Team Control Number

201958455

Problem Chosen

A

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ShuWei Cup

Summary Sheet

This paper mainly explores the following four problems, predict aging degree and medical demand, predict spectrum of disease in Sichuan province, solve the optimization of queuing problem in clinical laboratory and the discussion of cooperation and competition strategies among hospitals.

For question 1, we collected 10 sets of characteristic data. Using principal component analysis, five groups of main features were obtained by dimension reduction. G (1,1) was used to predict the main influencing factors. The fitting degree of the predicted result is 92.5%. Then, we used multivariate statistical analysis and least square method to establish the linear relationship between the five groups of features and the aging population and medical needs, and determined the weighted linear coefficient of the features. The fitting degree reached 95.5%. In addition, we forecast the aging population in the next five years. Finally, it concludes that urbanization rate, sex ratio and economic level are the main factors affecting the aging trend, and the aging will continue to accelerate in the next five years.

For the question 2, we collected the disease data and related characteristic data of Sichuan province and established a table according to the time sequence. After data preprocessing, we used BP neural network to train the training set data, and the error rate obtained was 1.5%. Then we use the grey prediction model to predict all kinds of major characteristic data in the next five years, and use the generated grey prediction data as the input of the neural network and all kinds of diseases as the output to predict the disease data in the next five years.

For question 3, we simplified each link of clinical lab into a simple queuing model and put forward important concepts such as arrival rate and service rate. By assuming that arrival time obeys poisson distribution and waiting time obeys negative exponential distribution, the average arrival time and average service time are solved. Based on what have been analyzed, the markov model of each queuing window and the relationship of state transition between each window are established. The functional relation between queue length and *arrival rate / service rate* and the distribution relation between the probability of state transition and queue length are deduced.

For question 4, We establish a duopoly cooperative competition game model based on the maximization of public and private hospitals' benefits, and use utility function to measure the total benefits of hospitals. By standardizing utility function into utility coefficient, we determine the function of utility coefficient about the scale of public hospital and private hospital. The utility coefficient is maximized under the cost constraint. By simplifying the cooperative competition game model to a nonlinear programming problem and initialization parameters, we obtain the distribution of the utility coefficients about the size of private hospitals and public hospitals, and determine the point where the maximum utility coefficients are located. In addition, we also consider that similar hospitals have a relationship between cooperation and competition. We extend the above model to n-oligopoly game model, determine the Lagrangian function of optimization problem, and find the equilibrium point of decision object according to kuhn-tucker theorem.

Key word: G(1,1); BP Neural Network; Queuing Theory; Game Theory

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1 Introduction

It is ture that with the flourish of China, the allocation of medical resources has become a universal concern. Due to the rapid development of economy and the improvement of people's living standard. The individuals demands higher quality medical services. At the same time, the explosive growth of the population and the aging trend have brought A growing challenge to the health care system.

2 Task1

2.1 Problem analysis

Task1 requires us to make a reasonable prediction on China's aging trend and residents' medical needs based on relevant statistical analysis data such as residents' income, population age structure and economic development level.

2.1.1 Fundamental assumptions

- No radical and unpredicted events will occur, causing utter shifting in the population structure.
- There will be no fundamental changes in our medical system in the predicted years.
- When we talk about aging and medical needs, we don't take into account national policy changes.
- We assume that there lative importance of various indicators doesnt change overtime.

2.1.2 Data analysis

We strongly believe that China's medical needs and the degree of aging are closely related to China's economic development level, population age structure and people's living standards and other indicators. We collected data on China's total population, gross domestic product, sex ratio, urban and rural incomes, number of beds in medical institutions, number of marriage reunions, number of universities and level of household consumption. We use these data to predict the aging trend and residents' medical needs. The aging trend of China is shown in figure 1.

Because we will be using indicators with different units, we must normalize all indicators and scale all values within the [0,1] range.ăFormula (1) gives the

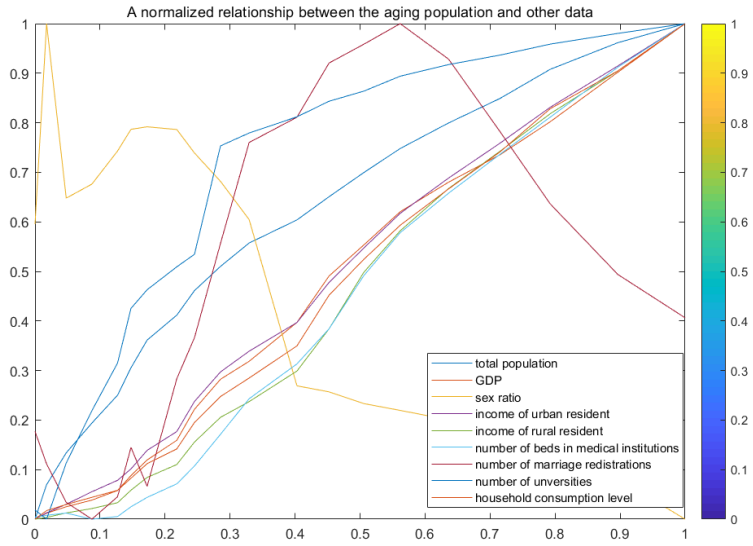


Figure 1: Changes in China's aging population

general form of the normalization adopted.

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

We first use the simple grey prediction G (1.1) model for prediction

2.1.3 Analysis of question

By means of smoothness test, quasi-exponential test and other tests, we preliminarily verified the feasibility of the model. By preprocessing the data, we processed the expected value of the age structure data. Obviously, the higher the expectation is, the more serious the aging is.
Then we did an accumulation of the data to generate a sequence X_0.

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \tag{2}$$

You can find X_0 in table 1. The sequence is then treated as follows

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)) \tag{3}$$

$$= (x^{(1)}(1), x^{(1)}(1) + x^{(0)}(2), \ldots, x^{(1)}(n-1) + x^{(0)}(n)) \tag{4}$$

In this equation.

$$x^{(1)}(k) = \sum_{1}^{k} x^{(0)}(i) \qquad (k = 0, 1, 2, \ldots, n) \tag{5}$$

Find the mean sequence.

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \qquad (k = 2, 3, \ldots, n) \tag{6}$$

$$z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)) \qquad (k = 2, 3, \ldots, n) \tag{7}$$

Based on what have been analyzed, we can build grey differential equation.

$$x^{(0)}(k) + az^{(1)}(k) = b, k = 2, 3, \ldots, n \tag{8}$$

Corresponding white differential equation.

$$\frac{dx^{(0)}}{dt} + ax^{(1)}(t) = b \tag{9}$$

Where $x^{(0)}(k)$ is called the gray derivative, a is called the development coefficient, $z^{(1)}(k)$ is called the albino background, b is called the gray action.
Select the appropriate alpha value alpha =0.5, there is Z_0 as table 1.

X_0	X_1	Z_1	E	P
1.7543	1.7794		0.0337	0.0192
1.7794	3.5589	2.6406	0.0179	0.0101
1.8021	5.361	4.5002	0.0046	0.0026
1.8271	7.1881	6.3439	0.0109	0.006
1.8439	9.032	8.1703	0.0182	0.0099
1.799	10.831	9.9789	0.0362	0.0201
1.8155	12.6465	11.7966	0.0293	0.0161
1.8341	14.4806	13.6335	0.0203	0.0111
1.8505	16.3311	15.4502	0.0136	0.0074
1.8661	18.1972	17.2429	0.0077	0.0041
1.8794	20.0766	19.0119	0.0042	0.0022
1.8944	21.971	20.7573	0.0009	0.0005

Table 1: generate the sequence

The least square method was used to fit figure 2. According to the above formula, we can know

$$a = -0.0052 \qquad b = 1.7742 \qquad \alpha = 0.5$$

So let's take the average age of 17 years

$$x^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a}, k = 1, 2, 3, \ldots, n-1 \tag{10}$$

The predicted value is 1.8935. The actual value is 1.8944. The predicted result is in line with the expectation.
Here we calculate the residual E and test level P, the result in table 1
Therefore, we use this model to predict the age expectation of the population in the next five years. The higher the expectation, the more serious the aging is.

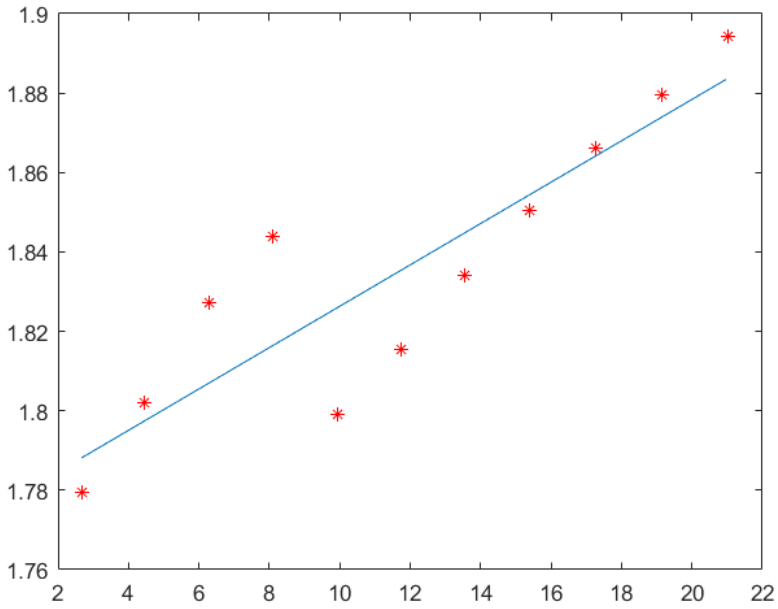


Figure 2: Least square fitting graph

2018	2019	2020	2021	2022
1.9033	1.9133	1.9233	1.9333	1.9434

Table 2: Population age expectations for the next five years

2.2 Model

Although we have predicted this problem, we still want to get more accurate models. Next, we build a more accurate model – a multiple regression model based on G (1,1). We extracted 10 sets of data (figure 3) that may be related to the degree of aging, and obtained the correlation graph after the normalization data processing.

According to the above table, we selected 5 sets of main data with good linearity, and the relationship between the data normalization and aging is shown as figue 4.

1.0365	1.0106	1.1198	1.3092	0.9926
1.1816	1.1496	1.3025	1.5353	1.1395
1.3471	1.3078	1.515	1.8005	1.3082
1.5357	1.4878	1.7621	2.1115	1.5019
1.7508	1.6926	2.0496	2.4762	1.7242

Table 3: Prediction data after normalization

After dealing with the G (1, 1) model of predicted value and actual value of 5

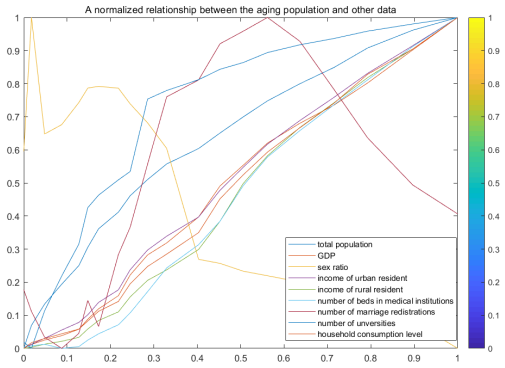


Figure 3: Normalized data

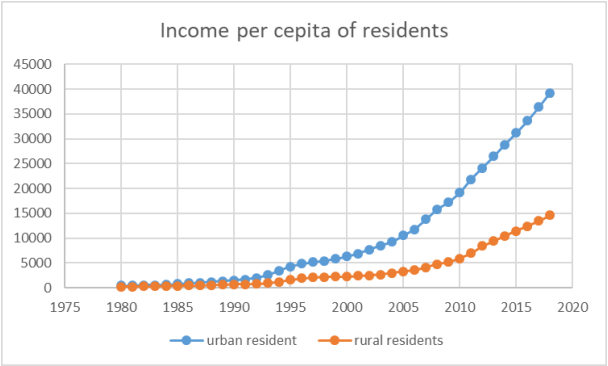


Figure 4: The aging of population is normalized with five major factors

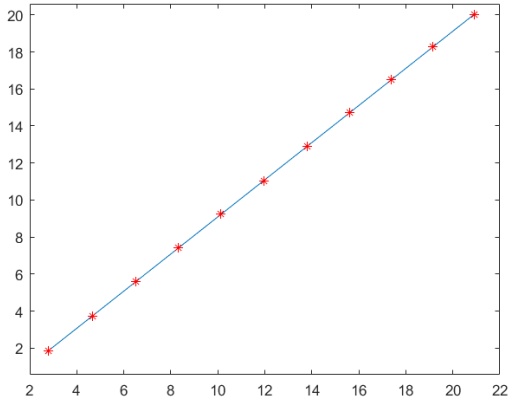


Figure 5: albinism data and fitting

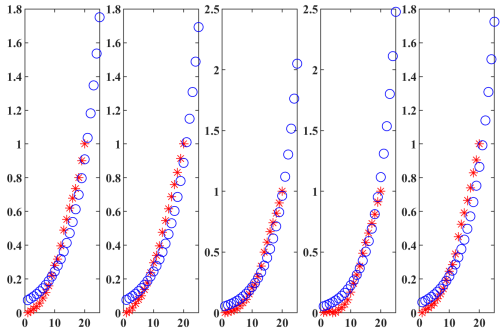


Figure 6: The predicted value of five influencing factors is compared with the actual value

factors such as above, using the forecast of 5 sets of data(figure 6), we carried on the multiple linear regression.
We establish a multiple regression prediction model based on the least square method and the index data.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{11}$$

Y is an aging population, $[X_1, X_2, \ldots, X_n]$ represents n features. β represents a const, $\beta_1 - \beta_n$ represents regression coefficient.
It is possible to define

$$B = [\beta_0, \beta_1, \ldots, \beta_n]^T$$

$$\therefore X = [X_0, X_1, X_2, \ldots, X_n]$$

$$X_0 = ones(m, 1)^1$$

[1]This equation represents unit vector of $m \times 1$, m represents the data sample dimension

$$\hat{B} = (X^T X)^{-1}(X^T Y)$$

Are derived $\hat{Y} = X\hat{B}^t$

Based on the regression correlation coefficient matrix and five groups of predicted data, the aging population theory and normal data in the future were predicted, and the results were shown in the figure 7.

