CO_2 emission in the coal-fired power plants in Michigan is from 1.01 to 1.95 billion dollars, 3.47 to 6.71 dollars in 30% scenario and 50% scenario, respectively. Recall that the 17% target will be achieved by 2016, thus there is no investment needed for CO_2 reduction in this scenario. According to Figure 13 and 14, in 30% and 50% scenarios, investing in natural gas power plants costs the least to achieve the goal of CO_2 emission reduction by 30% and 50% below 2005 level in the coal plant in Michigan. This means generating electricity from natural gas should be taken as priority to reduce CO_2 emission for electricity providers based on the least-cost criteria.

Table 8: The Total Cost of Reducing CO_2 Emission by Substituting Coal by Other Energy Sources (Million \$2009)

Energy Source	Year	30% Scenario	50% Scenario
Natural gas-Advanced Combined Cycle	2016	70.30	241.50
	2017	138.41	475.49
	2018	209.84	720.89
	2019	269.18	924.74
	2020	323.72	1,112.10
	Total	1,011.45	3,474.73
Advanced Nuclear	2016	107.76	370.19
	2017	206.59	709.73
	2018	291.48	1,001.37
	2019	328.87	1,129.79
	2020	347.86	1,195.02
	Total	1,282.56	4,406.10
Wind	2016	108.99	374.44
	2017	212.35	729.49
	2018	279.21	959.21
	2019	338.13	1,161.60
	2020	383.88	1,318.77
	Total	1,322.56	4,543.52
Solar PV	2016	171.15	587.98
	2017	306.64	1,053.44
	2018	423.22	1,453.93
	2019	499.17	1,714.84
	2020	551.95	1,896.16
	Total	1,952.13	6,706.35
Biomass	2016	126.41	434.27
	2017	255.25	876.87
	2018	357.89	1,229.50
	2019	432.02	1,484.16
	2020	488.90	1,679.58
	Total	1,660.47	5,704.38

Source: Authors calculation.

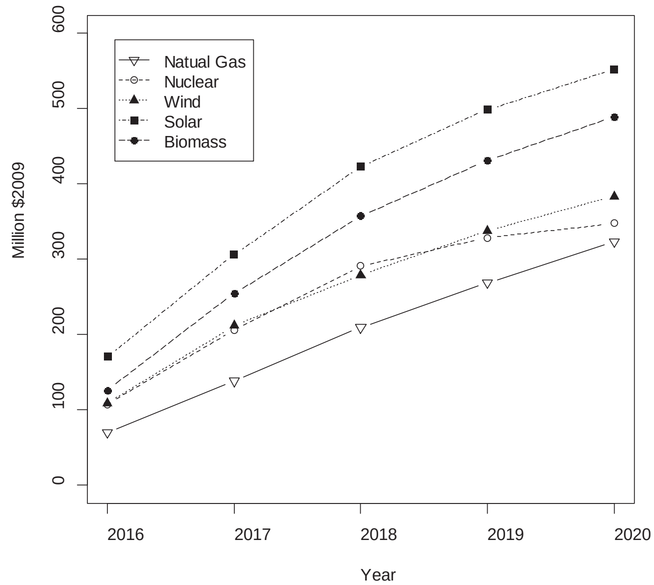

Figure 13: Total Cost of CO_2 Emission Reduction Technologies under the 30% Scenario

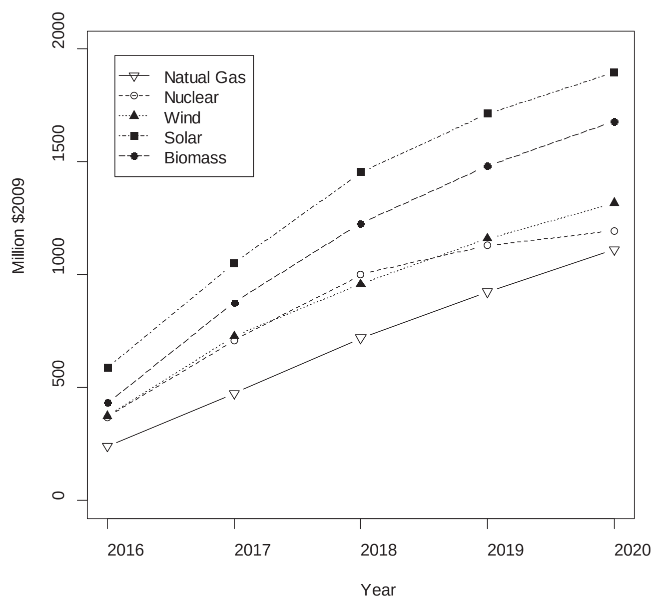

Figure 14: Total Cost of CO_2 Emission Reduction Technologies under the 50% Scenario

Chapter 5: Discussion

The CO_2 reduction costs of different technology-based power plants under three scenarios- 17%, 30% and 50% below 2005 emission levels- are calculated in Chapter 5. According to the results, it is found that generating electricity from advanced-combined-cycle natural gas power plant instead of coal plant is the least cost way to achieve annual CO_2 emission reduction goals in the 30% and 50% scenarios. Although no CO_2 emission is generated during renewable electricity production, the projected future LCEs of a renewable electric power plant cannot compete with natural gas power plant. For example, according to Table 7, the annual LCEs of a solar PV power plant is about as twice as much that a natural gas power plant.

The estimation of LECs is based on the current subsidy policies for different electric production technologies. As discussed in Chapter 4, the PTC for a wind power and closed-loop biomass power plant can have a 2.3¢/kWh PTC if they are under construction by the end of 2013. However, an advanced nuclear power plant can receive an $18.0/MWh PTC and there is no expiration date for that. This PTC makes the LCE of nuclear power plant lower than biomass energy and wind power plants in specific years (See Table 7). It is uncertain whether or not the wind power and biomass based power plants can continue to benefit from the current PTC policy after 2015. This chapter will compare the costs of CO_2 emission reduction technologies assuming the current PTCs for wind and biomass would not change from 2016 to 2020.

Another issue of generating electricity from renewable energy is the intermittency feature of some renewable energy technologies. Wind power electric production can be influenced by the speed of the wind and electricity generated from solar energy is limited by the sufficiency of the sunlight. The intermittency factor is not included in LCEs of wind and solar energy power plants in Chapter 5. What the cost would be if the intermittency of renewable energy taken into consideration will be also discussed in this Chapter.

