Advance Journal of Food Science and Technology 9(5): 389-392, 2015
DOI: 10.19026/ajfst.9.1921
ISSN: 2042-4868; e-ISSN: 2042-4876

Submitted: March 19, 2015 Accepted: March 24, 2015 Published: August 20, 2015

Research Article

Forecasting of Water Resource of China based on Grey Prediction Model

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Abstract: Water resource planning is very important for water resources management. A desirable water resource planning is typically made in order to satisfy multiple objectives as much as possible. Thus the water resource planning problem is actually a Multiple Attribute Decision Making (MADM) problem. The aim of this study is to put forward a new decision method to solve the problem of water resource planning in which attribute values expressed with triangular fuzzy numbers. The new method is an extension of projection method. To avoid the subjective randomness, the coefficient of variation method is used to determine the attribute weights. A practical example is given to illustrate the effectiveness and feasibility of the proposed method.

Keywords: GM (1, 1), grey prediction model, water resource

INTRODUCTION

China's total water resources are 2.8 trillion m^3, among which there are 2.7 trillion m^3 of surface water, 0.83 trillion m^3 of groundwater. Due to interconversion and mutual replenishment between surface water and groundwater, with 0.73 trillion m^3 deduction from repeated counting of the two, the net amount of groundwater resources is about 0.1 trillion m^3. In accordance with internationally recognized standards, the per capita water resources of less than 3,000 m^3 falls to the category of mild water shortage; less than 2,000 m^3/capita water to moderate water shortage; severe lack of water happens when there is less than 1000 m^3/capita water resources; water resources per capita less than 500 m^3 is of extreme water shortage. There are 16 provinces (autonomous regions and municipalities) in China per capita water resources (excluding transit) is below the line of severe water shortage, per capita water resources in six provinces, autonomous regions (Ningxia, Hebei, Shandong, Henan, Shanxi, Jiangsu) less than 500 m^3, is extremely dry areas.

China is facing increasing pressure on flesh water supplies (Liu and Tang, 2014; Cui *et al*., 2014). It is among the l3 lowest water availability countries in the world and the per capita water availability of China is about a quarter of the world average. Majority of the available water is concentrated in the south, 1eaving the northern and western China to experience perpetual droughts. Rivers, lakes and underground aquifers are literally drying up due to over drafts. Most of the remaining surface waters are so polluted that they are no longer suitable for human contacts. With population growth accelerated industrialization and urbanization and global climate change, China's water crisis is exacerbating (Liao *et al*., 2013; Zhang *et al*., 2013). Water shortage has become a major obstacle restricting China's economic development (Yi *et al*., 2011).

The aim of this study is to develop the grey prediction model to predict the water resource of China.

METHODOLOGY

Preliminaries: Grey prediction model is an important model in grey system theory, which proposed by Deng (1989). Grey prediction model has received great attention because it only requires a limited amount of data to estimate or measure data collected from an uncertain and indeterminate system and it has a good performance in prediction performance (Li *et al*., 2008; Yin and Tang, 2013; Hsu and Chen, 2003).

The 1st order gray prediction model, briefly denoted by GM (1, 1), is one of the most frequently used grey forecasting model first proposed by Deng (1989).

The GM (1, 1) model constructing process is described below (Deng, 1989):

In the positive sequence GM (1, 1) model, if we set the original data sequence in positive sequence with n entries as a vector $x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)]$. Here $x^{(0)}(1)$ is the beginning point.

The AGO transformation is defined as:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(k), k = 1, 2, \cdots, n \quad (1)$$

The positive sequence GM (1, 1) model can be constructed by establishing a first order differential equation $x^{(1)}(k)$ as:

$$\frac{dx^{(1)}(k)}{dt} + ax^{(1)}(k) = b \tag{2}$$

or:

$$\Delta x^{(1)}(k+1) + ax^{(1)}(k+1) = b \tag{3}$$

where,

$$\begin{aligned}\Delta x^{(1)}(k+1) &= x^{(1)}(k+1) - x^{(1)}(k) \\ &= x^{(1)}(k) + x^{(0)}(k+1) - x^{(1)}(k) \\ &= x^{(0)}(k+1)\end{aligned}$$

$$x^{(1)}(k+1) = \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k+1)\right]$$

So we derive Eq. (4) from (3):

$$x^{(0)}(k+1) = a\left[-\frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k+1)\right]\right] + b \tag{4}$$

where, $k = 1,2,...,n-1$.

Therefore, the solution of Eq. (2) can be obtained by using the least square method. That is:

$$\hat{x}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}} \tag{5}$$

where, $k = 0$ denotes the beginning position, $\left[\hat{a},\hat{b}\right]^T = \left[B^T B\right]^{-1} B^T Y$ and:

$$Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}, \quad B = \begin{pmatrix} -1/2\left[x^{(1)}(1) + x^{(1)}(2)\right] \\ -1/2\left[x^{(1)}(2) + x^{(1)}(3)\right] \\ \vdots \\ -1/2\left[x^{(1)}(n-1) + x^{(1)}(n)\right] \end{pmatrix}$$

We obtained $\hat{x}^{(1)}$ from Eq. (5). Let $\hat{x}^{(0)}$ be the fitted and predicted series:

$$\hat{x}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n), \cdots) \tag{6}$$

where,

$$\hat{x}^{(0)}(1) = x^{(0)}(1)$$

Applying the inverse AGO, we then have:

$$\hat{x}^{(0)}(k+1) = (1 - e^{\hat{a}})\left[x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}\right]e^{-\hat{a}k} \tag{7}$$

Here $k = 1,2,\cdots$ and $\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n)$ are called the GM (1, 1) fitted sequence, while $\hat{x}^{(0)}(n+1), \hat{x}^{(0)}(n+2), \cdots$ are called the GM (1, 1) forecast values.

