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2018

MCM/ICM

Summary Sheet

We Will Get O Prize(Not U Prize)

Summary

hello world

Keywords:

hello; world

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1 Overview

1.1 Background

The rapid development of modern social economy benefits from the development of energy production. The issue of energy usage and production has always been the focus of world economic development.

In the 21st century, with the economic development and improvement, the energy shortage and the increasing contradiction between supply and demand. Meanwhile, the production and use of fossil energy sources have had a huge negative impact on the environment. Therefore, developing clean and renewable energy is imperative.

The differences between states such as geography, industry, population, climate lead to the contradiction of energy supply. Interstate cooperation and joint management and development of clean and renewable energy are regarded as the best solution to these problems. Nowadays four state governors –California, Arizona, New Mexico and Texas –wish to form a realistic new energy compact. Texas leads the country in total (non-hydro) installed renewable energy capacity, almost all of which comes from the state's 9,410 MW of wind capacity. California is the leader in solar energy installed capacity, both for photovoltaic technology (738 MW) and concentrating solar power (364 MW).

1.2 Restatement of the Problem

We are required to provide an overview of energy profile for each of the four states and model how these profiles have evolved from 1960 to 2009. In addition, it is necessary to make our results understandable through discussion, including similarities and differences between 4 states. Then we need to establish a criteria model and choose the "best" profile use of cleaner, renewable energy usage targets. Finally, we need to give our suggestions about exact action to achieve the goal we set based on what we predict.

In order to determine whether it is clean and renewable energy, for which we check the information and classification of various types of energy.

cleaner, renewable energy (definition from SEDS and):

- Conventional hydroelectric power
- Solar thermal direct use energy and photovoltaic electricity net generation
- Electricity produced by wind
- Wood and wood-derived fuels, biomass waste
- Fuel ethanol minus denaturant

2 Notations and Assumptions

2.1 Assumptions and Justifications

We make the following basic assumptions in order to simplify the problem. Each of our assumptions is justified and is consistent with the basic fact.

1. Ignore the external costs caused by power generation other than coal:

In 2005, the mean external damage of coal in the United States due to coal combustion was 3.2 cents/kWh, The external cost of natural gas power generation is 0.16 cents/kwh, which is actually almost entirely caused by coal-fired power. Also life-cycle CO₂ emissions from nuclear, wind, biomass, and solar appear so small as to be negligible compared with those from fossil fuels.(information comes from the report "Hidden cost of energy unpriced consequences of energy production and use")

2. The conversion between generation and consumption is 100%, and the consumption is used to represent the amount of power generation to evaluate.

3. Economic growth and energy development are stable. We ignore the impact of major external emergencies

2.2 Notations

Symbol	Meaning
n	the number of samples
p	the number of original indicators
k	the number of principal component
X	$\{x_{ij}\}$ original data matrix ($i = 1, 2, \dots, n ; j = 1, 2, \dots, p$)
Z	$\{z_{ij}\}$ standardization matrix with z-scores ($i = 1, 2, \dots, n ; j = 1, 2, \dots, p$)
U	$\{u_{ij}\}$ partial covariance matrix ($i = 1, 2, \dots, n ; j = 1, 2, \dots, p$)
C	$\{c_{ij}\}$ covariance matrix ($j = 1, 2, \dots, p$)
R	$\{r_{ij}\}$ correlation matrix ($j = 1, 2, \dots, p$)
F	$\{f_{ij}\}$ The eigenvectors matrix of Z ($j = 1, 2, \dots, p$)
Y	$\{y_{ij}\}$ principal component matrix ($i = 1, 2, \dots, n ; j = 1, 2, \dots, k$)
V	$\{v_{ij}\}$ decision matrix ($i = 1, 2, \dots, n ; j = 1, 2, \dots, k$)
A^+ / A^-	positive / negative ideal profile
S_i^+ / S_i^-	positive / negative ideal profile
λ_j	the eigenvalues of Z ($j=1,2,\dots,p$)
y_i	principal component
C_i	the final performance score in TOPSIS method
kmo	the value of KMO test
p	autoregressive terms
d	differential times
q	average moving term
y_t	the original data sequence
y'_t	smooth data sequence
$\hat{\rho}_k$	the auto-correlation function
$\hat{\varphi}_{kk}$	partial auto-correlation function

Table 1: Abbreviation and Description

3 Statement of Our Model

3.1 Model Overview

Firstly, considering energy production and consumption, environmental impact, technology, economy, we extract 12 variables from 605 variables to get general energy profile of each state.

