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T1 ________________	**87042**	F1 ________________
T2 ________________		F2 ________________
T3 ________________	Problem Chosen	F3 ________________
T4 ________________	**C**	F4 ________________

2018
MCM/ICM
Summary Sheet

Cleaner Homeland, Further Expectations

Summary

"One world, one dream", that is, to make this world a better place. Currently the world is experiencing a "green revolution", and we just lay our focus on how to evaluate and estimate a region's "green" level. In this paper, we will demonstrate our model in assessing the given four states' renewable energy usage situations and predict their performances in the future till 2050. To address the proper renewable energy usage in the future, we devise a series of models with step-by-step connection.

Firstly, we focus on data cleaning and analysis. We classify the data into appropriate categories and generate a basic energy profile for each state, viewing from both Energy's Variety and Sector Distribution angles. We also manage to find out the percentage contribution between every energy and each sector.

Secondly, in terms of the data entries we have found, we characterize a more renewable-energy-targeted profile using four indices: Energy Efficiency (EEI), Energy Dependence (EDI), Renewable Ratio(RRI) and Green Potential (GPI). We weight these four factors using Analytic Hierarchy Process(AHP) methods.

After that, we employ TOPSIS to obtain the Energy Sustainable Expectation Index. We present with fifty-year, five-year and 2009 annual ESEI for each state to show their performances in different time length.

After setting up the evaluation model, we devise a further prediction model to get quantified results.

Based on the evaluation we have made, we devise our further prediction model based on dominant factors. We do research on the possible affectable factors and apply PCA(Principal Component Analysis) to decide the dominant ones. Then, we try linear regression(robust core) based on time series and Support Vector Machine (SVM) model to find the best-fitting one for each index we have decided. As the results indicates, we apply linear regression to model EEI and RRI (time series based), and SVM to simulate the other two indices. In this way, we get a quantified results for prediction with respect to time.

Finally, we validate our model by comparing our results with 2015 year's data provided by U.S. Energy Information Administration, which displays a very good fit within 10% error. According to our modeling, we try to come up with some concrete and specific proposals to help these states with their energy targets. Our model helps us find out the proper actions and deeper relationship between forms of renewable energy.

Keywords: **Renewable Energy, Energy Profile, Evaluation and Prediction**

Contents

1 Introduction

1.1 Problem Restatement

As an important portion of American economy, energy is of high priority in both national and regional development. The United States, in particular, ranks second in the amount of energy consumption, relatively high comparing with its population and economic aggregate. In addition, the United States currently relies heavily on coal, petroleum and natural gas for its energy, which are non-renewable energy that will eventually dwindle, becoming too expensive or too environmentally damaging to retrieve. On a long view, we should put emphasis on energy transformation.
Currently, four states along U.S. border with Mexico - California (CA), Arizona(AZ), New Mexico (NM), and Texas (TX) - are seeking for a new energy compact with the main emphasis on clean, renewable energy. We will form a model to better characterize their energy production development and be able to predict the future profiles respectively.

1.2 Planned Approach

Our objective is to set out the best strategy in two essential parts in this problem: (1) Estimation on both the past energy performance and future potential, (2) Prediction on a sustainable energy profile in the future, with our focus on clean, renewable energy performance. In the process of pursuing our objective, we set up and improve our model as needed. At last, we basically form a system, we form Energy Sustainable Estimation System (ESES) composed of Energy Sustainable Evaluation Model (ESEM) and Prediction Model (ESPM). The flow chart below clearly illustrates our modelling process.

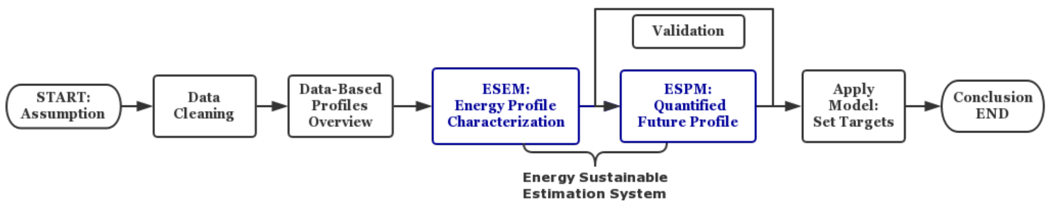


Figure 1. Flow chart on the entire modelling process in establishing ESES

In the preparation part, we will apply a manual data cleaning method to extract valid data. Given the data selected, we will analyze attributions for the four states. After having a brief understanding about different states' energy development, we will devote ourselves to model establishment.

ESE Model:

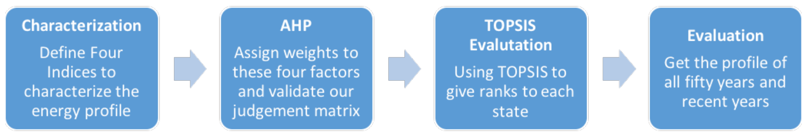


Figure 2. sub flow-chart on Energy Sustainable Estimation Model (ESEM)

We will form a weighted linear model with four predetermined indices the estimation input, and comprehensive assessment the output. After research and analyzing the trend of future energy development, we carefully define four indices to characterize the energy profile of a state, which includes Energy Efficiency Index (EEI), Energy Dependence Index (EDI), Renewable Ratio Index (RRI), and Green Potential Index (GPI). We use Analytic Hierarchy Process (AHP) to assign weights to the four. After validation of the weights, we take use of TOPSIS to evaluate the output result, namely, Energy Sustainable Expectation Index (ESEI). When applying the model in assessment, for a long period (more than 10 years), we use time-weighted method to calculate the weighted average value of the four input indices, while use simply average in assessing a short period's energy profile.

ESP Model:

After setting up the evaluation model (ESEM), we devise a further prediction model to get quantified results.

Firstly, we do research on the possible affectable factors and apply PCA(Principal Component Analysis) to decide the dominant ones. In the next step, we try linear regression(robust core) based on time series and Support Vector Machine(SVM) model to find the best-fitting one for each index we have decided. As the results indicates, we apply linear regression to model EEI and RRI (time series based), and SVM to simulate the other two indices.

2 Assumptions and Detailed Definitions

(1) We use consumption but not production to measure the energy usage between the states. To better attain the goal of increasing renewable usage, we need to emphasize on consumption rather than production when making an energy profile.

(2) We do not consider renewable energy export and import in our paper since it is almost impossible to transport renewable energy nowadays.

(3) Though clean energy includes renewable energy and nuclear energy, we just discuss about renewable energy use in our paper. Because only this part of energy is clean and renewable at the same time.

Notation	Meaning	Notation	Meaning
EEI	Energy Efficiency Index	C_I	Consistency indicator
EDI	Energy Dependence Index	R_I	Mean Random consistency
RRI	Renewable Ratio Index	C_R	Consistency Ratio
GPI	Green Potential Index	C1, C2, C3, C4	Scores for four indices
GDPRX	Real Gross Domestic Product	Cwt	Weighted Scores
TETCB	Total Energy Consumption	X_i	Four Indices
TETCV	Total Energy Expenditure	W	Weight Matrix
TEGDS	Energy expenditures as share of current-dollar GDP	λmax	Eigenvalue
RETCB	Total Renewable Energy Consumption		

Table 1. Detailed Definitions

3 Data Cleaning

There is rarely a model that can deal with 605 indicators and around a hundred thousand entries. Thus it's essential to understand them and choose the significant ones.
We easily recognize that many entries are of the same meaning while different units and that the entries are similar for each type of energy based on five different sectors. Therefore, we categorize most entries in two different dimensions - according to energy categorization as Figure.3 illustrate and according to different sectors that consume energy.

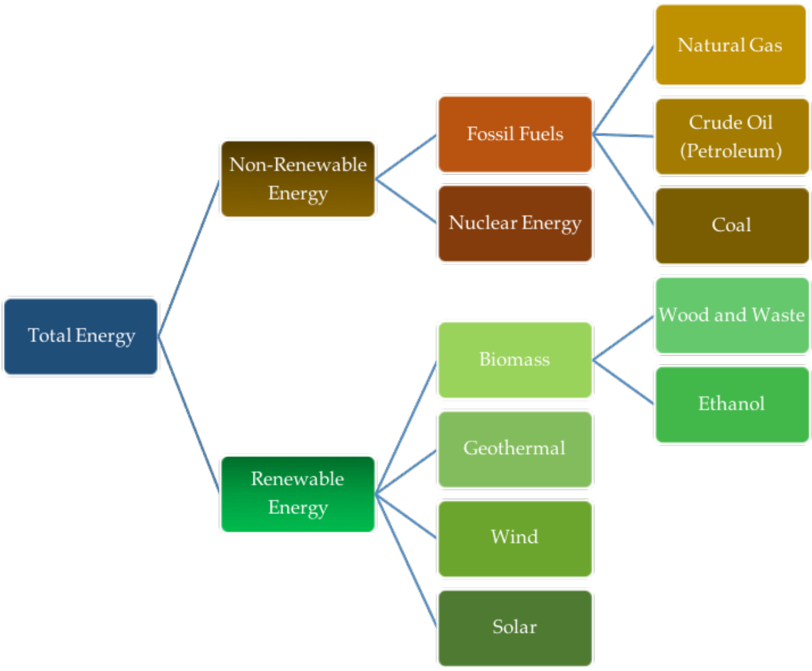


Figure 3. Energy Classification Tree

4 Data-Based Profiles Overview

Dealing with the effective data we've selected, we are able to have a general understanding about the energy situation of the four states. In this part, we look into the four in two dimensions - longitudinal and cross states.