5. 1 The Impacts of the PTC on the Cost of CO_2 Emission Reduction Technologies

It is assumed that close-loop biomass power plants and wind power plants will continue to have a 2.3¢/kWh PTC after 2015. The LCEs of alternative electric production technologies to reduce CO_2 emission in Michigan coal plants are shown in Table 9. Figure 15 shows the time series plot of LCEs of different electricity generation technologies if the PTCs for biomass energy and wind power plants continue in the future.

Table 9: LCEs of Technologies Selected for Reducing CO_2 Emission in Michigan Assuming PTCs for Wind Power and Biomass Power Plants Continue

Technology	Entering Service Year	Inflation Adjusted LCE (2009$/MWh)	LCE Before Inflation Adjusted ($/MWh)	Subsidies/ CO_2 Cost ($/MWh)	Cost Included Subsidies and CO_2 Cost ($/MWh)
Natural gas-Advanced Combined Cycle	2016	62.56	63.10	0.54	62.56
	2017	61.59	63.10	0.53	62.58
	2018	62.25	65.60	0.52	65.08
	2019	59.89	64.40	0.47	63.93
	2020	57.62	N/A	N/A	N/A
Advanced Nuclear	2016	95.90	113.90	18.00	95.90
	2017	91.93	111.40	18.00	93.40
	2018	86.47	108.40	18.00	90.40
	2019	73.17	96.10	18.00	78.10
	2020	61.92	N/A	18.00	N/A
Wind	2016	74.00	97.00	23.00	74.00
	2017	71.85	96.00	23.00	73.00
	2018	60.83	86.60	23.00	63.60
	2019	53.68	80.30	23.00	57.30
	2020	47.37	N/A	23.00	N/A
Solar PV	2016	152.32	210.70	58.38	152.32
	2017	136.45	152.70	14.07	138.63
	2018	125.55	144.30	13.04	131.26
	2019	111.06	130.00	11.45	118.55
	2020	98.24	N/A	N/A	N/A
Biomass	2016	89.50	112.50	23.00	89.50
	2017	90.94	115.40	23.00	92.40
	2018	84.17	111.00	23.00	88.00
	2019	74.57	102.60	23.00	79.60
	2020	66.06	N/A	23.00	N/A

Source: Author's calculation.
Note: The 2020 inflation adjusted LCEs are estimated by the author based on the trends from 2018 to 2019. Except for the PTCs for some power plants are known, other data are not available.

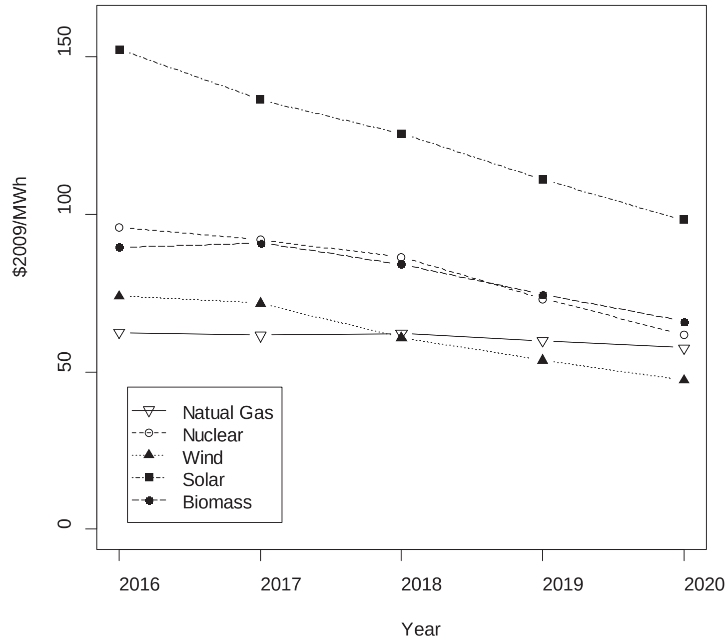

Figure 15: Annual LCEs for Different Types of Technology for CO_2 Emission Reduction in Michigan if the PTCs for Biomass Energy and Wind Power Plants Continue after 2015.

Comparing Figure 15 with Figure 12, there are some interesting findings: 1) the decreasing trends of all the LCEs do not change; 2) the LCEs of wind and biomass power plants become competitive if a 2.3¢/kWh PTC continue after 2016; 3) The LCE of biomass power plants is lower than nuclear power plant before 2019. If the PTC does not continue, then the cost of a biomass power plant is always higher than that of a nuclear power plant; 4) Benefiting from the PTC, the LCE of wind power energy becomes lower than that of an advanced-combined-cycle natural gas power plant after 2017. Based on the above findings, it is safe to conclude that PTCs for renewable energy projects have influential impacts on the cost of electricity generation from these sources. The existence of PTC makes the cost of electricity generated from renewable energy more competitive with natural gas and nuclear power plants.

Changes in LCEs will result in the changes of total costs of electric generation from different technologies. The total cost under 30% and 50% scenarios will be estimated as follows. Using the same approach as in Chapter 4, one can calculate the total costs by multiplying per unit cost of electricity production in Table 9 by the avoided electric production from coal-fired power plants for CO_2 emission reduction in Table 6. The results are presented in Table 10. Figure 16 and 17 are the time series plots of results in Table 10.

If the current PTCs for wind power and biomass energy continue after 2015 and if coal is replaced by only one type of energy resource for CO_2 emission reduction, the cost range is from 957.08 million to 1.95 billion dollars, 3.29 to 6.71 billion dollars in 30% scenario and 50% scenario, respectively. In all the scenarios, wind power energy becomes the least-cost electric generation technology to reduce CO_2 in the power plants of Michigan. When comparing results in Table 8 and Table 10, wind power takes the place of advanced-combined-circle natural gas power plants to become the primary strategy to achieve CO_2 emission reduction goals.