In order to show the evolution of energy production, we construct a comprehensive evaluation index system for the level of cleaner, renewable energy development. We use the **Principal Component Analysis** method to carry out the correlation cluster analysis of the index. To make the similarities and differences between 4 states understandable, we use **TOPSIS** method to show our results. At the same time, we can get the extracted principal component choosing the "best" profile from comprehensive evaluation results ranking.

After determining the "best" profile, we use **ARIMA** method to predict the energy profile of each state, especially as we evaluate the cleaner, renewable energy development in the future.

3.2 Model Theory

3.2.1 Principal Component Analysis Theory

The purpose of PCA is to use the idea of dimensionality reduction to convert multiple indicators into a few composite indicators. When using statistical methods to study multivariable problems, too many variables will increase the computational complexity and increase the complexity of analyzing the problems. We hope that in the process of quantitative analysis, fewer comprehensive variables are involved to make the results more intuitive.

The method can be summarized as follows:

1. **Organize the data set and normalization** Supposing that there are n samples, and each sample has P indicators, the original variable data X are arranged as a set of n data vectors with each representing a single grouped

observation of the p variables, which as shown in formula

$$X = \begin{bmatrix} x_1^T \\ x_2^T \\ \dots \\ x_n^T \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix}$$

We choose zero-mean normalization to standardize the original data matrix. The standard score of a raw score x_{ij} is shown as formula

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where: μ_j is the mean of the row j .

σ_j is the standard deviation of the row j.

2. **Determine the correlation between the indicators** Correlation test is a statistical test of how the variables are related and how relevant they are. Thus, it' s also the basis of principal component analysis. The Kaiser-MeyerOlkin (KMO) test method is used in this model. Correlation coefficient is a statistical indicator of the close relationship between the response variables, whose range of values between 1 to -1.
3. **Calculate the number of principal component** The correlation coefficient matrix of standardization matrix is calculated by Calculate the eigvalue of

$$C = \frac{Z^T Z}{n - 1}$$

Z and arrange in descending order. The cumulative contribution rate of top

$$|Z - \lambda E| = 0$$

k factors is shown in formula. The goal is to choose a value of k as small as possible while achieving a reasonably high value of α_k on a percentage basis. Generally, the value of $\alpha_{(k)}$ should be more than 80%.

$$\alpha_{(k)} = \frac{\sum_{j=1}^k \lambda_j}{\sum_{j=1}^p \lambda_j}$$

4. Determine the scores of principal components

The scores of principal components are calculate method is shown as formula.

$$y_m = F_m \times B(m = 1, 2, \dots, k)$$

3.2.2 Technique for Order Preference by Similarity to Ideal Solution

TOPSIS is a method of compensatory aggregation that compares a set of alternatives by identifying weights for each criterion, normalizing scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative, which is the best score in each criterion. The method is carried out as follows :

1. **Organize the data set and normalization** Construct normalized decision matrix. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. In our model, we use the principal component matrix calculated as formula(10) following.

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1k} \\ y_{21} & y_{22} & \dots & y_{2k} \\ \dots & \dots & \dots & \dots \\ y_{n1} & y_{n2} & \dots & y_{nk} \end{bmatrix}$$

2. **Calculate the weighted normalized criteria matrix** We use a set of weights from PCA for each criteria w_j . Multiply each column of the normalized decision matrix by its associated weight. An element of the new matrix is shown as formula(11) where
3. **Determine the ideal and negative ideal profiles** Positive ideal solution is determined as formula(13) where Negative ideal solution is determined as

$$v_{ij} = w_j y_{ij}, (i = 1, 2, \dots, n; j = 1, 2, \dots, k)$$

$$w_j = \frac{\lambda_j}{\sum_{j=1}^k \lambda_j}, (j = 1, 2, \dots, k)$$

$$A^+ = \{v_1^+, v_2^+, \dots, v_k^+\}$$

$$v_j^+ = \{ \max(v_{ij}), \text{if } j \in J_+; \min(v_{ij}), \text{if } j \in J_- \}$$

formula(15) where

$$A^- = \{v_1^-, v_2^-, \dots, v_k^-\}$$

$$v_j^- = \{ \min(v_{ij}), \text{if } j \in J_+; \max(v_{ij}), \text{if } j \in J_- \}$$

4. **Calculate the separation measures for each alternative** The separation from the positive ideal alternative is shown as formula(17): The separation

$$S_i^+ = \sqrt{\sum_{j=1}^k (v_{ij} - v_j^+)^2}, i = 1, 2, \dots, n$$

from the negative ideal alternative is shown as formula(18):

$$S_i^- = \sqrt{\sum_{j=1}^k (v_{ij} - v_j^-)^2}, i = 1, 2, \dots, n$$

5. **Calculate the relative closeness to the ideal profile** Calculate the similarity to the worst condition as formula(19): where if

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

$$C_i = 1$$

,the alternative sample has the best condition; and if

$$C_i = 0$$

,the alternative sample has the worst condition.

