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Problem Chosen

C

2018
MCM/ICM
Summary Sheet
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Energy production and consumption are always a significant problem in the society. With rapidly increasing pollution, people are actively seeking for a more environment-friendly way to produce and consume energy. Green energy, energy that is replenished by nature, has caught more and more attention. Numerous countries and states emphasized the development of green energy, which led to an unprecedented increase in green energy production and consumption. While governments spend millions of dollars supporting the industry every year, precisely predicting future production and consumption could avoid unnecessary waste of money, and provide a clear goal for governments. In this paper, we propose a Grey Prediction with rolling mechanism model (GPRM) with error cancelling to predict future consumption of both fossil energy and green energy. We also use factor analysis to determine the inner correlation between statistical data, and suggest several actions governments could take to produce more green energy.

To begin with, we processed all past data by data screening and data deleting. First, we normalize all data into the same unit, billion BTU, which eliminates upwards of 75% variables that repeats itself in different units. Also, we only focus on the energy consumption rather than electricity consumption or any other unrelated measures. As a result, we select 14 significant variables out of 605. we then generate individual energy consumption profile for the four states out of filtered data.

Second, we use Factor Analysis to figure out the inner correlation between significant variables. Though the four-dimension correlation we found cannot be visualized, it still provides insights of how variables are related and prominently helps decision making. For further prediction, we divide the 14 variables into the sectors, which consume energy, and the sources, which generate energy.

Grey Prediction with Rolling Mechanism model is then applied, which forecasts future status of the system satisfactorily. We use one degree grey model with one variable (GM(1, 1)) with rolling mechanism to predict future data. We select a different rolling size for each state, and use a modified error cancelling technique from Fourier Residual Modification. We ensure the prediction accuracy is generally above 95%.

Finally, we choose Arizona as the best state, using criteria adapted from the Organization for Economic Co-operation and Development (OECD). Based on our prediction, clear goals for each state, in the format of how much green energy consumption it should meet, are raised. We last propose several insightful actions governments may take to improve the state's green energy conditions, such as more investments in R&D and electric vehicles.

Problem C

February 12, 2018

Contents

1 Introduction

Energy is the backbone of modern economies. Every sector relies on it, not only to keep their lights on but for transportation as well. Energy policy has been an important issue; but one fraught with politics. The recent push has been towards renewable energy, such as wind, solar, and hydroelectric. This push has been led by both environmentalists fighting climate change and nationalists pushing for energy independence. The American Southwest features a wealth of energy resources. There are substantial fossil fuel reserves, including crude oil (particularly in Texas) and natural gas. The Southwest also features the majority of the United States's uranium production. There are also sparsely populated regions that receive large amounts of sunlight, and are suitable for large-scale solar production. There are also substantial amounts of available wind capacity. However, the scarce amount of water negatively impacts the availability of hydroelectric generation, while facilities such as the Hoover Dam exist, they are the exception rather than the rule.

The Southwest, particularly California, also has a history of energy activism. Efforts such as solar incentives and legislative mandates on renewable generation have aimed to promote renewable energy.

In order to increase usage of cleaner, renewable energy sources by forming a realistic new energy compact, the four states - California(CA), Arizona(AZ), New Mexico(NM), and Texas(TX) - need to understand the information about the assumptions of energy during the past 50 years, make appropriate predictions about that in 2025 and 2050, and realize the actions they should take to fulfill goals. This paper, and accompanying material, provides that analysis.

2 Assumptions & Simplifications

1. The given data is accurate for the past 15 years, and that time is representative of current trends.

2. The use of petroleum for non-generating purposes is unimportant for this analysis.

3. Nuclear serves as a clean energy source.

The amount of variables was reduced from 605 to 14. This was done through several techniques. Firstly, it was decided to normalise all data to use the same unit, billion BTU. This simplified analysis by removing unit conversions, and also eliminated upwards of 75% of the given variables.[1] As well, it was decided to focus solely on energy consumption, rather than electricity consumption or any other measure. This was done as it is the most general measure, electricity is a strict subset, and the major difference between them, the energy used to power motor vehicles and other transportation, which could also benefit from clean energy sources.