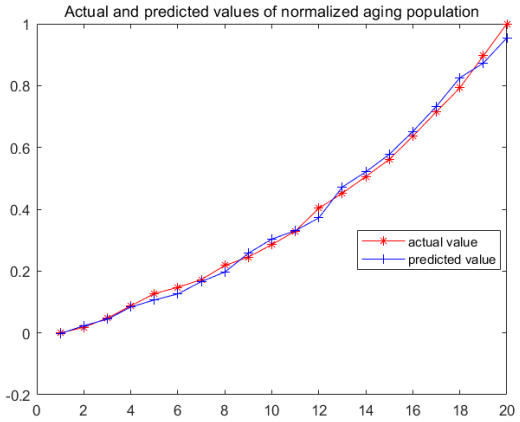


Figure 7: MLR prediction data

2.3 Strengths and Weakness

2.3.1 Strengths

We first use of grey forecasting G (1, 1) model to data preprocess, avoids the random error, moreover analyzes ten sets of data, the selection of five groups of beds with an ageing population and medical institutions better linearity groups of five factors of the grey prediction, the factors which influence the five groups using get forecast data with an ageing population and medical organization and personnel multivariate statistical regression, get forecast future aging population and medical institutions of beds, and other factors influence on it, here we use the combination model, and the selection of linearity is better data, Therefore, the data obtained by using multiple linear regression has a lot of credibility.

2.3.2 Weakness

Since it is linear regression, it is inevitable to omit the non-linear influence part, which will bring errors to the accuracy of the model.

2.4 Conclusion

For the first question, we collected 10 sets of characteristic data, including GDP per capita, urbanization rate and sex ratio, to determine the standard for measuring medical needs. By using principal component analysis (pca) and ranking according to correlation coefficient, the dimensionality reduction of 10 groups of feature data is finally obtained. On this basis, the grey model is used to predict the main influencing factors in China in the past 15 years, and the final prediction result is 92.5% in accordance with the actual value. Then we used the multivariate statistical analysis method and the least square method to establish the linear relationship between the five groups of characteristics and the aging population and medical needs. The weighted linear coefficient of the feature is determined, and the fitting degree of the result is 95.5%. Then we projected the aging population over the next five years. Finally, it concludes that urbanization rate, sex ratio and economic level are the main factors affecting the aging trend, and the aging will continue to accelerate in the next five years.

3 Task2

3.1 Problem analysis

Task2 asked us to predict common diseases in a province in the future and make Suggestions for public hospitals.

3.1.1 Data analysis

Obviously, the occurrence of disease is closely related to the lifestyle, economic level and medical level of residents in this area. Here we chose the following features to predict the disease.

- **Number of beds**
  The number of beds is an important index of the development level of a hospital.
- **number of people**
  Population determines a region's basic need for medical resources.
- **urbanization rate**
  Urbanization has a decisive impact on the allocation and utilization of medical resources
- **gross regional production**
  Regional GDP can determine the degree of development of a region. The more developed the region, the richer the medical resources.

- **per capital product**
  per capital product reflects the ratio of population to economic development in this region.

- **natality and death rate**
  natality and death rates are also important indicators of regional development.

- **growth rate Number of institutions**
  The natural rate of population growth determines the future strain on the region's health system

We found the main disease data in sichuan province through the statistics bureau of sichuan province. Major disease categories include respiratory system disease circulatory system disease tumour Injury and poisoning digestive system Endocrine immunity Urology and reproduction

3.1.2 Analysis of question

We decided to use BP neural network algorithm to deal with this prediction problem. Let's remember that there are m samples, and the features have sample x of

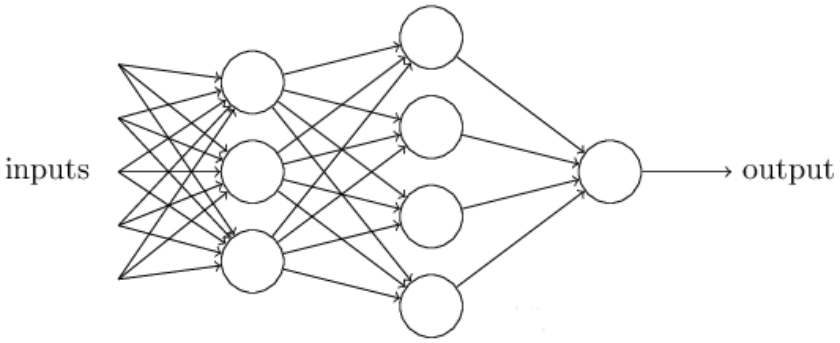


Figure 8: BP neural network

n dimensions as the output.
$X = [x_{ij}]_{m\times n}$, corresponding the output $Y = [y_{jk}]_{m\times p}$.

- **Forward process**
  The weights of node i and node j are w_{ij}, the threshold of node j is b_j, and the output of each node is x_j. According to the output value of the upper node, the weight of the node and the upper node, as well as the threshold and activation function of the current node, realize the output of the current layer.

S_j represents the output of node j:

$$S_j = \sum_{i=0}^{m-1} w_{ij} x_i + b_j \tag{12}$$

$$x_j = f(S_j) \tag{13}$$

The activation function in this paper is sigmod function.

$$f(x) = \frac{1}{1+e^{-x}} \tag{14}$$

- **The reverse process**
  First, determine the loss function.

$$E(w,b) = \frac{1}{2}\sum_{j=0}^{n-1}(\hat{y_j} - y_j)^2 \tag{15}$$

  The purpose of BP neural network is to realize the attenuation of error by correcting weights and thresholds of each layer until the required precision is achieved.

- **back-propagating**
  For the j node, the loss function can be reduced by modifying the weight method instead of blindly modifying the weight. The weight and threshold should be modified based on the gradient descent method along with the mean square error function (MSE) and the steepest descent method.

$$dw(i,h) = -n\frac{\partial E(w,b)}{\partial w(i,j)} \tag{16}$$

  n is called learning rate, and the size of n will affect the accuracy of the result. n is const here. If n is larger, the relative error will be larger, but the calculation time will decrease; if n is smaller, the relative error will be smaller, but the calculation time will increase.

- **Activation function selection**

$$f(x) = \frac{1}{1+e^{-x}} \tag{17}$$

$$f(x') = f(x)(1-f(x)) \tag{18}$$

- **calculate** $dw(i,j)$

$$\frac{\partial E(w,b)}{\partial w(i,j)} = (\hat{y_j} - y_j) * f(S_j) * x_i \tag{19}$$

  Defines $\hat{y_j} - y_j = \delta_j \qquad f(s_j)(1-f(j)(\delta_j) = \delta_i j$
  A represents the inverse error coefficient for point i in the j layer.
  In a similar way:

$$db_j = n\frac{\partial E(w,b)}{\partial b_j}$$

∴modifier formulas is:

$$|x| = \begin{cases} w_{ij} & = w_{ij} - n\delta_{ij}x_i \\ b_j & = b_j - n\delta_{ij} \\ \delta_{ij} & = (\hat{y_j} - y_j)f(s_j)(1 - f(s_j)x_i \\ s_j & = w_{ij}x_i + b_j \end{cases}$$

3.2 Fundamental assumptions

- No radical and unpredicted events will occur, causing utter shifting in the population structure.
- There will be no fundamental changes in our medical system in the predicted years.
- When we talk about aging and medical needs, we don't take into account national policy changes.
- We assume that there lative importance of various indicators doesnt change overtime.

3.3 Model

1. **The input data is preprocessed**

   $$X = [x_{ij}]_{m \times n}$$

   A represents each year, and b represents the number of features. Normalize the data to make the data in the interval of $[0, 1]$.

   $$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{20}$$

2. **Data initialization**
   The initial weights and threshold

   $$w_1 = 0.001rand(insize, hidesize) \tag{21}$$
   $$w_2 = 0.001rand(hidesize, 1) \tag{22}$$
   $$B_1 = 0.001rand(hidesize, outsize) \tag{23}$$
   $$B_2 = 0.001rand(outsize, 1) \tag{24}$$

   Learning efficiency:

   $$\alpha_1 = \alpha_2 = 0.01$$

   Because there are 10 features and 7 predicted disease outputs, the neural network system in this paper contains 10 input neurons, 20 hidden neurons and 7 output neurons.

3. **model training**
   The global error sum of squares loss is taken as the function $error = ||output - train - put||$ as the condition for the termination of the algorithm, and the maximum number of iterations is 150000. The error curve is shown as figure 9.
   Parameter updated to

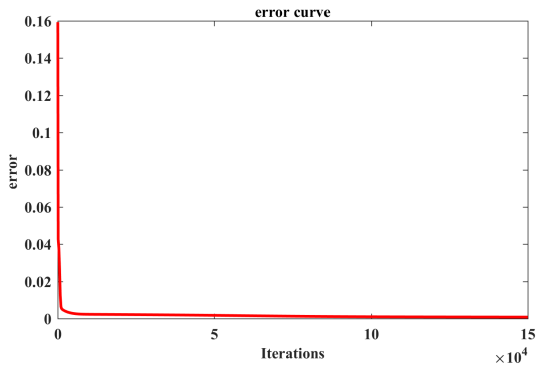


Figure 9: Error curve

$$\begin{cases} w_2 & = w_2 - \alpha_2 dw_2 \\ w_1 & = w_1 - \alpha_2 dw_1 \\ B_1 & = B_1 - \alpha_1 dB_1 \\ B_2 & = B_2 - \alpha_1 dB_1 \end{cases}$$

4. **The algorithm terminates when the end condition is satisfied.**

3.4 Test model

Firstly, due to the lack of data in relevant years, we used G(1, 1) model in task1 to predict the data of sichuan province from 2017 to 2019. The specific prediction results are shown in table 4 and 5.

We applied the method in the previous section to get the error function. Then we trained the BP neural network with the data we collected. The predicted data of the neural network after training are in good agreement with the actual values, and the comparison of one group is shown in figure 10. According to this, we determined the reliability of the model, and then used the data from 2005 to 2014 as the training set, 2015 to 2017 as the comparison set, and 2017 to 2020 as the prediction set. BP neural network algorithm was used to predict the future, one of which was shown in figure 11.

years	Number of beds	number of people	urbanization rate	GDP
2005	244119.00	400248.00	37.40	12601.23
2006	275555.00	437758.00	38.70	14151.28
2007	302061.00	467774.00	40.18	17185.48
2008	335151.00	505113.00	41.83	21026.68
2009	390122.00	549866.00	43.53	23872.80
2010	426378.00	595645.00	44.90	26392.07
2011	459588.00	627158.00	46.30	28536.66
2012	488719.00	647577.00	47.69	30053.10
2013	519149.00	671305.00	49.20	32934.54
2014	563419.00	710787.00	50.80	36980.22
2015	699640.00	819930.00	54.98	48754
2016	767150.00	871530.00	56.94	54682
2017	841170.00	926380.00	58.98	61332
2018	922340.00	984680.00	61.11	68790
2019	101130.00	104660.00	63.29	77155

Table 4: Factors Affecting Disease 1

years	CPC [2]	natality	death rate	growth rate	Number of institutions
2005	15495.00	9.54	7.15	2.39	71195.00
2006	17339.00	9.15	6.43	2.72	72907.00
2007	21182.00	8.93	6.62	2.31	74311.00
2008	26133.00	9.79	6.81	2.98	75814.00
2009	29608.00	9.89	6.92	2.97	76555.00
2010	32617.00	9.90	6.90	3.00	80039.00
2011	35128.00	10.22	7.02	3.20	81081.00
2012	36775.00	10.30	6.94	3.36	80114.00
2013	40003.00	10.48	6.99	3.49	79516.00
2014	44651.00	11.26	7.03	4.23	80480.00
2015	59077.00	11.17	7.23	4.01	83152
2016	66121	11.37	7.29	4.17	84064
2017	74005	11.57	7.36	4.34	84985
2018	82829	11.77	7.42	4.51	85917
2019	92709	11.98	7.49	4.69	86859

Table 5: Factors Affecting Disease 2

3.5 Strengths and Weakness

3.5.1 Strengths

- **Nonlinear mapping capability:**
  The BP neural network essentially realizes a mapping function from input to output, and the mathematical theory proves that the three-layer neu-

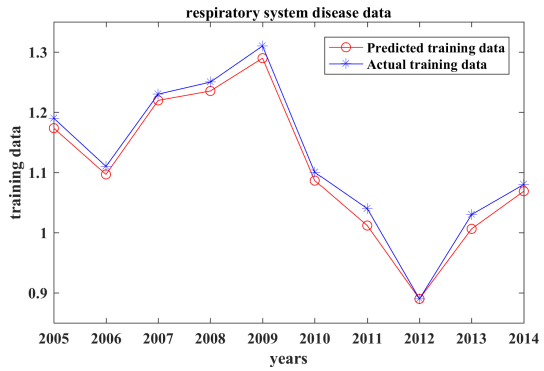


Figure 10: Comparison diagram of training data and actual data

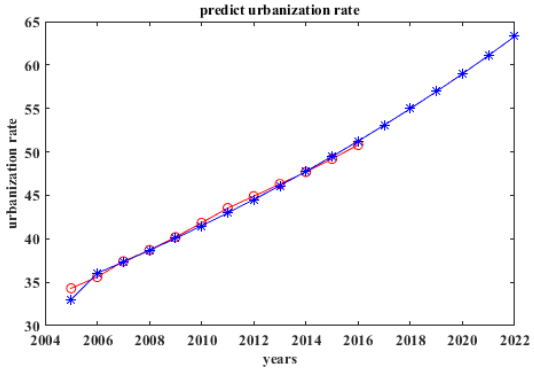


Figure 11: An example of neural network prediction results

ral network can approximate any nonlinear continuous function with arbitrary precision. This makes it especially suitable for solving problems with complex internal mechanism, that is, BP neural network has strong nonlinear mapping ability.