6. **Rank the preference order** Rank the alternatives using C_i index value in decreasing order. An alternative with largest index value (C_i) has shortest distance from positive ideal profile and farthest distance from negative ideal profile.

3.2.3 Autoregressive Integrated Moving Average Model

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots \varphi_p y_{t-p} + u_t$$

Predictive model establishment process:

1. Obtain and pretreat the data:

Do run-length test to determine whether the sequence is a smooth sequence. if it is a non-stationary sequence, using the difference method to make it smooth: $y'_{t-i} = y_t - y_{t-1}$, The sequence is preprocessed. After each difference, the data is run-tested until the difference data can pass the stationarity test and recorded as d-difference to obtain a new stationary sequence: y'_1, y'_2, y'_3 .

2. ARMA model recognition:

Model recognition was performed by calculating the (ACF) $\hat{\rho}_k$ and pre-processed (PACF) $\hat{\varphi}_{kk}$ of the preconditioned sequence y'_t .

$$\hat{\rho}_k = \frac{\sum_{t=1}^{N-k} y'_{t+k} y'_t}{N}$$

$$\begin{aligned}\hat{\varphi}_{11} &= \hat{\rho}_1 \\ \hat{\varphi}_{k+1,k-1} &= (\hat{\rho}_{k+1} - \sum_{j=1}^k \hat{\rho}_{k+1-j} \hat{\varphi}_{kj}) (1 - \sum_{j=1}^k \hat{\rho}_j \hat{\varphi}_{kj})^{-1} \\ \hat{\varphi}_{k+1,j} &= \hat{\varphi}_{jk} - \hat{\varphi}_{k+1,k+1} \hat{\varphi}_{k,k+1-j}, j = 1, 2, \dots, k\end{aligned}$$

3. Parameter Estimation and Model Ordering. ARIMA model parameter identification using Marquardt nonlinear least squares method.
4. Model test: First, we must test whether the model can satisfy the stability and reversibility. If the model is chosen properly, the residual sequence should be a white noise sequence. We can get a reliability prediction model.

$$y'_t = \hat{\varphi}_1 y'_{t-1} + \hat{\varphi}_2 y'_{t-2} + \dots + \hat{\varphi}_p y'_{t-p} + u_t$$

4 Model Implementation and Results

4.1 Principal Component Analysis Theory

4.1.1 Energy Profile

1. **Data extraction** To evaluate the performance of the energy profile (especially in C-R energy) for each states, we set 5 second grade indices , including energy supply, energy consumption, efficiency, Additional costs and C-R energy development prospects. On the basis of the second grade indicators, we set 10 third grade indices, including the total energy production, C-R energy production, C-R energy consumption ratio, C-R energy increase speed etc. The following table shows the index system for energy profile.
2. **Note:** The data comes from State Energy Data System (SEDS) Complete Dataset (All 50 states) (<https://catalog.data.gov/dataset/state-energy-data-system-seds-complete-dataset-through-2009#sec-dates>)

first grade	second grade	third grade
energy profile	Energy supply	Total energy supply x_1
		C-R energy production x_2
	Energy consumption	Total energy consumption x_3
		C-R energy consumption x_4
		Total energy consumption per capita x_5
	Efficiency	Total energy consumed per dollar of real GDP x_6
		Average price for non-renewable energy x_7
	Additional costs	Fossil energy environment cost x_8
	C-R energy development prospects	the proportion of C-R energy generation to total electricity generation x_9
		C-R energy increase rate x_{10}

3. Energy supply: the energy supply indicators are the most intuitive indicators showing the level of energy production and clean energy development in the region.
4. Energy consumption: the energy consumption indicators truly reflect the use of energy in each state. Total energy consumption and total energy consumption per capita show us the demand of energy. C-R energy consumption
5. Efficiency of energy utilization: the efficiency indicators describe energy production in technical aspect, which are the key factors that affect the development and utilization of energy.
6. Additional cost: the indicator directly reflect the effect of energy profile evaluation. It is measured mainly by the total amount of pollutants emitted from fossil energy. Compared to traditional fossil fuels, the application of clean energy can greatly reduce pollutant emissions.