Table 10: The Total Cost of Reducing CO_2 Emission by Substituting Coal by Other Energy Sources if PTC for Wind Power and Biomass Power Plants Continue (Million $2009)

Energy Source	Year	30% Scenario	50% Scenario
Natural gas-Advanced Combined Cycle	2016	70.30	241.50
	2017	138.41	475.49
	2018	209.84	720.89
	2019	269.18	924.74
	2020	323.72	1,112.10
	Total	1,011.45	3,474.73
Advanced Nuclear	2016	107.76	370.19
	2017	206.59	709.73
	2018	291.48	1,001.37
	2019	328.87	1,129.79
	2020	347.86	1,195.02
	Total	1,282.56	4,406.10
Wind	2016	83.15	285.65
	2017	161.47	554.71
	2018	205.05	704.44
	2019	241.27	828.85
	2020	266.14	914.29
	Total	957.08	3,287.94
Solar PV	2016	171.15	587.98
	2017	306.64	1,053.44
	2018	423.22	1,453.93
	2019	499.17	1,714.84
	2020	551.95	1,896.16
	Total	1,952.13	6,706.35
Biomass	2016	100.57	345.48
	2017	204.37	702.09
	2018	283.73	974.73
	2019	335.16	1,151.41
	2020	371.17	1,275.11
	Total	1,294.99	4,448.82

Source: Author's calculation.

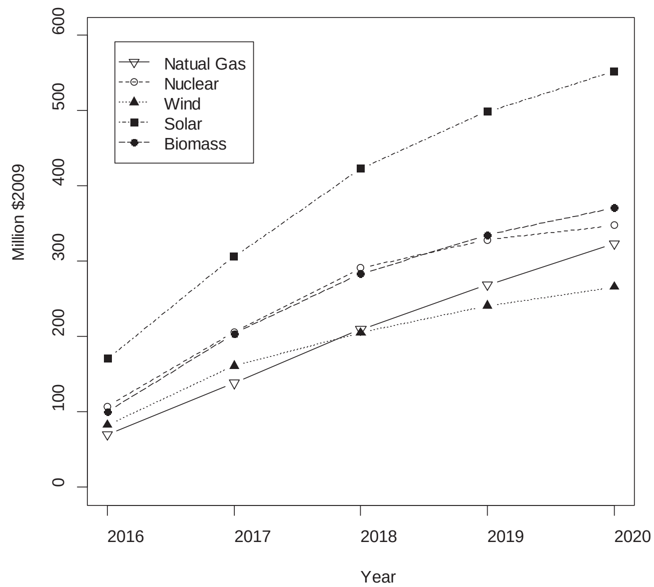

Figure 16 : Total Cost of CO_2 Emission Reduction Technologies under the 30% Scenario (If PTCs for Biomass Energy and Wind Power Plants Continue after 2015).

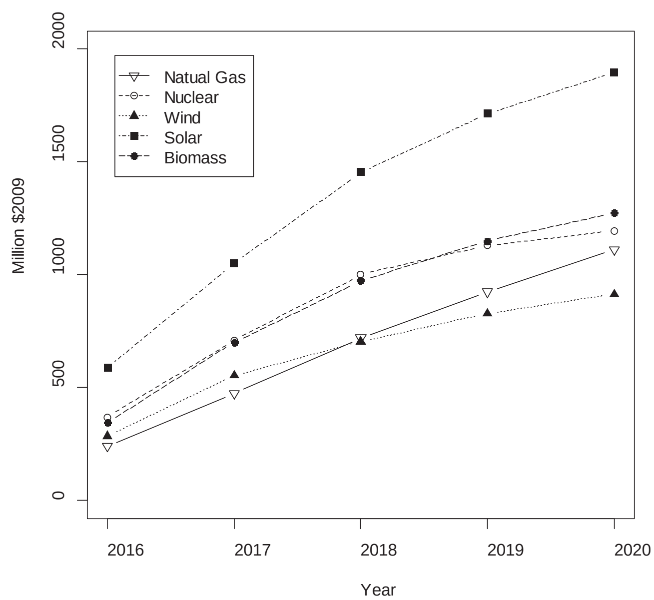

Figure 17: Total Cost of CO_2 Emission Reduction Technologies under the 50% Scenario (If PTCs for Biomass Energy and Wind Power Plants Continue after 2015).

Comparing Figure 16 and 17 with their counterparts in Chapter 4, the existence of PTC has influential impacts on the total costs of CO_2 mitigation technologies. The total cost of a biomass power plant is always higher than a nuclear power plant if there is no PTC in the future. However, benefiting from the PTC, the total costs of replacing coal by biomass to avoid CO_2 emissions in the electric power sector are lower than by using nuclear energy from 2016 to 2018. After 2018, the total cost of generating electricity from biomass power plant becomes higher than for a nuclear power plant. Also, for wind power plants, the total costs in the initial years (in 2016 and 2017) are higher than natural gas power plants. The turning point is 2018. From 2018, the total cost of wind power energy is competitive with not only a natural gas power plant but also all the other electric generation technologies. Recall that the total costs of natural gas power plants are lower than any other types of power plants if the PTC for wind power plants doesn't exist.

If the current PTCs for wind and biomass energy power plants still exists from 2016 to 2020, a combination strategy (applying natural gas and wind power technologies) for CO_2 emission reduction is the least-cost strategy based on the time series plots of total costs of electricity generation technology in Figure 16 and 17. In all these two scenarios, the electricity provider should substitute coal by natural gas to avoid CO_2 emissions from 2016 to 2017. For the total cost of wind power plant becomes lower than other types of power plants, from 2018 wind power will be the best candidate to replace coal for electricity generation. After calculations, the total costs of applying the combination of technologies to reducing CO_2 emission in coal-fired power plants are 921.17 million dollars and 3.16 billion dollars in the 30% and 50% scenario, respectively.

5.2 The Impacts of the Intermittency of Renewable Energy

Wind power and solar energy are intermittent renewable energy. These electric generation technologies are not continuously available and dispatchable. Also, they are unpredictable and variable. Electricity production in wind farms is limited by the speed of the wind, and solar electricity generation is highly influenced by solar radiation. The intermittency feature of renewable energy has negative impacts on the electric grid systems, which should be considered when estimating the cost of electric generation from wind power and solar energy.

Much research has been done to study the actual cost of intermittency. Smith et al. (2004) made a summary of studies of the impacts of wind power on the operating costs of electric power system. They concluded that about at 5% or less wind penetration, the impact of wind power is small. If the wind power can meet 50 percent of demand, the cost of intermittency is 1–2 ¢/kWh (DeCarolis and Keith 2005). Without sunshine at night, the users of large and utility scale solar PV systems must use additional generating units or the grid to acquire electricity (Sovacool 2009). Gowrisankaran et al. (2011) estimated that the welfare loss of unforecastable intermittency associated with a 20% solar photovoltaic mandate is 3% of the cost of solar energy. Based on the above studies, this thesis makes the following assumptions: 1 ¢/kWh and 2 ¢/kWh cost of intermittency are added to the LCE of wind power plant in the 30% and 50% scenarios. 3% of cost is imposed on the solar energy technology to reflect the welfare loss of intermittency. After calculation, the costs of generating electricity from solar energy and wind power, which include the intermittency costs, are shown in Table 11.

