Will the 100% clean energy commitment be on time? https://github.com/zl396/EVN872-Final-Project-Team-Lin-Liu-Wang

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Contents

Rationale and Research Questions	6
Introduction	6
Research Questions	6
Dataset Information	7
Dataset Wrangling	7
Exploratory Analysis	9
California	9
Connecticut	12
Illinois	14
Summary of Exploratory Analysis	15
Analysis	16
Question 1: What would the trend of clean energy generation be until the commitment years for	
each of the 12 states?	16
California	16
Connecticut	16
Illinois	17
Maine	17
Michigan	17
Minnesota	18
Nevada	18
New Mexico	18
New York	19
Oregon	19
Virginia	19
Washington	
Question 2: What would the trend of total energy generation be until the commitment years for each of the 12 states?	20
Connecticut	
Illinois	
Maine	
Michigan	
Minnesota	
Nevada	44

New Mexico	22
New York	23
Oregon	23
Virginia	23
Washington	24
Question 3: How does the clean energy generation growth compare to the total energy generation growth? (Does clean energy generation meet total energy generation?)	24
Summary and Conclusions	25
Limitations	25
Appendix	26
Maine	26
Michigan	27
Minnesota	30
Nevada	30
New Mexico	31
New York	33
Oregon	34
Virginia	36
Washington	37
References	40

List of Tables

1	Table summarizing the dataset structure	,
2	Table summarizing the major results of 12 states' generation	2^{4}

List of Figures

1	Clean Energy and Total Electricity Generation of State California, 01/2001 08/2023	(
2	Decomposition, Clean Energy, California	10
3	Decomposition, All Fuels, California	10
4	Clean Energy and Total Electricity Generation of State Connecticut, $01/2001$ $08/2023$	12
5	Decomposition, Clean Energy, Connecticut	12
6	Decomposition, All Fuels, Connecticut	13
7	Clean Energy and Total Electricity Generation of State Illinois, $01/2001$ $08/2023$	14
8	Decomposition, Clean Energy, Illinois	14
9	Decomposition, All Fuels, Illinois	15
10	Clean Energy and Total Electricity Generation of State Maine, 01/2001 08/2023 $$	26
11	Decomposition, Clean Energy, Maine	26
12	Decomposition, Clean Energy, Maine	27
13	Clean Energy and Total Electricity Generation of State Michigan, $01/2001$ $08/2023$	2
14	Decomposition, Clean Energy, Michigan	28
15	Decomposition, Clean Energy, Michigan	28
16	Clean Energy and Total Electricity Generation of State Minnesota, $01/2001$ $08/2023$	28
17	Decomposition, Clean Energy, Minnesota	29
18	Decomposition, Clean Energy, Maine	29
19	Clean Energy and Total Electricity Generation of State Nevada, $01/2001$ $08/2023$	30
20	Decomposition, Clean Energy, Nevada	30
21	Decomposition, Clean Energy, Nevada	31
22	Clean Energy and Total Electricity Generation of State New Mexico, $01/2001$ $08/2023$	3
23	Decomposition, Clean Energy, New Mexico	32
24	Decomposition, Clean Energy, New Mexico	32
25	Clean Energy and Total Electricity Generation of State New York, 01/2001 08/2023 $$	35
26	Decomposition, Clean Energy, New York	33
27	Decomposition, Clean Energy, New York	34
28	Clean Energy and Total Electricity Generation of State Oregon, $01/2001$ $08/2023$	34
29	Decomposition, Clean Energy, Oregon	35
30	Decomposition, Clean Energy, Oregon	35
31	Clean Energy and Total Electricity Generation of State Virginia, 01/2001 08/2023 $$	36
32	Decomposition, Clean Energy, Virginia	36
33	Decomposition, Clean Energy, Virginia	37
34	Clean Energy and Total Electricity Generation of State Washington, 01/2001 08/2023 $$	37
35	Decomposition, Clean Energy, Washington	38
36	Decomposition, Clean Energy, Washington	38

Rationale and Research Questions

Introduction

In addition to the "Renewable Energy Portfolios" (RPS) that requires certain percentages of energy to be generated from renewable energy sources, many states have enacted "Clean Energy Standards" (CES) that separates clean energy sources that are carbon-free or carbon-neutral from renewable sources which may generate carbon emissions (2021). Under CES, clean energy sources include nuclear, hydropower, solar power, wind, and other renewables. Most CES would include RPS as a part of the policy.

Currently, there are 12 states that have established 100% Clean energy goals though their times vary. In this analysis, we are interested in whether those states are able able to meet their clean energy commitments by the planned years under current development. The objective is to understand the clean energy development trends in different states in the past and the future, and which states should accelerate their clean energy transitions more rapidly than others. Therefore, the electricity generation data for each of the 12 states from EIA are chosen for the quantitative analysis. Our research questions revolves around the comparison between the growth of clean energy generation versus the growth of total energy generation in the 12 states.

Research Questions

- 1. What would the trend of clean energy generation be until the commitment years for each of the 12 states?
- 2. What would the trend of total energy generation be until the commitment years for each of the 12 states?
- 3. How does the clean energy generation growth compare to the total energy generation growth? (Does clean eenrgy generation meet total energy generation?)

Dataset Information

All datasets used in this analysis were obtained from the U.S. Energy Information Administration (EIA) website, utilizing the ELECTRICITY DATA BROWSER. The data comprises monthly net electricity generation across twelve states committed to achieving 100% carbon-free electricity in the near future. Specifically, it includes net generation figures for coal, petroleum liquids, petroleum coke, natural gas, other gases, nuclear, conventional hydroelectric, wind, geothermal, biomass, wood and wood-derived fuels, hydro-electric pumped storage, small-scale solar photovoltaic, utility-scale photovoltaic, and utility-scale thermal sources from January 2001 to August 2023.

Dataset Wrangling

The datasets for each state are downloaded and processed separately. Upon importing the data into R, a function is developed to eliminate extraneous information. The initial four descriptive rows, which don't contribute to the analysis, are removed. The raw data organizes dates in columns and net generation by sectors in rows. To facilitate analysis, the dataset is transposed. This transposed data is converted into a data frame, ensuring that columns remain as intended and are not converted into factors. Column names are set based on the first row of transposed data.

Following this, rows 2 to 4 (containing unnecessary information) are removed. Additionally, columns 11 to 13, representing 'All-utility scale solar' under the subset of other renewable sectors, are excluded. This step is necessary to prevent double counting since there's an independent sector for all solar.

A new 'Date' column is created, starting from January 1, 2001, incremented by one month, and ending based on the dataset's row count. Simultaneously, a 'State' column is added, assigning the respective state name to each row. Column names are then refined for better clarity using a dedicated function.