7. C-R energy development prospects: the prospect is characterized by C-R energy increase rate, the proportion of C-R energy generation to total electricity generation. We extract the average of last 5 years(2005-2009) and use the rank radar chart to indicate the energy profile of each state in each dimension.(exact data is given in the appendix). In addition, considering the purpose of 4 states, we will also analyze main energy usage proportion.

1. Energy profile of each state

2. Arizona:

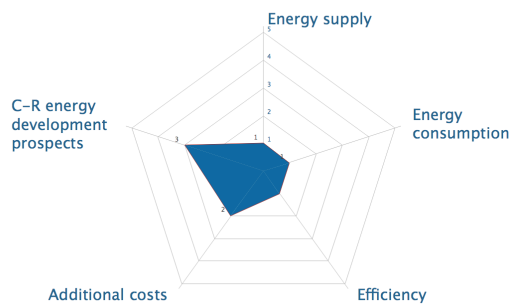


Figure 1: Figure example 2

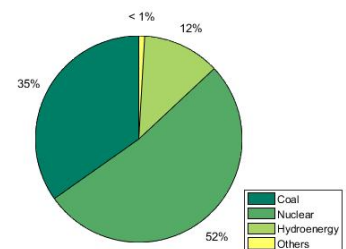


Figure 2: Figure example 3

Arizona has few energy production and energy consumption, but it does have abundant Nuclear and hydroenergy potential. The state's production utilization efficiency is low but with higher additional costs.

3. California:

California's total energy supply and demand is high, and all indicators are basically in a state of balance. California is also rich in energy resources. The state has an abundant supply of cleaner, renewable energy, including nuclear, Geothermal, wind etc.

4. New Mexico:

Though New Mexico uses fossil fuels to supply energy demand, it still does well in environment protection. Besides that, the state contains a wealth of fossil fuel and has abundant energy potential.

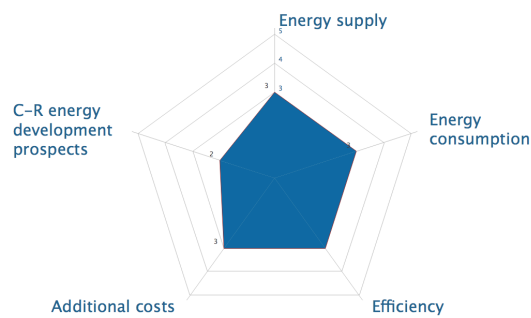


Figure 3: Figure example 2

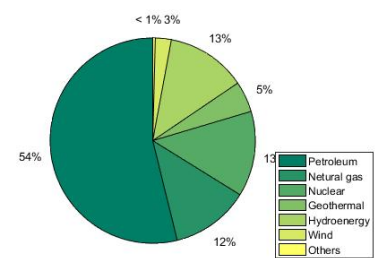


Figure 4: Figure example 3

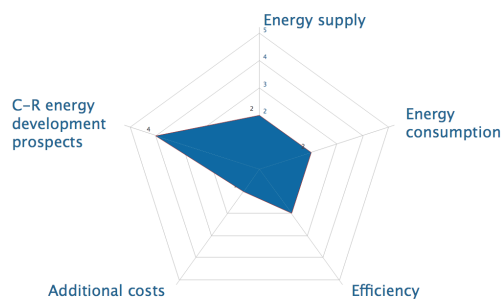


Figure 5: Figure example 2

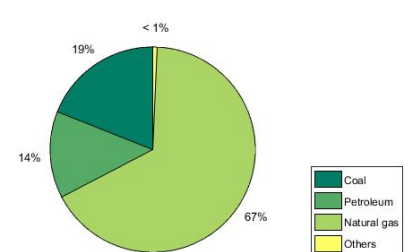


Figure 6: Figure example 3

5. Texas:

Texas has highest energy production, consumption and production utilization efficiency. And Texas is a large state with a wealth of energy resources. However, high environment damage and negative prospect of C-R energy development is considerable.

6.

