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Summary Sheet

Energy Outlook

Summary

In order to inform the four states' (California, Arizona, New Mexico and Texas) development of a set of goals for their interstate energy compact, we perform data analysis and build models to provide program. In this paper, we classify and combine the data provided in different four aspects: Price, Department ,Expenditure and Consumption and just choose related data of Consumption as sample for data analysis because it can reflect energy profile intuitively and clearly enough. Therefore, most analysis of this paper consider the consumption in the first place.

In the first part, we establish **Time Series Model** by Data Fitting and describe energy profile each of the four states. We choose Real GDP per capita(GDP_p), the proportion of renewable energy's consumption(PC_{re}), the proportion of fossil fuel's expenditure(PE_{ff}) as evaluation indexes to evaluate the four states' energy profile in 2009. What's more, we succeed in determining the weight of these three indexes by using **Topsis** method and nondimensionalizing the practical data. Then, calculate final weighting scores of the four states by summing the product of weight and nondimensionalized data($\sum weight*data$). We conclude that California appeared to have the "best" profile in 2009. We establish **Autoregression Model**(AR) and **BP-Neural Network** algorithm to predict energy profile of four states on 2025 and 2050. Result shows that the proportion of renewable energy's consumption(PC_{re}) can reach to at least 5% on 2025 and 8% on 2050 of these four states. Consumption of Fossil Fuel(C_{ff}) will decline slightly, consumption of nuclear fuel(C_{nf}) verges to be stable and consumption of renewable energy(C_{re}) increases constantly.

In the second part, we choose the proportion of renewable energy's consumption(PC_{re}) as "best" profile to evaluate the four states' energy profile. To realize evaluation, we establish **Regression Model** to work out the relational expression between PC_{re} and its impact factors. We find out that we can use linear regression model to simulate and its reliability can reach 80%. Additionally, we discuss three actions for four states to meet their energy compact based on Regression Model.

Keywords: Topsis; BP-Neural Network; Regressive Model

1 Introduction

With the development of the world economy and ecological environment, energy structure, production and use have huge influence on countries. On account of the different development degrees, geographic positions, business structures and other factors, different states have different energy profiles.

California, Arizona, New Mexico and Texas are the four states along the U.S border with Mexico. Because of the effects of various factors, their energy structure ,production and use have difference and similarities more or less. In order to optimize energy structure, these four states want to form their interstate energy compact. In this paper, we do data analysis and build model to provide throretical support for setting common goals between the four states.

According to the data provided, we extract four key words from the data: Price, Department, Expenditure and Consumption. On account of these four key words, we classify the data in four aspects and create energy profile for each of the four states. In consid-eration of the complexity of problem, we just consider the consumption of energy and ignore the other three key words and classify energy into three main kinds: fossil fuel, nuclear fuel, renewable energy. By data fitting, we establish time series model and get the difference and similarities of the four states according to partical matters.

We choose weighting score of three evaluation indexes as "best" profile. We choose Real GDP per capita(GDP_p), the proportion of renewable energy's consumption(PC_{re}), the proportion of fossil fuel's expenditure(PE_{ff}) as evaluation indexes. Then, to determine the ranks of the four states' three evaluation indexes, we choose Topsis method to calcu-late the weight of GDP_p , PC_{re} , PE_{ff} . Then, nondimensionalized pratical data of the four states and calculate the final weighting scores of the four states. We arrive at the conclusion that California appeared to have the "best" profiles in 2009 finally.

In order to predict the four states' energy profile on 2025 and 2050, we establish Autore-gressive Model(AR) and BP-Neural Network algorithm to realize prediction. By testing, if the order of AR model is 3 can reach the optimum prediction. That is, from 1960's data, use classified data of the following three years to predict the 4th year following. By parity of reasoning, it can realize prediction. Predicted results show that PC_{re} of CA reaches 6% and 21% in 2025 and 2050, PC_{re} of AZ reaches 6% and 13% in 2025 and 2050, PC_{re} of NM reaches 7% and 8% in 2025 and 2050, PC_{re} of TX reaches 2% and 3% in 2025 and 2050.

We establish Regression Model to set the goal for four states. To simply the problem, we set PC_{re} as goal which will be affected by GDP_p and PE_{ff} and find out the relational expression between GDP_p , PE_{ff} and GDP_p and PC_{re} . We determine linear regression model to express their relationship according to scatter diagrams and set different PC_{re} values which is suitable to each state as goals. Because the result produced ignore the policy change, we identify three actions for the four states to meet their energy compact goal.

2 Assumptions

- Ignore any policy changes in perdicting energy profile each of the four states.

- Policy have no effect on GDP_p and it can make PE_{ff} approach to a stable value.
- Ignore inter-effect between GDP_p and PE_{ff} .
- There is no worldwide economic or energy crisis from 2009 to 2050.
- Energy development have Markov property.

3 Notation

| Symbols | Definitions |
|-------------------|--|
| GDP_p | Real GDP per capita |
| PC_{re} | the proportion of renewable energy's consumption |
| PC_{nf} | the proportion of nuclear fuel's consumption |
| PC_{ff} | the proportion of fossil fuel's consumption |
| PE_{ff} | the proportion of fossil fuel's expenditure |
| A | set of the four states |
| C | set of three evaluation indexes |
| w_j | weight of indexes |
| Y | normalized matrix |
| V | weighted normalized matrix |
| V^+ | positive ideal solution |
| V^- | negative ideal solution |
| d_i^+ | Euclidean distance to positive ideal solution |
| d_i^- | Euclidean distance to negative ideal solution |
| $L^+(w, \lambda)$ | Lagrange function |
| lag | Autoregressive order |
| β | Regression Coefficient |
| γ | Confidence level |
| b | Estimated Value |
| $bint$ | Confidence Interval of b |
| r | Residual Vector |
| $rint$ | Confidence Interval of r |
| C_{ff} | Consumption of Fossil Fuel |
| C_{nf} | Consumption of Nuclear Fuel |
| C_{re} | Consumption of Renewable Energy |

Table 1: Notation

4 Model Implementation and Results

4.1 Energy Profile

Create energy profile for each state. First, we extract four key words from the data: Price, Department, Expenditure and Consumption according to the data provided. On account of these four key words, we classify and combine the data in four aspects as shown in Figure1 and Figure2.