Furthermore, a function is designed to convert all columns, excluding the last two (date and state), to a numeric format. Finally, a new data frame encompassing data from the 12 states is generated by merging the individual datasets based on the state name. The following table presents the processed data structure.

Table 1: Table summarizing the dataset structure

Column_name	Unit	
All fuels	thousand megawatthours	
coal	thousand megawatthours	
petroleum liquids	thousand megawatthours	
petroleum coke	thousand megawatthours	
natural gas	thousand megawatthours	
other gases	thousand megawatthours	
nuclear	thousand megawatthours	
conventional hydroelectric	thousand megawatthours	
other renewables	thousand megawatthours	
other renewables:wind	thousand megawatthours	
other renewables:geothermal	thousand megawatthours	
other renewables:biomass	thousand megawatthours	
biomass:wood and	thousand megawatthours	
wood-derived fuels		
biomass:other biomass	thousand megawatthours	
hydro-electric pumped storage	thousand megawatthours	
other	thousand megawatthours	
all solar	thousand megawatthours	
small-scale solar photovoltaic	thousand megawatthours	

Column_name	Unit					
all utility-scale solar	thousand megawatthours					
all utility-scale	thousand megawatthours					
solar:utility-scale photovoltaic						
all utility-scale	thousand megawatthours					
solar:utility-scale thermal						
Date	day-month-year					
State	Michigan, Minnesota, Nevada, New_Mexico, California, Connecticut,					
	Illinois, Maine, New_York, Oregon, Virginia, Washington					

Exploratory Analysis

In this exploratory analysis, we will investigate the net generation data of clean energy and total electricity generation across 12 states. Our objective is to examine whether these time series datasets exhibit any obvious trends or seasonality patterns from January 2001 to August 2023. Here we will first generate the graphs of both clean energy and total electricity generation to observe any obvious trend, then decompose the graphes to see more detailed trend and seasonality display. We will also use Augmented Dickey Fuller test to find out whether the graph is stationary so that we can continue our projection process. Understanding these patterns is crucial as they can significantly impact the accuracy of our future forecasts.

California

Below are the plots of clean energy and total electricity generation of state California. we can see that both plots are experiencing a concave-down curve before 2012 and an increase after. However, the increasing trend of clean energy electricity generation after 2012 is way stronger than the total generation one.

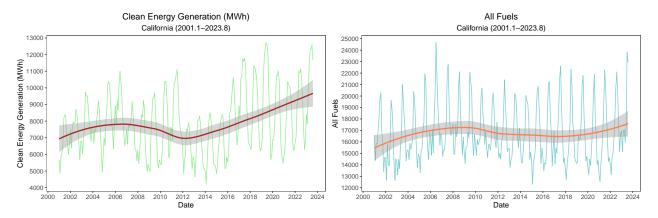


Figure 1: Clean Energy and Total Electricity Generation of State California, 01/2001 08/2023

Following the plots are the graph of the decomposed clean energy and total electricity generation time series dataset. From both graphs, while the trend now is not very clear, we can observe obvious seasonality, thus we may need to perform AD-Fuller test to see whether both time series are stationary to perform forecasts.

Decomposition of time series of clean energy electricity generation in CA

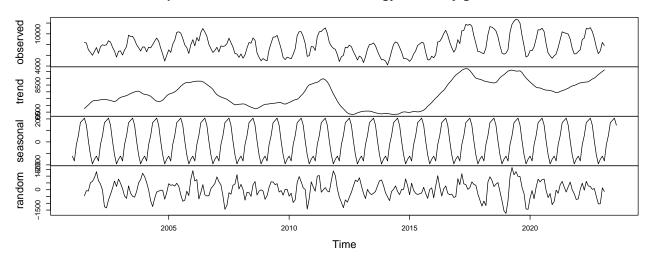


Figure 2: Decomposition, Clean Energy, California

Decomposition of time series of total electricity generation in CA

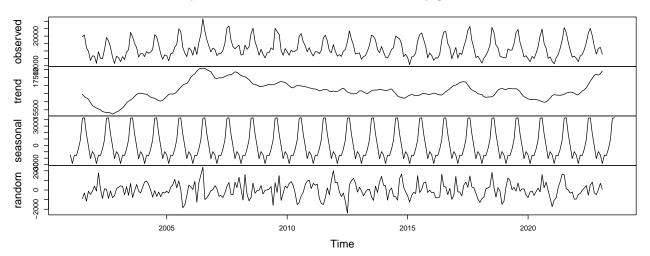


Figure 3: Decomposition, All Fuels, California

The results of both time series for state California is listed as follow:

```
##
## Augmented Dickey-Fuller Test
##
## data: CA.clean.ts
## Dickey-Fuller = -4.6006, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: CA.all.ts
## Dickey-Fuller = -6.6317, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

From the	tests,	we ca	an tell	$_{\mathrm{that}}$	the ;	p-values	of	both	data	are	$\operatorname{smaller}$	than	the	signifance	level,	indicating
that both	data a	are st	ationa	ry.												

Connecticut

Below are the plots of clean energy and total electricity generation of state Connecticut. While the clean energy generation in the past two decades has stayed at the same level, there is an clear increase for the all fuel electricity generation plots.

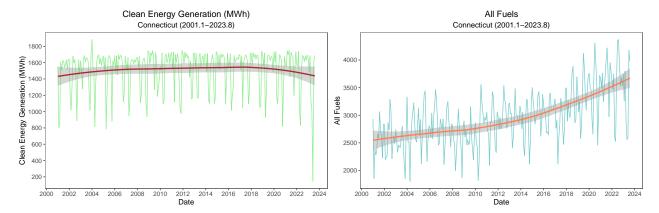


Figure 4: Clean Energy and Total Electricity Generation of State Connecticut, 01/2001 08/2023

Following the plots are the graph of the decomposed clean energy and total electricity generation time series dataset. From both graphs, while we only observe trend for the total generation graph, there exist obvious seasonality, thus we may need to perform AD-Fuller test to see whether both time series are stationary to perform forecasts.

Decomposition of time series of clean energy electricity generation in CT

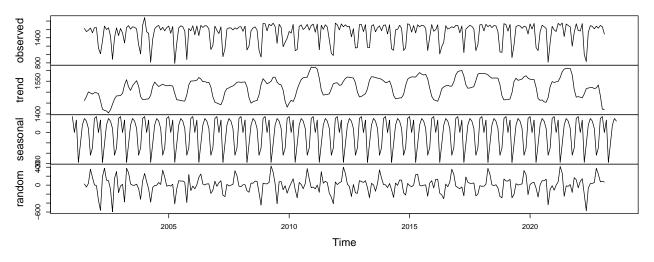


Figure 5: Decomposition, Clean Energy, Connecticut

Decomposition of time series of total electricity generation in CT

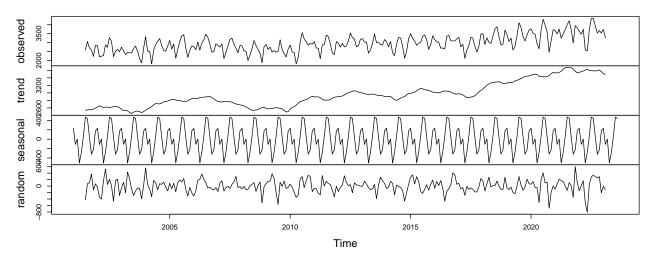


Figure 6: Decomposition, All Fuels, Connecticut

The results of both time series for state Connecticut are listed as follow:

```
##
## Augmented Dickey-Fuller Test
##
## data: CT.clean.ts
## Dickey-Fuller = -12.553, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: CT.all.ts
## Dickey-Fuller = -10.331, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

From the tests, we can tell that the p-values of both data are smaller than the signifiance level, indicating that both data are stationary.

Illinois

For state Illinois, while its total electricity generation was increasing before 2012 and went downward since then, it's electricity generation from clean energy is always going upward in the past two decades. What's more, both plots seem to exhibit seasonality. We now need to take a closer to by decomposing the two time series data to confirm our observations.

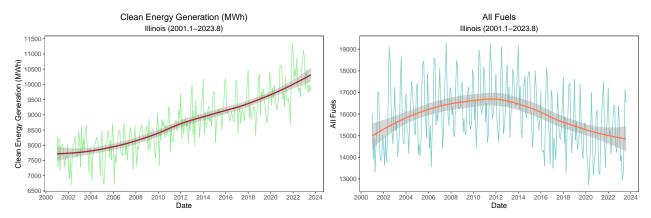


Figure 7: Clean Energy and Total Electricity Generation of State Illinois, 01/2001 08/2023

Below are the graphs of the decompose of two time series data. From both graphs we can actually see a upward trend and seasonality. We need to perform AD-Fuller test to see whether both graphs are stationary so that we can perform a more accurate forecast.