- **Self-learning and adaptive ability:**
  During the training of BP neural network, it can automatically extract the output and "reasonable rules" between the output data through learning, and then memorize the learning content in the weights of the network adaptively. That is, BP neural network has high self-learning and adaptive ability.

- **Generalization ability:**
  the generalization ability refers to that when designing the pattern classifier, it is necessary to consider whether the network can correctly classify the required classification objects, and whether the network can correctly classify the unknown patterns or the patterns with noise pollution after training. That is to say, BP neural network has the ability to apply learning results to new knowledge.

3.5.2 Weakness

Local minimization problem:
from the mathematical point of view, the traditional BP neural network as a local search optimization method, it is a complex nonlinear problem to solve, the network weights is through the partial improvement direction gradually adjusted, so can make the algorithm into local extremum, weights of convergence to the local minimum points, thus cause the failure of network training. In addition, BP neural network is very sensitive to the initial network weight. When the network is initialized with different weights, it tends to converge to different local minima. This is also the fundamental reason why many scholars get different results every time they train.

3.6 Conclusion

We divide the data into three sets of data: training set, test set and prediction set. The BP neural network was used to train the data of the training set, and the error rate was 1.5%. Then, the grey prediction model is used to predict all kinds of main characteristic data in the next five years, and the generated data predicted in this paper is used as the input of the neural network, and all kinds of diseases are used as the output to predict the disease data in the next five years. You can find the predicted data in appendix **??**

4 Task3

4.1 Problem analysis

4.1.1 Queuing theory

Queuing theory is a widely used branch of operations research. This theory has been successfully used in almost all kinds of environments with waiting conditions. As a important brach of operations research which is the earliest quantitative optimization problem.

Determination of optimization objectives:

- The purpose of queuing model is to determine the features of queuing system, such as average waiting time, average Line length, or to build a service system to meet a specific customer service level.
- There is a set of service systems in the queuing system. If the facility is idle, the arriving customer is served immediately; otherwise, the customer will wait or leave

4.2 Fundamental assumptions

- The interval of patient arrival time obeys a memoryless poisson distribution.
- Patient queuing rules follow the first come, first served principle, if there are special circumstances follow the first served principle.
- The patient's family members cause queues.
- The service rules of the service desk follow the mode of multi-service desk mixed connection.

4.3 Model

4.3.1 Modeling

Based on the assumption of 4.2, we established the mathematical model according to the following process.

1. **Patient model**
   In queuing theory, the simplest stream refers to the arrival of k customers in the period from 0 to t.
   $v_k(t)$ satisfies the poisson distribution:

$$v_k(t) = e^{-\lambda t}\frac{(\lambda t)^k}{k!} \tag{25}$$

   λ is the mathematical expectation of $v_k(t)$, $\frac{1}{\lambda}$ represents the time interval between adjacent customers.

2. **Service time distribution**
   In addition to the fixed time of laboratory tests, other time is not fixed, with great randomness and complexity. We found that the hospital service time with high complexity obeys exponential distribution. Its distribution probability is:

$$F(t) = 1 - e^{-ut} \tag{26}$$

   $F(t)$ is the probability that the queue time is in some interval. $E(t) = \frac{1}{u}$ represents the average service time. [3]

3. **markov process**
   The state of the system is determined by the queue length. The process $n \to n+1$ indicates that one people entering the system and the waiting time is $\frac{1}{\lambda}$. $n \to n+1$ means one people is leaving, and the service time is $\frac{1}{u}$. Let's say that at some point the system is p_i, and there are a lot of states that are connected to state i. The flow of a transition line is [4] $r_{ij}p_i$. When the state of r_{ij} is "out", $r_{ij} = u$. When the state of r_{ij} is "in", $r_{ij} = \lambda$.

On the basis of the above, we can build the model.

1. **equilibrium equation of state**

$$\lambda p_1 = up_2, \lambda p_2 + up_2 = \lambda p_1 + up_3, \ldots . \lambda p_n + up_{n+1} \tag{27}$$

   Because of $\sum_{i=1}^{n} p_i = 1$ we can infer that

$$p_n = (\frac{\lambda}{u})^{n-1} p1$$

[3] $E(t) = \int_0^\infty F'(t)dt = \int_0^\infty tue^{-ut}dt = -\frac{1}{u}\int_0^\infty e^{-a}da = \frac{1}{u}$
[4] from state i to state j

We can think of p_1 as $(\frac{\lambda}{u})p_0$

$$\therefore \qquad p_i = (\frac{\lambda}{u})^i(1-\frac{\lambda}{u})$$

Let $\alpha = (\frac{\lambda}{u}) = \lambda\frac{1}{u}$

$$\therefore \qquad p_i = \alpha^i(1-\alpha) \tag{28}$$

α is the ratio of arrival rate to service rate, which is called busy rate. It means the number of customers arriving in an average service time. If $\alpha > 1$, the Line length will increase. Based on the data found, we can get λ, u and α.

2. **Mathematical expectation Line length**
If the influence of the line length of stay is considered, set the length of stay as T. Little formula gives the relationship between the line length, the length of stay, and the arrival rate.

$$L = \lambda T \tag{29}$$

$$L = \sum_{i=0}^{\infty} ip_i = \sum_{i=0}^{\infty}(1-\alpha)i\alpha^i = (1-\alpha)\sum_{i=0}^{\infty} i\alpha^i \tag{30}$$

From the above, we can get the following equation.

$$L_e = 0 * p_0 + \sum_{i=0}^{\infty}(n-1)p_n = \frac{\lambda^2}{u(u-\lambda)} = \frac{\rho^2}{1-\rho} \tag{31}$$

L_e is the average number of patients waiting in line for service.

4.3.2 Model description

- The use of $\lambda_j(i = 1, 2, 3\ldots)$ represents the average arrival rate of patients in the level i, which is divided into three levels. The first level is emergency patients, the second level is special patients[5], and the third level is ordinary patients.
- Service time is the same at the same level.
- The probability of n patients in t queued system is p_n

$$p_n = \alpha^n(1-\alpha) \tag{32}$$

$$\alpha = \frac{\lambda}{u} \tag{33}$$

The relationship between transfer rate and α like figue 12

$$p_0 = 1-\alpha \tag{34}$$

[5]Military personnel, cadres and other priority groups for medical treatment.

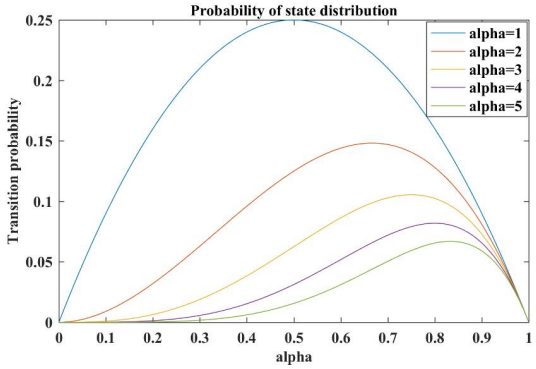


Figure 12: The relationship between transfer rate and α

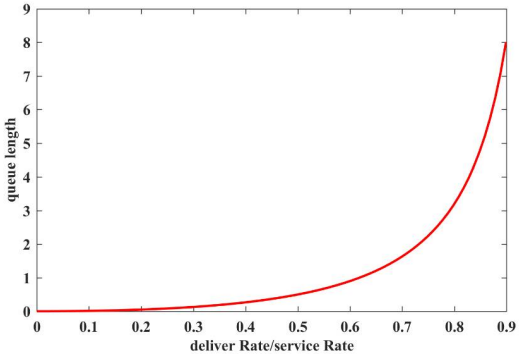


Figure 13: The relationship between queue length and α

- Average queue length.

$$L = \frac{\lambda}{u - \lambda} \tag{35}$$

  The relationship between queue length and α like figure 13

- Average number of patients waiting in line for service.

$$L_e = \sum_{n=0}^{\infty} np_n - \sum_{0}^{n=1} p_n = L - \alpha = \frac{\lambda^2}{u(u-\lambda)} \tag{36}$$

- The average time spent in a single queue is denoted as T_0, including wait time w_e, and service time $\frac{1}{u}$.

$$T_0 = w_e + \frac{1}{u} \tag{37}$$

5 Task4

Task4 asked us to analyze the cooperation and competition among several hospitals and provide them with the best cooperation and competition strategies.

5.1 Problem analysis

The main difference between public and private hospitals is that Private hospitals are for-profit organizations, including sino-foreign joint ventures, joint-stock hospitals and private hospitals.

- Funding comes from different sources. Private hospitals are funded by investment.

- Different management system, private hospitals implement enterprise management.

Taking public and private hospitals as decision makers, we establish an asymmetric two-person game model based on collaborative competition. As a scarce resource of hospital cooperation, benefit distribution is the key. Through the stability analysis of the model, the cooperation mechanism between public and private hospitals is simulated. Finally, the paper puts forward some Suggestions for public and private hospitals from the perspectives of policy, investment, tax payment and scale.
The goal of private hospitals is to obtain the largest medical market, but the high cost of obtaining medical service experts to improve medical technology requires the resources of public hospitals. On the other hand, public hospitals can also obtain the highest paying customers from private hospitals to improve their service level

5.2 Fundamental assumptions

If only one public and private participate in the game, establish the duopoly model.
$I = |1|$ is public hospital, $I = |2|$ is civilian battalion hospital.
$S_1 = S_2 = |competition, cooperation|$ as the decision set, which have two decisions: potential service objects and service resources.If two hospitals cooperate, they will combine their own resources. If two hospitals compete, one side will get all the benefits.
The expert team is a relatively scarce resource. If the public and private independently complete the business marketing cost is $c1$, the acquisition cost of the expert is $g2$, $c_2 > c_1 > 0$, the service fee paid by the customer is F, the public hospital gains $R1$, and the private hospital gains $R2$.

$$R1 + R2 = F$$

Payment matrix for public and private hospitals:

$$N_1 = \begin{pmatrix} F - C_1 & F \\ 0 & R_1 \end{pmatrix}$$

$$N_2 = \begin{pmatrix} F - C_2 & F \\ F & R_2 \end{pmatrix}$$

5.3 Model

- **Stability analysis**
  When $F > C_2$, the decision is $|(competition, competition)|(competition, competition)|$
  When $C_2 > F > C_1$, the decision is

$|(competition, cooperation)|(competition, cooperation)|$ When $C_2 > F > C_1$, the decision is
$|(competition, cooperation)|(competition, cooperation)|$
or $|(cooperation, competition)|(cooperation, competition)|$

- **Establish n oligopoly cooperation - competition model**
Assuming that private hospitals and private hospitals as well as public hospitals and public hospitals also have competitive and cooperative relations, a game model of n oligarchs 'cooperative and competitive relations is established. Suppose there is n hospital, and the number of people served by the hospital is $x_i \in X_i$. $C_i(x_i) = cx_i$.
The inverse demand function, a is Potential demand.

$$p(x) = a - \sum_{i=1}^{n} x_i$$

profit:

$$u_i(x) = px_i - c_i x_i$$

They maximize utility coefficients through cooperation and competition.

$$uc_i(x) = \frac{4x_i(a - c - \sum_{i=1}^{n} x_i)}{(a-c)^2} \qquad (i = 1, 2, \ldots, n) \tag{38}$$

We can stablish an optimization model

$$\underset{x \in X}{max} \underset{i \in N}{min} \frac{4x_i(a - c - \sum_{i=1}^{n} x_i)}{(a-c)^2} \tag{39}$$

Through referring to the literature, the nonlinear programming problem such as equation 39 can be transformed into equation (40)

$$\begin{cases} max & v \\ s.t. & v < x_i(a - c - \sum_{i=1}^{n} x_i) \\ & x \leftarrow X \end{cases} \tag{40}$$

Lagrange function of equation (40) is

$$L(v, x) = v + \sum_{i=1}^{n} \lambda_i x_i (a - c - \sum_{i=1}^{n} x_i - v) \tag{41}$$

According to the Kuhn-Tucker theorem

$$(\sum_{k=1}^{n} x_k - a - c)(n\lambda i - 1) = 0$$

When

$$\sum_{k=1}^{n} x_k - a - c = 0$$

$$\therefore \qquad u_c i(x) = 0$$

When

$$n\lambda i - 1$$

$$\therefore \qquad u_{ci}(x) = \frac{1}{n}$$

Based on what have been analyzed, we can make sure that equilibrium is

$$(\frac{a-c}{2n}, \ldots, \frac{a-c}{2n})$$

And Equilibrium utility is

$$u = (\frac{(a-c)^2}{4n}, \ldots, \frac{(a-c)^2}{4n})$$

set $a = 3$ $\quad c = 1$ $\quad x_1 = [0.2 \times 10^4]$ $\quad x_2 = [0.4 \times 10^4]$

5.4 Conclusion

We got the result as figure 14 by testing the model.
Both public and private hospitals should seek the point with the highest equilibrium utility. We believe that private hospitals should transform to specialized hospitals, focusing on a certain aspect of medical services, while public hospitals should transform to a more comprehensive and more affordable medical service system.