Table 11: LCEs of Wind and Solar Power Plant Including the Cost of Intermittency (Excluding PTCs for Wind and Biomass Power Plants) (2009$/MWh)

Technology	Year	30% Scenario	50% Scenario
Wind	2016	107.00	117.00
	2017	104.33	114.17
	2018	92.40	101.96
	2019	84.60	93.96
	2020	77.46	86.59
Solar PV	2016	156.89	156.89
	2017	140.54	140.54
	2018	129.32	129.32
	2019	114.40	114.40
	2020	101.20	101.20

Source: Author's calculation.

Definitely, adding the cost of intermittency to wind and solar energy power plants does not impact the cost of other electric production technologies. Using the same approach in Chapter 4, the total cost of replacing coal by other low-carbon emission energy sources, which includes the intermittency cost, can be calculated. The results are shown in Table 12. If considering the cost of intermittency, the cost range is from 1.01 to 2.01 billion dollars and 3.47 to 6.91 billion dollars in the 30% and 50% scenario, respectively. Building natural-gas power plants for CO_2 emission reduction is least cost way in all the scenarios. Using solar energy to replace coal to generate electricity will be the most expensive option. One can compare the cost trend of individual CO_2 mitigation technologies using the time series plots are shown in Figure 18 and 19.

Table 12: The Cost of Reducing CO_2 Emission by Substituting Coal by Other Energy Sources Including the Cost of Intermittency (Excluding PTCs for Wind and Biomass Power Plants) (Million $2009)

Energy Source	Year	30% Scenario	50% Scenario
Natural gas-Advanced Combined Cycle	2016	70.30	241.50
	2017	138.41	475.49
	2018	209.84	720.89
	2019	269.18	924.74
	2020	323.72	1,112.10
	Total	1,011.45	3,474.73
Advanced Nuclear	2016	107.76	370.19
	2017	206.59	709.73
	2018	291.48	1,001.37
	2019	328.87	1,129.79
	2020	347.86	1,195.02
	Total	1,282.56	4,406.10
Wind	2016	120.23	451.64
	2017	234.46	881.43
	2018	311.47	1,180.75
	2019	380.24	1,450.80
	2020	435.18	1,671.21
	Total	1,481.58	5,635.83
Solar PV	2016	176.29	605.62
	2017	315.83	1,085.01
	2018	435.93	1,497.59
	2019	514.18	1,766.41
	2020	568.57	1,953.27
	Total	2,010.80	6,907.90
Biomass	2016	126.41	434.27
	2017	255.25	876.87
	2018	357.89	1,229.50
	2019	432.02	1,484.16
	2020	488.90	1,679.58
	Total	1,660.47	5,704.38

Source: Author's calculation.

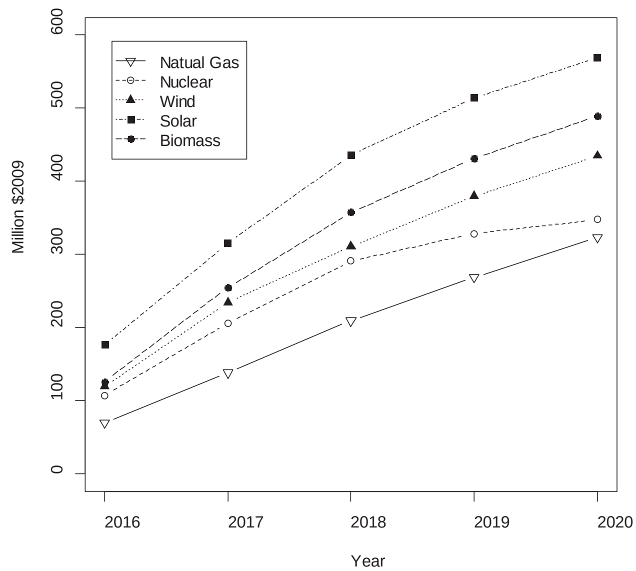

Figure 18: Total Cost of CO_2 Emission Reduction Technologies under the 30% Scenario without PTCs for Wind and Solar Power Plants (Including the Cost of Intermittency of Wind Power and Solar Energy).

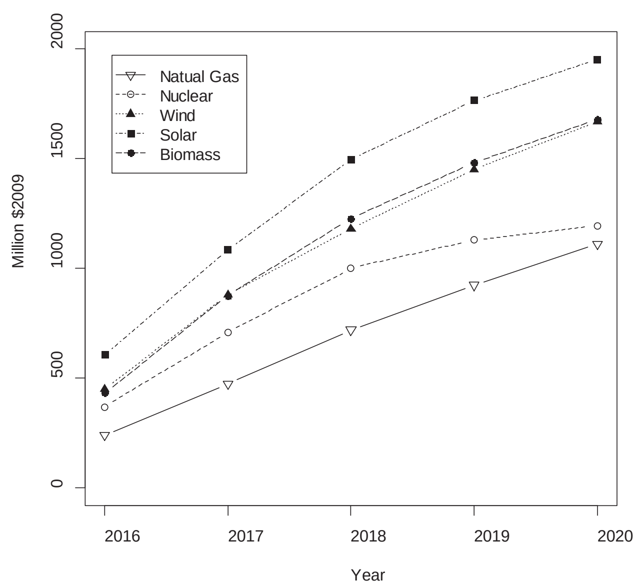

Figure 19: Total Cost of CO_2 Emission Reduction Technologies under the 50% Scenario without PTCs for Wind and Biomass Power Plants (Including the Cost of Intermittency of Wind Power and Solar Energy).

The above analysis does not take the future possible PTC policies for wind and biomass power plants into account. In Section 5.1, PTC decreases the cost of renewable electricity generation significantly. Whether the PTC would exist or not has great impacts on the cost analysis of CO_2 emission reduction technologies and the final results. Table 13 shows the results of cost of CO_2 mitigation technologies, which includes the cost of intermittency and assumes that the current PTCs for wind power and biomass energy plants will not change after 2015. If considering replacing coal by only one technology to generate electricity, the cost range under 30% and 50% scenario varies from 1.01 to 2.01 billion dollars and 3.47 to 6.91 billion dollars, respectively. The cost range in each scenario is the same with its counterpart in Table 12. The time series plot of the cost of different CO_2 mitigation technologies are shown in Figure 20 and 21.