[1]A large portion of the variables are redundant, carrying different units, the variables ending with 'B' indicate the unit of measure was billions of BTU.

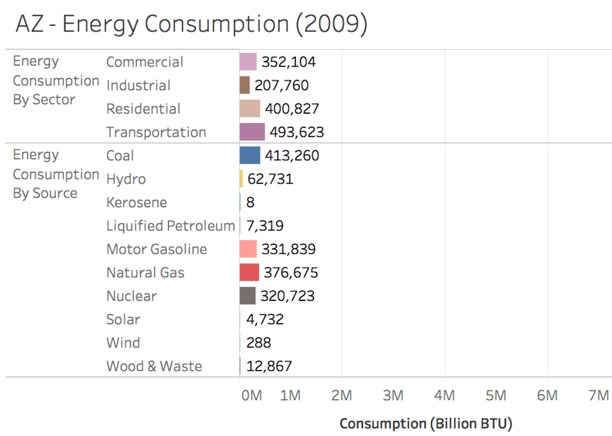
Next, it was decided to focus on two areas: the sectors which were consuming the energy, and the sources which the energy was coming from. Understanding where the energy is being used allows for targeted efforts to reduce consumption, i.e. by encouraging households to use more energy-efficient appliances if residential usage is high. The energy sources are crucial to understanding how clean a state's energy use is. The OECD[9] finds the fractional of energy produced by renewables to be a key factor in determining this, and the one most easily calculated from the available data. The selected energy sources were chosen largely on a basis of importance. Natural gas and motor gasoline are both massive sources of energy, and while most other sources are less important, almost all others are either a significant portion, or (in cases such as solar) important renewable sources. Wood & Waste is included as a significant biofuel, while kerosene is largely included for historical purposes.

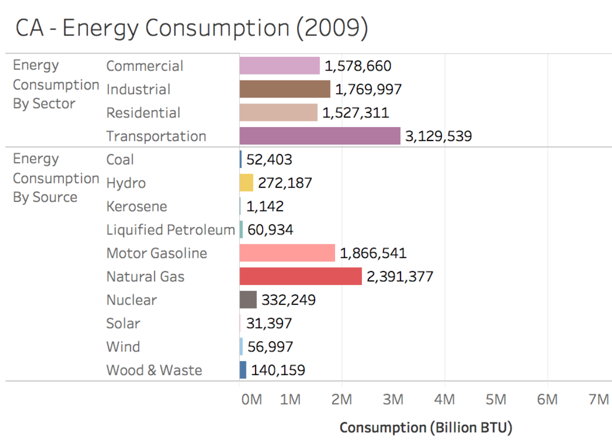
For ease of analysis, two modifications were made. The resulting data was normalised by population[2]. This was done to better understand and model the energy profile rather than population growth, which is not the purpose of this model. Next, it was simplified to model just two variables, the total fossil fuel consumption and total clean energy consumption. Each was created by taking the sum of their respective energy types, fossil fuel was taken from coal, kerosene, liquified petroleum gas, motor gasoline, and natural gas, while clean energy was taken from hydro, nuclear, solar, wood & waste, and wind.

Only the past 15 years of data was used for modeling green energy consumption. This was done to allow the model to cope with the rapid growth in clean energy in recent years without resorting to heavy exponential methods to deal with the previously near-zero generation of clean power.