Decomposition of time series of clean energy electricity generation in IL

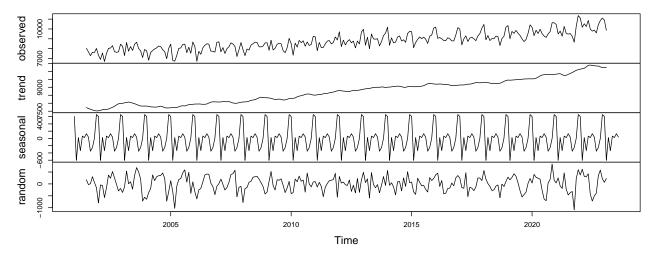


Figure 8: Decomposition, Clean Energy, Illinois

Decomposition of time series of total energy electricity generation in IL

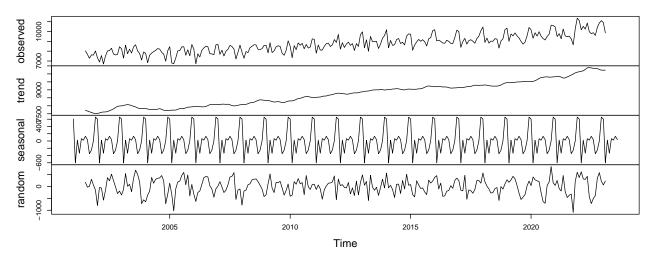


Figure 9: Decomposition, All Fuels, Illinois

The results of both time series for state Illinois is listed as follow:

```
##
## Augmented Dickey-Fuller Test
##
## data: IL.clean.ts
## Dickey-Fuller = -12.688, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: IL.all.ts
## Dickey-Fuller = -9.3631, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

From the tests, we can tell that the p-values of both data are smaller than the signifiance level, indicating that both data are stationary.

Summary of Exploratory Analysis

Above are the plots and results of three states that we randomly chose as example to perform the exploratory analysis. For the purpose of conciseness of our analysis, we will put the results of the rest 9 states in the Appendix page at the end. For the rest 9 states, while trend varies with state and fuels for electricity generation, they all exhibit strong seasonality. However, when performing AD-Fuller tests under all the scenarios, all of the p-values are below significant level, thus indicating stationarity.

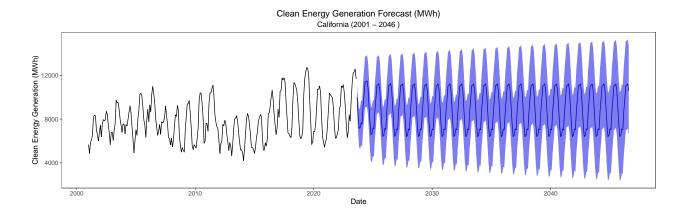
Analysis

To compare the future trend of clean energy and total energy generation, we choose to use ARIMA model to forecast the future trends. The ARIMA model captures the patterns, seasonality, and trends of stationary data, which is particularly useful for forecasting future values that are correlated with past values.

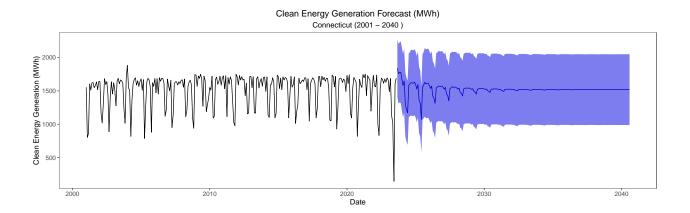
Question 1: What would the trend of clean energy generation be until the commitment years for each of the 12 states?

The following line charts depicts the forecast trend of clean energy generation until each state's commitment year:

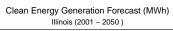
California

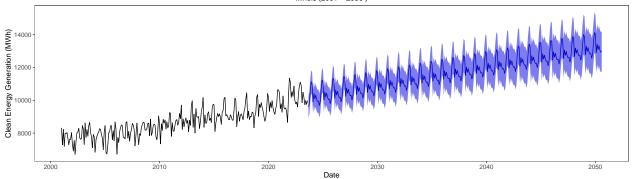


Connecticut

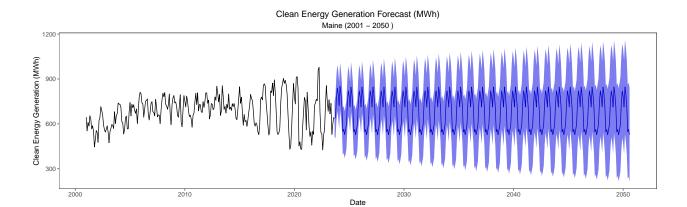


Illinois

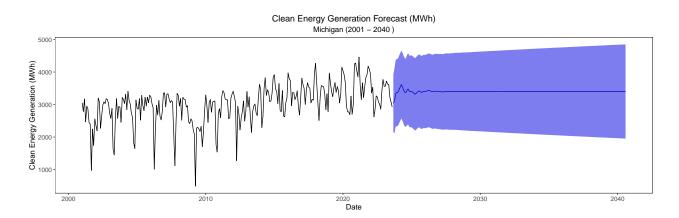




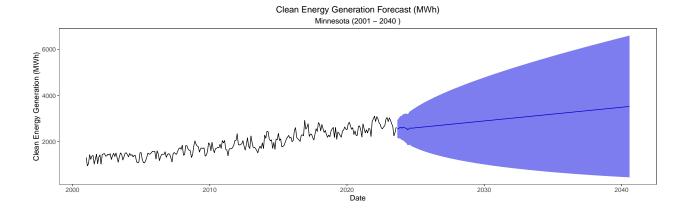
Maine



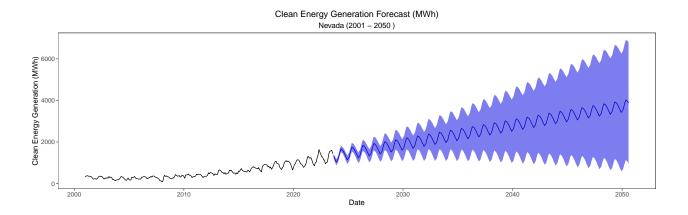
Michigan



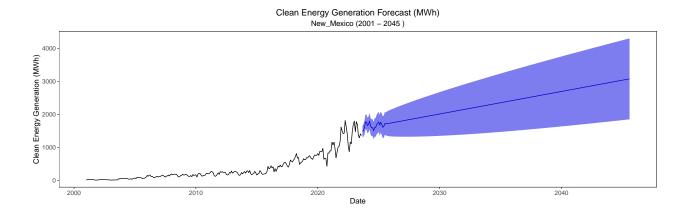
Minnesota



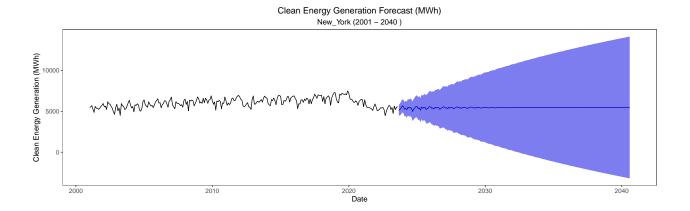
Nevada



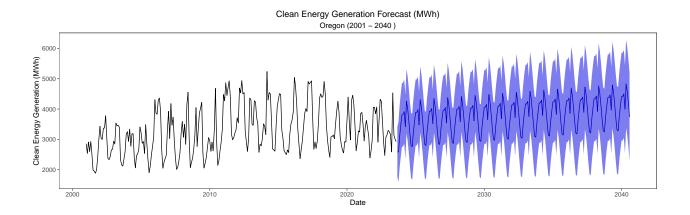
New Mexico



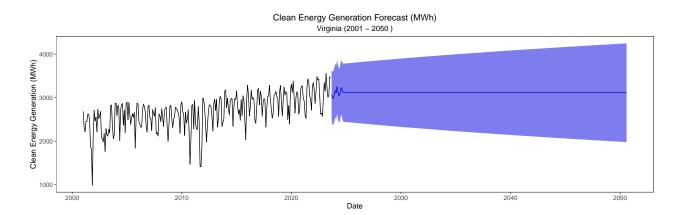
New York



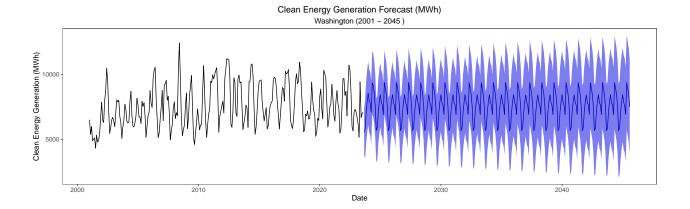
Oregon



Virginia

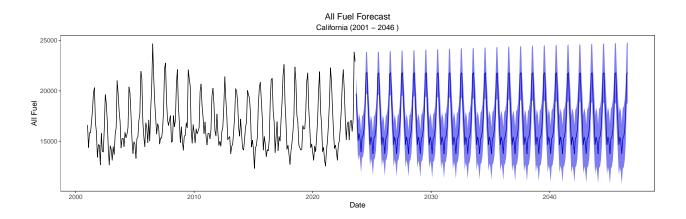


Washington

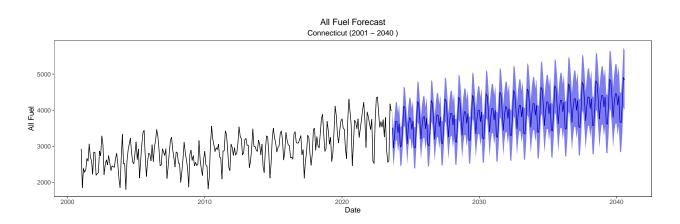


Question 2: What would the trend of total energy generation be until the commitment years for each of the 12 states?

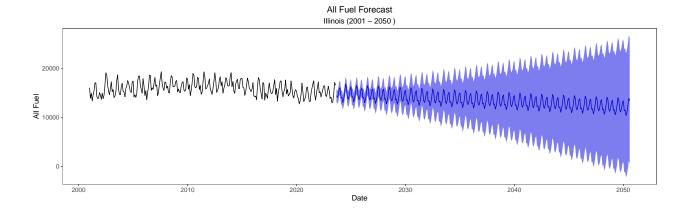
The following line charts depicts the forecast trend of total energy generation until each state's commitment year: ### California



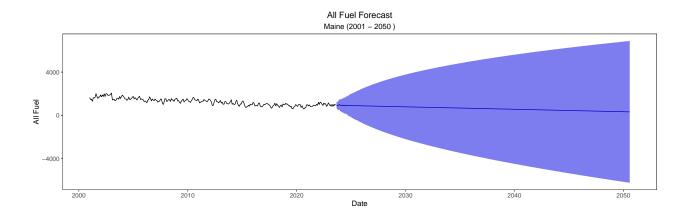
Connecticut



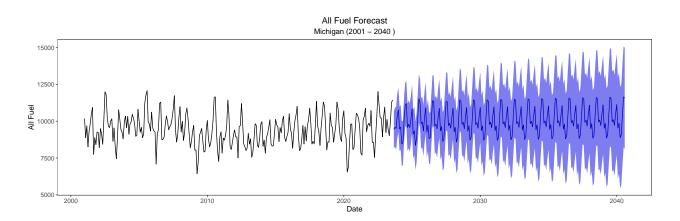
Illinois



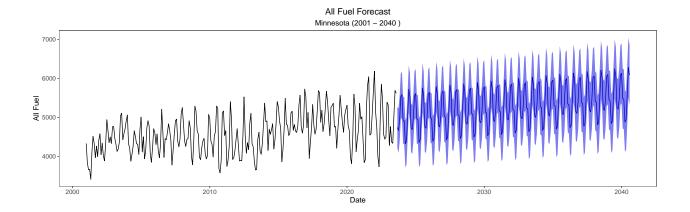
Maine



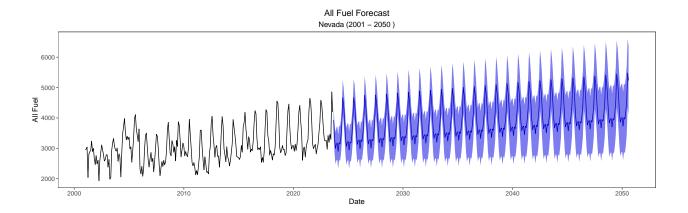
Michigan



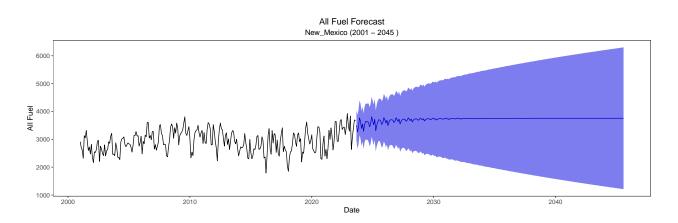
Minnesota



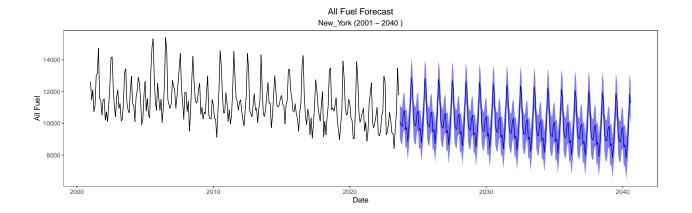
Nevada



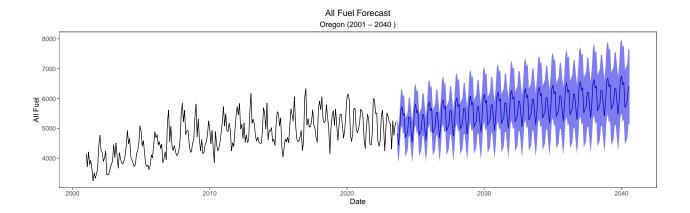
New Mexico



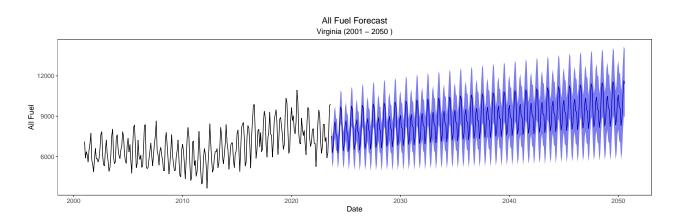