4.1 General View on Longitudinal Changes

Figure 4 illustrates a general understanding about the aggregate energy usage along 1960-2009 among the four states. Texas and California lead the other two over the years with Texas ranking first and California the second. Arizona and New Mexico have lower starting points mostly due to their smaller population. Regardless of the difference in amount, one thing in common is their synchronous growing trend. The total energy consumption increased over fifty years with similar slight fluctuations midway.

Figure 5 shows that California possesses the lowest energy consumption per capita and continues to reduce, while Texas the largest, still. We can draw that California, in the past fifty years, have made efforts to increase energy efficiency and restrained energy demand growth. In contrast, Texas' high rank in its aggregate energy consumption and per capita consumption marks the opposite.

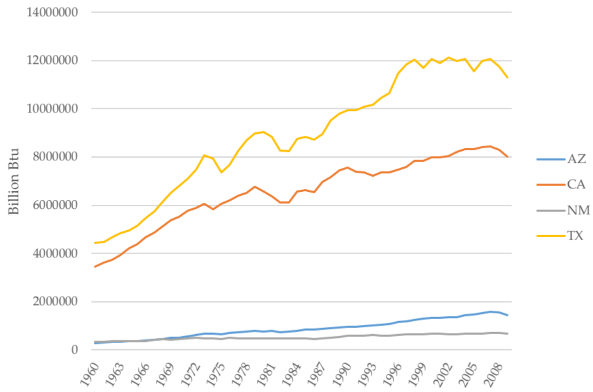


Figure 4. Total Energy Consumption of the Four States (1960-2009)

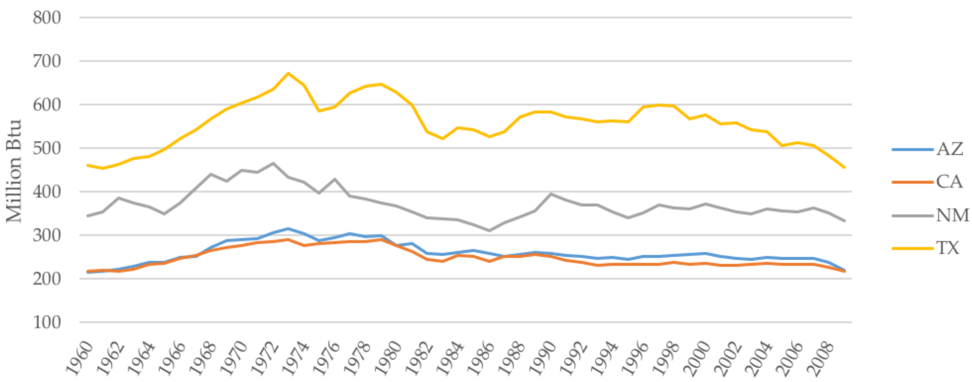


Figure 5. Total Energy Consumption per capita in Four States (1960-2009)

4.2 Cross-states Comparison on Energy's Variety and Sector Distribution

Other than their aggregate energy consumption, it's significant to go more detailed and focus on how the distribution is like and where the energy goes. Now we use a dual-direction diagram to promote understanding. The graphs below display the energy sources and sector energy distribution from year 2000 to year 2009, as well as the percentage contribution with one another. Through the analyses, we will briefly introduce the basic sources conditions and distinguish characteristics of the four states respectively.

4.2.1 California

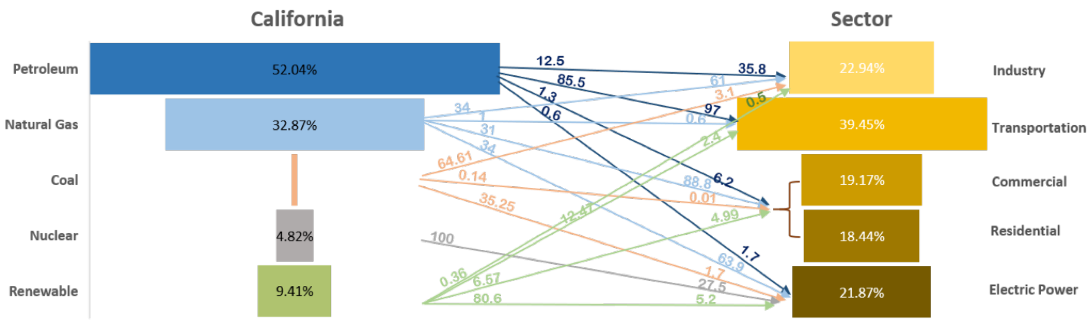


Figure 6. Variety and Sector Distribution Diagram of Energy Sources in California

California's energy variety distribution is of hourglass shape and diverse in the proportion, whereas relatively homogeneous in the sectors part. California has a large petroleum reserves on account of the geologic basins along the Pacific Coast as well as in its Central Valley. The state's abundant supply of crude oil accounts for its conspicuous large portion of petroleum usage. Despite rich resources, California has the largest ratio in use of renewable energy among the four. It's also worth notice on the energy sources of electricity generation that California largely depended on natural gas rather than petroleum that the other three states relies on most.

4.2.2 Arizona

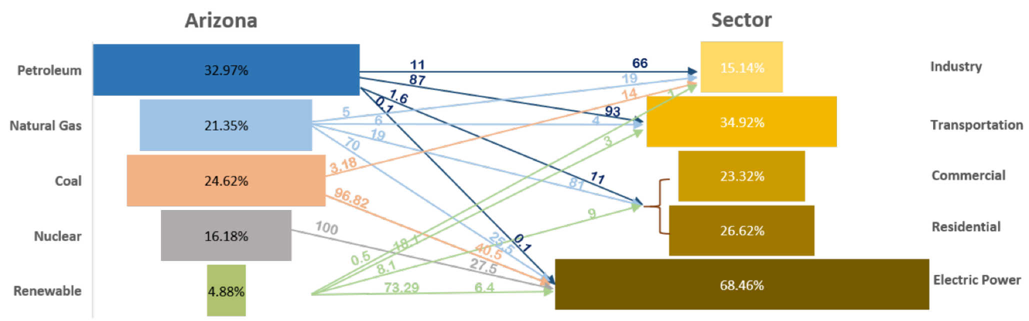


Figure 7. Variety and Sector Distribution Diagram of Energy Sources in Arizona

Famous for its varied terrain from the Grand Canyon in the north to the Saguaro deserts in the south, Arizona possesses its greatest wind potential along the more than 100-mile long, steep slope of the Mogollon Rim. Although Arizona has few fossil fuel resources, it does take a "gorgeous turn" from energy shortage with the aid of cleaner, renewable energy. Other than wind energy, the state made good use of its abundant solar and geothermal energy potential. Hydroelectric power also has long dominated Arizona's renewable electricity generation. In its way of going "clean", Arizona also developed the nation's largest nuclear plant and it's notable that its nuclear energy portion ranks first among the four states during this period.

4.2.3 New Mexico

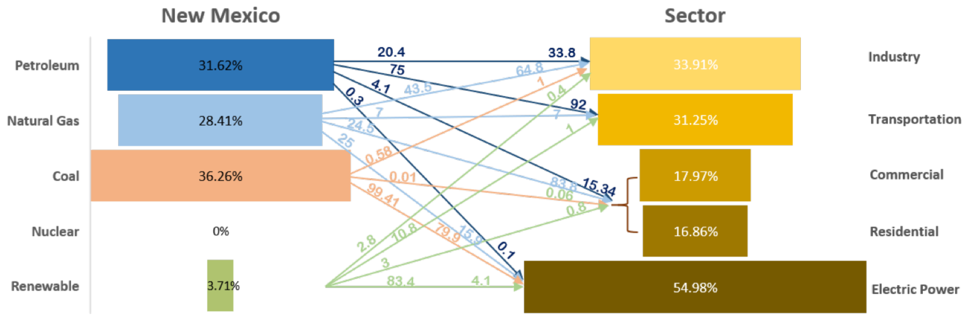


Figure 8. Variety and Sector Distribution Diagram of Energy Sources in New Mexico

New Mexico has a more varied topography than Arizona and it contributes to its multiple, substantial renewable resources including hydroelectric, biomass, geothermal energy, particularly from wind and solar. However, it's the only state without nuclear energy. Its endeavor towards sustainable development is beyond the diagram. New Mexico has created a Renewable Energy Transmission Authority (RETA) in 2007 to encourage the development of the state's renewable energy resources by helping connect renewable projects to the electric grid.