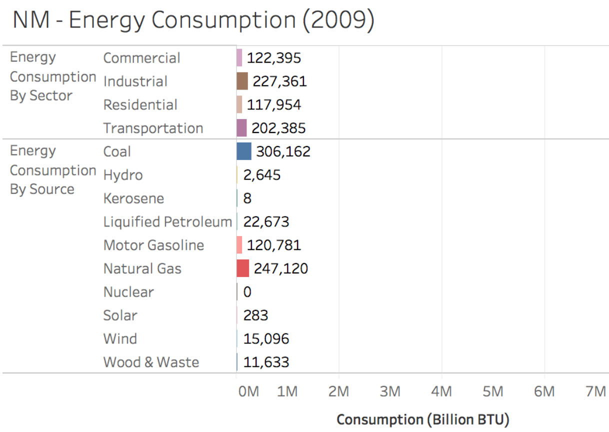
3 Energy Profiles

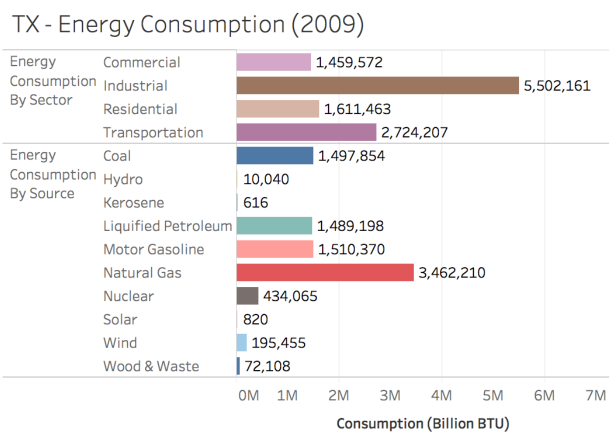
The energy profiles of each of the states for the year 2009 were created.





[2]Population data from [8]





These energy profiles show many of the characteristics of each state. Texas fulfills its reputation as a land of oil with its large consumption of Liquified Petroleum, outstripping every state in that regard. California also uses large amounts of energy on transportation and motor gasoline, understandable given its breadth and famously busy motorways such as those surrounding Los Angeles.

4 Factor Analysis

4.1 Definition

Factor Analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. It allows investigation of the energy consumptions that are not easily measured directly by collapsing 14 variables into a few interpretable underlying factors. The key concept of factor analysis is that multiple observed variables have similar patterns of responses because they are all associated with a latent variable. In order to investigate if observable variables $(X_1, X_2, ...X_N)$ are linearly related to a small number of unobservable factors $F_1, F_2...F_K$ with $K < N$. The variables from X_1 to X_N are expressed as linear combinations of F_1 to F_K. The coefficients of all those unobserved factors are what we defined as factor loadings. Rotation serves to make the output more understandable by seeking a pattern of loadings where items load most strongly on one factor and much more weakly on the factors.

4.2 Application

Factor analysis was conducted using the R statistical software and the "psych" and "nFactors" packages. The Cattle scree plot was used to determine that 4 factors should be extracted. "varimax" rotation, which is an orthogonal rotation of the factor axes to maximize the variance of the squared loadings of a factor, was used to differentiate the

Variable	F_1	F_2	F_3	F_4
TEACB	-0.311	0.419	0.753	0.113
TECCB	0.272	0.106	0.889	-0.266
TEICB	-0.218	0.953	0.029	0.168
TERCB	0.347	0.601	0.510	-0.172
CLTCB	0.071	-0.047	0.801	-0.094
HYTCB	0.153	-0.540	-0.232	-0.216
KSTCB	-0.247	0.308	0.204	0.674
LGTCB	-0.077	0.962	0.092	-0.169
MGTCB	-0.132	0.362	0.748	0.226
NGTCB	-0.360	0.775	0.061	0.486
NUETB	0.993	-0.045	0.008	-0.073
SOTCB	0.630	-0.324	-0.032	-0.058
WWTCB	-0.292	0.059	-0.257	-0.036
WYTCB	-0.049	0.022	0.106	-0.309

Table 1: Factor loadings.

original variables by extracted factor, aiding interpretation.

The table clearly shows the variable with the strongest association to the underlying latent variable. For example, factor 1, is NUETB, with a factor loading of 0.99372282. Since factor loadings can be interred like standardized regression coefficients, one could also say that the variable NUETB has a correlation of 0.99372282 with factor 1. This would be considered a strong analysis for a factor analysis. Given this, the natural progression of factor analysis would involve grouping the variables based on their positions on the respective factor axes and identifying the characteristics that define each factor.