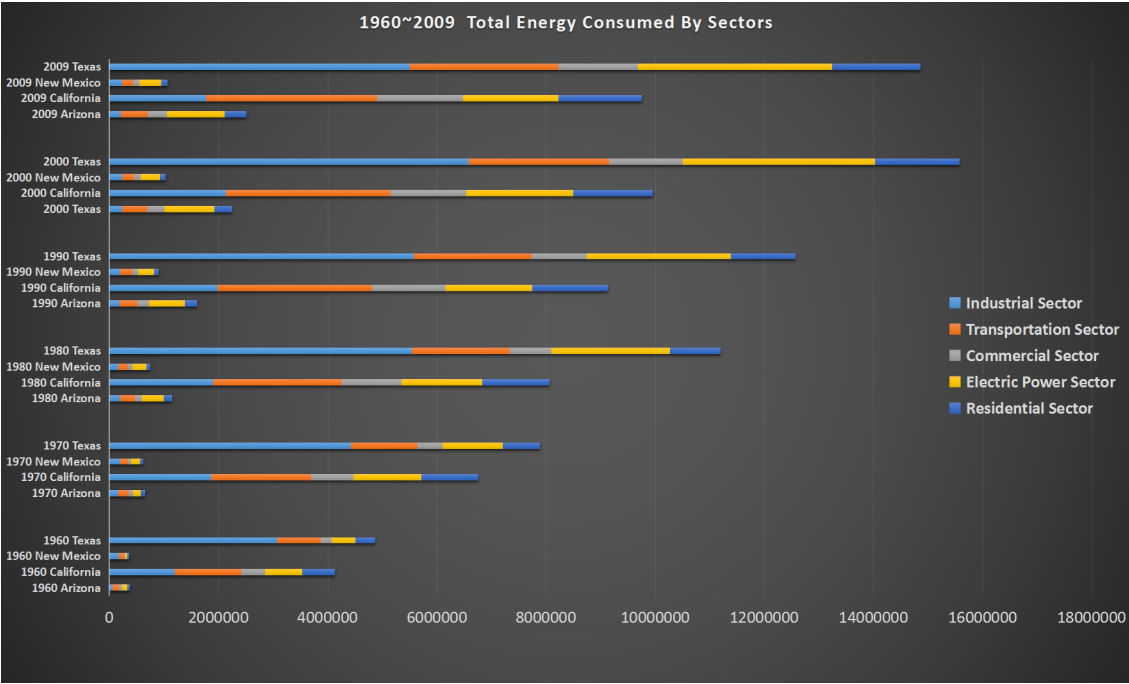
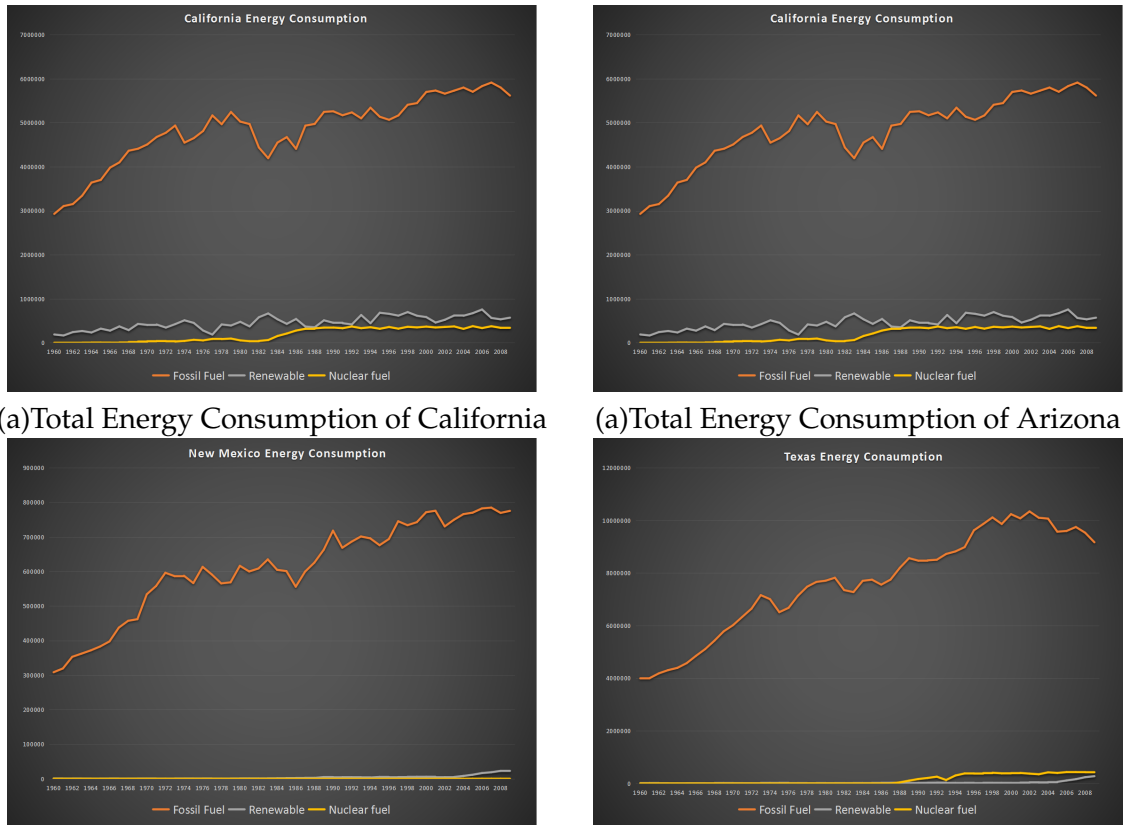


Figure 1: Total Energy Consumption by Sectors



(a)Total Energy Consumption of California

(a)Total Energy Consumption of Arizona

(a)Total Energy Consumption of New Mexico

(b)Total Energy Consumption of Texas

Figure 2: Total Energy Consumption by Fuel

4.2 Data Fitting and Time Series Model

Consumption can reflect energy profile intuitively and clearly so that we describe energy profile of the four states by describing the consumption of the four states rather than considering all four aspects we mentioned above. [1] Based on the result of problem A and Figure3,4,5,6, we establish time series model by data fitting and work out the gradient of each year by difference equation. Finally we arrive at the conclusion:

(1) California:

- C_{ff} : From 1960 to 2009, C_{ff} appear to have steady-state growth. While appearing to have declining trend in 1980s.
- C_{nf} : Before 1980s, California have not to use nuclear fuel, thus C_{nf} is zero. Since 1983, San Onofre nuclear power station have been come into service. C_{nf} begin to increase and verge to be stable.
- C_{re} : From 1960 to 2009, C_{re} appear to have slow-growth.