4.2.4 Texas

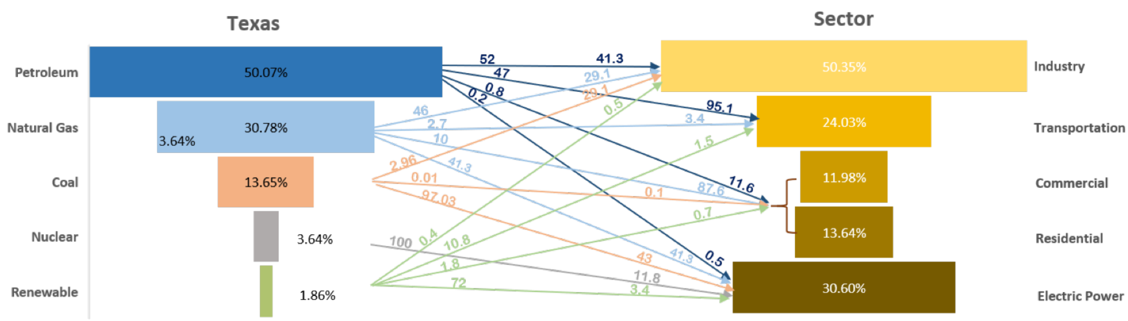


Figure 9. Variety and Sector Distribution Diagram of Energy Sources in Texas

Texas, leading the nation in energy production, primarily depended on crude oil and natural gas, which are present across the entire state. From the sector perspective, we can draw that it used to develop energy-intensive industry. However, Texas didn't have a large ratio of renewable sources, of which wind energy takes a large ratio on electricity generation.

5 Energy Profile Characterization Model: ESEM

To better evaluate the energy profile of each states with concrete values, we invent our first model including using ROI (return on investment) method. They display the energy level in these four states and also serve as a function of time.

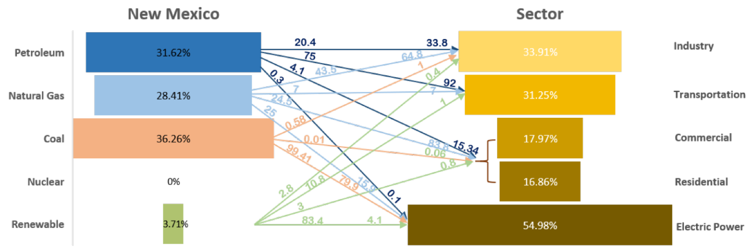


Figure 8. Total Energy Consumption per capita in Four States (1960-2009)

5.1 Energy Efficiency Index (EEI)

We expect a state to have more GDP output accompany with smaller energy consumption, which indicates this state has a higher energy efficiency. This is typical ROI type index. A high ROI means the investment's gains compare favorably to its cost. We would use this index as one of the criteria to evaluate the four states. We represent EEI as

$$EEI(t) = \frac{GDPRX(t)}{TETCB(t)}$$

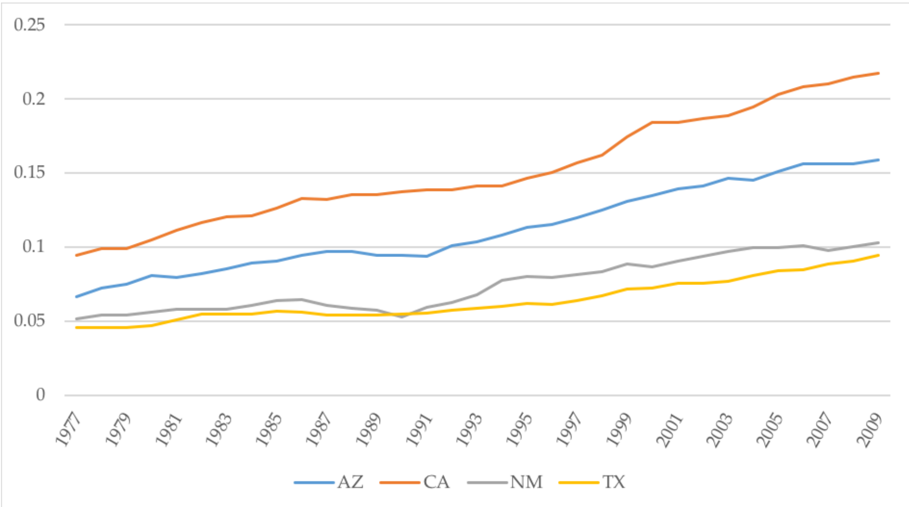


Figure 10. Energy Efficiency Index for Each State

We can see that for all four states, their EEI generally increased overtime. Arizona, New Mexico and California's EEI value have all grown steadily over last 50 years while New Mexico showed a fall between 1987 and 1990. California stays the highest energy efficiency (over 0.2 in 2009) with Arizona the next. What worth noticing is that Texas have shown a rapid growth in recent years and is likely to exceed New Mexico in the future.

5.2 Energy Dependence Index (EDI)

How can we indicate economy dependence on energy? Therefore, we create Energy Dependence Index (EEI) to suggest the proportion of GDP government has spent on consuming energy. This index also can reveal the effect of some policy from the government. A higher EDI suggests a higher degree of reliance on energy. We define EDI as

$$EDI(t) = \frac{total\ energy\ expenditure\ (TETCV(t))}{TETCB(t)} = TEGDS(t)$$

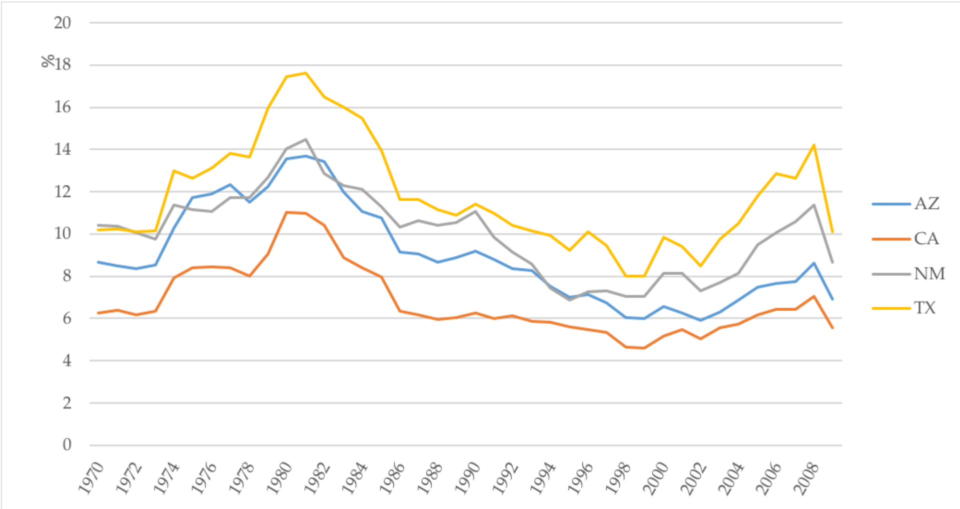


Figure 11. Energy Dependence of the Economy

EDI is a low optimal index. We can see Texas has the highest percentage, following by New Mexico, Arizona and California. Nevertheless, the difference between these states are rather small, not bigger than 4% during a specific time. All these four states show similar patterns over years, which may be determined by economic conditions and national policies back then.

5.3 Renewable Ratio Index (RRI)

One of the most important objective of each state is to have a cleaner, renewable energy usage. So to show the outcome of their effect, the ratio of renewable energy usage in total energy is also vital for our criteria. It can reveal the situation of a state with using renewable sources. So we devise

$$RRI(t) = \frac{total\ renewable\ energy\ consumption\ (RETCB(t))}{total\ energy\ consumption\ (TETCB(t))}$$

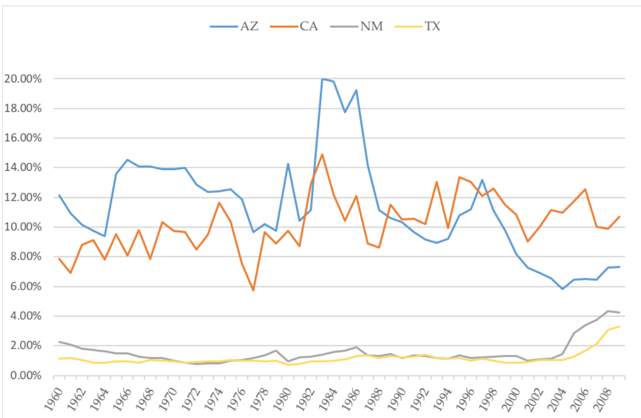


Figure 12. Percentage of Renewable Energy Use in Four States (1960-2009)

From this graph, we notice that Arizona had the highest percentage of renewable energy before 1988 (increasing fiercely between 1982-1984) while in the past two decades (1988-2005), its percentage showed a generally decreasing trend with a temporary peak at 1996. However, California shows a steady and high ratio of renewable resources around 10% in last 50 years. Besides, two other states (New Mexico and Texas) stayed similarly low level (below 3%) in the last four decades and their ratio of renewable sources increase significantly from 2004.