4.3 Limitations

Unfortunately, having physical meanings behind the factors is not necessarily possible. In this case, there is no such mapping. Rather, they are grouped into “Sector Energy Consumption” and “Source Energy Consumption” in the energy profile, based on physical differences (one is measuring where the energy goes, the other is measuring where it comes from).

5 Model

Grey Prediction with Rolling Mechanism (GPRM) was used to model the consumption of both green energy and traditional fossil fuel. Grey Prediction model, developed by Deng[1], is widely used to forecast energy consumption. Due to its simplicity and strong ability to characterize a partially known system, Grey Prediction is among the most popular models in time-series prediction. Rolling Mechanism is applied on the model. It is an efficient technique to increase the prediction accuracy, minimizing errors from chaotic data set.

5.1 Reasons for Selection

Accurately forecast energy consumption simply from past data is never easy, especially when the influencing factors (policies, labor, economy performance, &c.) remain unknown, or outside the scope of analysis. The growth of green energy consumption was not linear or even monotonic. Numerous factors, such as economic trends and climate, greatly affected the data. In some state, political reasons may be the main factor. The energy consumption is relevant to so many variables, and it is impossible to precisely predict with a causal model like logistic or regression. However, as mentioned in Wang[2], Grey Prediction model works well in a system with unknown variables. Given only past data, the model could forecast future status of the system satisfactorily.

5.2 Grey Prediction Model

The GPRM Model used is based on one degree Grey Model with one variable, $GM(1,1)$. First raised by Deng in 1982, $GM(1,1)$ is the most frequently used model of such kind. It works as following:

1. The previous data is written as:
$$X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), ...x^{(0)}(n)\} \quad (1)$$
2. Accumulated Generating Operation (AGO) is applied to $X^{(1)}$ to form $X^{(1)}$.
$$X^{(0)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, ...n \quad (2)$$
Note that $x^{(0)}(k) = x^{(1)}(k) - x^{(1)}(k-1)$.
3. The Grey differential equations are established as:
$$\begin{gathered} x^{(0)}(k) + az^{(1)}(k) = b, k = 2, ...n \\ z^{(1)} = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k-1) \end{gathered} \quad (3)$$
a represents the development coefficient, while b represents the driving coefficient. α indicates the degree to which the data depends on the immediately previous value. α was set to 0.8 for this model, because a state's green energy production highly depends on current policy and economic status in the state, and therefore depends more on data from the most recent year.
4. a and b are estimated using ordinary Least Squares:
$$\begin{gathered} [a, b]^T = (B^T B)^{-1} B^T Y_N \\ B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \\ Y_N = [x^{(0)}(2), x^{(0)}(3), ...x^{(0)}(n)]^T \end{gathered} \quad (4)$$
5. Set up the Grey Reflection Equation:
$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (5)$$
6. Solving it results in:
$$\hat{x}^{(1)}(k+1) = [x^{(0)}(1) - \frac{b}{a}]e^{-ak} + \frac{b}{a} \quad (6)$$
7. Solve for the original variable, yielding:
$$\hat{x}^{(0)}(k+1) = (1-e^{a})(x^{(0)}(1) - \frac{b}{a})e^{-ak}, k = 1, 2, ... \quad (7)$$

5.3 Rolling Mechanism

In $GM(1,1)$, all past data is used to predict data at time $(k+1)$. Though it may be accurate, solely $GM(1,1)$ is not sufficient in this case. To forecast future for green energy consumption, which changes quickly and increased explosively during the past few decades, it doesn't make much sense to include data 50 years ago, when most states hadn't started pushing green energy. As proved by Kumar and Jain[3], adding a rolling mechanism to Grey Model is useful to predict rapidly changing system. Instead of using the whole set of past data, only a subset of past years are used. For example, to predict energy consumption at year k, data from year $k-a$ to $k-1$ is used, with $a<8$. Year k is then used to predict year $k+1$, so the window is then year $k–a+1$ to k. By applying the rolling mechanism, the model is more accurate and reliable in long term prediction.