New York



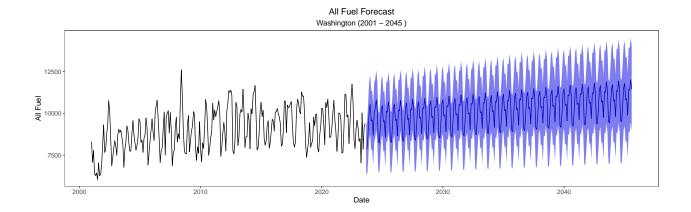
Oregon



Virginia



Washington



Question 3: How does the clean energy generation growth compare to the total energy generation growth? (Does clean energy generation meet total energy generation?)

Shown in the following table, we can compare the forecast clean energy generation with the total energy generation in the last year of the states' committment goals. If the clean energy generation is equal or greater than the total energy generation, we can say that the state's clean energy goal is met.

Table 2: Table summarizing the major results of 12 states' generation

State	Forecasted.Year	Clean.Energy.Forecast	All.Energy.Forecast
California	2046	10598.7061	21795.4304
Connecticut	2040	1518.4439	4839.6758
Illinois	2050	12962.6326	13381.0504
Maine	2050	527.4345	327.2215
Michigan	2040	3402.5286	11567.6698
Minnesota	2040	3526.0418	6087.8588
Nevada	2050	3876.8363	5236.0172
New_Mexico	2045	3075.7632	3756.3205
New_York	2040	5469.7078	11287.0255
Oregon	2040	3738.6002	6388.3217
Virginia	2050	3113.1367	11424.4139
Washington	2045	7501.1405	11457.0276

Summary and Conclusions

There is obvious seasonality for clean energy and total energy generation, while we are focusing on the trend. The forecast data for comparison between is based on forecast in the month August where the energy generation peaks. Out of the 12 states that have committed to 100% clean energy goals, only Maine is projected to be able to meet the goal. All other states will likely to fail to meet their commitments, though Illinois is close to meet the goal. However, many states have just begun accelerating clean energy transition process in recent years, old data may not provide applicable information for forecasting, resulting in underrated clean energy generation.

Limitations

There exists several limitations in our time series forecasts. First, our analysis primarily relies on two single-variable time series forecasts: one for electricity generated by clean energy and another for total electricity generated. However, it's worth noting that these variables may exhibit correlations or dependencies that are not considered in our current approach. Future research could explore multivariate time series models to capture potential interactions and dependencies between different types of fuels, leading to more precise forecasts. Second, clean energy has experienced different rates of development over the past two decades, with drastic growth in the past 10 years and more smooth increase in the first decade. This may introduce uncertainty into our forecasts, as past data may not fully reflect future trends. Last, our forecasts are based on historical data, which may not account for unforeseen factors that could emerge in the future and significantly impact the development of clean energy. As new technologies, policies, and global events unfold, they may alter the trajectory of clean energy generation. Therefore, our models may not capture the full range of potential influences on future outcomes.

Appendix

Maine

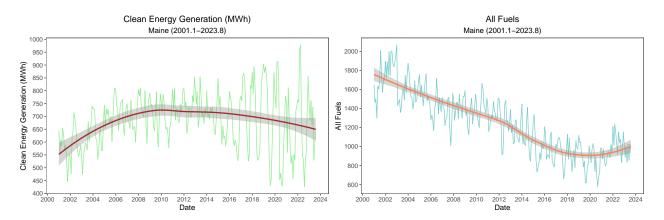


Figure 10: Clean Energy and Total Electricity Generation of State Maine, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in ME

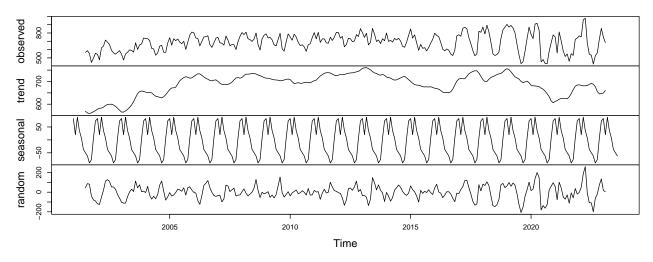


Figure 11: Decomposition, Clean Energy, Maine