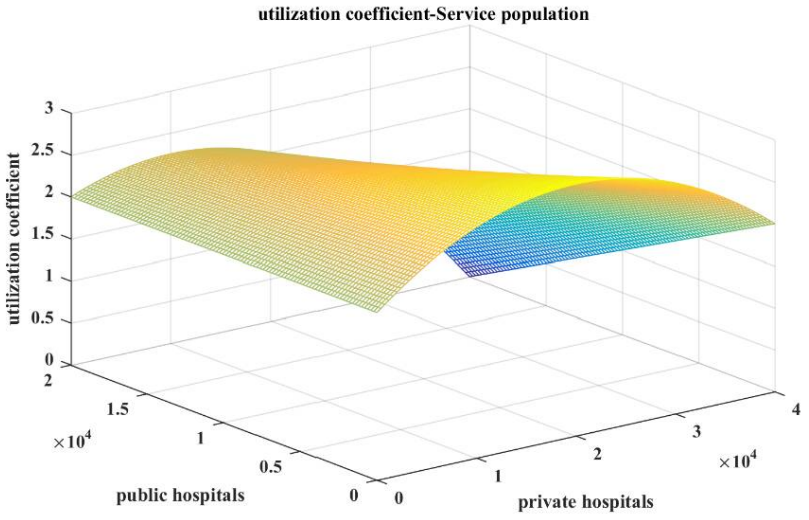


Figure 14: Equilibrium utility

References

[1] Wendy L. Martinez, Exploratory Data Analysis with MATLAB(second edition), 2018

[2] Hai Ming Zhan, MATLAB Numerical Calculation Practice ,2018

[3] http://www.stats.gov.cn/

[4] http://tjj.sc.gov.cn/tjcbw/tjnj/

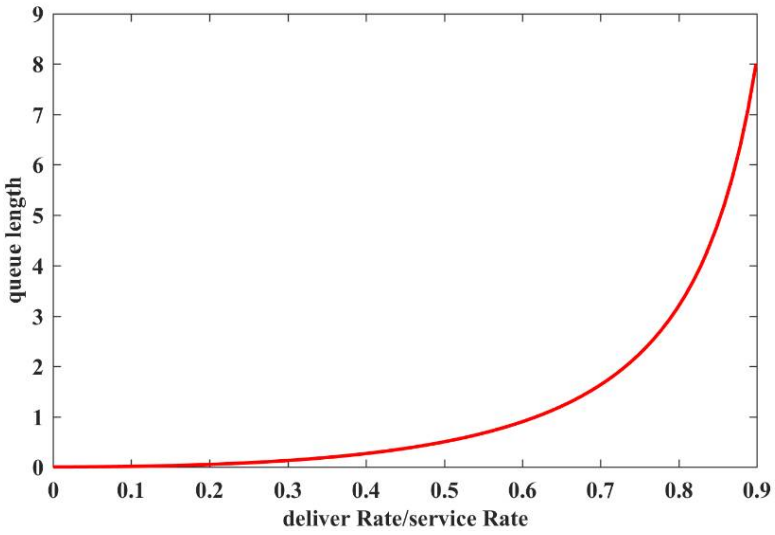
[5] Qi Yuan Jiang, mathematical modeling (the fourth edition), 2011

Appendices

Appendix A Letter to the health and family planning commission

Dear Mr. Wang
I am a college student from China. Thank you very much for taking time out of your busy schedule to read my letter.
Recently, I collected some data about China's medical industry and found some surprising patterns. As is known to all, almost all countries in the world have the phenomenon of aging, and China's aging phenomenon is increasingly significant. In order to understand the aging process of China, we collected 10 sets of data on China's economy, demographic structure, medical level and other aspects, and analyzed these data with what we have learned.Under the condition that the short-term forecast data are more consistent with the reality, the forecast data for the future shows that the aging situation in China is becoming increasingly severe.Here we hope you can pay more attention to the urbanization rate, gender ratio and GDP.According to our research, these three indicators are closely related to the degree of aging. Such an aging trend worries us that our health care system may be facing challenges.
In addition, the future disease spectrum of sichuan province is analyzed and predicted by neural network algorithm and gray scale prediction. We used data from 2005 to 2015 to train the neural network.By inputting grayscale prediction data into the neural network system, we were surprised to find that this algorithm could predict the data from 2005 to 2015 well, and the data from 2016 to 2018 well.The results show that with the development of economy and the improvement of medical treatment, cancer and circulatory diseases will replace respiratory diseases as the biggest enemies of people's health. We hope that our prediction results can provide a limited reference for the medical industry in sichuan.

We also studied the clinical laboratory of the hospital. Through the queuing theory, we studied the relationship between the state transition probability and the number of queuers, as shown in the figure. We hope that our quantitative research can provide ideas for the optimization of resource allocation in the hospital in the future.



We get the results through the game theory model. In order to achieve a win-win situation between private hospitals and public hospitals, I suggest that private hospitals should transform to specialized hospitals and focus on certain aspects of medical services, while public hospitals should transform to a more comprehensive and more affordable medical service system. So those are our findings and some Suggestions.

Best wishes
XX

Appendix B Code for task1

```
clc,clear
A=xlsread('solve1.xlsx','sheet1','e3:e14'); %ř¿čt'£¿han1.txt
x0=A(:,1);
m=size(x0);
x1=[];
x1(1)=x0(2);
for i=2:m(1)
    x1(i)=x0(i)+x1(i-1);
end
%źű
for k=2:m(1)
    rou(k)=x0(k)/x1(k);
```

```
end
r=zeros(1,m(1));
for i=2:m(1)
    r(i)=x0(i-1)/x0(i);
end
aa=exp(-2/(m(1)+1));
bb=exp(2/(m(1)+1));
alpha=0.5;n=length(x0);
x00=x0(2:end)';
z1=alpha*x1(2:n)+(1-alpha)*x1(1:n-1);
C1=polyfit(z1,x00(1:n-1),1);
a=-C1(1);b=C1(2);
z1i=z1(1):0.1:z1(end);
x1i=polyval(C1,z1i);
x11=x00(1:n-1);
plot(z1i,x1i,z1,x11,'r*');
x14=[];
for k=1:12
x14(k)=(x0(1)-b/a)*(exp(-a*k)-exp(-a*(k-1)));
end
%ij
x000=x0';
e=abs(x000-x14);
%¿
p=e./x000;
figure(2)
plot(x0);hold on
plot(x14)
```

```
%
clear,clc;
A=xlsread('solve1_2.xlsx','sheet1');
%¿żŕ
for i=1:20
    for j=2:11
        A1(i,j)=(A(i,j)-min(A(:,j)))/(max(A(:,j))-min(A(:,j)));
    end
end
plot(A1(:,2),A1(:,3:11),'*')
title('A normalized relationship between the aging population and other data')
legend('total population','GDP','sex ratio','income of urban resident','income of rur
Y=A1(:,2);
X=A1(:,3:11);
b=regress(Y,X);
alpha=0.5;
[b,bint,r,rint,stats]=regress(Y,X,alpha);
 rcoplot(r,rint);
```

```
clear,clc;
A=xlsread('solve1_2_1.xlsx','sheet1');
%¿żŕ
for i=1:20
    for j=1:6
        A1(i,j)=(A(i,j)-min(A(:,j)))/(max(A(:,j))-min(A(:,j)));
    end
```

```
end
figure(1)
plot(A1(:,1),A1(:,2:6),'*');
title('A normalized relationship between the aging population and five major factors'
legend('GDP','income of urban resident','income of rural resident','number of beds in
Y=A1(:,1);
X1=A1(:,2:6);
X=[ones(20,5),X1];
[b0,bint,rint,stats]=regress(Y,X1);
y=zeros(20,5);
for i=1:5
    y(:,i)=b0(i).*A1(:,i+1);
end
Y=zeros(20,1);
for j=1:5
    Y=y(:,j)+Y;
end
figure(2)
n=[20:-1:1]';
plot(n,A1(:,1),'r*-',n,Y,'b+-')
title('Actual and predicted values of normalized aging population')
legend('actual value','predicted value')
%G(1,1)ń¿t'ęö
X2(1,:)=X1(2,:);
m=size(X1);
for j=1:m(2)
for i=2:m(1)
    X2(i,j)=X1(i,j)+X2(i-1,j);
end
end
alpha=0.5;
z1=alpha.*X2(2:m(1),:)+(1-alpha).*X2(1:m(1)-1,:);
for i=1:m(2)
    C1(i,:)=polyfit(z1(:,i),X1(1:end-1,i),1);
end
a=-1.*C1(:,1);b=C1(:,2);
figure(3)
for i=1:m(2)
z1i(:,i)=min(z1(:,i)):((max(z1(:,i))-min(z1(:,i)))/100):max(z1(:,i));
x1i(:,i)=polyval(C1(i,:),z1i(:,i));
end
for i=1:m(2)
    subplot(1,m(2),i)
    plot(z1(:,i),X1(1:end-1,i),'r*')
    hold on
    plot(z1i(:,i),x1i(:,i))
    title('Albinism data and fitting')
end
for k=1:m(1)+5
    for j=1:m(2)
X11(k,j)=(X1(1,j)-b(j)/a(j))*(exp(-a(j)*k)-exp(-a(j)*(k-1)));
end
end
figure(4)
for i=1:m(2)
```

```
subplot(1,m(2),i)
    plot(X1(:,i),'r*')
    hold on
    plot(X11(:,i),'bo')
end
result=X11(m(1)+1:m(1)+5,:);
for i=1:5
    yni(:,i)=b0(i).*result(i,:);
end
for j=1:5
    jieguo(j)=sum(yni(j,:));
end
jieguo
```

Appendix C Code for task2

```
%% ¿
input_data=NIR';
out_data=octane(:,1)';
temp=1:13;
Train_xdata=input_data(:,temp(1:10));
Train_ydata=out_data(temp(1:10));
Test_xdata=input_data(:,temp(11:end));
Test_ydata=out_data(temp(11:end));
%% ¿t'ę
Max_train_ydata=max(Train_ydata);
Max_test_ydata=max(Test_ydata);
Min_train_ydata=min(Train_ydata);
Min_test_ydata=min(Test_ydata);
train_xdata=mapminmax(Train_xdata,0,1);%ůßÿś¿źżŕ
train_ydata=mapminmax(Train_ydata,0,1);
test_xdata=mapminmax(Test_xdata,0,1);
test_ydata=mapminmax(Test_ydata,0,1);
%% w
insize=10;
hidesize=20;
outsize=1;
iter=1;
maxiter=100000;
W1=0.01*rand(insize,hidesize);
B1=0.01*rand(hidesize,1);
W2=0.01*rand(hidesize,outsize);
B2=0.01*rand(outsize,1);
alpha1=0.01;
alpha2=0.01;
Train_SampleNum=size(train_xdata,2);
Test_SampleNum=size(test_xdata,2);
E_maxvalues=1e-6;
E_record=[];
iter=0;
```

```
%%
for i=1:maxiter
      hidein=W1'*train_xdata+repmat(B1,1,Train_SampleNum);
      hideout=sigmod(hidein);
      output=W2'*hideout+repmat(B2,1,Train_SampleNum);
      error=output-train_ydata;
      E=sumsqrt(error);%¿ů¡ž-žŕ
      delta2=error;
      delta1=(W2*delta2).*hideout.*(1-hideout);
      dB2=delta2*ones(Train_SampleNum,1);
      dW2=hideout*delta2';
      dB1=delta1*ones(Train_SampleNum,1);
      dW1=train_xdata*delta1';
      B2=B2-alpha2*dB2;
      W2=W2-alpha2*dW2;
      B1=B1-alpha1*dB1;
      W1=W1-alpha1*dW1;
      E_record=[E_record,E];
      if E<E_maxvalues
          break;
      end
      iter=iter+1;
end
%%
figure(1);
plot(E_record,'r','LineWidth',1.8);
xlabel('Iterations')
ylabel('error ')
title('error curve')
%% šŕ
figure(2);
a0=test_xdata;
z1=W1'*a0+repmat(B1,1,Test_SampleNum);
a1=sigmod(z1);
a2=W2'*a1+repmat(B2,1,Test_SampleNum);
plot(test_ydata,'b-*')
test_error=a2-test_ydata;
E_testvalues=sumsqrt(test_error);
test_ydata1=(a2-min(a2))*(Max_test_ydata-Min_test_ydata)+Min_test_ydata;
plot(test_ydata1','r-o');
hold on;
plot(Test_ydata','b-*');
legend('Predictive test data','Actual test data')
xlabel('years')
ylabel('test data')
title('test data')
axis([1,3,0,30])
%% wijŕ
figure(3);
hidein=W1'*train_xdata+repmat(B1,1,Train_SampleNum);
hideout=sigmod(hidein);
output=W2'*hideout+repmat(B2,1,Train_SampleNum);
plot(train_ydata,'b-*');
title(['E=',num2str(E)])
train_ydata1=(output-min(output))*(Max_train_ydata-Min_train_ydata)+Min_train_ydata;
```

```
plot(2005:1:2014,train_ydata1',’r-o’);
hold on;
plot(2005:1:2014,Train_ydata’,’b-*’);
legend(’Predicted training data’,’Actual training data’)
xlabel(’years’)
ylabel(’training data’)
title(’digestive system  disease data’)
pre_data=[train_ydata1,test_ydata1]’;
```

```
%% ¿
input_data=NIR’;
out_data=octane’;
temp=randperm(60);
Train_xdata=input_data(:,temp(1:50));
Train_ydata=out_data(temp(1:50));
Test_xdata=input_data(:,temp(51:end));
Test_ydata=out_data(temp(51:end));
%% ¿t’ę
Max_train_ydata=max(Train_ydata);
Max_test_ydata=max(Test_ydata);
Min_train_ydata=min(Train_ydata);
Min_test_ydata=min(Test_ydata);
train_xdata=mapminmax(Train_xdata,0,1);%űßÿś¿źżŕ
train_ydata=mapminmax(Train_ydata,0,1);
test_xdata=mapminmax(Test_xdata,0,1);
test_ydata=mapminmax(Test_ydata,0,1);
%% w
insize=401;
hidesize=20;
outsize=1;
iter=1;
maxiter=100000;
W1=0.01*rand(insize,hidesize);
B1=0.01*rand(hidesize,1);
W2=0.01*rand(hidesize,outsize);
B2=0.01*rand(outsize,1);
alpha1=0.01;
alpha2=0.01;
Train_SampleNum=size(train_xdata,2);
Test_SampleNum=size(test_xdata,2);
E_maxvalues=1e-6;
E_record=[];
iter=0;
%%
for i=1:maxiter
      hidein=W1’*train_xdata+repmat(B1,1,Train_SampleNum);
      hideout=sigmod(hidein);
      output=W2’*hideout+repmat(B2,1,Train_SampleNum);
      error=output-train_ydata;
      E=sumsqrt(error);%¿ů¡ž-žŕ
      delta2=error;
      delta1=(W2*delta2).*hideout.*(1-hideout);
      dB2=delta2*ones(Train_SampleNum,1);
      dW2=hideout*delta2’;
      dB1=delta1*ones(Train_SampleNum,1);
```

```
      dW1=train_xdata*delta1';
      B2=B2-alpha2*dB2;
      W2=W2-alpha2*dW2;
      B1=B1-alpha1*dB1;
      W1=W1-alpha1*dW1;
      E_record=[E_record,E];
      if E<E_maxvalues
          break;
      end
      iter=iter+1;
end
%%
figure(1);
plot(E_record,'LineWidth',1.5);

%% šŕ
figure(2);
subplot(2,1,1)
a0=test_xdata;
z1=W1'*a0+repmat(B1,1,Test_SampleNum);
a1=sigmod(z1);
a2=W2'*a1+repmat(B2,1,Test_SampleNum);
plot(a2,'r-o');
hold on;
plot(test_ydata,'b-*')
test_error=a2-test_ydata;
E_testvalues=sumsqrt(test_error);
legend('źżśš¿','źżśš¿')
title(['E=',num2str(E)])
subplot(2,1,2);
test_ydata1=(a2-min(a2))*(Max_test_ydata-Min_test_ydata)+Min_test_ydata;
plot(test_ydata1,'r-o');
hold on;
plot(Test_ydata,'b-*');
legend('š¿','š¿')

%% wijŕ
figure(3);
subplot(2,1,1);
hidein=W1'*train_xdata+repmat(B1,1,Train_SampleNum);
hideout=sigmod(hidein);
output=W2'*hideout+repmat(B2,1,Train_SampleNum);
plot(output,'r-o');
hold on;
plot(train_ydata,'b-*');
legend('źżśšw¿','źżśw¿')
title(['E=',num2str(E)])
subplot(2,1,2);
train_ydata1=(output-min(output))*(Max_train_ydata-Min_train_ydata)+Min_train_ydata;
plot(train_ydata1,'r-o');
hold on;
plot(Train_ydata,'b-*');
legend('šw¿','w¿')
```

```
%% data input
```

```
input_data=NIR';
out_data=octane(:,2)';
temp=1:13;
Train_xdata=input_data(:,temp(1:10));
Train_ydata=out_data(temp(1:10));
Test_xdata=input_data(:,temp(11:end));
Test_ydata=out_data(temp(11:end));
%% data processing
Max_train_ydata=max(Train_ydata);
Max_test_ydata=max(Test_ydata);
Min_train_ydata=min(Train_ydata);
Min_test_ydata=min(Test_ydata);
train_xdata=mapminmax(Train_xdata,0,1);%ŭßÿś¿źżŕ
train_ydata=mapminmax(Train_ydata,0,1);
test_xdata=mapminmax(Test_xdata,0,1);
test_ydata=mapminmax(Test_ydata,0,1);
%% w
insize=9;
hidesize=20;
outsize=1;
iter=1;
maxiter=100000;
W1=0.01*rand(insize,hidesize);
B1=0.01*rand(hidesize,1);
W2=0.01*rand(hidesize,outsize);
B2=0.01*rand(outsize,1);
alpha1=0.01;
alpha2=0.01;
Train_SampleNum=size(train_xdata,2);
Test_SampleNum=size(test_xdata,2);
E_maxvalues=1e-6;
E_record=[];
iter=0;
%%
for i=1:maxiter
      hidein=W1'*train_xdata+repmat(B1,1,Train_SampleNum);
      hideout=sigmod(hidein);
      output=W2'*hideout+repmat(B2,1,Train_SampleNum);
      error=output-train_ydata;
      E=sumsqrt(error);%¿ů¡ž-žŕ
      delta2=error;
      delta1=(W2*delta2).*hideout.*(1-hideout);
      dB2=delta2*ones(Train_SampleNum,1);
      dW2=hideout*delta2';
      dB1=delta1*ones(Train_SampleNum,1);
      dW1=train_xdata*delta1';
      B2=B2-alpha2*dB2;
      W2=W2-alpha2*dW2;
      B1=B1-alpha1*dB1;
      W1=W1-alpha1*dW1;
      E_record=[E_record,E];
      if E<E_maxvalues
          break;
      end
      iter=iter+1;
```