5.4 Error Cancelling

Though GPRM works well in most cases, the forecasting error may still be a problem when working with rapidly fluctuating data. To further reduce the error, the result is modified with a technique called Fourier Residual Modification (FRM). Used by Ying and Zakaria[4], the modification reduced error in their prediction of Malaysia market performance. The modification proved useful in this model. The idea of FRM is simple, and can be expressed by the following equations:

$$\epsilon^{(0)}(k) \approx \frac{1}{2}a_0 + \sum_{i=1}^{z}[a_i cos(k\frac{2\pi i}{T}) + b_i sin(k\frac{2\pi i}{T})] \quad k=2,3,...n, T=n-1 \quad z=\frac{n-1}{2}-1 \tag{8}$$

The error is expressed by $\epsilon^{(0)}(k)$, a and b are the same as above, and n is the amount of data points used.

Therefore, the estimated error can be subtracted, yielding

$$x_{Pf}^{(0)}(k) = x_p^{(0)}(k) - \epsilon_p^{(0)}(k), k=2,3,...n+1 \tag{9}$$

This increased the accuracy of the model.

5.5 Error Evaluation

To evaluate the accuracy of the model, it is given earlier years and asked to predict a later one (2009). The mean absolute percentage error (MAPE) is calculated with the equation

$$e(k+1) = abs(\frac{x^{(0)}(k+1) - \hat{x}^{(0)}(k+1)}{x^{(0)}(k+1)}) \tag{10}$$

The average of this value is calculated, and it remains low.

5.6 Applying the Model

Although the idea of green energy has been popular for decades, have not incentivised production until recently. In the expected future, countries and states will continue pushing the consumption of green energy. Therefore, the model uses only the past 15 years of data, assuming that the older data doesn't represent the current trend.

For Arizona, a data series of size 7 was chosen. The estimation error was 1.20% for fossil fuel energy consumption per capita, and 7.88% on green energy consumption per capita.

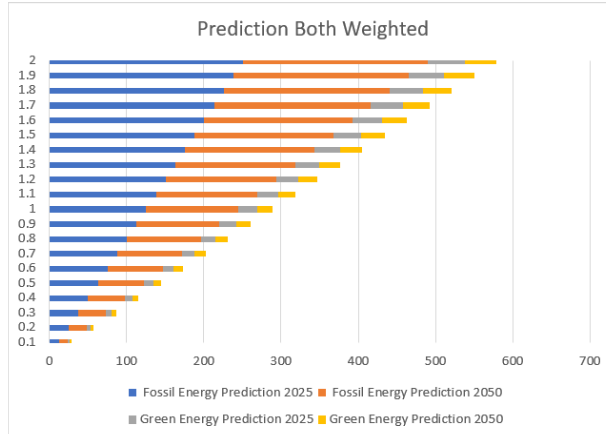
For California, a data series of size 7 was chosen. The estimation error was 1.36% for fossil fuel energy consumption per capita, and 1.54% on green energy consumption per capita. These errors show a high degree of accuracy.

For New Mexico, a data series of size 4 was chosen. The estimation error was 3.30% for fossil fuel energy consumption per capita, and 17.6% on green energy consumption per capita. The errors in green energy are due to New Mexico's low clean energy production, and their efforts only began in 2005, providing too few data points for accurate predictions.

For Texas, a data series of size 6 was chosen. The estimation error was 4.16% for fossil fuel energy consumption per capita, and 1.93% on green energy consumption per capita. These errors show a high degree of accuracy.

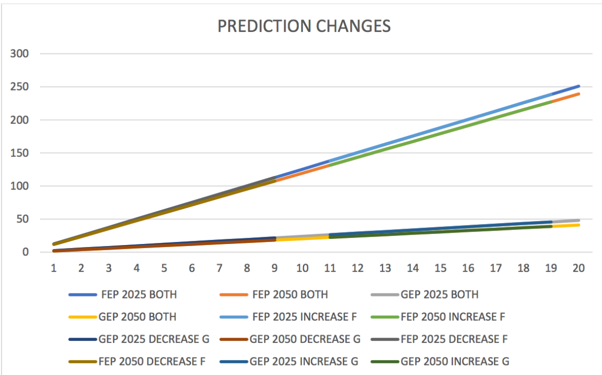
6 Sensitivity Analysis

If the input is changed, the model is still capable of predicting future data, with a linear error.