```
##
## Augmented Dickey-Fuller Test
##
## data: ME.clean.ts
## Dickey-Fuller = -6.9464, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: ME.all.ts
## Dickey-Fuller = -8.4179, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Decomposition of time series of total electricity generation in ME

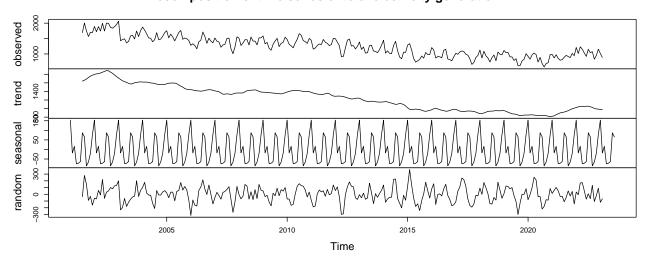


Figure 12: Decomposition, Clean Energy, Maine

Michigan

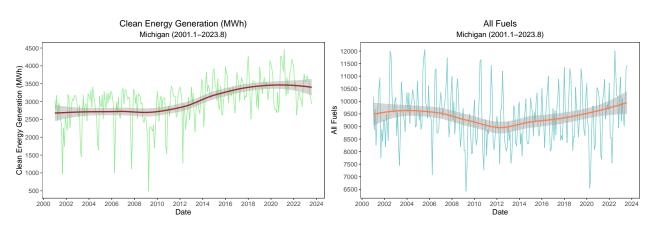


Figure 13: Clean Energy and Total Electricity Generation of State Michigan, 01/2001 08/2023

```
##
## Augmented Dickey-Fuller Test
##
## data: MI.clean.ts
## Dickey-Fuller = -9.8635, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: MI.all.ts
## Dickey-Fuller = -9.3883, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Decomposition of time series of clean energy electricity generation in MI

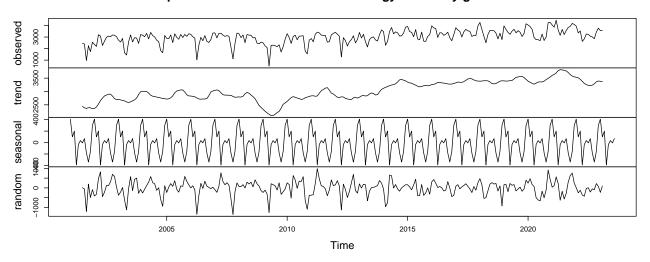


Figure 14: Decomposition, Clean Energy, Michigan

Decomposition of time series of total electricity generation in MI

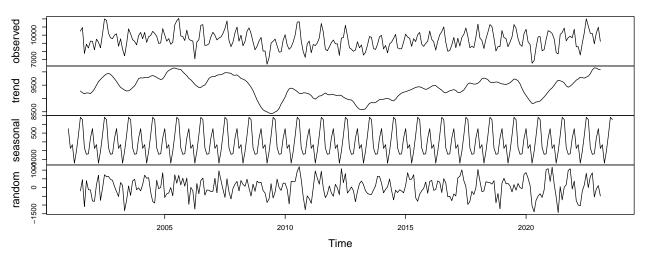


Figure 15: Decomposition, Clean Energy, Michigan

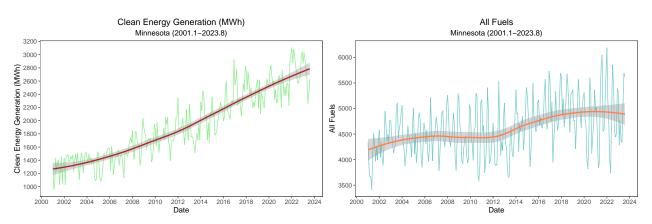


Figure 16: Clean Energy and Total Electricity Generation of State Minnesota, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in MN

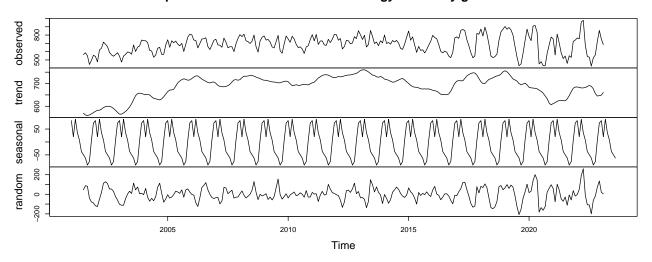


Figure 17: Decomposition, Clean Energy, Minnesota

Decomposition of time series of total electricity generation in MN

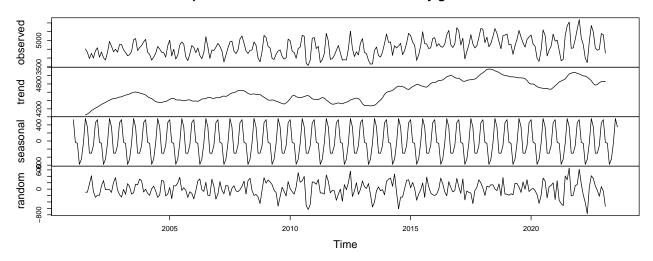


Figure 18: Decomposition, Clean Energy, Maine

Minnesota

```
##
## Augmented Dickey-Fuller Test
##
## data: MN.clean.ts
## Dickey-Fuller = -6.9464, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
##
## Augmented Dickey-Fuller Test
##
## data: MN.all.ts
## Dickey-Fuller = -9.9591, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Nevada

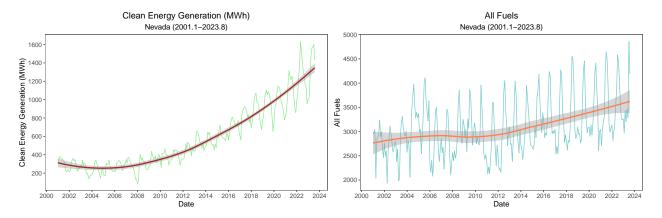


Figure 19: Clean Energy and Total Electricity Generation of State Nevada, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in NV