From our data process, we find out that both Arizona and California have large part of hydroelectricity usage in renewable energy during the history (we will further analyze this point in our forecasting model); the large volume of water power makes their RRI value high. Besides, their RRI are very much decided by precipitation and weather conditions. We then can interpret some fluctuates in their figures.

a. Arizona Hurricane: 1983, 1997 with high peaks in RRI profile

October 1983: The largest precipitation total occurred in Mount Graham, which saw 12.00 inches (305 mm) of rain overall.

September 1997: Hurricane Nora produced 11.97 inches (304 mm) of rainfall over the Harquahala Mountains in Western Arizona, causing some flash flooding in the area.

So between both years, heavy rainfall caused the amount of hydroelectricity rose abruptly, which lead to a distinct increase of RRI, as shown in the graph.

b. California drought: 1976, 1986 with abrupt falls in RRI profile

1976-1977: 1977 had been the driest year in state history to date.

1986-1992: California endured one of its longest droughts ever, observed from late 1986 through early 1992.

The low rainfalls could lead to the falling of water power; it also contributes to the obvious decrease of RRI index.

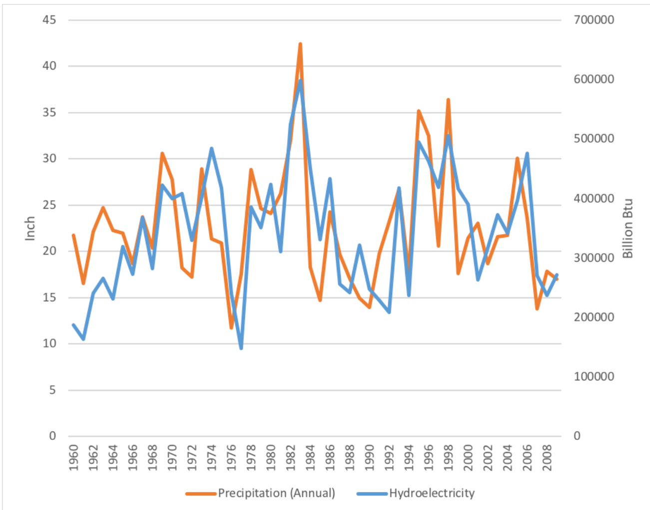


Figure 13. The Similar Pattern Between Precipitation and Hydroelectricity Production

From this figure, we can observe that the pattern between annual precipitation and hydroelectricity production is rather alike with a little delay. This confirms our reasoning for weather and climate factors for the differences in RRI between years.

Consequently, we find that Arizona and California have much water power as their renewable energy. Their profile for renewable energy have a good base score; however, for New Mexico and Texas, they both just start off their development in renewable energy so their foundation is comparatively weak.

5.4 Green Potential Index (GPI)

A relatively wide range of renewable energy usage is not sufficient to show the potential of a state to keep their green growth step. Thus, GPI is an index for indicating the growth speed of renewable energy consumption. We define it as the derivative of renewable energy as

$$GPI(t) = \frac{d(RETCB(t))}{dt}$$

We have calculated all the GPI values for each state in 1960-2009. The graph below shows the average number for GPI; a darker color means a higher potential (in this graph, the rank is New Mexico = Texas > California >Arizona)

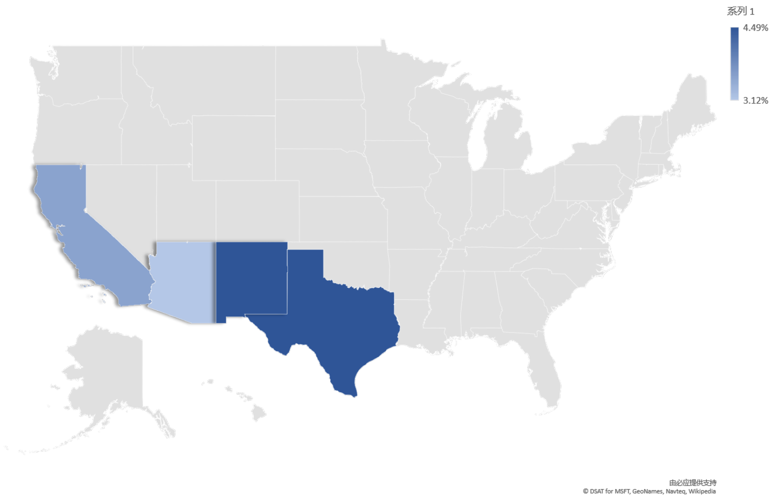


Figure 14. GPI for each state (supported by Bing.com)

Analysis: Why New Mexico and Texas could have such great potential in renewable energy source?

Texas (Policy Factor): In 2005, the state legislature in Texas made the goal of 5,880 megawatts come from renewable sources by 2015. Surprisingly, Texas surpassed the 2015 goal in 2005 and the 2025 goal in 2009, almost entirely with wind power. Besides, the state encouraged construction of wind farms on its wide plain.

We can detect the rapid growth of wind energy consume in the following graph.

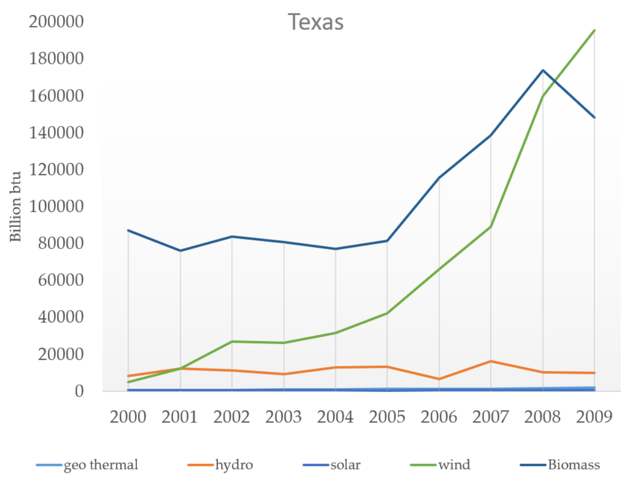


Figure 15. Texas Renewable Energy Sources Change Last 10 Years

New Mexico (Geography Factor): New Mexico possesses substantial renewable resources, particularly from wind and solar, but also from hydroelectric, biomass, and geothermal energy. New Mexico has abundant natural renewable resources in storage, but it fails to make best of it. The rapid growth in wind power shows its great potential in increasing usage of renewable resources.

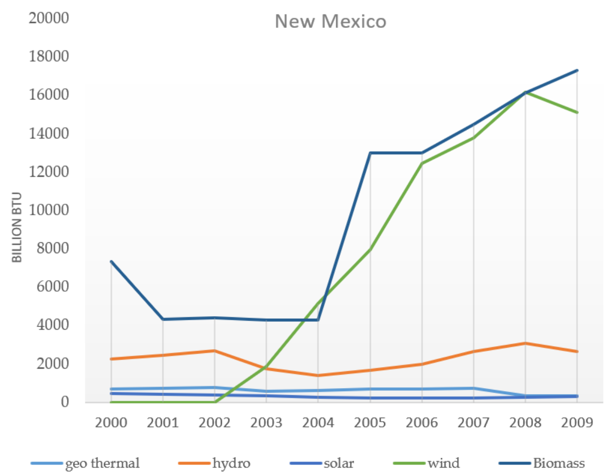


Figure 16. The Similar Pattern Between Precipitation and Hydroelectricity Production

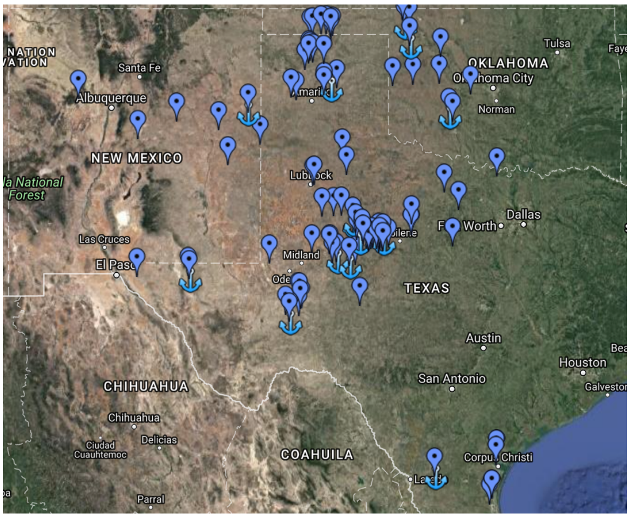


Figure 17. Wind Power Plants in New Mexico, Texas and Oklahoma

New Mexico's wind potential is mostly on the high plains in the eastern half of the state. We can see after government's encouragement, Texas has much more wind power plants than New Mexico. However, New Mexico has a rather small population (low total energy consumption) with rich energy resources, thus only several power plants could also contribute to significant GPI growth. Its potential in renewable energy usage is unmeasurable.