Table 13: The Cost of Reducing CO_2 Emission Technologies Including the PTCs for Wind Power and Biomass Energy Plant After 2015 (Cost of Intermittency Included) (Million $2009)

Energy Source	Year	30% Scenario	50% Scenario
Natural gas-Advanced Combined Cycle	2016	70.30	241.49
	2017	138.41	475.49
	2018	209.84	720.89
	2019	269.18	924.74
	2020	323.72	1,112.11
	Total	1,011.45	3,474.73
Advanced Nuclear	2016	107.76	370.19
	2017	206.59	709.73
	2018	291.48	1,001.37
	2019	328.87	1,129.79
	2020	347.88	1,195.11
	Total	1,282.58	4,406.18
Wind	2016	94.39	362.86
	2017	183.58	706.72
	2018	237.31	925.98
	2019	283.38	1,118.21
	2020	317.25	1,265.96
	Total	1,115.91	4,379.72
Solar PV	2016	176.29	605.62
	2017	315.83	1,085.01
	2018	435.93	1,497.59
	2019	514.18	1,766.26
	2020	568.57	1,952.93
	Total	2,010.80	6,907.41
Biomass	2016	100.57	345.48
	2017	204.37	702.09
	2018	283.73	974.73
	2019	335.16	1,151.41
	2020	371.17	1,275.11
	Total	1,294.99	4,448.82

Source: Author's calculation.

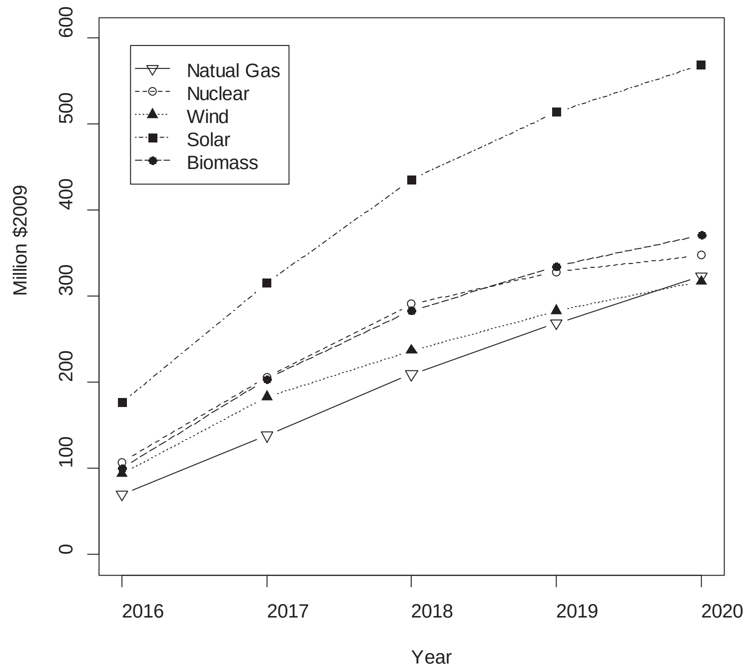

Figure 20: Total Cost of CO_2 Emission Reduction Technologies under the 30% Scenario (The Current PTCs for Wind and Biomass will not Change after 2015 and the Cost of Intermittency is Included).

Based on the plots in Figure 20, one can conclude that from 2016 to 2019, natural gas power plant is the least-cost option to help reduce CO_2 emissions. However, in 2020, the cost of wind power becomes slightly lower than natural gas. Thus, the combination of technologies-natural gas (from 2016 to 2019) and wind power (2020) is the least cost strategy and total cost is 1.00 billion dollars.

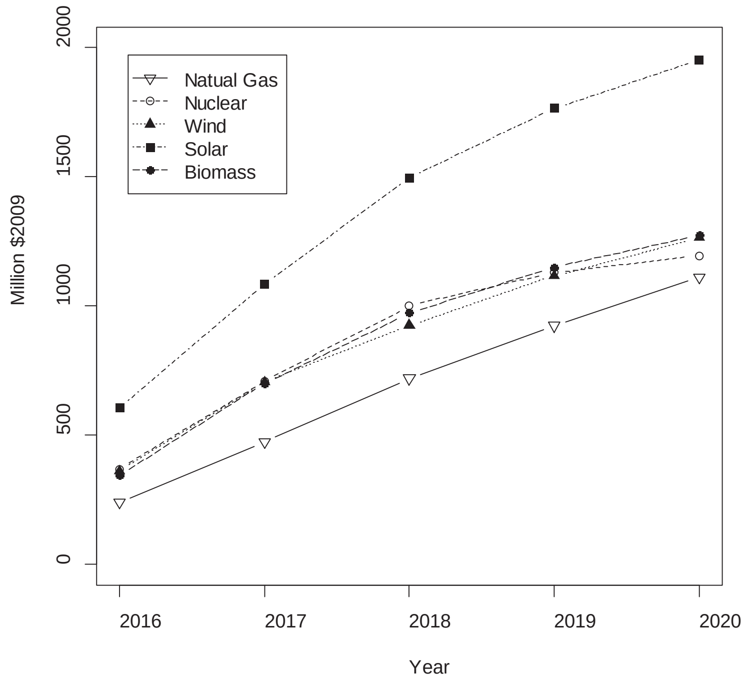

Figure 21: Total Cost of CO_2 Emission Reduction Technologies under the 50% Scenario (The Current PTCs for Wind and Biomass will not Change after 2015 and the Cost of Intermittency is Included).

In the 50% scenario, the natural gas is best candidate to replace coal to generate electricity for CO_2 emission reduction. Compared with wind power and biomass energy, the cost of nuclear energy has a slow increase rate. Although the costs of these three technologies are very close in 2016, 2017 and 2019, the cost of nuclear becomes somewhat lower in 2020.

Chapter 6 Conclusion

This thesis attempts to investigate the possible impacts of the EPA's proposed CO_2 regulation on existing coal-fired power plants by estimating and comparing the costs of CO_2 mitigation technologies in Michigan. The ultimate goal is to find the least-cost strategy to help electricity providers reduce CO_2 emission under the proposed standards. An ARIMA model was built to forecast coal consumption for electricity generation from 2016 to 2020 in Michigan. Then this thesis calculated the cost of reducing CO_2 emissions by replacing coal by other energy sources under three emission reduction scenarios- reduction to 17%, 30% and 50% below the 2005 emission level. The impacts of PTCs for wind and biomass power plants are discussed in this thesis, despite the uncertainty of whether or not the current PTC policies for these two sources of power will continue. Also, the influence of intermittency of renewable energy resources on the total cost is also examined. The major findings of this study are shown in Table 14.