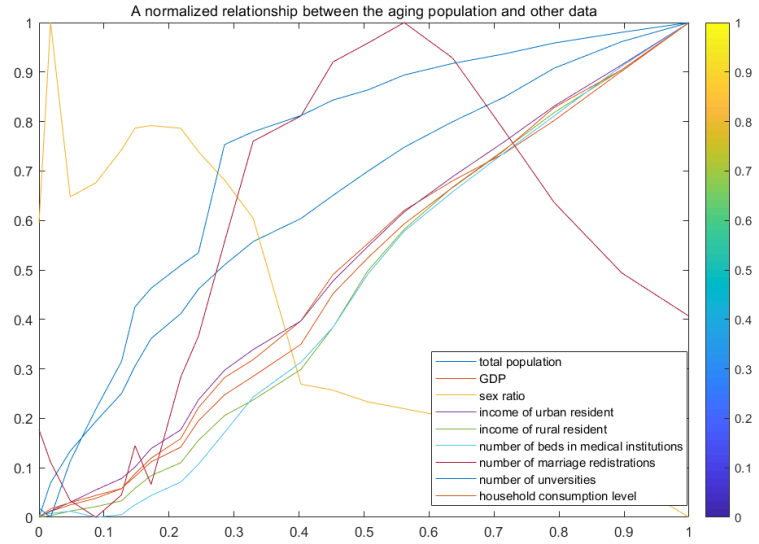
```
end
%%
figure(1);
plot(E_record,'r','LineWidth',1.8);
xlabel('Iterations')
ylabel('error ')
title('error curve')
%% Test
figure(2);
a0=test_xdata;
z1=W1'*a0+repmat(B1,1,Test_SampleNum);
a1=sigmod(z1);
a2=W2'*a1+repmat(B2,1,Test_SampleNum);
plot(test_ydata,'b-*')
test_error=a2-test_ydata;
E_testvalues=sumsqrt(test_error);
test_ydata1=(a2-min(a2))*(Max_test_ydata-Min_test_ydata)+Min_test_ydata;
plot(test_ydata1','r-o');
hold on;
plot(Test_ydata','b-*');
legend('Predictive test data','Actual test data')
xlabel('years')
ylabel('test data')
title('test data')
axis([1,3,0,30])
%% Trining
figure(3);
hidein=W1'*train_xdata+repmat(B1,1,Train_SampleNum);
hideout=sigmod(hidein);
output=W2'*hideout+repmat(B2,1,Train_SampleNum);
plot(train_ydata,'b-*');
title(['E=',num2str(E)])
pre_ydata1=(output-min(output))*(Max_train_ydata-Min_train_ydata)+Min_train_ydata;
plot(2005:1:2014,pre_ydata1','r-o');
hold on;
plot(2005:1:2014,Train_ydata','b-*');
legend('Predicted training data','Actual training data')
xlabel('years')
ylabel('training data')
title('digestive system  disease data')
pre_data=[pre_ydata1,test_ydata1]';
%% Predict
figure(4);
predict_xdata=NIR(11:end,:)';
hidein=W1'*predict_xdata+repmat(B1,1,5);
hideout=sigmod(hidein);
output=W2'*hideout+repmat(B2,1,5);
pre_ydata1=(output-min(output))*(Max_train_ydata-Min_train_ydata)+Min_train_ydata;
plot(pre_ydata1','r-o');
xlabel('years')
ylabel('predicted data')
title('digestive system  disease data')
```

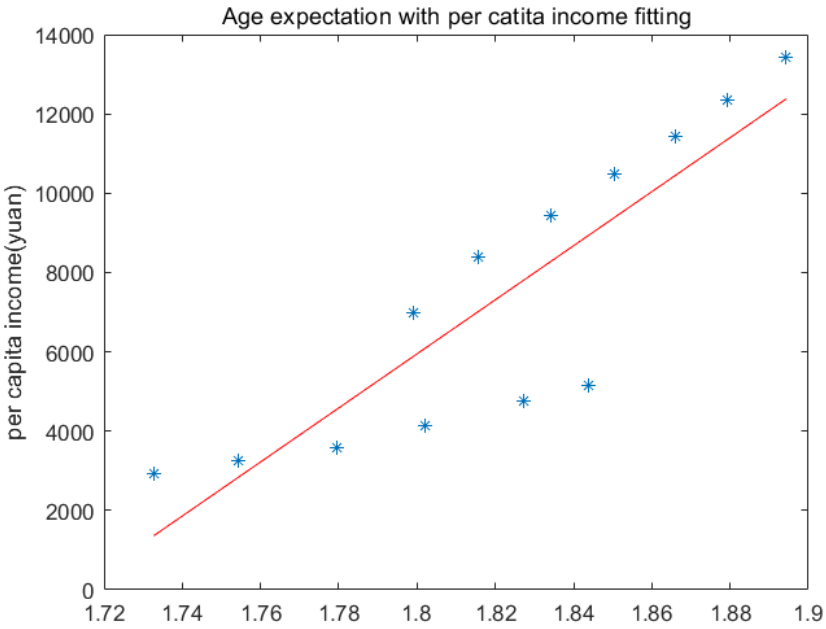
```
x0=octane(:,7);
m=size(x0);
```

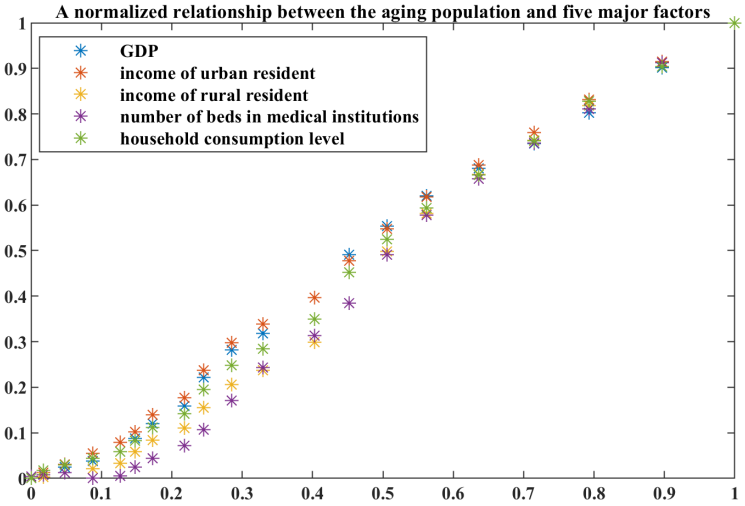
```
x1=[];
x1(1)=x0(1);
for i=2:m(1)
    x1(i)=x0(i)+x1(i-1);
end
%źű
for k=2:m(1)
    rou(k)=x0(k)/x1(k);
end
r=zeros(1,m(1));
for i=2:m(1)
    r(i)=x0(i-1)/x0(i);
end
aa=exp(-2/(m(1)+1));
bb=exp(2/(m(1)+1));
alpha=0.5;n=length(x0);
x00=x0(2:end)';
z1=alpha*x1(2:n)+(1-alpha)*x1(1:n-1);
C1=polyfit(z1,x00(1:n-1),1);
a=-C1(1);b=C1(2);
z1i=z1(1):0.1:z1(end);
x1i=polyval(C1,z1i);
x11=x00(1:n-1);
plot(z1i,x1i,z1,x11,'r*');
x14=[];
x14(1)=x0(1);
for k=2:18
x14(k)=(x0(1)-b/a)*(exp(-a*k)-exp(-a*(k-1)));
end
%ij
x000=x0';
plot(2005:2016,x0(2:end),'r-o')
hold on;
plot(2005:2022,x14(1:end),'b-*')
xlabel('years')
ylabel('number of people')
title('predict number of people')
```

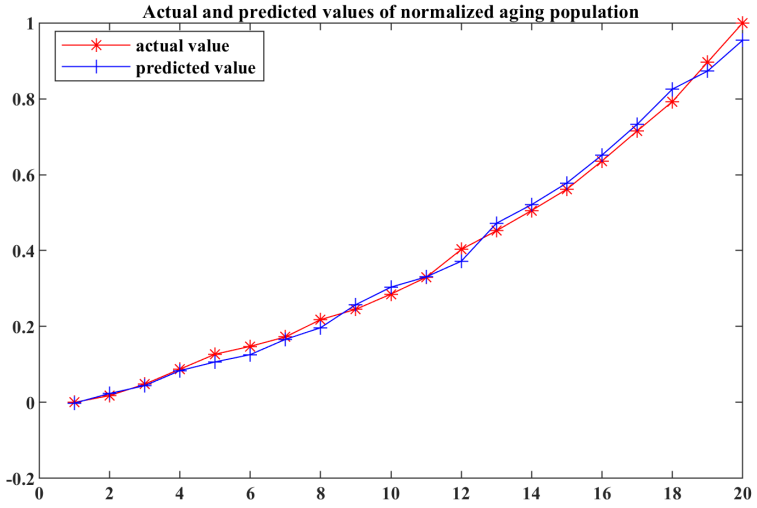
```
function [t,seat,aisle]=OI6Sim(n,target,seated)
pab=rand(1,n);
for i=1:n
    if pab(i)<0.4
       aisleTime(i)=0;
    else
        aisleTime(i)=trirnd(3.2,7.1,38.7);
    end
end
```