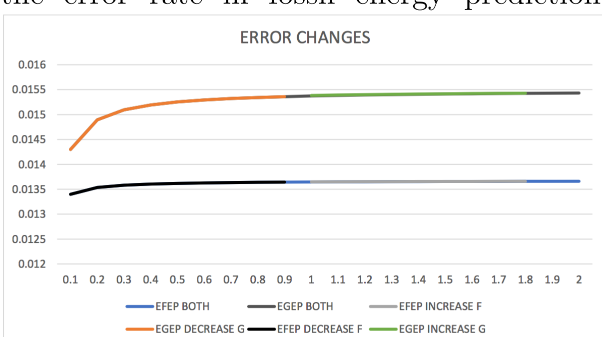


The first test conducted multiplied both Fossil Energy Consumption and Green Energy Consumption by a weight from 0.1 to 2. Though the numerical values of both consumption changed, the trend they show should not be altered. Therefore, the predictions of different weights should (and did) have a linear relationship, with 0.1 has the lowest prediction and 2 has the highest.

Next, the fossil energy consumption is increased (multiply it with 1.1, 1.2 … 1,9) and clean energy consumption is decreased (multiply it with 0.9, 0.8 … 0.1). The reverse is done as well. Even though there may be some correlation between fossil energy and green energy consumption in real world, the model treats them as two independent data groups. No matter how much one changes, it will not influence the other. This characteristic helps prevent unexpected data loss in one group. It is still possible to predict one without the other. The result of the test is shown below. Because the two data groups are independent, data (1.2 FEP, 1.2 GEP) and (1.2 FEP, 0.8 GEP) give the same prediction for fossil energy.

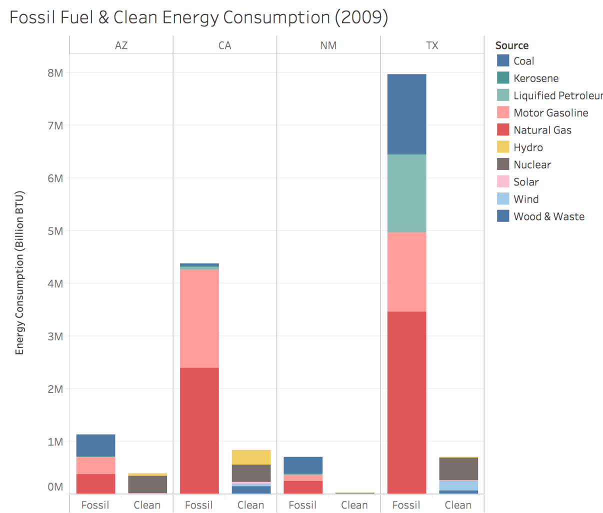


Error remains largely constant as well. For error in fossil energy prediction, it varies from about 1.34% to 1.37%; for error in green energy prediction, it varies from 1.43% to 1.55%. The error changes are negligible, it stays approximately the same. Additionally, since the two data groups are independent, data (1.2 FEP, 1.2 GEP) and (1.2 FEP, 0.8 GEP) give the error rate in fossil energy prediction.



The bilinear response to the input variables gives strong error resistance, minimising the amount that skew can affect it.

7 Best State



The evaluation of how clean a given energy profile is done on simple criteria, adapted from [9]. The majority of factors used are outside the scope of the model, such as energy awareness, strength of the clean energy economy, and research and development spending into green energy. However, it does include factors included in our model, most notably the total energy consumption and clean energy fraction. We use the clean energy fraction, defined as the sum of the clean (Wind, Hydro, Solar, Nuclear, and Wood & Waste) energy consumption divided by the total energy consumption.