Based on the forecast in this thesis, the CO_2 emissions from coal-fired power plants in 2016 will be 17% lower than their 2005 emission level in the business as usual scenario. Thus, it is not surprising to find that the cost of CO_2 reduction under the 17% emission reduction scenario is zero. In most of the scenarios, replacing coal by natural gas is the most cost-effective way to reduce CO_2 emission in Michigan electric power sector, even though the cost of CO_2 emission standards on new natural gas power plants have been included. If the current PTC for wind power plants continues from 2016 to 2020, in specific years the CO_2 mitigation cost of using wind power for electricity

Table 14: Cost Ranges of CO_2 Emission Reduction and Least-cost Strategies (2009$)

17% Scenario				
Cost of Intermittency	N	N	I	I
PTCs for Wind & Biomass	N	I	N	I
Lower Range	0	0	0	0
Upper Range	0	0	0	0
Least-cost Strategy	/	/	/	/
30% Scenario				
Cost of Intermittency	N	N	I	I
PTCs for Wind & Biomass	N	I	N	I
Lower Range	1.01B	921.17M	1.01B	1.00B
Upper Range	1.95B	1.95B	2.01B	2.01B
Least-cost Strategy	Natural Gas	**2016-17:** Natural Gas **2018-20:** Wind	Natural Gas	**2016-19:** Natural Gas **2020:** Wind
50% Scenario				
Cost of Intermittency	N	N	I	I
PTCs for Wind & Biomass	N	I	N	I
Lower Range	3.47B	3.16B	3.47B	3.47B
Upper Range	6.71B	6.71B	6.91B	6.91B
Least-cost Strategy	Natural Gas	**2016-17:** Natural Gas **2018-20:** Wind	Natural Gas	Natural Gas

Source: Author's calculation.
Note: "N" and "I" represents "Not Included" and "Included"; "M" and "B" means "million" and "billion", respectively.

generation becomes lower than advanced-combined-cycle natural gas power plants. In this situation, a combination strategy is regarded as the least-cost option for CO_2 reduction.

The results of the analysis strongly recommend that electricity providers that generating electricity from natural gas should be regarded as the primary choice to achieve CO_2 emission reduction targets under both the 30% and 50% reduction scenarios based on the least-cost criterion. If the cost of intermittency of renewable energy is considered in either 30% or 50% scenario, building natural gas power plants is still the best CO_2 mitigation strategy to realize CO_2 emission reduction goal. However, if the current PTC for wind power plants will continue after 2015, even taking the intermittence of wind power into account, wind power plants replace natural gas power plants and becomes the least cost technology to reduce CO_2 emission in the future. In this situation, it is suggested that utilities should generate electricity from natural gas power plants in the initial two years and turn to wind power technology from 2018 to 2020 if not considering the impact of intermittency of wind power; when thinking of the cost of intermittency, the cost-effective plan is generating electricity from natural gas from 2016 to 2019 and from wind power in 2020.

This thesis analyzed the cost of CO_2 emission reduction for coal power plants from 2016 to 2020 based on some important assumptions. Also, one should be cautious about the limitations of this study when using the results of this thesis. The limitations of this study originate from two aspects: the insufficiency of the forecast model and the accuracy of the energy cost estimates.

The ARIMA model, which was built to forecast future coal consumption for electricity generation in Michigan, is based on Box-Jenkins methodology. Some scholars argue against the accuracy of the forecasting results by using this approach. The most common criticism stems from the integrated part of the model. Makridakisand and Hibon (1997) argue that differencing the data to have a stationary mean is the major problem. Based on some empirical examples, the accuracy of a simple time series method can be better than ARIMA model. In this study, a linear regression model is initially established to check whether or not a simple model can generalize most of the information of the data. However, the results are less than satisfactory. Definitely, one can test the accuracy of other simple approaches, which are not mentioned in this thesis. It is possible that some simple model can make more accurate forecast than can the ARIMA model.

Also, not only can differencing lose one observation each time, but also unnecessary correlations can be introduced by overdifferencing, which makes the modeling process more complicated (Cryer and Chan 2008). The final model in this thesis is ARIMA (0,2,1), which is differenced twice to achieve a stationary mean. Based on the ACF of the second difference of the original time series data in Figure 5, differencing the data twice does not introduce serious correlations (except lag 1). Thus, it is assumed that the there is no negative impacts from differencing in this model.

One can argue that the residuals of ARIMA (0,2,1) (see Figure 8) are a little heteroskedastic and some of residuals on the right tail of the Q-Q plot (see Figure 9) are somewhat wandering off. Both of these shortcomings may reflect that the final model is not perfect.

The other limitation of this study is applying the LCE approach to calculating the cost of electricity generation from different sources. For Michigan, LCE data are not available, the thesis uses the national average figure for approximation. As noted in EIA's levelized cost of new generation resources in the Annual Energy Outlook, the costs of non-dispatchable technologies vary by region significantly. It is possible that a big difference exists between Michigan figures and the national average figures, which would greatly influence the results in this thesis. Future studies on the same topic can make more precise estimation if the LCE in Michigan can be acquired.

Moreover, this thesis cannot answer the question what impacts are on the price and supply of natural gas in Michigan if the utilities replace large quantity of coal by natural gas for power generation to reduce CO_2 emissions based on suggestions in this study. It is possible that using more natural gas in the power plants can cause an increase in natural gas price. Thus, building natural gas power plants would not be the least coast strategy for CO_2 emission reduction in some scenarios.

Also, this thesis assumes that the electricity providers will build new power plants to replace electricity generation from coal. For some power plants, the capacity investment accounts for the major cost of generating electricity. It is likely that utilities prefer using the existing electric capacity instead of investing in new ones to minimize cost. However, it is uncertain whether or not the current electric capacity is enough for generating extra electricity. This question can be solved by fully studying Michigan's electric system via engineering approaches, which is out of the scope of this thesis.

The methods and the reasoning procedures in this thesis can contribute to the future studies and research on similar topics in other states. Although it is impossible to reduce CO_2 emission to 30% and 50% below 2005 emission level in a short period of time, this study provides cost ranges of CO_2 emission reduction by generating electricity from low carbon energy sources instead of coal. The results in this study can be applied to compare with the costs of other CO_2 mitigation strategies, such as increasing the efficiency of existing coal-fired power plants, to help utility regulators make wise CO_2 emission reduction plans in Michigan.