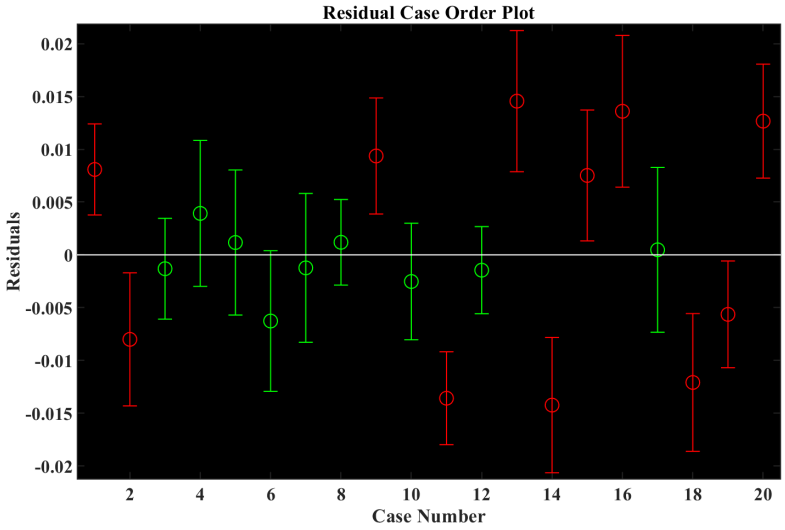
Appendix D Figure of task1

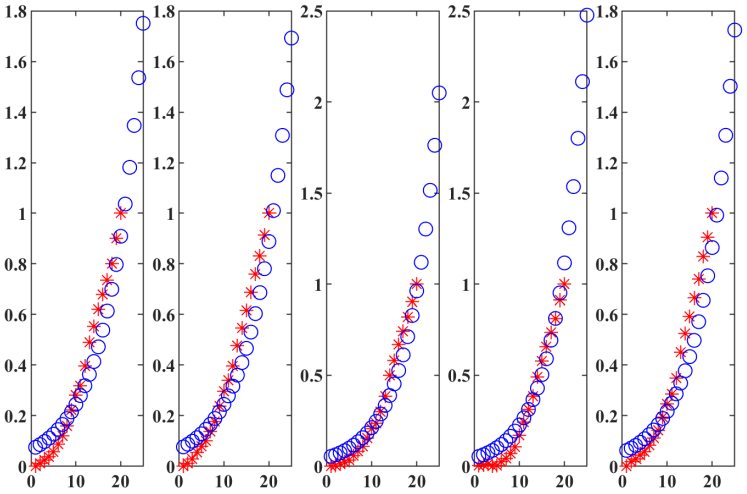


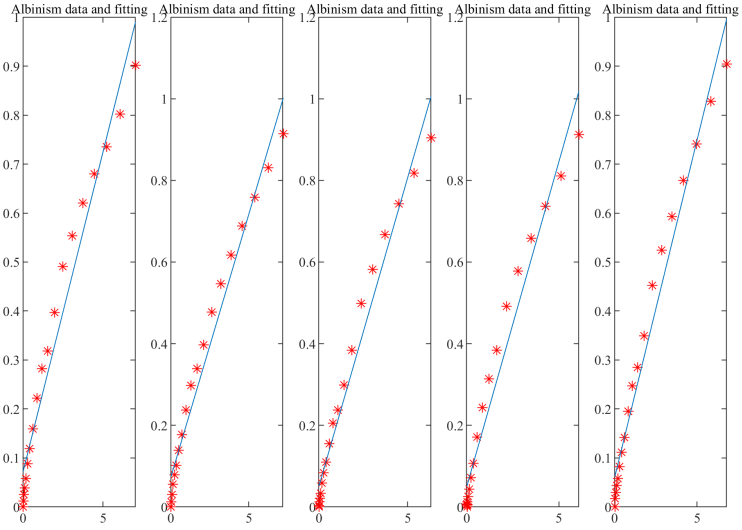


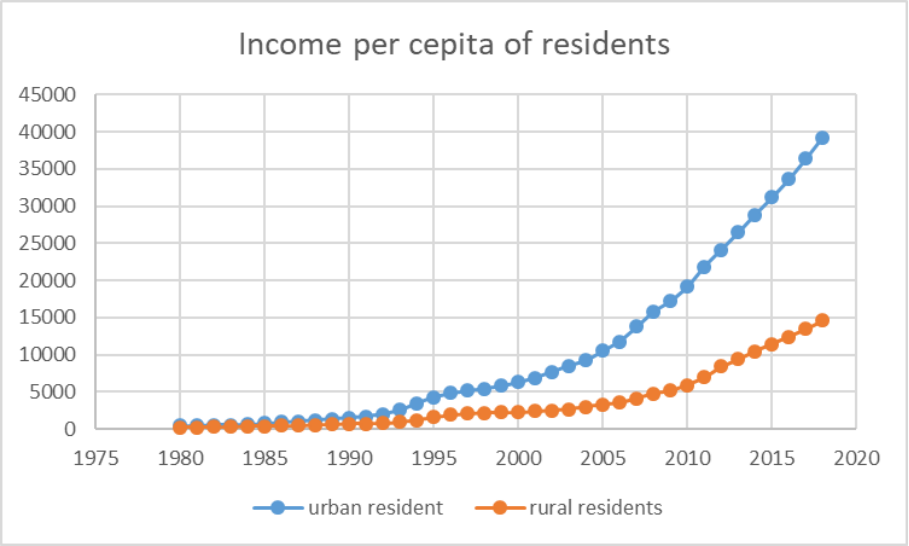

A normalized relationship between the aging population and five major factors
GDP
income of urban resident
income of rural resident
number of beds in medical institutions
household consumption level

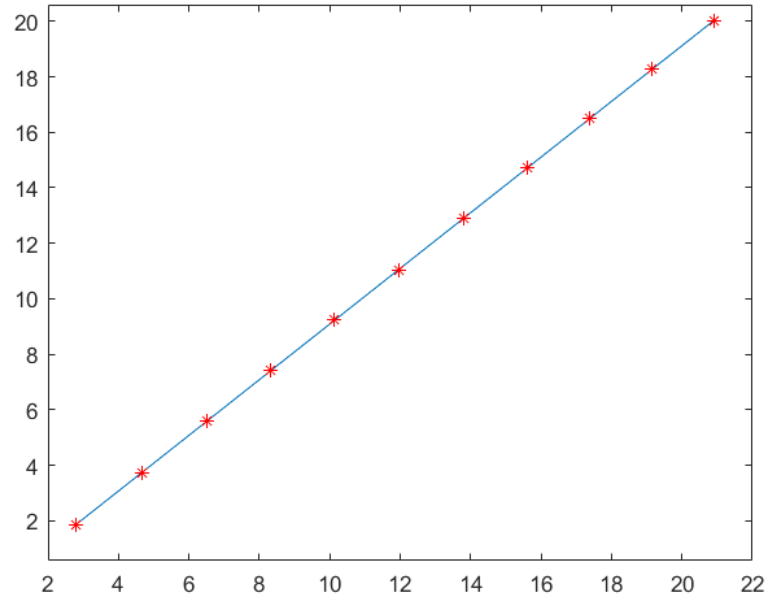

Actual and predicted values of normalized aging population
actual value
predicted value

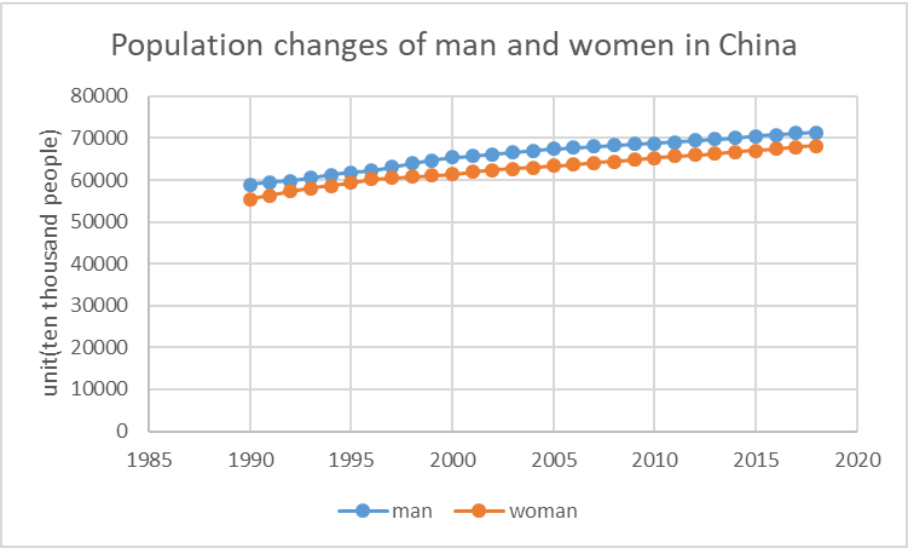

Residual Case Order Plot
Residuals
Case Number

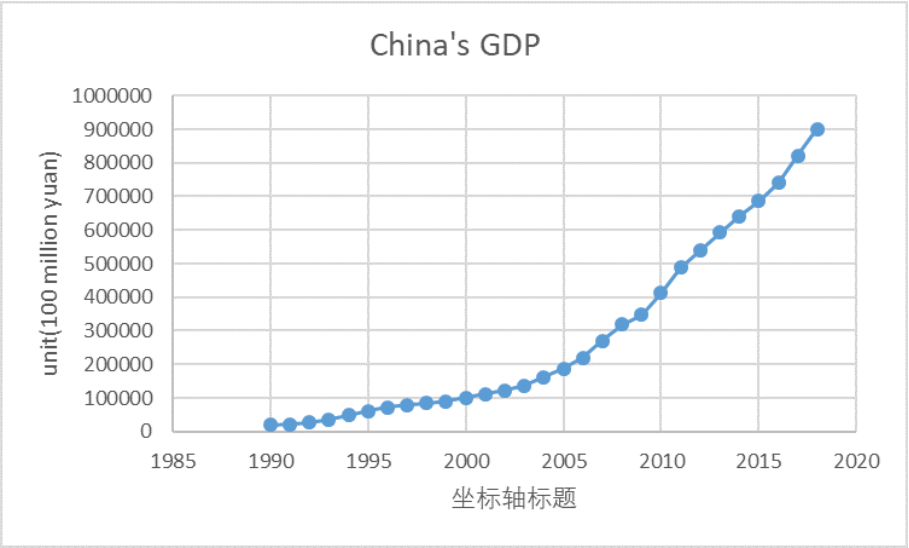


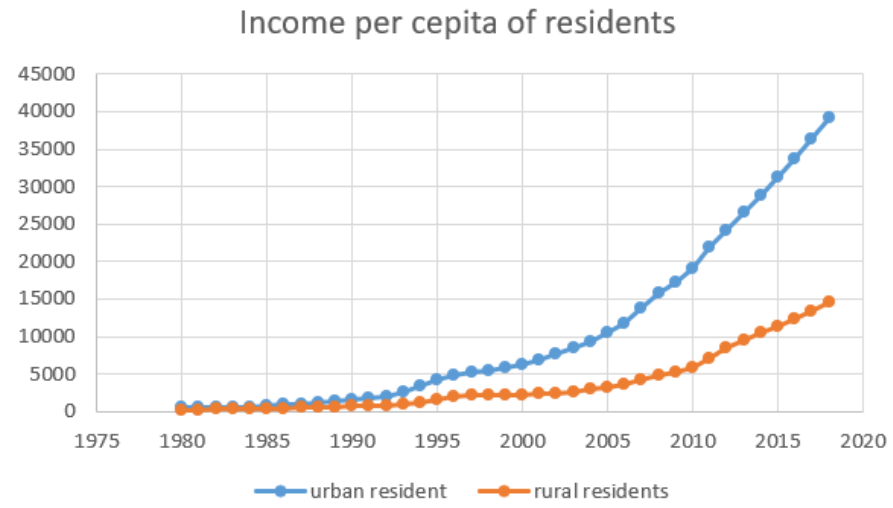

Albinism data and fitting
Albinism data and fitting
Albinism data and fitting
Albinism data and fitting
Albinism data and fitting

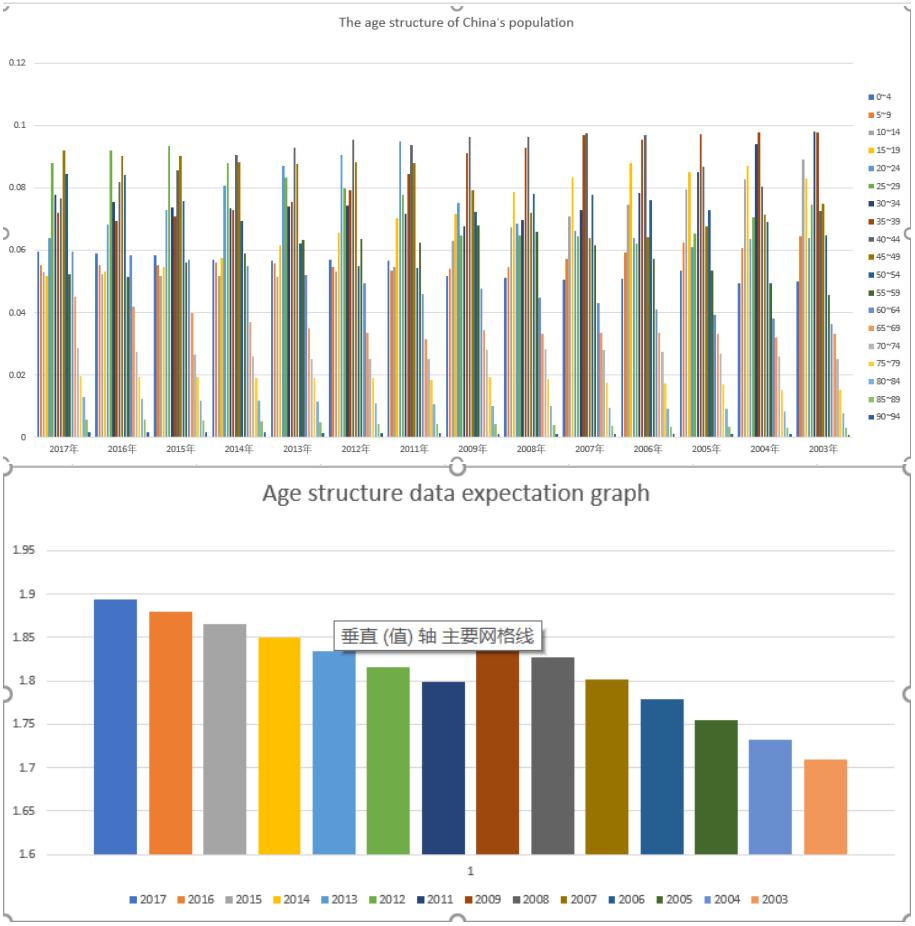

Income per cepita of residents
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
urban resident
rural residents


20
18
16
14
12
10
8
6
4
2
2
4
6
8
10
12
14
16
18
20
22


Population changes of man and women in China
unit(ten thousand people)
80000
70000
60000
50000
40000
30000
20000
10000
0
1985
1990
1995
2000
2005
2010
2015
2020
man
woman