By this metric, in 2009 Arizona is the best state, with renewable factor of 0.262, followed by California with 0.160, Texas with 0.082, and New Mexico with 0.041. Arizona's performance is largely due to nuclear power. While it consumes about as much nuclear power as California, and three quarters of that of Texas, the much smaller total energy consumption allows it to achieve a high clean energy fraction. California's large investments in green energy show, with it leading in solar production. It also has substantial nuclear and hydro power production. Texas features the most wind production, as well as nuclear production, but the massive fossil fuel consumption dwarfs that of renewables.

8 Consumption Forecasting

The model was used to predict the consumption of fossil fuels and clean energy for the years 2025 and 2050.

State	Type	2009	2025	2050
AZ	Fossil	178.00	180.45	176.79
	Clean	63.27	87.37	99.75
CA	Fossil	118.30	127.49	123.57
	Clean	22.54	33.06	37.89
NM	Fossil	342.08	386.17	386.22
	Clean	14.56	4.09	3.55
TX	Fossil	320.95	412.71	395.76
	Clean	28.73	49.78	149.96

Table 2: Projection of fossil fuel and clean energy consumption. Data is in Million BTU/capita.

The data shows a general increase in the consumption of renewable energy. Fossil fuel consumption increases by 2025 and then levels off slightly below that. New Mexico's clean energy breaks the strongly positive trend. It quickly falls off to near-zero. This shows limitations of the model; the small numbers and large fluctuations, combined with the negative slope near the end of the data analysed, confuse it.

9 Goals

The goals were determined by modelling a world with slightly higher values for clean energy and slightly lower values[3] for fossil fuel usage. This allows for a goal for modest improvements, as it simulates a world slightly better than the current one, and naturally allows for growth to be accounted for. Additionally, given the near-linearity of the model, goals can be specified directly, and then modelled accordingly.

State	Type	2009	2025	2050
AZ	Fossil	178.00	144.94	141.99
	Clean	63.27	102.10	116.3
CA	Fossil	118.30	102.61	99.45
	Clean	22.54	38.6	43.95
NM	Fossil	342.08	306.15	302.52
	Clean	14.56	2.91	0.46
TX	Fossil	320.95	330.16	316.57
	Clean	28.73	58.85	171.66

Table 3: Goals for Fossil Fuel and Clean Energy consumption. Data is in Million BTU/capita.

The achievability of these goals encourages adoption. Rather than ambitious goals which discourage participation when states

[3] In this case, a 20% increase and decrease, respectively.

inevitably fall behind, modest goals remain attainable despite setbacks, including economic downturn. In fact, the reduced overall energy consumption during economic downturns can help with achieving these goals, so long as states ensure that fossil fuels are the ones throttled down in times of lower demands.

10 Actions

Governmental actions taken in order to encourage the use of cleaner energy can be divided into two categories: those encouraging renewable resources and environmentalism and those discouraging fossil fuels. Encouraging renewables can have a more positive economic impact, limiting disruptions to businesses and consumers, but can be expensive to implement, while legislation targetting fossil fuels can be revenue generating.

10.1 Clean Energy Investments

A powerful method for encouraging clean energy production is using government funds, directly or indirectly, to develop it. This can manifest in several ways. A common one is tax incentives, where people such as homeowners are eligible for tax credits in exchange for taking some action such as installing solar panels at their home. This is a simple and effective method for guiding consumer action, although it can be expensive.

Alternatives include subsidies and tax incentives for large scale constructions, lower taxes for renewable projects can be offered, and development efforts into renewable energy can be made tax deductible. Additionally, when issuing contracts for new power development, states can require that a portion or all of the production comes from renewable sources.

10.2 Electric Cars & Public Transportation

Electric cars can also serve to increase renewable energy usage. While they do not do this by themselves, they encourage the use of electric energy, which can be renewable, rather than motor gasoline, which is guaranteed to not be. In states that suffer from particularly high motor gasoline usage, such as California, public transportation could be used as well. Public transport reduces the overhead occurred in passenger vehicles, and can also be electric-powered easily. Therefore, encouraging public transportation usage, by lowering fares and expanding service, can lower fossil fuel consumption as well.