(2) Arizona:

- C_{ff} : From 1960 to 2009, C_{ff} appear to have steady-state growth. While appearing to have declining trend in 1980s.
- C_{nf} : Since mid of 1980s, nuclear fuel come into service and C_{nf} increase in a higher level. Because Arizona have the second largest nuclear power station in the U.S, its C_{nf} is higher than the other three states.
- C_{re} : From 1960 to 2009, C_{re} appear to have slow-growth.

(3) New Mexico:

- C_{ff} : From 1960 to 2009, C_{ff} appear to have steady-state growth . While appearing to have declining trend in 1980s.
- C_{nf} : Before 2009, New Mexico did not use nuclear fuel which make C_{nf} is zero.
- C_{re} : New Mexico's consumption of renewable energy approach to zero until 2005, it begin to increase slightly by 2009.

(4) Texas:

- C_{ff} : From 1960 to 2009, C_{ff} appear to have steady-state growth.
- C_{nf} : From 1960 to 2009, C_{nf} appear to have slow-growth.
- C_{re} : From 1960 to 2009, C_{re} appear to have slow-growth.

Because the first oil crisis in 1970s, price of oil rised by 4 times, C_{ff} appear to decline trend in 1970s.

4.3 Determine "Best" profile Based on Topsis

In order to determine which of the four states appeared to have the "best" profile for use of cleaner, renewable energy in 2009, we have to definite an resonable and sci-entific evaluation criterion. In consideration of multiaspects, we choose Real GDP per capita(GDP_p), the proportion of renewable energy's consumption(PC_{re}), the proportion of fossil fuel's expenditure(PE_{ff}) as evaluation indexes. The most important point of evaluation criterion is to set resonable weight for per evaluation index. We build a model based on Topsis to calculate the weights of the three evaluation indexes. Then, nondi-mensionalize the practical datas of evaluation indexes and calculate the final weighting scores of four states[2].

set $A = \{A_1, A_2, \dots, A_m\}$ represents the sets of four states, set $C = \{C_1, C_2, \dots, C_n\}$ represents the sets of three evaluation indexes. $X = (x_{ij})_{m \times n}$ represents the ranks of each state's evaluation indexes. w_j represents the weight of each evaluation index.

Step1, determine the normalized matrix $Y = (y_{ij})_{m \times n}$,

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^m (x_{ij})^2} (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (1)$$

Step2, determine weighted normalized matrix V.

$$V = (v_{ij})_{m \times n} = (w_j y_{ij})_{m \times n} \quad (2)$$

Step3, determine the positive and negative ideal solution of V matrix.

positive ideal solution:

$$(V)^+ = \{(v_1)^+, (v_2)^+, \dots, (v_n)^+\} = \{(w_1)^+(y_1)^+, (w_2)^+(y_2)^+, \dots, (w_n)^+(y_n)^+\} \quad (3)$$

negative ideal solution:

$$(V)^- = \{(v_1)^-, (v_2)^-, \dots, (v_n)^-\} = \{(w_1)^-(y_1)^-, (w_2)^-(y_2)^-, \dots, (w_n)^-(y_n)^-\} \quad (4)$$

Step4, determine four states' Euclidean distance to positive and negative ideal solu-tion.

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \\ &= \sqrt{\sum_{j=1}^n (y_{ij} - y_j^+)^2 (w_j^+)^2} \end{aligned} \quad (5)$$

$$\begin{aligned} d_i^- &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \\ &= \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2 (w_j^-)^2} \end{aligned} \quad (6)$$

Step5, build optimization model to calculate the weight $(w_j)^+$ and $(w_j)^-$.

$(w_j)^+$ solution:

$$\begin{aligned} \min F(1) &= \sum_{i=1}^m [(d_i)^+]^2 \\ \text{s.t. } &\sum_{j=1}^n (w_j)^+ = 1 \\ &\text{s.t. } (w_j)^+ \geq 0, j = 1, 2, \dots, n \end{aligned} \quad (7)$$

construct Lagrange function to calculate $(w_j)^+$:

$$L^+(w, \lambda) = \sum_{i=1}^m [(d_i)^+]^2 + \lambda^+ \left(\sum_{j=1}^n (w_j)^+ - 1 \right) \quad (8)$$

assume that, $\frac{\partial L^+}{\partial (w_j)^+} = 0, \frac{\partial L^+}{\partial \lambda} = 0$

$$(w_j)^+ = \left\{ \sum_{j=1}^n \frac{1}{\sum_{i=1}^m [y_{ij} - (y_j)^+]^2} * \sum_{j=1}^m [y_{ij} - (y_j)^+]^2 \right\}^{-1} \quad (9)$$

$(w_j)^-$ solution:

$$\begin{aligned} \max F(2) &= \sum_{i=1}^m [(d_i)^-]^2 \\ \text{s.t. } &\sum_{j=1}^n (w_j)^- = 1 \\ &\text{s.t. } (w_j)^- \geq 0, j = 1, 2, \dots, n \end{aligned} \quad (10)$$

Obviously, if $(w_j)^- = 1$, function F(2) has the maximum. we can get weight calculating formula as shown below:

$$w_j = \alpha (w_j)^+ + (1 - \alpha) (w_j)^- \quad (0 \leq \alpha \leq 1) \quad (11)$$

α represents the degree to approach the positive ideal solution. In this paper, we ignore the situation which the "best" solution keep away from the negative ideal solution. Thus, we can choose $\alpha = 1$.

we divide each evaluation index into five ranks:

According to the data supported and ranks, we conclude four states' ranks of three evaluation indexes as shown below.