4.1.2 Evolution model

- Determine the linear equation of principal components** Firstly, we extract principal components from 10 indicators. We use the average of last 5 years as a training set to determine the linear combination equations between principal components and evaluation index system. The indicators are as following:

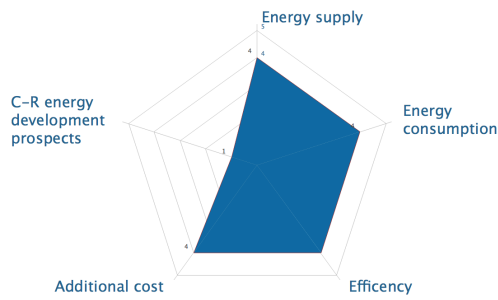


Figure 7: Figure example 2

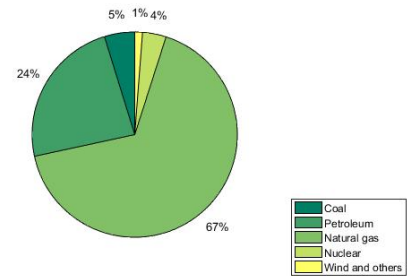


Figure 8: Figure example 3

Total energy supply x_1
C-R energy production x_2
The proportion of C-R energy generation to total electricity generation x_3
Average price for non-renewable energy x_4
Total energy consumption x_5
C-R energy consumption x_6
Total energy consumption per capita x_7
Fossil energy environment cost x_8
Total energy consumed per dollar of GDP x_9
renewable energy increase rate x_{10}

Table 2: indicators of evaluation system

Through the standard processing of these data, the relative value of each index is obtained, as shown in table 1.

Based on the standard data, we use the KOM test, and the value is 0.9145. So these data is very suitable for Principal Component Analysis. The coefficient matrix is shown in Appendix.

The characteristic values of the correlation coefficient matrix are

	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10
AZ	-0.7767	-0.5675	0.5419	-1.0061	-0.7565	-0.6559	-0.7178	-0.2267	-0.5546	-0.7419
CA	-0.3178	1.4478	1.0651	1.3715	0.5125	1.4381	-0.8089	-0.8225	-1.1043	-0.9612
NM	-0.3737	-0.7518	-0.4292	-0.3243	-0.9112	-0.7760	-0.4032	-0.4032	-0.6093	-1.0211
TX	1.4683	-0.1284	-1.1779	-0.0411	1.1553	-0.0963	1.14524	1.14524	1.0496	0.6719

Table 3: Standardized results of index data for 4 states

calculated. According to the calculation results, the last three principal components are listed in Table 3, since the characteristic value of the seventh principal component approaches zero. The characteristic values of principal components and the contribution rate of variance of the index system are shown in Table 3. In this study, the characteristic values of the last three principal components are larger, that is, the last three principal components contribute the most to the explanatory variables. Therefore, the extraction of the Last three principal components is the most appropriate and the cumulative variance contribution rate is 99%, which combines most of the information on the level of clean energy development. The feature vectors of each principal component are calculated according to the matrix and the characteristic values, as shown in Table 4. Table 4 shows the expression of the three principal components y_1 , y_2 , y_3 .

The linear combination equations between principal components and evaluation index system are shown as formulas.

It can be seen from the above expressions that the variance contribution rate of the principal , component y_3 is 59.513%. Total energy consumption, fossil energy environment cost and renewable energy consumption ratio and other five indices accounted for a larger proportion in the main component y_3 , so the main component y_3 mainly reflects **the cost for energy**.

The variance contribution rate of principal component y_2 is 34.019%. Total energy consumed per dollar of real GDP, total energy consumption per capita and total energy consumed per dollar of real GDP in the main component of y_2 is relatively large, so the main component of y_2 mainly reflects **the degree for renewable energy exploit**.

components	Total	Variance	Cumulative Variance
y_1	0.6468	6.468%	6.468%
y_2	3.4019	34.019%	40.487%
y_3	5.9513	59.913%	99.999%

Table 4: Eigenvalue and contribution rate of variance of the principal components

The variance contribution rate of principal component y_1 is 6.468%, which mainly reflects **the tendency of the renewable energy use**.

4.1.3 "best" profile

Our goal is to determine the "best" profile of C-R energy use. From PCA analysis, we can conclude that y_1 , y_2 associated with the criteria having a positive impact, and y_3 associated with the criteria having a negative impact. TOPSIS method is applied to rank the four states in usage of C-R energy. The priority weights of states with respect to criteria, calculated by PCA can be used in TOPSIS. The weighted normalized decision matrix can be seen from table.

Then, using TOPSIS method, the ranking of states are calculated. Table shows the evaluation results and final ranking of energy profiles for usage of C-R energy.

The "best" profile for use of C-R energy belongs to New Mexico.