10.3 Carbon Tax

An extremely powerful tool for discouraging fossil fuel consumption is by imposition of a carbon tax. This can be implemented at the original sources, or where it is generated, by simply measuring the amount of CO_2 or other greenhouse gas emitted, and then taxing based on that amount. This has the advantage that the rate can be carefully tuned to guide clean energy adoption, ensuring a clean transition.

It also produces market incentives in order to accomplish the goals. This allows for more efficient transitions, ensuring that companies help, rather than hinder, this transition.

10.4 Grid Unification

A possible difficulty in the process of the formation of this compact is that Texas has an electrical grid that is separate form the rest of the nation, and most importantly the other states in the compact. By integrating the electrical grids together, supply and demand can be better balanced across the states, and shortfalls caused by factors such as cloudy days can be dealt with by simply averaging the load across a greater amount of suppliers.

11 Strengths and Weaknesses

Strengths

- Achievable goals and approaches are set for each state.
- Factor Analysis indicates the inner correlation between variables.
- Small amount of data is needed to perform precise predictions, which fit well with the situation that green energy isn't emphasized until the recent 15 years.
- Manipulating data does not undermine the prediction model.
- More green energy will be produced and consumed under given suggestions.

Weaknesses

- The inaccuracy of input data is not considered.
- The correlation between green energy consumption and fossil energy consumption is not illustrated in Grey Prediction Model.
- Predictions for detailed green energy consumption are not stated in paper.

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Energy Consumption Goals and Actions
Memorandum

To: Governors in California(CA), Arizona(AZ), New Mexico(NM), and Texas(TX)
From: Team 84408
Date: 2/11/2018

I. Summary of the energy profiles for four states in 2009

Arizona, California, and Texas all have a diverse mix of energy resources. New Mexico, however, does not. The nuclear power consumed by Arizona allows it to top the list of clean states, but it (along with all of the other states) have massive room for expansion, particularly in solar power, given their vast potential. Texas lives up to its name, consuming the most oil by far; while California consumes large amounts of motor gasoline. California's investments in renewable energy also show, with substantial consumption of energy from hydroelectric power. Arizona also consumes large amounts of hydroelectric of power, but also relies on a large amount of coal. New Mexico uses almost entirely natural gas and coal, with little renewable production, despite large production potential.

II. Predictions for 2025 and 2050

We try two models to analyze data we have and want to use them to get the predictions for 2025 and 2050. We first use Factor Analysis to figure out the inner correlation between significant variables. Though the four-dimension correlation we found cannot be visualized, it still provides insights of how variables are related and prominently helps decision making, revealing that motor gasoline is directly correlated with energy used in transportation. We then divide the 14 variables into the sectors which were consuming the energy and the sources which the energy was coming from, based on physical differences. Our second and considerate model is the Grey Prediction with Rolling Mechanism, which could forecast future status of the system satisfactorily. Unlike the causal model like logistic and regression, our model could work well in a system with unknown variable. So by using the model, our predictions for 2025 and 2050 are that without further action, fossil fuel usage will increase in 2025 before leveling off slightly below 2025 levels. Green energy usage looks to continue to increase, except in New Mexico where the poor investment results in no growth.

III. Recommended actions

The governments could achieve these goals in different aspects. The first is to apply a host of potential financial tools, including:

A) Tax incentives that help improve the economics of either initial investment or operations in renewable technologies.

B) Contracts and other government funding specifically earmarked for work with renewables.

Next, the governments, particularly that of California, can take action to reduct the amount of fossil fuels and energy spent on transportation by encouraging electric cars and public transportation, perhaps by lowering rates and expanding access.

They can then impose a carbon tax to allow market forces to shape clean energy adoption.When implementing this, they must be mindful of Texas's disconnected electrical system, and work to unify it.