On the basis of formulas above, selection matrix is:

$$\begin{bmatrix} 4 & 5 & 5 \\ 2 & 3 & 3 \\ 1 & 1 & 2 \\ 3 & 5 & 2 \end{bmatrix}$$

| GDP_p /dollars | Rank |
|------------------|------|
| 32500-37500 | 1 |
| 37500-42500 | 2 |
| 42500-47500 | 3 |
| 47500-52500 | 4 |
| 52500-57500 | 5 |

Table 2: Ranks of Real GDP per capita

| $PE_{ff}/\%$ | Rank |
|--------------|------|
| 12.5-14.5 | 1 |
| 14.5-16.5 | 2 |
| 16.5-18.5 | 3 |
| 18.5-20.5 | 4 |
| 20.5-22.5 | 5 |

Table 3: Ranks of the proportion of fossil fuel's consumption

| $PC_{re}/\%$ | Rank |
|--------------|------|
| 0-2 | 1 |
| 2-4 | 2 |
| 4-6 | 3 |
| 6-8 | 4 |
| 8-10 | 5 |

Table 4: Ranks of the proportion of renewable energy's consumption

| State | GDP_p | PE_{ff} | PC_{re} |
|-------|---------|-----------|-----------|
| CA | 4 | 5 | 5 |
| AZ | 2 | 3 | 3 |
| NM | 1 | 1 | 2 |
| TX | 3 | 5 | 2 |

Table 5: Four states' ranks of three evaluation indexes

normalized matrix is:

$$\begin{bmatrix} 0.133 & 0.083 & 0.119 \\ 0.067 & 0.050 & 0.071 \\ 0.033 & 0.017 & 0.048 \\ 0.010 & 0.083 & 0.048 \end{bmatrix}$$

positive ideal solution is: $Y^+ = \{0.133, 0.083, 0.119\}$

weights of three evaluation indexes is shown below:

| GDP_p | PE_{ff} | PC_{re} |
|---------|-----------|-----------|
| 0.20 | 0.56 | 0.24 |

Table 6: weights of three evaluation indexes

After getting the weights of three evaluation indexes w_j , we nondimensionalize the practical datas and of evaluation indexes each state and get the final score of four states in

accordance of formula.

nondimensionalized practical datas is:

| State | GDP_p | PE_{ff} | PC_{re} |
|-------|---------|-----------|-----------|
| CA | 0.296 | 0.292 | 0.450 |
| AZ | 0.223 | 0.231 | 0.250 |
| NM | 0.214 | 0.188 | 0.150 |
| TX | 0.267 | 0.290 | 0.150 |

Table 7: Four states' nondimensionalized practical datas

Therefore, we get the final weighting scores: CA(0.33)>TX(0.25)>AZ(0.23)>NM(0.18). California appeared to have the "best" profile for use of clearer, renewable energy in 2009.

4.4 BP-Neural Network and Autoregressive Model

What we try to solve in this part is mainly a prediction problem which can predict the four states's energy profile on 2025 and 2050. Consumption can reflect energy profile intuitively and clearly so that we predict energy profile of the four states in 2025 and 2050 by predicting the consumption of the four states rather than considering all four aspects we mentioned.

Energy profile is nonlinear. And the BP-Neural Network is also a nonlinear, dynamic system, which can realize the nonlinear map between different variates in different precision[3]. Typical BP-ANNs contain three layers: input layer, hidden layer and output layer. Each of them connect with the upper layer and next layer, just like the synapses connect the layers of neurons. In learning process, input data and output data supported will be sent into the system and it will learn to gain the reasonable results by training again and again. Then, the model can be used in new input data without output data. In addition, its well self-adaption ability, self-learning ability and generalization ability satisfy our requirement.

Autoregressive Model is a kind of prediction method with higher accuracy which can adapt different kinds of time series. We can use statistical approaches to validate the adaption of model, so as to adjust the order of model and get the most ideal results.

Based on the reasons mentioned above, we choose the BP-Neural Network and Autoregressive Model to realize the prediction of the four states' profile.

First, determine the autoregressive order (*lag*) of AR models. Energy profile can be affected not only by economy, population and other indexes, but also have the relationship to energy profile of the past few years. Energy profile is a time series problem. Thus, determine the order of AR model for BP-Neural Network is vital. We need to predict the 2025 and 2050 energy profile according to 1960-2009 period's data. Here, we choose *lag*=3.

Second, send consumption data into AR model and train by BP-Neural Network system. We divide each state's consumption into three parts: fossil fuel consumption, nuclear fuel consumption and renewable energy consumption. Send per part's data into

AR model to analyse. Among AR model, we use BP-Neural Network algorithm to realize prediction which have the less error on data. From 1960's consumption, use consumption of the following 3 years to predict the 4th year's consumption following and compare the predicted consumption with practical consumption to observe the disparity.

Third, predict 2025 and 2050's consumption by BP-Neural Network system. It regard three years consumption data past as input layer, then predict the next consumption data. By parity of reasoning, we get the prediction curve of fossil fuel consumption, renewable energy consumption and nuclear fuel consumption each state as shown below.