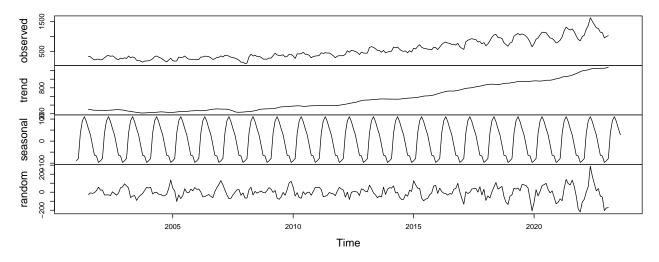


Figure 20: Decomposition, Clean Energy, Nevada

Decomposition of time series of total electricity generation in NV

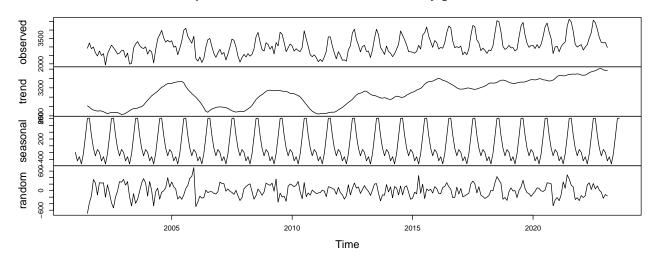


Figure 21: Decomposition, Clean Energy, Nevada

```
##
## Augmented Dickey-Fuller Test
##
## data: NV.clean.ts
## Dickey-Fuller = -3.7927, Lag order = 0, p-value = 0.01982
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: NV.all.ts
## Dickey-Fuller = -6.9584, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

New Mexico

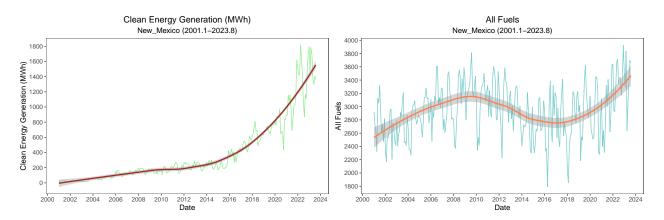


Figure 22: Clean Energy and Total Electricity Generation of State New Mexico, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in NM

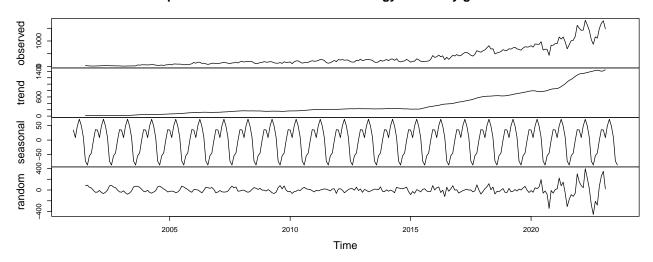


Figure 23: Decomposition, Clean Energy, New Mexico

Decomposition of time series of total electricity generation in NM

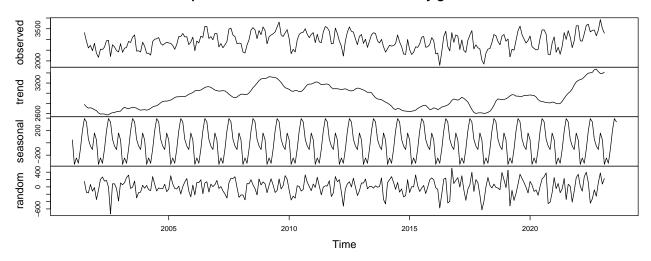


Figure 24: Decomposition, Clean Energy, New Mexico

```
## Augmented Dickey-Fuller Test
##
## data: NM.clean.ts
## Dickey-Fuller = -3.2887, Lag order = 0, p-value = 0.07347
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: NM.all.ts
## Dickey-Fuller = -8.1626, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

New York

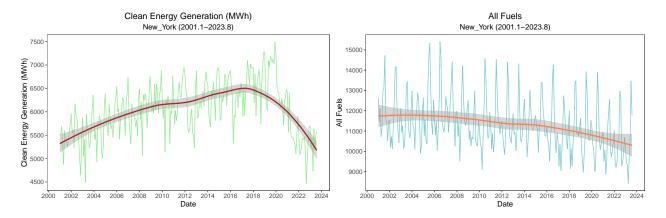


Figure 25: Clean Energy and Total Electricity Generation of State New York, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in NY

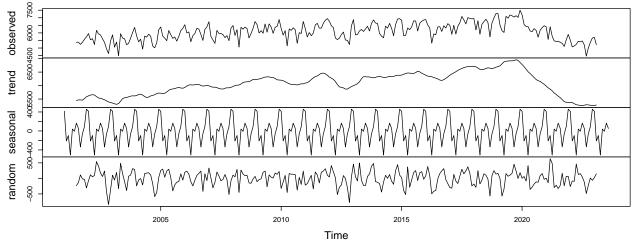


Figure 26: Decomposition, Clean Energy, New York

##
Augmented Dickey-Fuller Test

Decomposition of time series of total electricity generation in NY

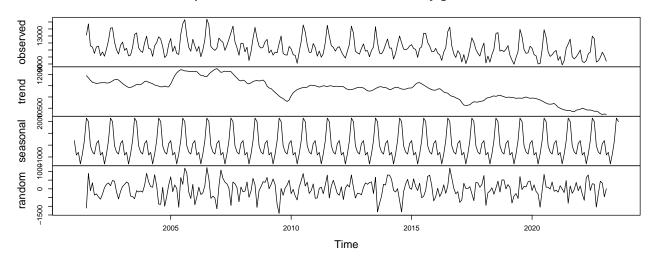


Figure 27: Decomposition, Clean Energy, New York

```
##
## data: NY.clean.ts
## Dickey-Fuller = -7.1955, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: NY.all.ts
## Dickey-Fuller = -9.2854, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Oregon

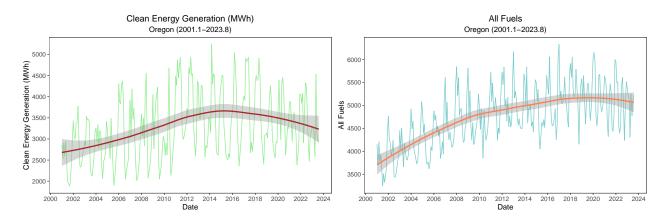


Figure 28: Clean Energy and Total Electricity Generation of State Oregon, 01/2001 08/2023