The basic idea of this ARIMA model is to assume that the time series under study is a non-stationary time series generated by a random process. The non-stationary time series is treated several times to make it a stationary time series. Then the time series observations Value to establish the autoregressive moving average model of the stochastic process, using the optimal model established to

	y_1	y_2	y_3
AZ	-0.800	1.853	-1.100
CA	1.106	-1.636	-1.736
NM	0.2707	1.559	0.405
TX	-0.5759	-1.177	2.431

Table 5: The weighted normalized decision matrix

States	C_i	Ranking
AZ	0.554	3
CA	0.443	4
NM	0.687	1
TX	0.597	2

Table 6: The final evaluation and ranking of states

predict.ARIMA model has 3 parameters. It is usually recorded as ARIMA(p,d,q). ARIMA is one of ARMA's expansion. ARMA's general expression is as followed:

4.2 Autoregressive Integrated Moving Average Model

4.2.1 Estimate

In order to determine whether our model can predict the change correctly, we selected the known 33 sets of data, of which 23 are for training and the remaining 10 are for testing.

The test results show that, within a certain margin of error, the arima model can well reflect the future trend of things.

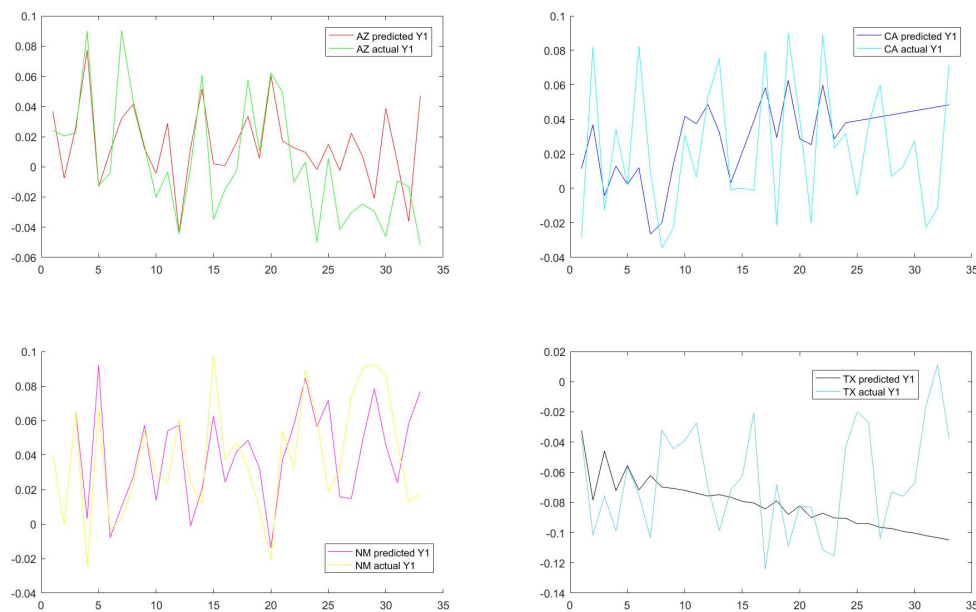


Figure 9: Estimate

4.2.2 Results

The model predicts future results as shown below.