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Appendices

Appendix A: Coal Consumption for Electricity Generation from 1960 to 2011 in Michigan

Table A1: Coal Consumption for Electricity Generation from 1960 to 2011 in Michigan

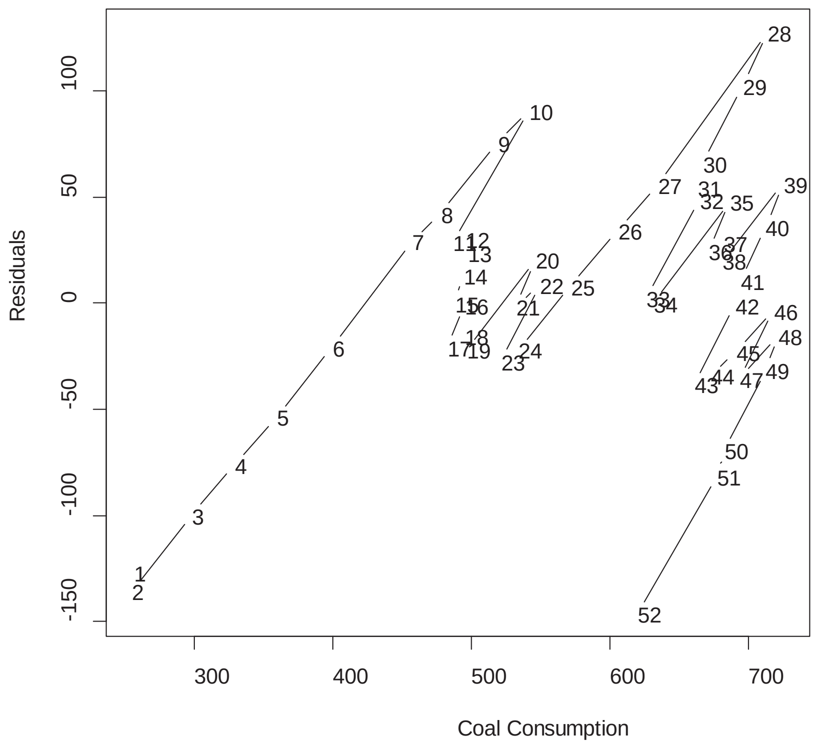
Year	Coal (Trillion Btu)	Year	Coal (Trillion Btu)
1960	256.3	1986	634.4
1961	255.1	1987	713.6
1962	298.5	1988	696
1963	329.6	1989	667
1964	359.7	1990	663.5
1965	399.9	1991	665.1
1966	457.5	1992	626.5
1967	478	1993	631.4
1968	519	1994	686.7
1969	541.7	1995	671.2
1970	487	1996	682.1
1971	496.1	1997	681.4
1972	497.4	1998	725.3
1973	494.2	1999	712.2
1974	488.4	2000	694.7
1975	494.9	2001	690.5
1976	482.6	2002	660.8
1977	495.5	2003	672.6
1978	496.5	2004	691.2
1979	546.5	2005	718.2
1980	532.2	2006	693.4
1981	549.8	2007	721.3
1982	521.3	2008	712.4
1983	534.2	2009	682.5
1984	571.6	2010	677.6
1985	605.8	2011	620.4

Appendix B: The Linear Regression Results of Coal Consumption against Year from Using the R Program

```
Call:
lm(formula = consumption ~ t)

Residuals:
Min       1Q   Median       3Q      Max
-146.009  -23.680    1.667   31.608  127.679

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 375.3518    16.0881   23.33   <2e-16 ***
t            7.5203     0.5283   14.24   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 57.17 on 50 degrees of freedom
Multiple R-squared:  0.8021,  Adjusted R-squared:  0.7982
F-statistic: 202.7 on 1 and 50 DF,  p-value: < 2.2e-16
```

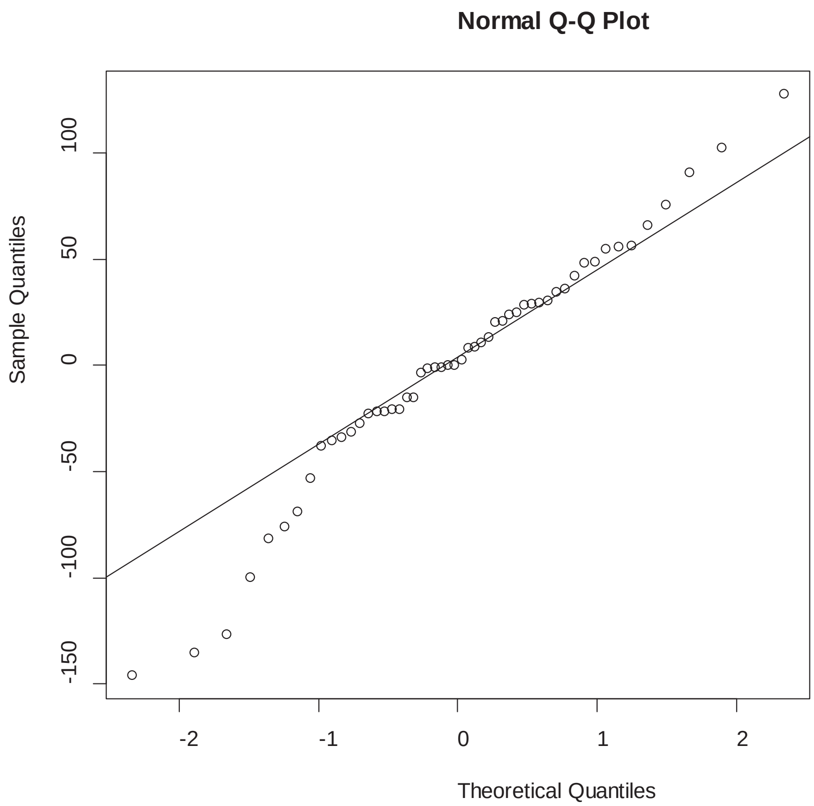
Appendix C: Residual Plot Against the Independent Variable from the Linear Regression Approach

Figure A1: Residual Plot Against the Independent Variable from the Linear Regression Approach