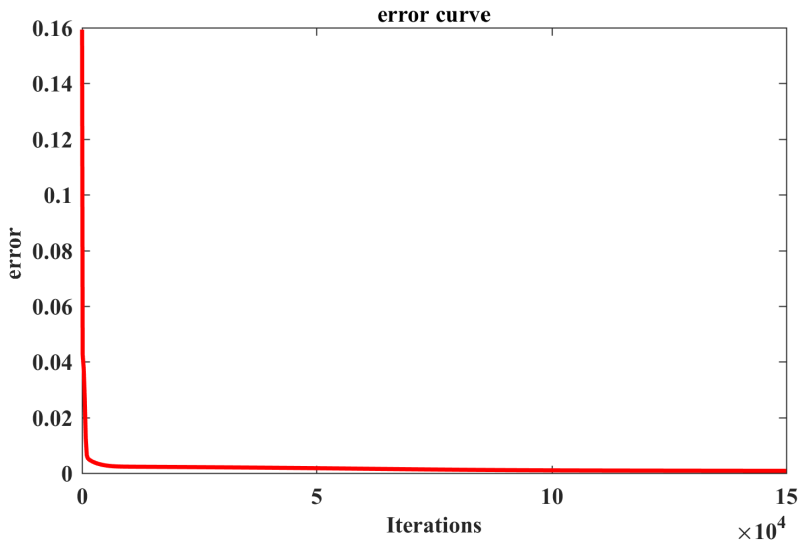

China's GDP
unit(100 million yuan)
1000000
900000
800000
700000
600000
500000
400000
300000
200000
100000
0
1985
1990
1995
2000
2005
2010
2015
2020
坐标轴标题

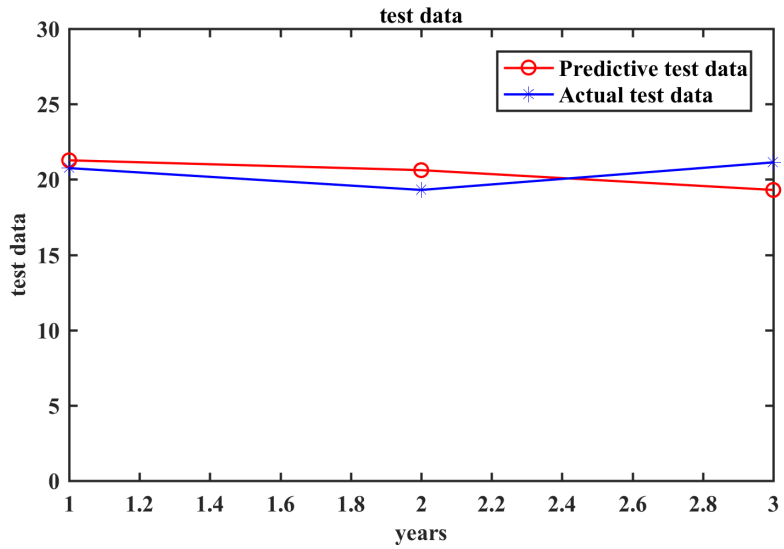

Income per cepita of residents
45000
40000
35000
30000
25000
20000
15000
10000
5000
0
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020
urban resident
rural residents

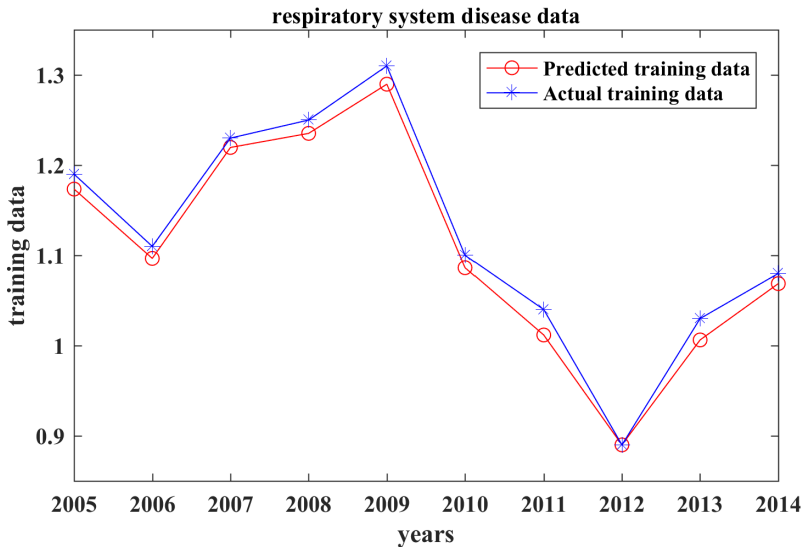

The age structure of China's population
0.12
0.1
0.08
0.06
0.04
0.02
0
2017年
2016年
2015年
2014年
2013年
2012年
2011年
2009年
2008年
2007年
2006年
2005年
2004年
2003年
0~4
5~9
10~14
15~19
20~24
25~29
30~34
35~39
40~44
45~49
50~54
55~59
60~64
65~69
70~74
75~79
80~84
85~89
90~94

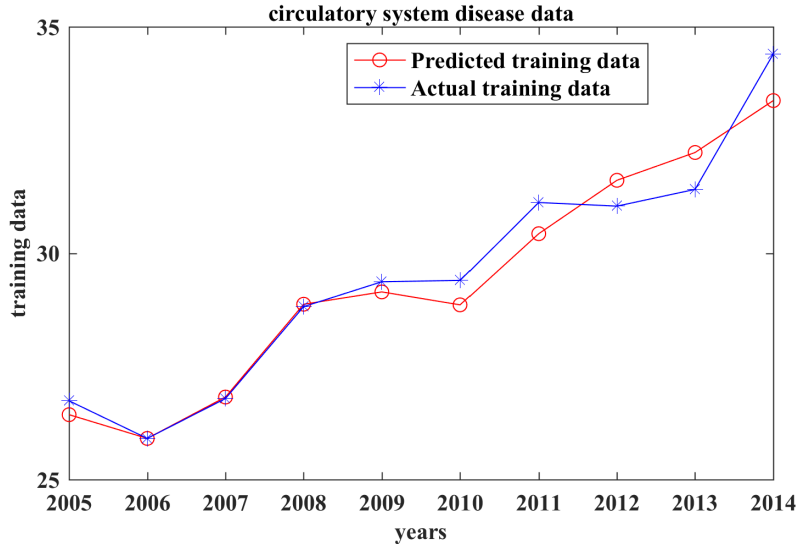
Age structure data expectation graph
1.95
1.9
1.85
1.8
1.75
1.7
1.65
1.6
垂直 (值) 轴 主要网格线
1
2017
2016
2015
2014
2013
2012
2011
2009
2008
2007
2006
2005
2004
2003

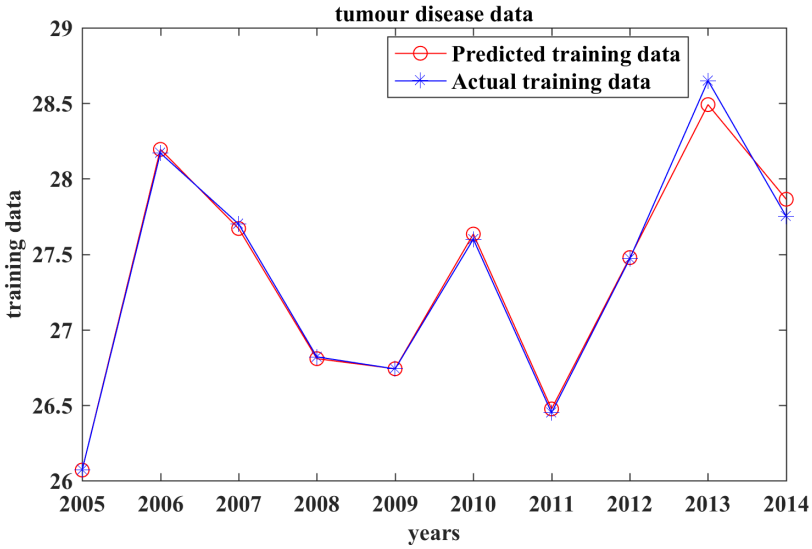
Appendix E Figure of task2

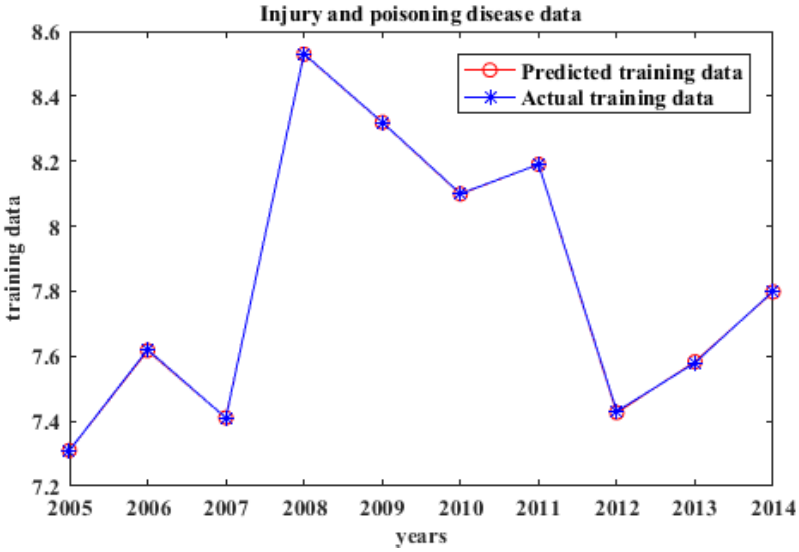


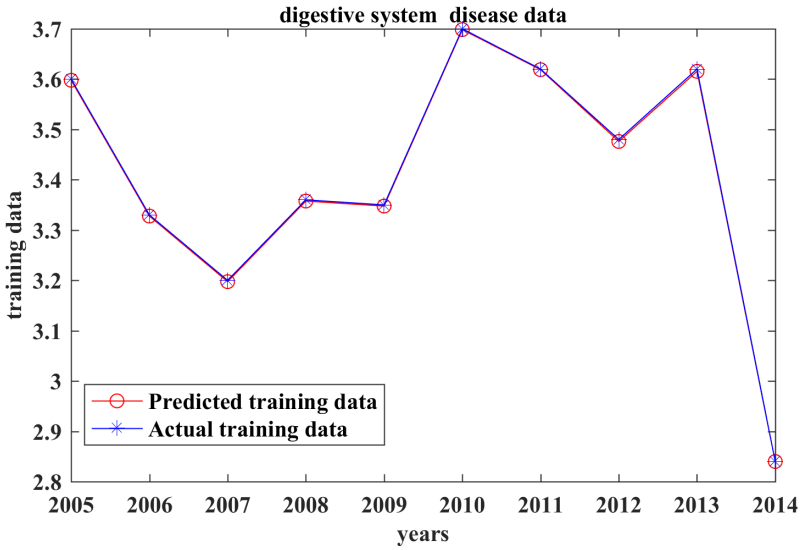


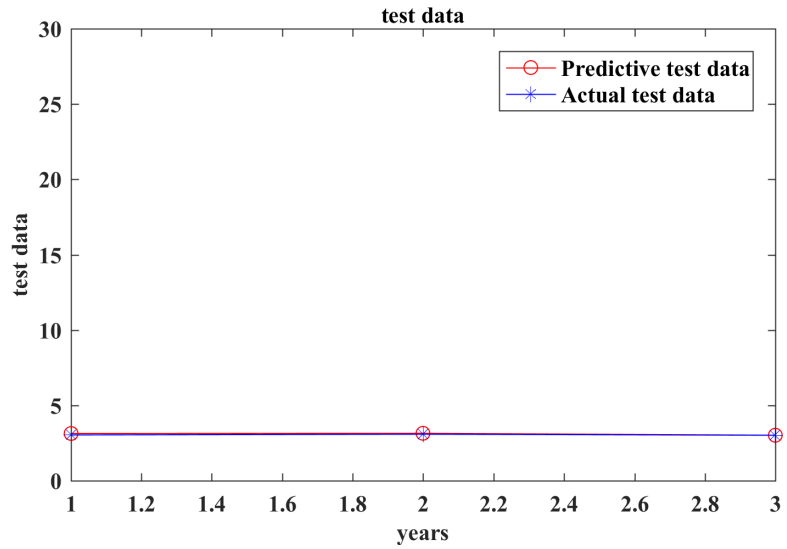


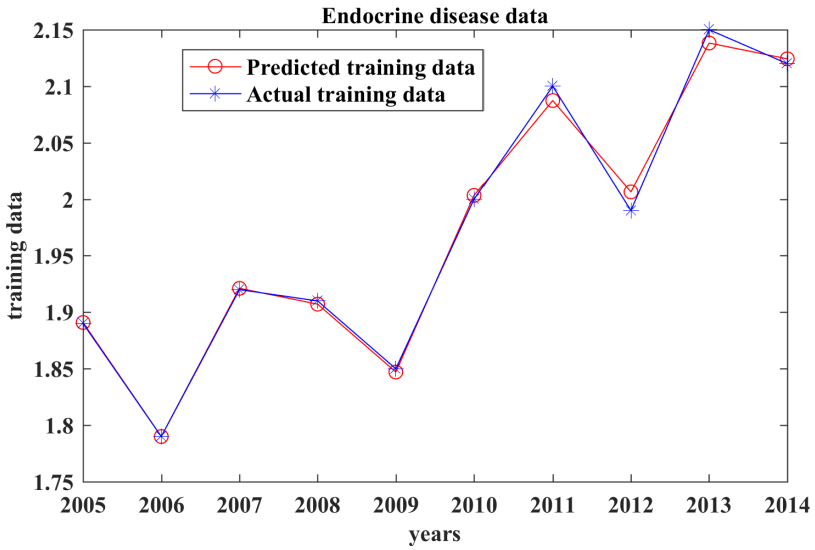

circulatory system disease data
Predicted training data
Actual training data
training data
years
35
30
25
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