5.5 Add Weights Using AHP

Next step we use AHP (analytic hierarchy process) to add weights to each index.

5.5.1 Create two-by-two judgement matrix

We represent the four indices as x_1, x_2, x_3, x_4; we create this matrix by comparing the importance between EEI, EDI, RRI, RPI.

$Scale$	$Comparison\ result\ for\ i\ and\ j's\ indicators$
1	$K_i\ and\ K_j\ are\ equal\ important$
3	$K_i\ is\ a\ little\ important\ than\ K_j$
5	$K_i\ is\ important\ than\ K_j$
7	$K_i\ is\ rather\ important\ than\ K_j$
9	$K_i\ is\ extremely\ important\ than\ K_j$
$2, 4, 6, 8$	$The\ importance\ is\ in\ between$

(The same for the reciprocal between i and j)

Table2. The meaning of the scales

Because governments are encouraged to use more renewable energy, we attach more importance to X_3, X_4 index. Besides, we think energy efficiency is more significant than energy dependence, since when the technology is immature so the cost of producing renewable energy may be high. Thus, to better judge a state's renewable current condition, x_1 can reflect more than x_2. Furthermore, we consider the potential of renewable energy growth is of slightly more importance than the present usage level. If a state pays more attention to clean energy than before, the development could be fast and remarkable. So the current level does not so comprehensively reflects the true situation.

5.5.2 Get Weight Matrix

After several times of adjustment, we finally work out the judgement matrix A as

$$A = \begin{bmatrix} 1 & 2 & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{2} & 1 & \frac{1}{2} & \frac{1}{3} \\ 3 & 2 & 1 & 1 \\ 3 & 3 & 1 & 1 \end{bmatrix}$$

$$M_i = \prod a_{ij} \ , i = 1, 2, 3, 4$$

$$\overline{W_i} = \sqrt[4]{M_i}$$

$$W_i = \frac{\overline{W_i}}{\sum_{i=1}^{n} \overline{W_i}}$$

We can get matrix $W = [0.152\ 0.119\ 0.346\ 0.383]^T$ which is accord with our expectations mentioned before: $X_3(RRI)\ and\ X_4(GPI)$ have more weight than $X_1(EEI)\ and\ X_2(EDI)$. Meanwhile, X_1 has more weight than X_2 and X_4 has a little bit more weight than X_3.

5.5.3 The Validation of Weight Matrix

a. Calculate the Eigenvalue λ_{max} of W

$$\lambda_{max} = 4.117$$

b. Consistency test

$$The\ consistency\ indicator\ C_I = \frac{\lambda_{max} - n}{n - 1} = 0.039$$

When $n = 4$, according to Mean Random Consistency Index Table, we can get $RI = 0.89$, Further we can get consistency ratio

$$C_R = \frac{C_I}{R_I} = 0.0438 < 0.1$$

Our weight matrix successfully passes the test.

5.6 Using TOPSIS to Complete the Profile

After that, we apply our computed weight to TOPSIS method to get a more comprehensive view of these states energy usage. We will calculate the ranks for each state in three ways: a) calculate accumulated scores from 1960 to 2009, using weighted moving average method for last 50 years; b) use the average value of data for latest 5 years as sources for scoring; c) find the "best" profile for cleaner, renewable energy in 2009. We will show the results from a long-time period of 50 years to a short moment of one year.

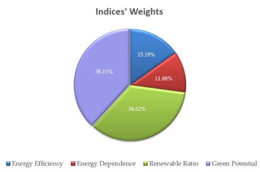


Figure18. Indices' Weights

5.6.1 Past 50-Year Energy Characteristic Profile

a. Our weighted system is also time-related, since all our defined index are functions on time. Thus, it can be only used to reveal the performance for a single year. To present an all-sided profile for last 50 years, we need to take all these years' scores into account. However, we think more recent data contains more information about future and is more useful for governors to think over their policy. Hence, we adopt a weighted moving average method for EEI/EDI/RRI. Notice that we do not use this method to GPI because we think it already is a growth rate factor, we just need to calculate its average growth rate.

$$C_{wt}(I) = \frac{w_1 C_{t-n+1}(I) + \ + w_n C_t(I)}{w_1 + w_2 + ... + w_n}$$

$$(symbol I can be replaced by EEI/EDI/GPI, N = 50)$$

1960, we give weight 1 with equal interval 1 afterwards$(wn = 50)$

$$C_{wt}(GPI) = 1/N * (C_{t-n+1}(GPI) + \ + C_t(GPI))(N = 49)$$

After calculation, we get the final score as displayed in the following table.

b. Using TOPSIS, we get the best score by criteria for each state. We define the final output as Energy Sustainable Expectation Index (ESEI). It presents the synthetic ability of a state to attain its clean and renewable growth, depending on both current performance and future potential.

	$C1(EEI)$	$C2(EDI)$	$C3(RRI)$	$C4(GPI)$	$ESEI$	$Rank$
$California$	0.17156	6.292374	0.107620	0.035458	0.834734	1
$Arizona$	0.12736	8.128636	0.102843	0.031235	0.738636	2
$New\ Mexico$	0.08375	9.372663	0.017274	0.044939	0.2381689	3
$Texas$	0.07123	11.27848	0.012914	0.044931	0.223074	4

Table3. Input and output indices for last fifty years

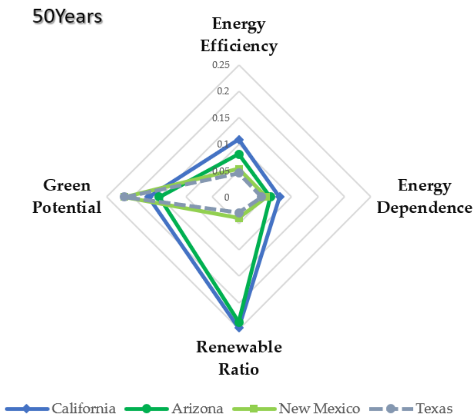


Figure19. Energy Sustainable Expectation Radar Map (last 50 years)

California gets the highest rank, which is consistent with most of our analysis on each individual indicator.

5.6.2 Recent 5-Year Energy Characteristic Profile

In addition to a longitudinal analysis of each state, we would also like to provide governors with some visualized data indicating current situation. This time our input scores are average scores for five years, considering a short period of time. The scores and computed rank using TOPSIS:

	$C1$	$C2$	$C3$	$C4$	$FinalScore$	$Rank$
$California$	0.2105111	6.324182	0.1097832	0.2205838	0.5882313	1
$Arizona$	0.1556225	7.686896	0.0680569	0.2504869	0.4038363	3
$New\ Mexico$	0.100291	10.037162	0.0371062	0.4947338	0.4612522	2
$Texas$	0.0885323	12.32388	0.0228617	0.2354737	0.0307285	4

Table4. input and output indices for last five years

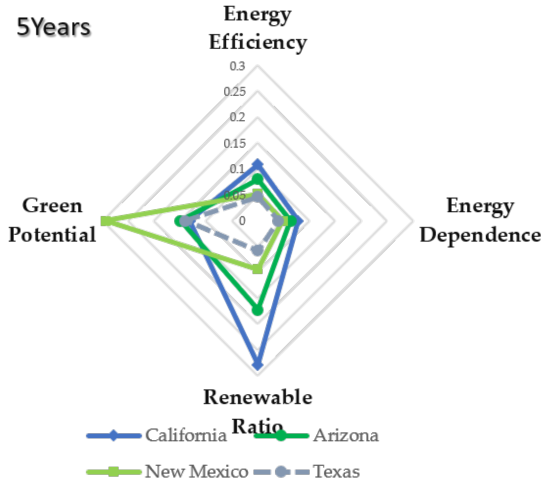


Figure20. Energy Sustainable Expectation Radar Map (last 5 years)

We discover that New Mexico performs better than Arizona in last 5-year profile, which is only difference compared with last 50-year results. It is because New Mexico have showed great potential in recent years.