Appendix D: Q-Q Plot for the Residuals of Linear Regression Approach

Figure A2: Q-Q Plot for the Residuals of Linear Regression Approach



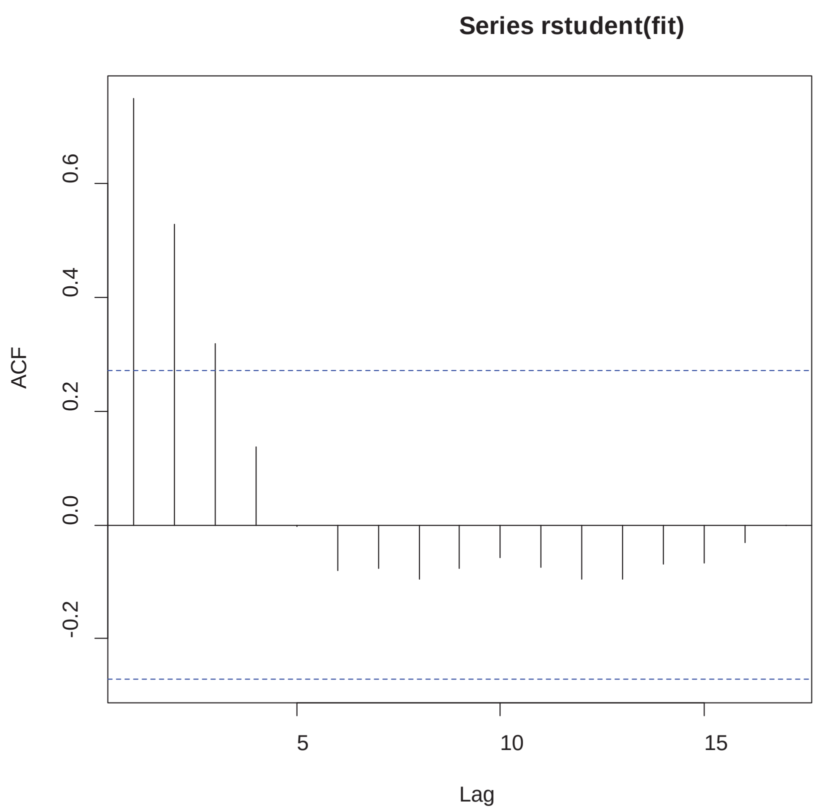
Appendix E: The R Outputs of Durbin-Waton Test for the Residuals of the Linear Regression Approach

lag	Autocorrelation	D-W Statistic	p-value
1	0.7922468277	0.1652762	0.000
2	0.5650104192	0.4003861	0.000
3	0.3626701852	0.6995635	0.000
4	0.1817266364	1.0129067	0.000
5	0.0283205356	1.3000105	0.062
6	-0.0682106101	1.4844298	0.220
7	-0.1002996112	1.5388353	0.378
8	-0.1245178899	1.5687102	0.554
9	-0.1009631457	1.4793590	0.404
10	-0.0641832454	1.3511096	0.282
11	-0.0688906813	1.3511055	0.302
12	-0.0654606135	1.3342687	0.362
13	-0.0516896089	1.2969253	0.362
14	-0.0339195014	1.2505636	0.372
15	-0.0278413113	1.2359721	0.368
16	-0.0119287651	1.2005294	0.342
17	-0.0064370471	1.1873522	0.434
18	0.0141016401	1.1389306	0.462
19	-0.0005383361	1.1679815	0.608
20	-0.0176500126	1.1957020	0.790

Alternative hypothesis: rho[lag] != 0

Appendix F: Sample ACF for the Standardized Residuals of the Linear Regression Model

Figure A3: Sample ACF for the Standardized Residuals of the Linear Regression Model



Appendix G: The R Outputs of Dickey-Fuller Test of the Fist difference of Coal Consumption for Electricity Generation in Michigan

Augmented Dickey-Fuller Test
data: coal.diff
Dickey-Fuller = -3.1324, Lag order = 3, p-value = 0.1191
alternative hypothesis: stationary

Appendix H: The R Outputs of Durbin-Waton Unit Root Test of the Second Difference of Coal Consumption for Electricity Generation in Michigan

Augmented Dickey-Fuller Test
data: coal.diff2
Dickey-Fuller = -3.7986, Lag order = 3, p-value = 0.02561
alternative hypothesis: stationary

Appendix I: The R Outputs of Estimating the Parameters of ARIMA (2,2,1) by Maximum Likelihood Method

```
Series: x
ARIMA(2,2,1)

Coefficients:
        ar1     ar2      ma1        xreg
     0.0683  0.1152  -0.9241     18.2447
s.e. 0.1606  0.1562   0.0761  28292.5527

sigma^2 estimated as 835.9:  log likelihood=-239.96
AIC=487.92   AICc=489.29   BIC=497.48
```

Appendix J: The R Outputs of Estimating the Parameters of ARIMA (0,2,1) by Maximum Likelihood Method

```
Series: x
ARIMA(0,2,1)

Coefficients:
         ma1     xreg
     -0.8906  18.2447
s.e.  0.0872      NaN

sigma^2 estimated as 847.4:  log likelihood=-240.29
AIC=484.58   AICc=485.1   BIC=490.32
```

Appendix K: The R Outputs of the *auto.arima* Function to Find the Appropriate ARIMA Model

```
Series: consumption
ARIMA(0,2,1)

Coefficients:
         ma1
     -0.8907
s.e.  0.0871

sigma^2 estimated as 847.4:  log likelihood=-240.29
AIC=484.58   AICc=484.83   BIC=488.4
```

Appendix L: The R outputs of Box-Ljung Test for the Residuals of ARIMA (0, 2, 1) Model

```
Box-Ljung test

data:  data.fit1$residual

X-squared = 0.0122, df = 1, p-value = 0.9122
```

Appendix M: The R Outputs of the Predicted Values, 95% Prediction Intervals, and Standard Errors of Prediction

Table A2: The R Outputs of the Predicted Values, 95% Prediction Intervals, and Standard Errors of Prediction

Year	Coal Consumption (Trillion Btu)	The Lower Prediction Intervals (Trillion Btu)	The Upper Prediction Intervals (Trillion Btu)	Standard Errors
2012	613.880	556.823	670.936	29.110
2013	607.360	522.142	692.577	43.478
2014	600.839	490.850	710.829	56.117
2015	594.319	460.752	727.886	68.147
2016	587.799	431.058	744.539	79.970
2017	581.278	401.396	761.161	91.777
2018	574.758	371.563	777.954	103.671
2019	568.238	341.439	795.037	115.714
2020	561.718	310.952	812.483	127.942