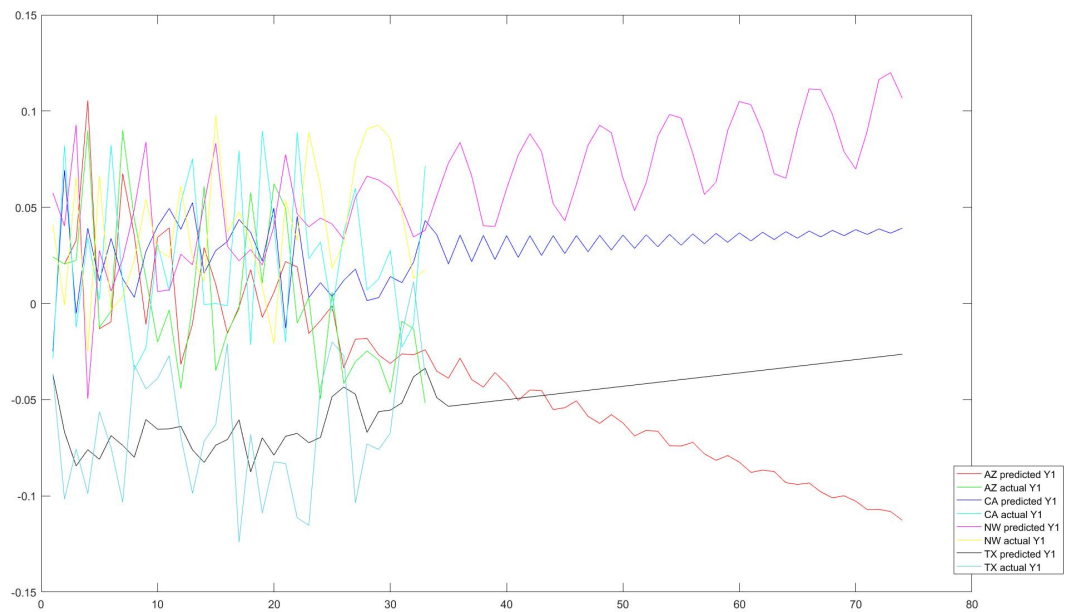


Figure 10: Y1 prediction

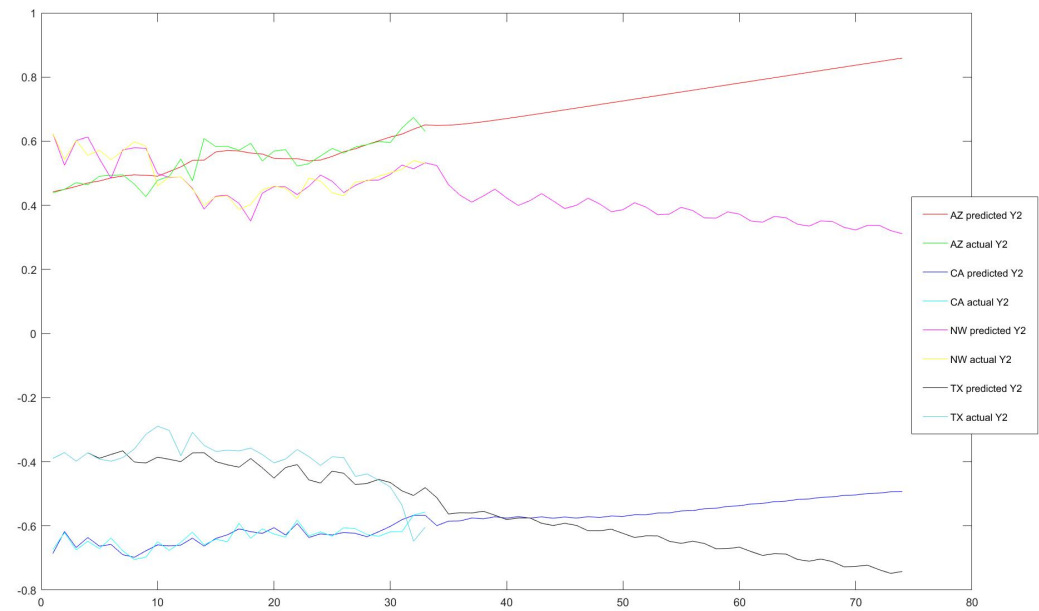


Figure 11: Y2 prediction

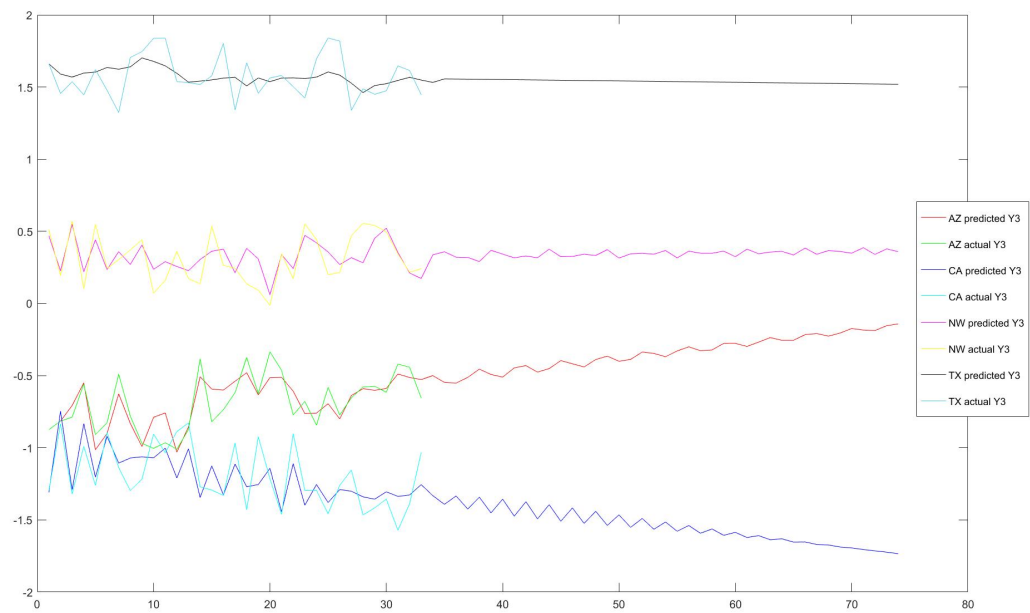


Figure 12: Y3 prediction

5 Our suggestions to the governor

$$a^2 \tag{1}$$

$$\begin{pmatrix} *20ca_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} = \frac{Opposite}{Hypotenuse} \cos^{-1} \theta \arcsin \theta$$