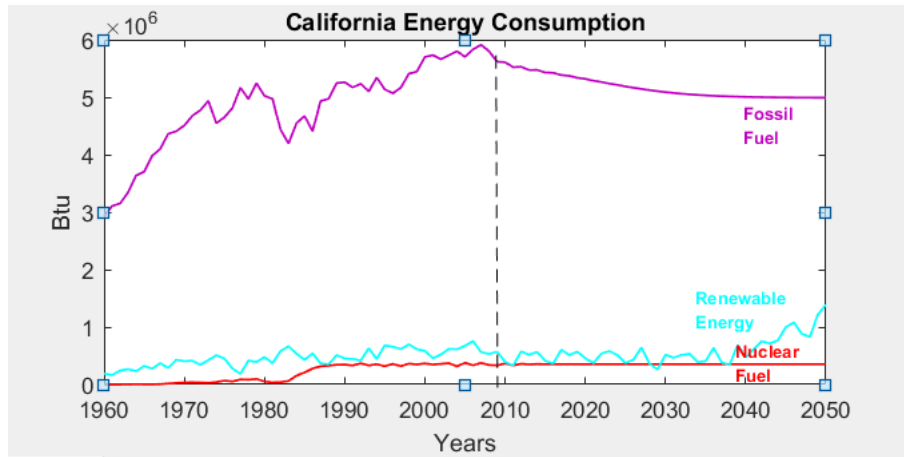


Figure 3: California Energy Consumption

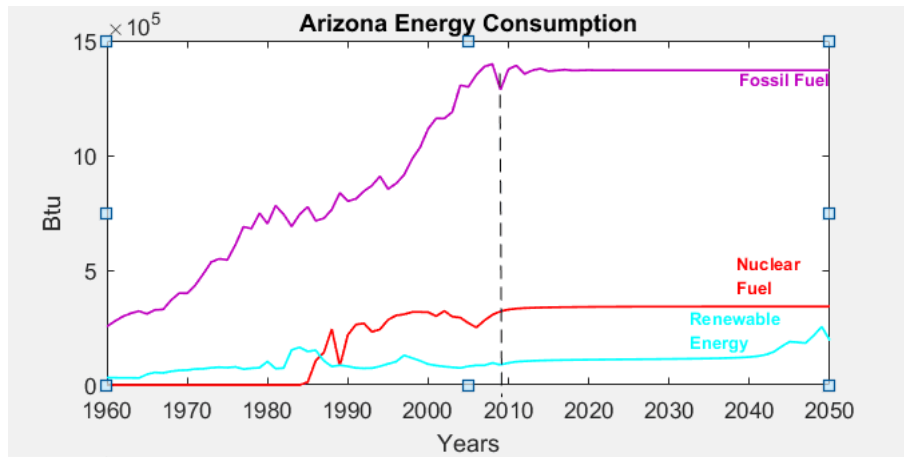


Figure 4: Arizona Energy Consumption

According to the prediction curve Figure3,4,5,6, we draw pic charts of consumption on 2025 and 2050 as shown in Figure7,8,9,10. From the pic charts, we conclude that:

- California: From 2009 to 2025, C_{nf} and C_{re} verge to be stable, and C_{ff} decline slightly. PC_{nf} reach to 6% and PC_{re} reach to 6%. From 2025 to 2050, C_{nf} verge

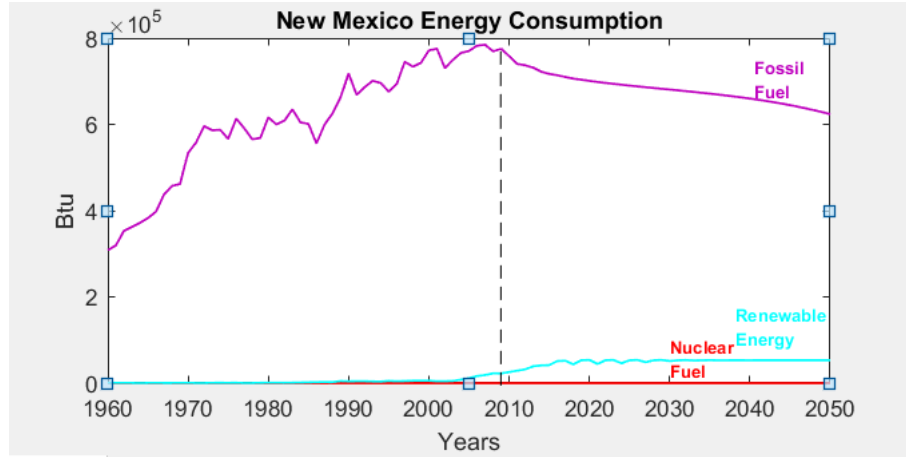


Figure 5: New Mexico Energy Consumption

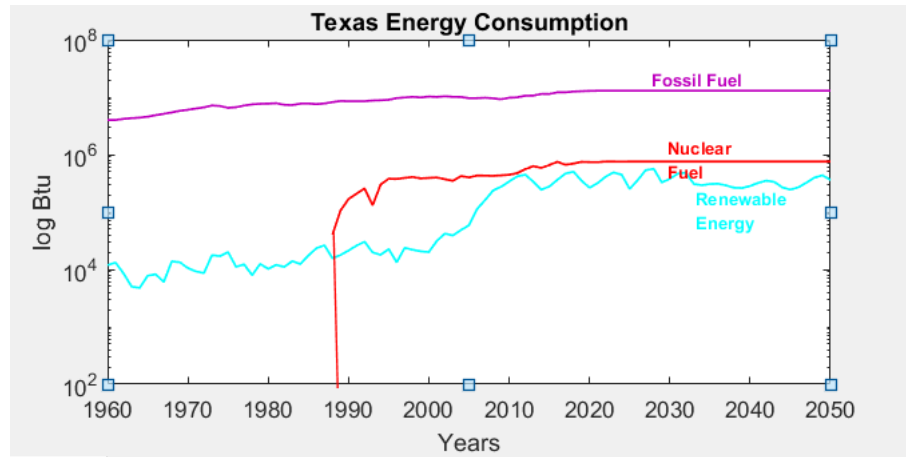


Figure 6: Texas Energy Consumption

to be stable, C_{re} increase slightly and C_{ff} decline slightly. PC_{nf} reach to 5% and PC_{re} reach to 21%.