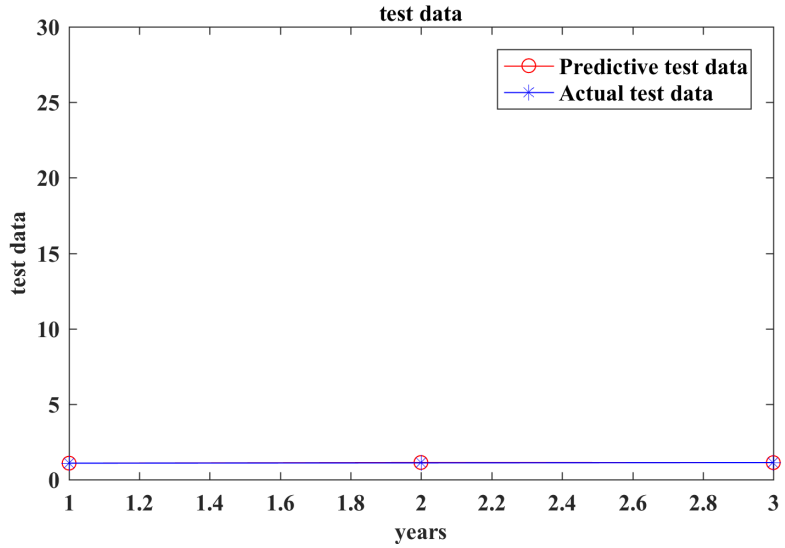

tumour disease data
Predicted training data
Actual training data
training data
years
29
28.5
28
27.5
27
26.5
26
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

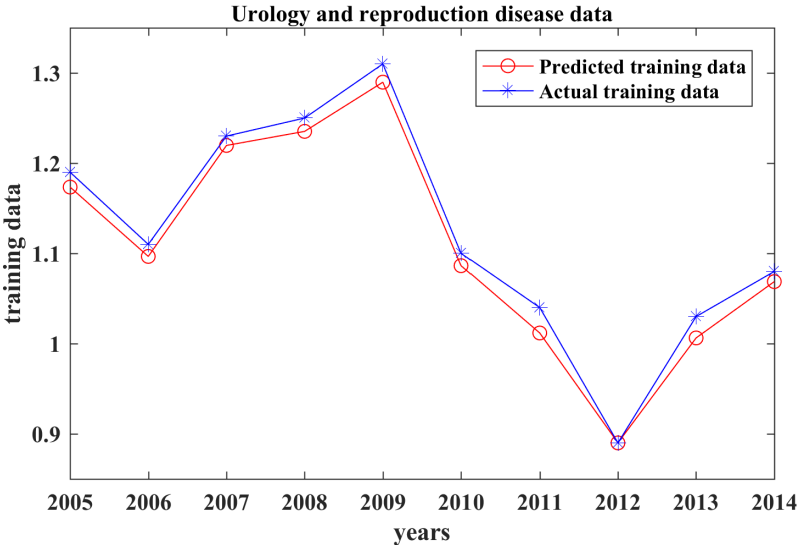

Injury and poisoning disease data
Predicted training data
Actual training data
training data
years
8.6
8.4
8.2
8
7.8
7.6
7.4
7.2
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

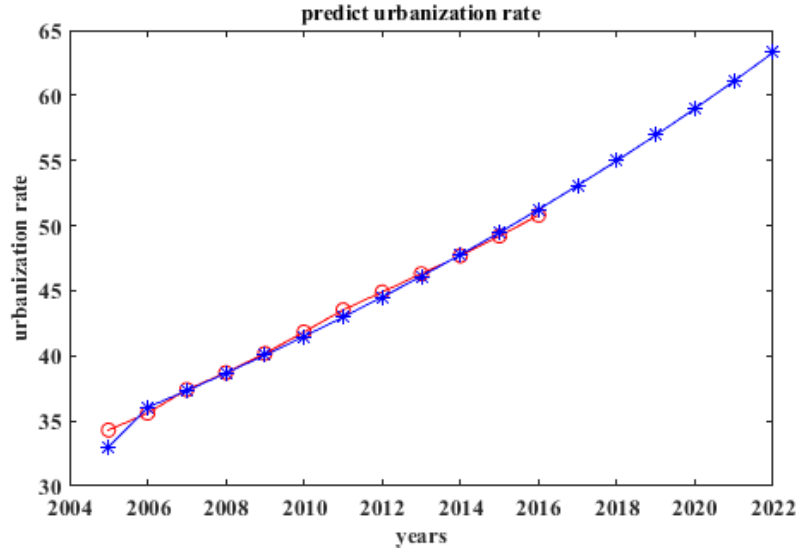

digestive system disease data
training data
years
Predicted training data
Actual training data
3.7
3.6
3.5
3.4
3.3
3.2
3.1
3
2.9
2.8
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

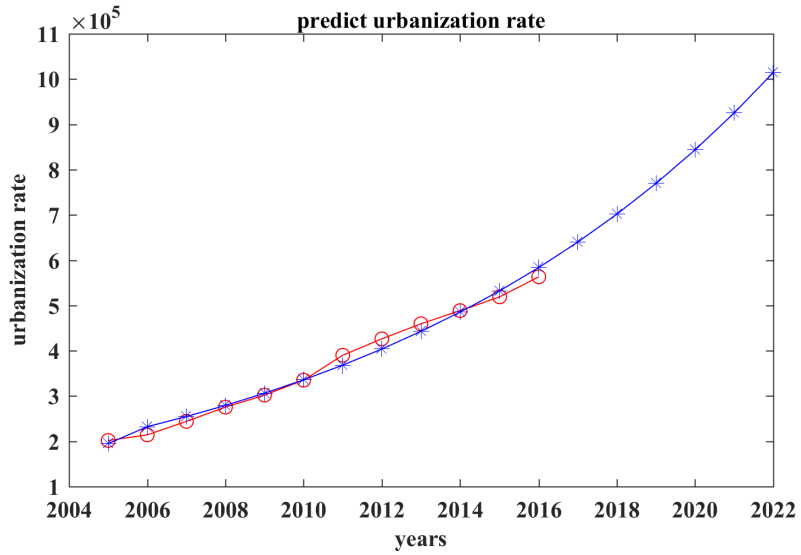

test data
test data
years
Predictive test data
Actual test data
30
25
20
15
10
5
0
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3

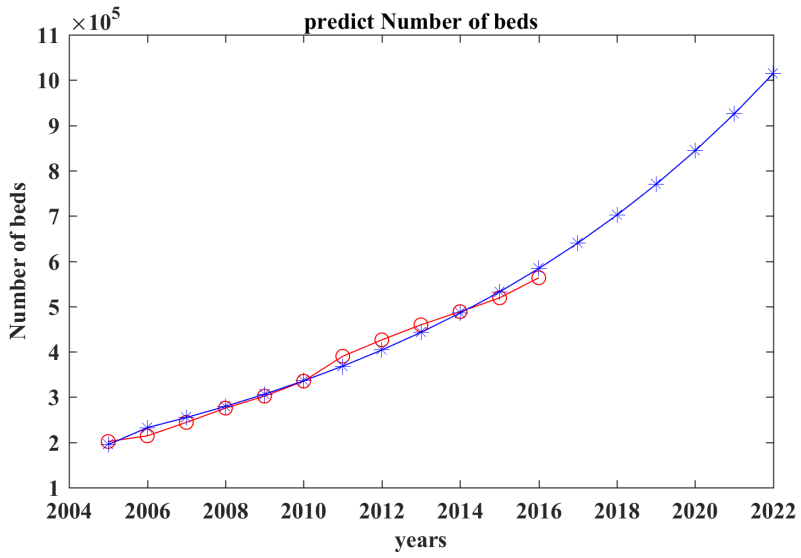

Endocrine disease data
training data
years
Predicted training data
Actual training data
2.15
2.1
2.05
2
1.95
1.9
1.85
1.8
1.75
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

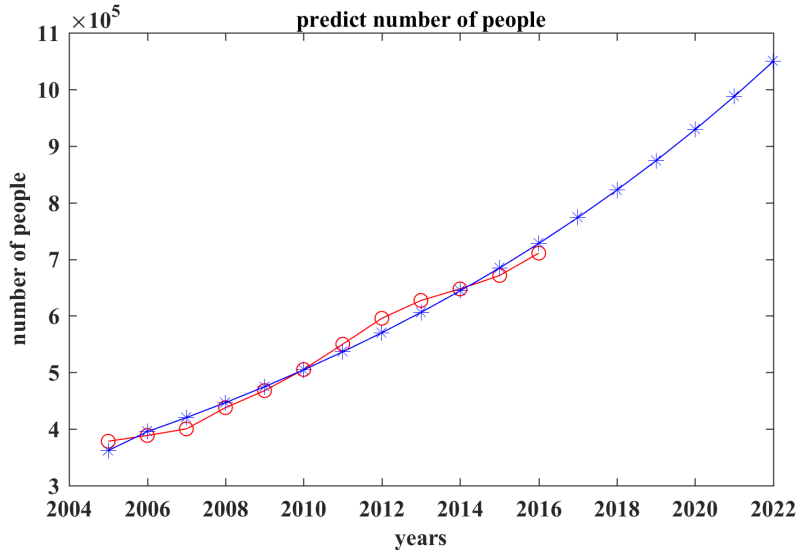

test data
Predictive test data
Actual test data
test data
years
30
25
20
15
10
5
0
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
2.8
3


Urology and reproduction disease data
Predicted training data
Actual training data
training data
years
1.3
1.2
1.1
1
0.9
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

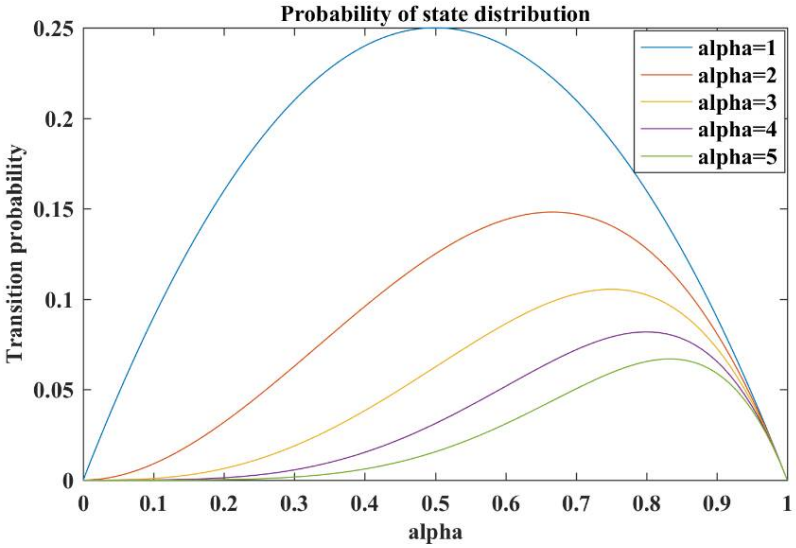

predict urbanization rate
urbanization rate
years
65
60
55
50
45
40
35
30
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022

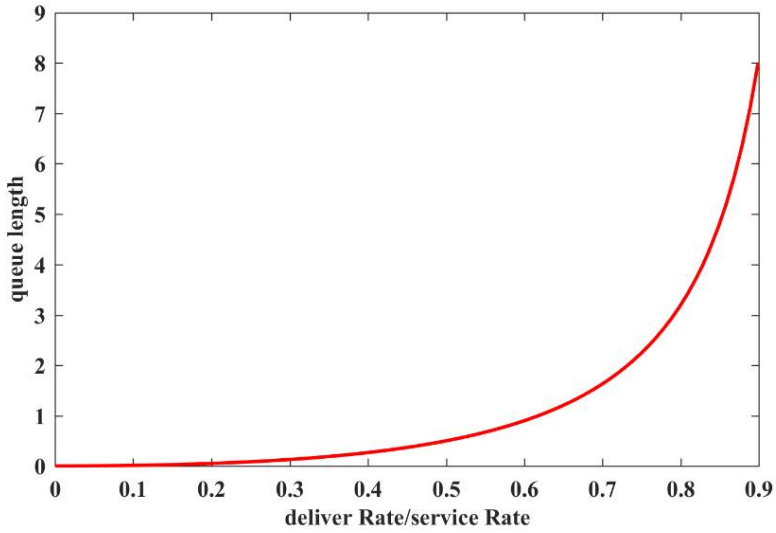
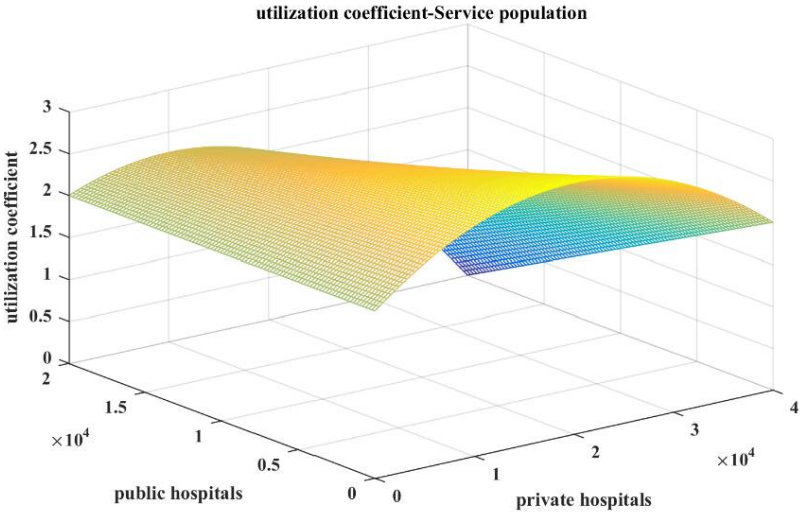

predict urbanization rate
×10^5
urbanization rate
years
11
10
9
8
7
6
5
4
3
2
1
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022


predict Number of beds
×10^5
Number of beds
years
11
10
9
8
7
6
5
4
3
2
1
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022


predict number of people
×10^5
number of people
years
11
10
9
8
7
6
5
4
3
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022

Appendix F Figure of task3





Appendix G Figure of task3