5.6.3 "Best" Profile for use of renewable energy in 2009

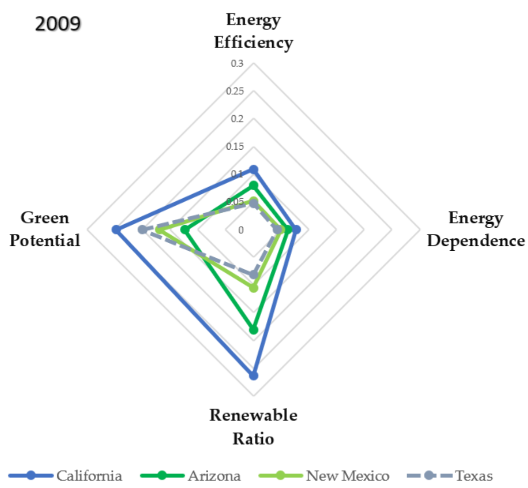


Figure21. Energy Sustainable Expectation Radar Map (2009)

	$C1(EEI)$	$C2(EDI)$	$C3(RRI)$	$C4(GPI)$	$ESEI$	$Rank$
$California$	0.216963	5.55661	0.106936	0.285593	1	1
$Arizona$	0.158740	6.90255	0.073179	0.142923	0.409371	2
$New\ Mexico$	0.103048	8.67649	0.042613	0.195378	0.2159	4
$Texas$	0.094397	10.09536	0.033137	0.231457	0.276332	3

Table 5. input and output indices of 2009

In 2009, ESEI shows that California still dominates in these four states. So our conclusion for the best profile in 2009 is California.

6 Quantified Prediction Model: ESPM

To predict the energy profiles in the future by states and set targets more accurately, we develop a quantified prediction model based on the former evaluation model. It aims at finding more deeply rooted indicators for four criteria of Energy Sustainable Expectation Index (ESEI) and simulate their trend, providing quantitative support for prediction. Principal Component Analysis (PCA), GM(1,1) Grey Model, Markowitz Model, linear regression (robust) based on time series, and Support Vector Machine (SVM) are applied in this model.

6.1 Independent Variable Selection

To decide factors of Energy Efficiency and Energy Dependence, we apply Principal Component Analysis on five potential indicators concerning demography and economy. The component reduction criterion of PCA is that the specify explained variance should be no less than 95 percent. In this way, population is finally chosen as the most significant indicator.
As for Green Potential and Renewable Ratio, we notice that they could be explained by some indicators about net generation in the electric power industry (EIA) through tough manual selection. Especially, we define an indicator called "Renewable Backbone" for integration. This indicator is the net electric power generation of a renewable energy source in a state which takes the largest proportion of total renewable energy and contributes most to the change of the total renewable energy. These two features are quantified as "Quantity Contribution" and "Trend Contribution" respectively. Amazingly, Renewable Backbone could be found in each of four states (shown in the figure below): Hydro Conventional (excluding pumped storage) for California and Arizona, Wind for New Mexico and Texas.

California (GWh)	2005	2006	2007	2008	2009	Quantity Contribution (%)	Trend Contribution (%)
Renewables Total	63,286	71,963	52,173	48,912	53,428		
-Geothermal	13,023	12,821	12,991	12,883	12,853	22.7 (±3.5)	-0.1 (±11.9)
-Hydro Conventional	39,632	48,047	27,328	24,128	27,888	**56.7 (±7.6)**	**95.8 (±9.0)**
-Solar	537	495	557	670	647	1.0 (±0.2)	-1.2 (±1.5)
-Wind	4,262	4,883	5,585	5,385	5,840	9.2 (±2.3)	5.0 (±5.9)
-Biomass	5,832	5,717	5,712	5,846	6,200	10.3 (±1.7)	0.6 (±5.1)
Arizona (GWh)	2005	2006	2007	2008	2009	Quantity Contribution (%)	Trend Contribution (%)
Renewables Total	6,484	6,846	6,639	7,400	6,630		
-Geothermal	-	-	-	-	-	0.0 (±0.0)	0.0 (±0.0)
-Hydro Conventional	6,410	6,793	6,598	7,286	6,427	**98.6 (±1.0)**	**100.5 (±9.9)**
-Solar	14	13	9	15	14	0.2 (±0.0)	-0.6 (±1.0)
-Wind	-	-	-	-	30	0.1 (±0.2)	-1.0 (±1.9)
-Biomass	60	40	32	99	159	1.1 (±0.8)	-0.2 (±7.8)
New Mexico (GWh)	2005	2006	2007	2008	2009	Quantity Contribution (%)	Trend Contribution (%)
Renewables Total	964	1,476	1,677	1,974	1,851		
-Geothermal	-	-	-	-	-	0.0 (±0.0)	0.0 (±0.0)
-Hydro Conventional	165	198	268	312	271	15.4 (±1.4)	22.4 (±14.0)
-Solar	-	-	-	-	-	0.0 (±0.0)	0.0 (±0.0)
-Wind	795	1,255	1,393	1,643	1,547	**83.5 (±1.0)**	**80.2 (±9.1)**
-Biomass	4	23	16	19	33	1.1 (±0.5)	-2.5 (±6.6)
Texas (GWh)	2005	2006	2007	2008	2009	Quantity Contribution (%)	Trend Contribution (%)
Renewables Total	6,668	8,480	11,932	18,679	22,133		
-Geothermal	0	0	0	0	0	0.0 (±0.0)	0.0 (±0.0)
-Hydro Conventional	1,333	662	1,644	1,039	1,029	10.4 (±6.5)	-4.5 (±27.0)
-Solar	0	0	0	0	0	0.0 (±0.0)	0.0 (±0.0)
-Wind	4,237	6,671	9,006	16,225	20,026	**79.0 (±10.5)**	**104.8 (±27.6)**
-Biomass	1,098	1,147	1,282	1,415	1,078	10.6 (±4.6)	-0.3 (±6.4)

Table 6. Electric Power Industry Net Generation
by Renewable Energy Source and "Renewable Backbone" Analysis by States, 2005-2009

6.2 Indicator Estimation

Thanks to "Renewable Backbone", the estimation of annual electric power net generation of renewable energy could be divided into two parts: that of renewable backbone and that of other renewable resources. For Hydro Conventional, since it fluctuates with precipitation, so we apply fluctuation simulation around historical average. For Wind, since its development in New Mexico is at a primary stage, the growth rate is nearly exponential at first. Thus, we use Grey Model for its estimation from 2010 to 2014. As for the estimation of population and other parts of renewable energy, we apply linear regression on them. Here is a brief introduction to GM(1,1). Suppose $X^{(0)}$ is a raw matrix of annual wind electric power net generation from 2005 to 2009, $X^{(0)} = x^{(0)}(ti), i = 1, 2, .., n$. By one time accumulated generating operation (1-AGO), first order linear differential equation and least square method, we could get

$$x^{(1)}_{esti}(t_k) = (\frac{b}{a} + (x^{(0)}(t_1) - \frac{b}{a}) * e^{-a(t_k - t_1)})$$

$$k = 1, 2, .., n.\ a\ and\ b\ are\ two\ estimated\ parameters$$

6.3 Prediction of Energy Sustainable Expectation Index (ESEI) from 2010 to 2050

We apply Linear Regression (robust) and Support Vector Machine (SVM) based on time series in the MATLAB for Energy Efficiency, Renewable Ratio and Energy Dependence, Green Potential respectively. Noticeably, the fitting of Arizona's Renewable Ratio is not satisfactory. The main deviation is from quite a portion of hydroelectric power which is converted to pumped storage.

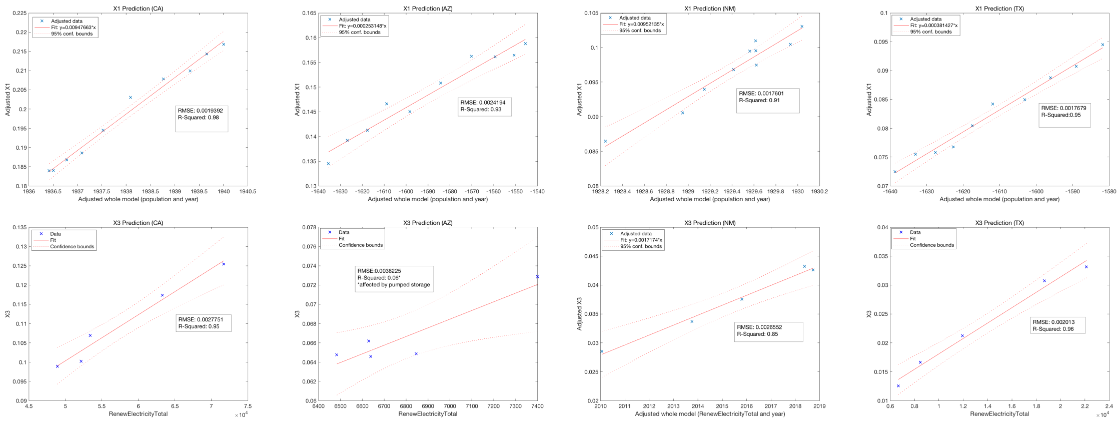


Figure. Linear Regression (Robust) Prediction of Energy Efficiency and Renewable Ratio for Four States

Therefore, we could get a full table of Energy Sustainable Expectation Index (ESEI) from 2010 to 2050, which is attached in the appendix. ESEI in 2025 and 2050 of four states in the absence of any policy changes are shown below.