- Arizona: From 2009 to 2025, C_{nf} , C_{re} and C_{ff} verge to be stable. PC_{nf} reach to 19% and PC_{re} reach to 6%. From 2025 to 2050, C_{nf} , C_{re} and C_{ff} verge to be stable. PC_{nf} reach to 17% and PC_{re} reach to 13%.
- New Mexico: From 2009 to 2025, C_{nf} verge to be stable, C_{re} increase slightly and C_{ff} decline slightly. PC_{re} reach to 7%. From 2025 to 2050, C_{nf} , C_{re} verge to be stable, C_{ff} decline. PC_{re} reach to 8%.
- Texas: From 2009 to 2025, C_{nf} , C_{re} and C_{ff} verge to be stable. PC_{nf} reach to 5% and PC_{re} reach to 2%. From 2025 to 2050, C_{nf} , C_{re} and C_{ff} verge to be stable. PC_{nf} reach to 5% and PC_{re} reach to 3%.

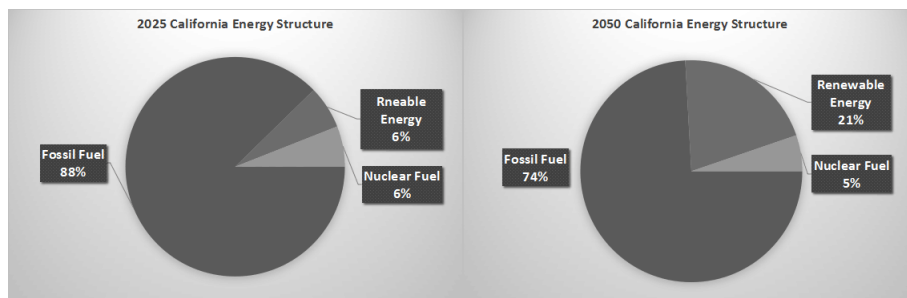


Figure 7: California Energy Structure in 2025 and 2050

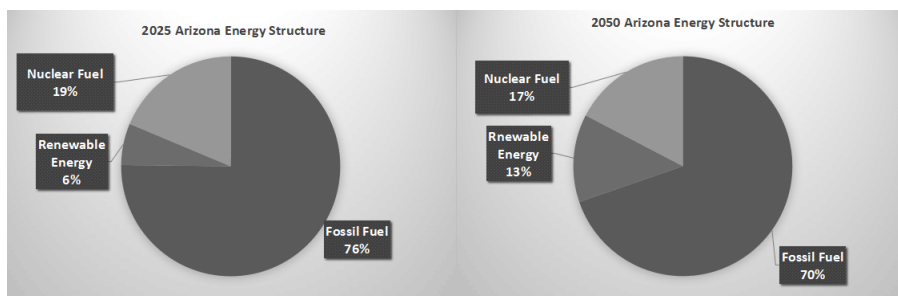


Figure 8: Arizona Energy Structure in 2025 and 2050

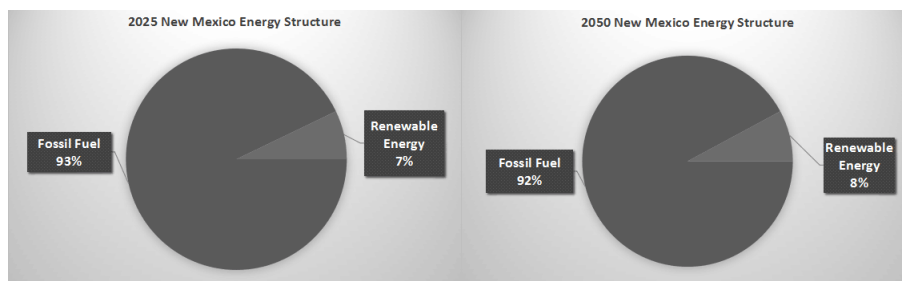


Figure 9: New Mexico Energy Structure in 2025 and 2050

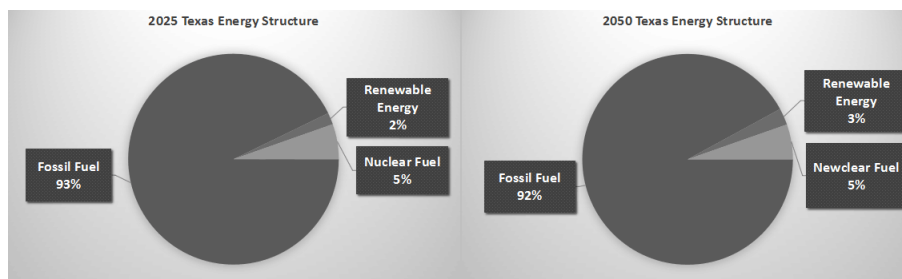


Figure 10: Texas Energy Structure in 2025 and 2050

4.5 Regression Model

Based on the Problem C, We choose the proportion of renewable energy's consumption (PC_{re}) as the goal factor (GF) and the left two evaluation indexes, Real GDP per capita (GDP_p), the proportion of fossil fuel's expenditure (PE_{ff}) as impact factors (IF). In order to get the relationship between the goal factor (GF) and two impact factors (IF), we establish Regression Model to find out their relational expression. We establish four models for CA, AZ, NM, TX and choose the model for TX as example in this paper.

Step1, we draw the scatter diagrams of PC_{re} with GDP_p and PE_{ff} to analyse their relational expression roughly. Then, observe the scatter diagrams and establish regression model.

β represents regression coefficient, γ represents confidence level, b represents estimated value of β , $bint$ represents confidence interval of b , r represents residual vector, $rint$ represents confidence interval of r . By observing the scatter diagrams, we choose

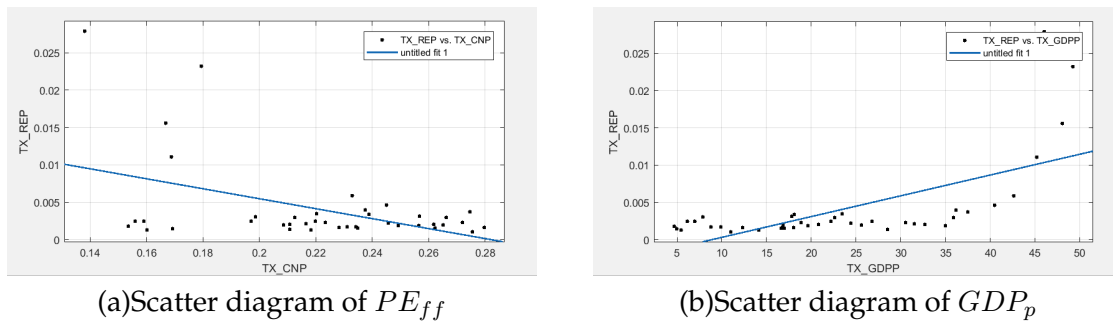


Figure 11: Scatter diagrams

linear model to match and get the expressions:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon. \quad (12)$$