```
##
## Augmented Dickey-Fuller Test
##
```

Decomposition of time series of clean energy electricity generation in OR

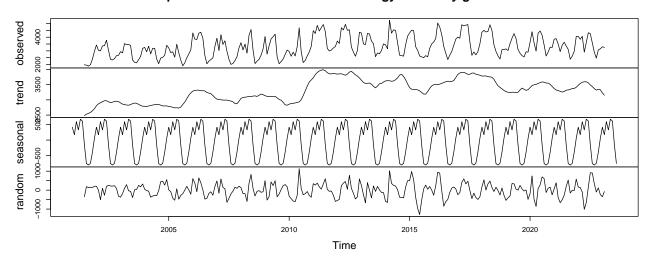


Figure 29: Decomposition, Clean Energy, Oregon

Decomposition of time series of total electricity generation in OR

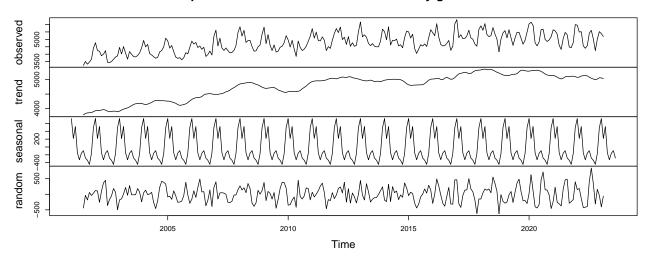


Figure 30: Decomposition, Clean Energy, Oregon

```
## data: OR.clean.ts
## Dickey-Fuller = -7.1352, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: OR.all.ts
## Dickey-Fuller = -8.8239, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Virginia

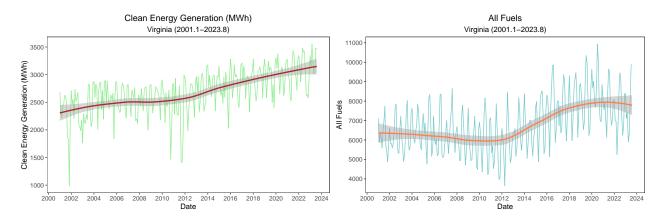


Figure 31: Clean Energy and Total Electricity Generation of State Virginia, 01/2001 08/2023

Decomposition of time series of clean energy electricity generation in VA

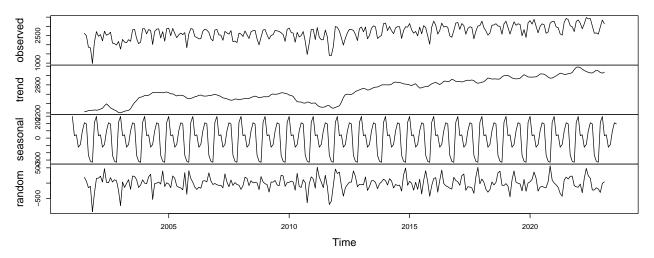


Figure 32: Decomposition, Clean Energy, Virginia

```
##
## Augmented Dickey-Fuller Test
##
## data: VA.clean.ts
```

Decomposition of time series of total electricity generation in VA

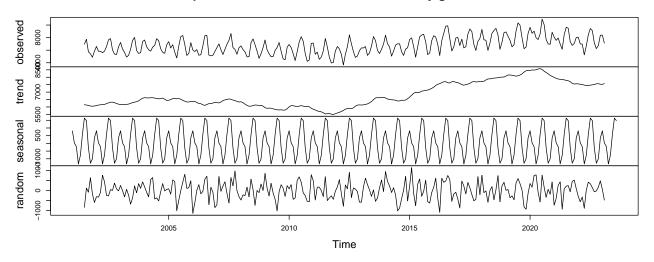


Figure 33: Decomposition, Clean Energy, Virginia

```
## Dickey-Fuller = -11.057, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary

##
## Augmented Dickey-Fuller Test
##
## data: VA.all.ts
## Dickey-Fuller = -8.8231, Lag order = 0, p-value = 0.01
## alternative hypothesis: stationary
```

Washington

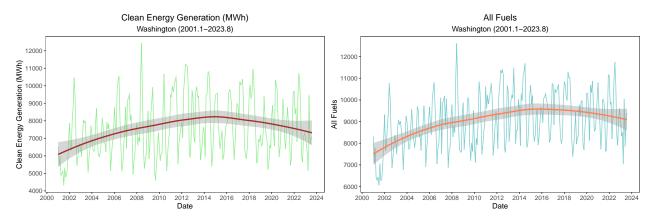


Figure 34: Clean Energy and Total Electricity Generation of State Washington, 01/2001 08/2023

```
##
## Augmented Dickey-Fuller Test
##
## data: WA.clean.ts
## Dickey-Fuller = -7.37, Lag order = 0, p-value = 0.01
```

Decomposition of time series of clean energy electricity generation in WA

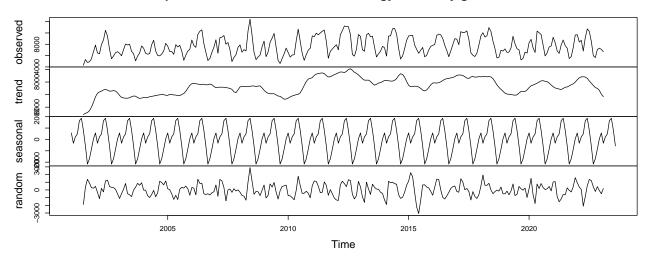


Figure 35: Decomposition, Clean Energy, Washington

Decomposition of time series of total electricity generation in WA

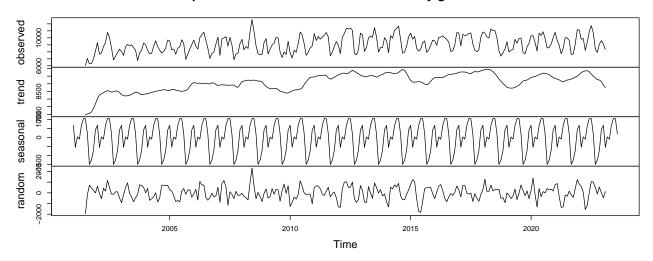


Figure 36: Decomposition, Clean Energy, Washington

```
## alternative hypothesis: stationary

##

## Augmented Dickey-Fuller Test

##

## data: WA.all.ts

## Dickey-Fuller = -8.8034, Lag order = 0, p-value = 0.01

## alternative hypothesis: stationary
```

References

Brief state renewable portfolio standards and goals. National Conference of State Legislatures. (2021, August 31). https://www.ncsl.org/energy/state-renewable-portfolio-standards-and-goals