$$p_j = \begin{cases} 0, & \text{if } j \text{ is odd} \\ r!(-1)^{j/2}, & \text{if } j \text{ is even} \end{cases}$$

$$\arcsin \theta = \bigoplus_{\varphi} \lim_{x \rightarrow \infty} \frac{n!}{r!(n-r)!} \tag{1}$$

6 Model analysis

6.1 Sensitivity Analysis

6.2 Strength and weakness

Year	theta	S_1^-	S_2^-	S_3^-	S_4^+	S_5^+	S_6^+
2016	1	0	0	0.0001	0	0	0
2017	0.9997	0.0555	0	0.2889	0.1844	0.463	0
2018	0.9994	0	0	0.0012	0.3269	0.7154	0
2019	0.9993	0	0	0	0.4325	1.0473	0
2020	0.9991	0	0	0	0.5046	1.2022	0
2021	0.999	0	0	0	0.5466	1.2827	0
2022	0.9989	0.0017	0	0.3159	0.562	1.2995	0
2023	0.9989	0	0	0.0109	0.5533	1.2616	0
2024	0.9989	0	0	0	0.5232	1.1769	0
2025	0.9989	0	0	0.1009	0.4738	1.0521	0
2026	0.9991	0	0	0	0.4071	0.8929	0
2027	0.9992	0.0004	0	0.1195	0.3248	0.7042	0
2028	0.9994	0.0164	0	0.046	0.2287	0.4902	0
2029	0.9997	0	0	0.0609	0.12	0.2545	0
2030	1	0	0	0	0	0	0

7 Conclusions

年份	指标	
2017	0.9997	0.0555
2018	0.9994	0
2019	0.9993	0

Let's to see Table 7.

年份	指标	
2017	0.9997	0.0555
2018	0.9994	0
2019	0.9993	0

Table 7: NAME

合并		测试
		0.9997
2019	0.9993	0

年份	指标		
合并	2017	0.9997	0.0555
	2018	0.9994	0
	2019	0.9993	0

- **Applies widely**

This system can be used for many types of airplanes, and it also solves the interference during the procedure of the boarding airplane, as described above we can get to the optimization boarding time. We also know that all the service is automate.

- **Improve the quality of the airport service**

Balancing the cost of the cost and the benefit, it will bring in more convenient for airport and passengers. It also saves many human resources for the airline.

-

References

- [1] D. E. KNUTH The \TeX book the American Mathematical Society and Addison-Wesley Publishing Company , 1984-1986.
- [2] Lamport, Leslie, \LaTeX : " A Document Preparation System ", Addison-Wesley Publishing Company, 1986.
- [3] <http://www.latexstudio.net/>

[4] <http://www.chinatex.org/>

Appendices

Appendix A First appendix

Here are simulation programmes we used in our model as follow.

Input matlab source:

```
function [t,seat,aisle]=OI6Sim(n,target,seated)
pab=rand(1,n);
for i=1:n
    if pab(i)<0.4
        aisleTime(i)=0;
    else
        aisleTime(i)=trirnd(3.2,7.1,38.7);
    end
end
end
```

Appendix B Second appendix

some more text **Input C++ source:**

```
//=====
// Name      : Sudoku.cpp
// Author    : wzlf11
// Version   : a.0
// Copyright  : Your copyright notice
// Description : Sudoku in C++.
//=====

#include <iostream>
#include <cstdlib>
#include <ctime>
```



```
using namespace std;

int table[9][9];

int main() {

    for(int i = 0; i < 9; i++){
        table[0][i] = i + 1;
    }

    srand((unsigned int)time(NULL));

    shuffle((int *)&table[0], 9);

    while(!put_line(1))
    {
        shuffle((int *)&table[0], 9);
    }

    for(int x = 0; x < 9; x++){
        for(int y = 0; y < 9; y++){
            cout << table[x][y] << " ";
        }

        cout << endl;
    }

    return 0;
}
```