Step2, calculate β by regress command in MATLAB.

| Paramant | Estimated Value | Confidence Interval |
|-----------|-----------------|---------------------|
| β_0 | 0.0122 | [0.0053,0.0192] |
| β_1 | 0.000278 | [0.000189,0.000367] |
| β_2 | -0.0665 | [-0.0960,-0.0369] |

Table 8: Result of Regression Model

$$R^2=0.8237, F=30.6602, P=1.4505 \times 10^{-8}, S^2=1.275 \times 10^{-5}$$

R^2 represents coefficient of determination, F represents statistic value, P represents probability value of F , S^2 represents residual variance.

Assume that policy have no effect on GDP_p and policy can make PE_{ff} approach to a stable value. Therefore, We need to regard PE_{ff} as a constant and GDP_p as a variate which have nothing to do with policy. Thus, we choose PE_{ff} of the four states on 2009 as the "best" PE_{ff} . According to the prediction of the U.S's official website, we get the prediction of GDP and population of the U.S on 2025 and 2050 which is shown below.

| GDP/million dollars | CA | AZ | NM | TX |
|---------------------|---------|--------|--------|---------|
| 2025 | 2506972 | 322448 | 95896 | 1566742 |
| 2050 | 3916011 | 467854 | 142608 | 2570407 |

Table 9: GDP of four states on 2025 and 2050

| Population/thousand | CA | AZ | NM | TX |
|---------------------|---------|--------|--------|---------|
| 2025 | 42573.5 | 7603.1 | 2316.7 | 28588.3 |
| 2050 | 49441.1 | 8829.6 | 2690.4 | 33220.6 |

Table 10: Population of four states on 2025 and 2050

| $PC_{re}/\%$ | CA | AZ | NM | TX |
|--------------|----|----|----|----|
| 2025 | 18 | 15 | 17 | 15 |
| 2050 | 24 | 19 | 22 | 21 |

Table 11: "Best" PC_{re} of four states on 2025 and 2050

We work out the four states' "best" profile by setting the PC_{re} in a certain value:

In order to achieve the "best" profile we work out, we identify three actions as shown below:

- Perform strict power quota system of renewable energy. It demand power suppliers to produce or purchase a part of power produced by renewable energy.
- Allow housing consumers and enterprises to purchase power produced by renewable energy.
- Carry out financial stimulating policy, such as subsidy, loan and tax credit to support the development of renewable energy.

5 Model Analysis

5.1 Validating the Model

For regression model used to set goal for four states. R^2 reaches to 82.37% which illustrate that about 82.37% data can be confirmed by model. What's more, F exceeds critical values and p less than γ which both can illustrate the model is robust. In addition, compare the predicted value of PC_{re} and "best" value, we can find out that all the "best" value calculated by this model are greater than predicted value which can reflect the practicality of our model.

For BP-Neural Network and Autoregressive Model, we draw the error figure about predicted values and practical values as shown in Figure12. We can find out that predicted values' variation trend calculated by AR model and BP-Neural Network algorithm all most the same with practical variation trend though there are just few points exist error.

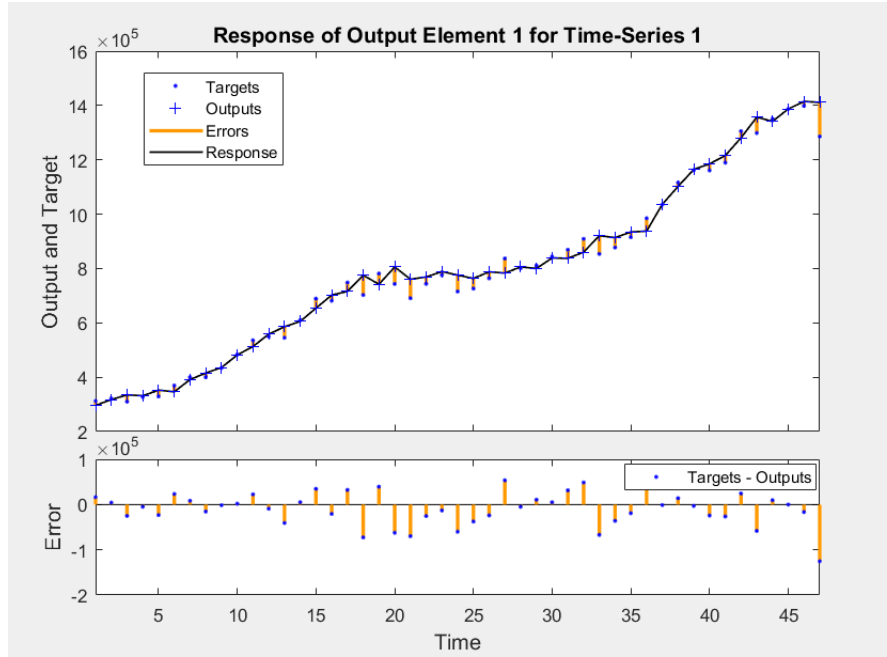


Figure 12: Error Curve

5.2 Sentivity Analysis

For regression model, we discuss the effect caused by x_1 and x_2 on y . Here, we use relative effect to measure the sensitivity of our model and determine the definition:

$$S(y, x) = \frac{dy/y}{dx/x} \quad (13)$$

Because x_1 is constant, we do not need to process sentivity analysis for it. For x_2 , according to definition above, we can get formula below:

$$S(y, x_2) = \frac{dy/y}{dx_2/x_2} = \beta_1 * \frac{x_2}{\beta_0 + \beta_1 x_1 + \beta_2 x_2} = \frac{\beta_1}{\beta_1 + \frac{c}{x_2}} \quad (14)$$

If x_1 is infinitely great, we can calculate that $S=1$. x_1 represents GDP_p thus, we can regard $S=1$ approximatively.