$Year$	$California$	$Arizona$	$New\ Mexico$	$Texas$
2025	0.6168 (1)	0.3859 (3)	0.4037 (2)	0.1211 (4)
2050	0.4780 (2)	0.2688 (4)	0.5881 (1)	0.3565 (3)

Table 7. Energy Sustainable Expectat

6.4 Model Validation

As we have computed all four evaluation indices using our Quantified Prediction Model from 2009 to 2050, we can compare some of the results with the real data available. The most easily compared results are Renewable Ratio Index, since we can get access to the database in U.S. Energy Information Administration. To better confirm the credibility of our prediction model, we choose the data of year 2015 to compare. And we get the following results.

2015 *Renewable Consumption Ratio*	*California*	*Arizona*	*New Mexico*	*Texas*
Real (fromEIA)	11.15%	10.23%	6.54%	5.05%
Predicted	11.94%	8.13%	6.57%	5.65%
Error	7.09%	20.53%	0.46%	11.88%

Table 8. Real vs Predicted Renewable Consumption Ratio in 2015

Because our model is devised in the absence of any policy changes, it is natural that our predicted value to have some deviation from the real value. We think the error around 10% is acceptable. However, we observe that for Arizona, the error has reached up to 20%. After our discussion, we consider this large deviation is caused by two reasons: a) Arizona began to have wind power in 2009, which is the end of our available data for prediction; it is hard for us to predict its wind power in the future depended on only one data value; b) Arizona has a large portion of hydroelectricity usage in total renewable energy usage, yet the amount of water power is fluctuant because of weather conditions. Thus, the error could also result from the unstable behavior of water power.

7 Strategies

7.1 Targets and Goals

As we quantify the Energy Sustainable Expectation Index (ESEI) as well as its four indices through 2050, we have already obtained predicted values of total electric power net generation by renewable energy and the consumption ratio of renewable energy by states by year during the prediction process. Therefore, we round their predicted values to get these numerical targets below in a quantitative and reasonable way (no more than 3% above predicted values due to rounding).

Goals	Renewable Energy Consumption Ratio			Total Net Generation of Electric Power by Renewable Energy (GWh)		
Year	2009	2025	2050	2009	2025	2050
California	10.68%	16.5%	24.2%	53428	72500	81500
Arizona	6.62%	14.3%	17.1%	6630	12000	12500
New Mexico	4.26%	19.1%	33.9%	1851	6500	7000
Texas	3.31%	21.5%	32.5%	22133	81000	101000

Table 9. Targets of Total Electric Power Net Generation by Renewable Energy and the Consumption Ratio of Renewable Energy

7.2 Actions

After considering a combination of factors, we identify the following actions. They might be taken to meet each states' energy compact goals.

1. According to each state's special geography and climate advantage, vigorously promote and make full use of the advantageous renewable resources, e.g. Arizona and California's water power system, New Mexico and Texas' wind power system. Additionally, governments need to advance technology progress on their backbone renewable energy forms. They should find ways to increase energy conversion efficiency and the cost of production. So when the potential of a specific energy is almost fully used, they can turn

to seek higher quality instead of quantity.
2. Realize the diversified development of renewable energy. All states should energetically develop their rarely used new energy forms, such as solar energy, ethanol fuels and geothermal energy.
For solar energy and geothermal energy, California has the largest consumption (far beyond others) while other three states have very little usage. However, they all have very good solar potential with abundant sunshine; New Mexico has rich geothermal potential and Texas has a unique untapped geothermal resource. Thus, governments in other three states can consider introducing advanced energy-related technology from California, so as to fully tap their renewable energy potential.
Ethanol fuels, which is transformed from biomass energy, is cleaner and more environmentally friendly. It is most often used as a motor fuel, mainly as a biofuel additive for gasoline in US. So ethanol fuel is mostly used in transportation sector. The figure below displays the percentage of biomass energy into producing ethanol fuels. We can see that the percentage is generally low (mainly below 30%) in past 10 years. Especially for California, the ratio is below 10%; about three-fifths of California's biomass generating capacity comes from plants fueled by wood and wood waste. In terms of our data analysis, transportation sector consumes nearly 40% of California's total energy and around 30% in other states; over 90% of this sector's energy comes from petroleum. Thus, if government can elevate the percentage usage of ethanol in motor fuels, they can greatly improve renewable energy usage and protect the environment in the meantime.

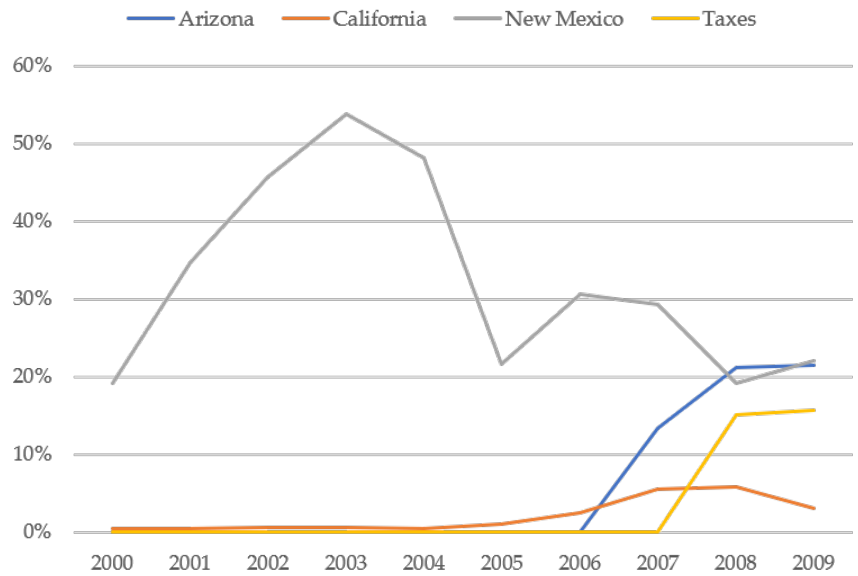


Figure23. percentage of biomass energy into producing ethanol fuels (2000-2009)
3. Try to seek cooperation in renewable energy-delivery system. The figure below shows the scale of total energy production(TEPRB) and total energy consumption(TETCB). New Mexico is the only state which has much more energy production than consumption, since it has affluent energy storage with small population to consume energy. We think New Mexico can offer some renewable energy production to other states which are relied on imported energy, like Arizona and California. In 2007, New Mexico had already created a Renewable Energy Transmission Authority (RETA) to encourage the development of the state's renewable energy resources by helping to connect renewable projects to the electric grid. Thus, if interstate energy transmission is possible, governments should work together to push such plan forward more quickly. This action can not only boost

the amount of renewable energy to receivers, but the producers, motivating them to exploit more renewable resources.

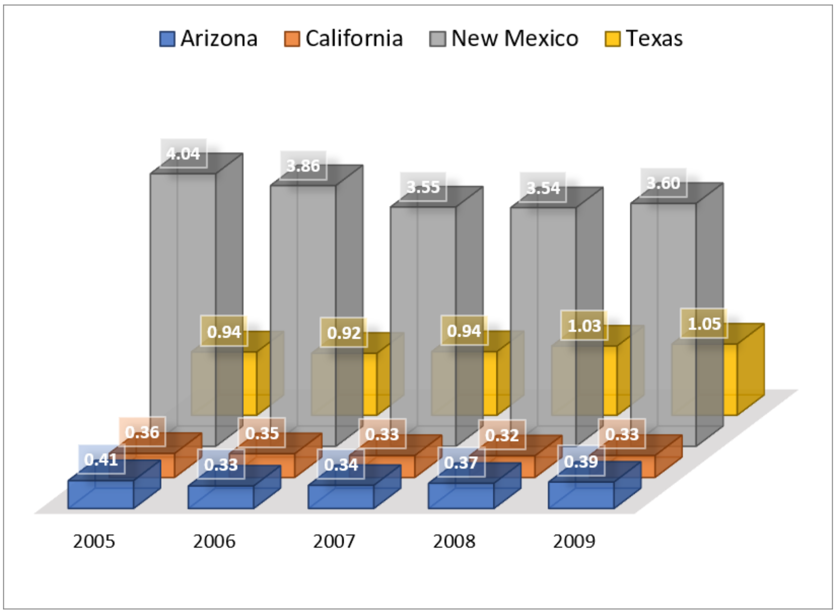


Figure24. TEPRB/TETCB of the four states (last 5 years)

4. Cut down on the dependence on fossil fuels. When people use less of non-renewable energy, then they will automatically come to use more renewable energy. Most of the states have very rich fossil fuels resources (except Arizona) and are badly depended on fossil fuels energy, so this action is rather direct and effective.

8 Strengths and weaknesses

8.1 Strengths

- Select data with different dimensions. Before devising our model, we extracted our data from different time period, sectors, kinds of energy forms. For each state, we managed to form a complete and solid view individually.

- Construct criteria comprehensively. We have considered two sides of the state energy service condition when giving an energy profile. We are not limited to the characteristics of renewable resources.

- Quantitatively predict the use of renewable energy for each state from 2009 to 2050. We use our model to compute all data for each year rather only for two discrete years (2025 and 2050). This adds credibility to our final results.

- Synthesize methods in creating the model. We have adopted different data analysis methods in different stage of our modeling. We build our model from basic definitions with continuous steps. Two parts of evaluation and prediction are correlated with each other.

8.2 Weaknesses

- We have not considered the possible technology revolution in the future when building our model. This factor could lead to a more quick growth on renewable energy usage.
- We have not taken the effect of financial crisis from 2009 and forwards into account. This severe crisis influenced almost all energy sectors with distinct sliding downward for a couple of years.
- We have not included the possible effect caused by nuclear power. As a form of clean energy, it has developed over the years and has provided more power with wider influence.

9 MEMORANDUM

TO: Governors of Four States
FROM: Team #87042
DATE: February 12, 2018
SUBJECT: Energy Profile of 2009, Predictions and Goals for Future

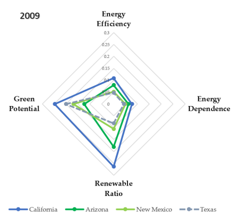
The four states along U.S. border with Mexico- California, Arizona, New Mexico and Texas, will form a realistic new energy compact. Our team's goal is to provide some suggestions on this compact.
Our team applied our model to produce the energy profile for each state of 2009. In our model, we create four indices (EEI, EDI, RRI, GPI) to give a relatively complete overview of each state.
Definition of the indices:
EEI - Energy Efficiency Index
EDI - Energy Dependency Index (the lower, the better)
RRI - Renewable Ratio Index
GPI - Green Potential Index
ESEI - a weighted optimal scores in terms of four indices above

	$C1(EEI)$	$C2(EDI)$	$C3(RRI)$	$C4(GPI)$	$ESEI$	$Rank$
$California$	0.216963	5.55661	0.106936	0.285593	1	1
$Arizona$	0.158740	6.90255	0.073179	0.142923	0.409371	2
$New\ Mexico$	0.103048	8.67649	0.042613	0.195378	0.2159	4
$Texas$	0.094397	10.09536	0.033137	0.231457	0.276332	3

In 2009, California has the best profile for the use of renewable energy with rank 1 in all indices.
Our prediction model shows the ESEI for the four states as below:

$Year$	$California$	$Arizona$	$New\ Mexico$	$Texas$
2025	0.6168 (1)	0.3859 (3)	0.4037 (2)	0.1211 (4)
2050	0.4780 (2)	0.2688 (4)	0.5881 (1)	0.3565 (3)

*rank is labelled beside ESEI value
Our recommended goals for the energy compact to adopt:
1. By 2025, California should at least have 16.5% renewable energy in total energy and 72500 GWh electric Power by renewable energy; Arizona should at least have the amount of 14.3% and 12000 GWh; New Mexico should at least have the amount 19.1% and 7000 GWh; Texas should at least have the amount of 21.5% and 81000 GWh.
2. By 2050, California should at least have 24.2% renewable energy in total energy and 81500 GWh electric Power by renewable energy; Arizona should at least have the amount 17.1% and 12500 GWh; New Mexico should at least have the amount 33.9% and 7000 GWh; Texas should at least have the amount of 32.5% and 101000 GWh.
Attachments: Energy Sustainable Expectation Radar Map of 2009



10 References

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Appendices

Linear Regression (Robust) Prediction:

```
function [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% [trainedModel, validationRMSE] = trainRegressionModel(trainingData)
% returns a trained regression model and its RMSE. This code recreates the
% model trained in Regression Learner app. Use the generated code to
% automate training the same model with new data, or to learn how to
% programmatically train models.
%
%  Input:
%      trainingData: a table containing the same predictor and response
%       columns as imported into the app.
%
%  Output:
%      trainedModel: a struct containing the trained regression model. The
%       struct contains various fields with information about the trained
%       model.
%
%      trainedModel.predictFcn: a function to make predictions on new data.
%
%      validationRMSE: a double containing the RMSE. In the app, the
%       History list displays the RMSE for each model.


% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'year', 'RenewElectricityTotal'};
predictors = inputTable(:, predictorNames);
response = inputTable.X3;
isCategoricalPredictor = [false, false];

% Train a regression model
% This code specifies all the model options and trains the model.
concatenatedPredictorsAndResponse = predictors;
concatenatedPredictorsAndResponse.X3 = response;
linearModel = stepwiselm(...
    concatenatedPredictorsAndResponse, ...
    'linear', ...
    'Upper', 'interactions', ...
    'NSteps', 1000, ...
    'Verbose', 0);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
linearModelPredictFcn = @(x) predict(linearModel, x);
trainedModel.predictFcn = @(x) linearModelPredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedModel.RequiredVariables = {'year', 'RenewElectricityTotal'};
trainedModel.LinearModel = linearModel;

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
```

```
inputTable = trainingData;
predictorNames = {'year', 'RenewElectricityTotal'};
predictors = inputTable(:, predictorNames);
response = inputTable.X3;
isCategoricalPredictor = [false, false];

% Perform cross-validation
KFolds = 5;
cvp = cvpartition(size(response, 1), 'KFold', KFolds);
% Initialize the predictions to the proper sizes
validationPredictions = response;
for fold = 1:KFolds
    trainingPredictors = predictors(cvp.training(fold), :);
    trainingResponse = response(cvp.training(fold), :);
    foldIsCategoricalPredictor = isCategoricalPredictor;

    % Train a regression model
    % This code specifies all the model options and trains the model.
    concatenatedPredictorsAndResponse = trainingPredictors;
    concatenatedPredictorsAndResponse.X3 = trainingResponse;
    linearModel = stepwiselm(...
        concatenatedPredictorsAndResponse, ...
        'linear', ...
        'Upper', 'interactions', ...
        'NSteps', 1000, ...
        'Verbose', 0);

    % Create the result struct with predict function
    linearModelPredictFcn = @(x) predict(linearModel, x);
    validationPredictFcn = @(x) linearModelPredictFcn(x);

    % Add additional fields to the result struct

    % Compute validation predictions
    validationPredictors = predictors(cvp.test(fold), :);
    foldPredictions = validationPredictFcn(validationPredictors);

    % Store predictions in the original order
    validationPredictions(cvp.test(fold), :) = foldPredictions;
end

% Compute validation RMSE
isNotMissing = ~isnan(validationPredictions) & ~isnan(response);
validationRMSE = sqrt(nansum(( validationPredictions - response ).^2) / numel(response(isNotMis
```

Year	California	Arizona	New Mexico	Texas
2010	0.7405	0.3600	0.3004	0.0138
2011	0.7540	0.3460	0.2848	0.0020
2012	0.7501	0.3773	0.2985	0.0000
2013	0.7652	0.3815	0.2838	0.0000
2014	0.7707	0.3760	0.2819	0.0000
2015	0.7697	0.4014	0.2941	0.0000
2016	0.7824	0.3925	0.2805	0.0000
2017	0.7743	0.4524	0.2930	0.0000
2018	0.7615	0.4637	0.3072	0.0000
2019	0.7470	0.4681	0.3165	0.0000
2020	0.7454	0.4503	0.3027	0.0000
2021	0.7217	0.4306	0.3208	0.0189
2022	0.7043	0.4078	0.3305	0.0406
2023	0.6581	0.4398	0.3720	0.0703
2024	0.6334	0.4014	0.3911	0.0971
2025	0.6168	0.3859	0.4037	0.1211
2026	0.6016	0.3693	0.4184	0.1447
2027	0.5928	0.3513	0.4306	0.1747
2028	0.5637	0.3603	0.4595	0.2038
2029	0.5501	0.3512	0.4746	0.2395
2030	0.5441	0.3366	0.4894	0.2885
2031	0.5277	0.3327	0.4976	0.2834
2032	0.5285	0.3214	0.5126	0.3176
2033	0.5187	0.3191	0.5178	0.3108
2034	0.5156	0.3005	0.5424	0.3478
2035	0.4661	0.2713	0.5853	0.3693
2036	0.5173	0.3132	0.5259	0.3212
2037	0.4999	0.3074	0.5351	0.3378
2038	0.4997	0.3023	0.5452	0.3421
2039	0.4985	0.2948	0.5553	0.3632
2040	0.4947	0.2934	0.5568	0.3586
2041	0.4880	0.2902	0.5610	0.3626
2042	0.4835	0.2885	0.5630	0.3589
2043	0.4898	0.2833	0.5700	0.3694
2044	0.5007	0.2809	0.5729	0.3694
2045	0.4923	0.2819	0.5713	0.3577
2046	0.4719	0.2754	0.5801	0.3713
2047	0.4904	0.2768	0.5778	0.3598
2048	0.4640	0.2695	0.5875	0.3674
2049	0.4810	0.2729	0.5825	0.3509
2050	0.4780	0.2688	0.5881	0.3565

Prediction of Energy Sustainable Expectation Index (ESEI) from 2010 to 2050