6 Strengths and weaknesses

6.1 Strengths

- Our models can be well applied in other states and we just need to collect the previous data and redo the analysis of regression.
- Our data comes from the official website such as Central Statistical Office, U.S. Census Bureau, which is believable.
- Model is rebust.

6.2 Weakness

- Our model didn't consider some other factors, such as the price, departments. We mainly focus on the energy consumption ratio, expense proportion and GDP per capita. So we need to add them to the further discussion and hope we can solve it in the future.
- The data of some parameters is forecast data such as GDP per capita. So there exist some errors in working out the "best" goals.

7 Evaluate of the Model

- We only choose GDP_p , PE_{ff} and PC_{re} as parameters in establishing models. We can choose more parameters to realize regressive analysis.
- We can match GDP_p and PE_{ff} in regression model not only in linear relational expression simply but also consider polynomial relational expression which may make result more precise.
- We can take inter-effect of GDP_p and PE_{ff} into consideration which may increase coefficient of determination R^2 so as to improve model.
- In this paper, we assume that PE_{ff} is constant. However, it may float in fact. In order to suit practical need, we can set float section for PE_{ff} .

8 Memo

To: Governor Offices of California State, Arizona State, New Mexico State and Texas State

From: Team #91605

Date: February 12, 2018

Subject: Our Research Results on Energy Production

Mr. Governor,

We have sent our paper to your e-mail, but we also wanted to quickly discuss our results on energy profile.

Firstly, we want to summarize the energy profile for four states. Each state's consumption of fossil fuel appears to have steady growth from 1960 to 2009, while appearing to be on a decline in 1980s. Thanks to the operation of the San Onofre nuclear plant, California's consumption of nuclear fuel begins to increase and verges to be stable. Arizona and Texas also begin to use nuclear power in 1980s and the three states' consumption of nuclear fuel verge to a stable level. However, New Mexico haven't begun to use the nuclear power until now.

Secondly, we want to explain our prediction to the trend of the three kinds of energy based on our model. Our model is anchored in the AR model and BP-Neural Network. In our prediction, California's consumption of fossil fuel decline a little from 2009 to

2050 while nuclear fuel and renewable energy remain to be stable. The proportion of California's consumption of renewable energy reach up to 21%, with the proportion of nuclear fuel remaining 5%. For Arizona, the consumption of fossil fuel and nuclear fuel verges to be stable, while renewable energy rise slightly from 2040 to 2050. Because of the increasing consumption of renewable energy, the proportion of fossil fuel's consumption is down to 70%(76% in 2009), the proportion of nuclear fuel declines to 17%(19% in 2009). As for New Mexico, it's consumption of fossil fuel decline a little(down to 92%) from 2009 to 2050, while it's renewable energy rise slightly(up to 8%) at the same time. Without new policy on nuclear plant, the consumption of nuclear fuel remains 0. Texas has developed very well on its rich fossil fuel, but its proportion of renewable energy is rather low in that case. Though the consumption of renewable energy rise a lot but its proportion only rise to 3%(2% in 2009).

Finally, we arrive at the criteria for "Best" profile. Because of the differences in economy, population and other factors, we create goals for every four states to take the basic information into consideration. In order to get the exact proportion of renewable energy, we build a model based on regression model. In our model, the proportion of California's consumption of renewable energy is 18% in 2025 and 24% in 2050. New Mexico State's percentage is 17% in 2025 and 22% in 2050. Arizona State's proportion is 15% in 2025 and 19% in 2050. Texas State's proportion is 15% in 2025 and 21% in 2050. We recommend these proportion of renewable energy as goals for this new four-state energy compact, policies may focus on the improvement of GDP of the development of renewable energy.

Best,

Team #91605

References

- [1] WANG shuang, ZHAO peng. TOPSIS Based Weights Determining Method for Evaluating Indexes in Passenger's Travel Choice Behavior. Beijing Jiaotong University. Beijing. China. 2009
- [2] Liu Yan. Renewable Energy Utilization Assessment and Structure Optimization of a Factory in Zunyi. College of Urban Construction and Environmental Engineering of Chongqing University. Chongqing. China. May 2014.
- [3] Tan Xiuhui. The Prediction of Stock Market Based on BP Neural Network and Autoregressive Model. North University. China. April 2010.
- [4] Brook W. Abegaz, Satish M. Mahajan. Optimal Energy Management for a Smart Grid using Resource-Aware Utility Maximization. 2015-0154
- [5] L. Suganthi, Anand A. Samuel. Energy models for demand forecasting: A review[J]. Renewable and Sustainable Energy Reviews, 2011, 16(2).

Appendices

Appendix A Code for Autoregression Model

```

lag=3; % order of regression
iinput=AZFo' ;
n=length(iinput);
%deal with the inputdata and outputdata
inputs=zeros(lag,n-lag);
for i=1:n-lag
    inputs(:,i) = iinput(i : i + lag - 1)';
end
targets=iinput(lag+1:end);
%build the network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);
% percent
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
%train
[net,tr] = train(net,inputs,targets);
yn=net(inputs);
errors=targets-yn;
figure, ploterrcorr(errors)
figure, parcorr(errors)
[h,pValue,stat,cValue]= lbqtest(errors) ;
figure,plotresponse(con2seq(targets),con2seq(yn))
figure, ploterrhist(errors)
figure, plotperform(tr)
fn=41; %predict length
fin = iinput(n - lag + 1 : end)';
fout = zeros(1, fn); %predict output

```

```
for i=1:fn
     $f_{out}(i) = net(f_{in});$ 
     $f_{in} = [f_{in}(2 : end); f_{out}(i)];$ 
end
figure,plot(1960:2009,iinput,'b',2009:2050,[iinput(end), $f_{out}$ ],'r');
```