The time sequence calculated from the model includes $x^{(0)}(2), \cdots, x^{(0)}(n)$. The residual error paralleled to time I can be depicted as follows:

$$\varepsilon^{(0)}(k) = x^{(0)}(i) - \hat{x}^{(1)}(k), i = 2,3,\cdots,n$$

The mean residual error and corresponding equation can be denoted as:

$$\overline{\varepsilon} = \frac{1}{n-1}\sum_{i=2}^{n}\varepsilon^{(0)}(i), \quad s_1^2 = \frac{1}{n-1}\sum_{i=2}^{n}(\varepsilon^{(0)}(i) - \overline{\varepsilon})^2$$

While the average value and equation of the initial datum are computed according to:

$$\overline{x}^{(0)} = \frac{1}{n-1}\sum_{i=2}^{n}x^{(0)}(i) \quad S_2{}^2 = \frac{1}{n-1}\sum_{i=2}^{n}(x^{(0)}(i) - \overline{x}^{(0)})^2$$

A quantity $C = S_1 / S_2$ named posterior variance ratio is used to test the prediction.

CASE STUDY

China is facing severe water problems including scarcity and pollution which are now becoming key factors restricting developments. The problem is to determine an effective, feasible and cost-efficient water strategy for 2014 to meet the projected water needs of China in 2025 and identify the best water strategy. To predict how many provinces of China is water resource shortage and how much the shortage degree is. Here we will apply GM (1, 1) to predict the water consumptions in China.

According to China's 31 provinces and cities in the past nine years (2003-2011 years), Gray prediction model GM (1, 1) is used to predict water amount of China's 31 provinces and cities by 2025 the 14 years (2012-2025) years and according to the amount of water resources in the shortage of water resources occupancy of the degree of the corresponding ranking.

According to China's geographical situation, we study per capita water resources of the China's 31 provinces. With the gray forecast predict GM (1, 1) model, per capita consumption demand is predicted from 2013-2015, based on the data from 2003-2011. Using MATLAB software, we get C = 0.45, then from Table 1 we know that the prediction is acceptable. The predicted values are given in the following Table 2.

Table 1: Posterior-variance-test criterion for model evaluation

C	Forecasting ability
C<0.35	High forecasting
0.35<C<0.50	Good forecasting
0.50<C<0.65	Weak forecasting
C>0.65	Fail forecasting

Table 2: Thirty one provinces per capita water resources (cu.m/person) from 2012-2025

	Year						
Region	2012	2013	2014	......	2023	2024	2025
Beijing	117.840	110.690	103.970	…	59.190	55.600	52.230
Tianjing	87.682	81.481	75.719	…	39.130	36.363	33.791
Hebei	189.971	186.346	182.790	…	153.691	150.758	147.881
Shanxi	332.845	351.311	370.800	…	602.808	636.250	671.548
Inner Mong	1789.901	1858.452	1929.629	…	2706.300	2809.948	2917.567
Liaoning	951.099	1025.152	1104.970	…	2169.759	2338.697	2520.787
Jilin	1750.654	1851.483	1958.119	…	3241.251	3427.931	3625.362
Heilongjiang	2243.679	2395.462	2557.513	…	4609.728	4921.572	5254.513
Shanghai	57.541	44.310	34.121	…	3.249	2.502	1.927
Jiangsu	501.600	485.701	470.306	…	351.955	340.800	329.998
Zhejiang	2156.824	2276.887	2403.635	…	3913.910	4131.785	4361.789
Anhui	1449.765	1556.710	1671.543	…	3171.815	3405.790	3657.025
Fujian	3265.449	3335.238	3406.518	…	4120.648	4208.714	4298.661
Jiangxi	3871.021	4122.055	4389.368	…	7726.740	8227.816	8761.386
Shandong	355.870	361.567	367.355	…	423.797	430.581	437.473
Henan	451.173	460.316	469.644	…	562.581	573.982	585.614
Hubei	2006.850	2155.008	2314.104	…	4393.276	4717.614	5065.897
Hunan	2598.088	2699.624	2805.129	…	3960.942	4115.740	4276.589
Guangdong	1951.085	2002.341	2054.944	…	2595.119	2663.295	2733.261
Guangxi	4005.365	4204.610	4413.766	…	6832.219	7172.085	7528.857
Hainan	7440.125	8596.210	9931.934	…	36439.719	42101.912	48643.927
Chongqing	2110.371	2247.146	2392.785	…	4210.713	4483.613	4774.199
Sichuan	3534.035	3790.379	4065.318	…	7634.866	8188.669	8782.642
Guizhou	2850.905	3029.052	3218.331	…	5553.246	5900.257	6268.952
Yunnan	4572.077	4803.648	5046.948	…	7873.139	8271.906	8690.870
Tibet	181615.043	194940.880	209244.487	…	395743.649	424780.974	455948.887
Shaanxi	1746.629	1987.783	2262.233	…	7245.231	8245.567	9384.019
Gansu	935.088	969.145	1004.444	…	1385.974	1436.453	1488.772
Qinghai	16428.470	17760.120	19199.711	…	38719.859	41858.394	45251.330
Ningxia	7.042	3.799	2.050	…	0.008	0.004	0.002
Xinjiang	4527.424	4631.560	4738.091	…	5814.174	5947.906	6084.714

Table 3: Beijing per capita water resources (cu.m/person) from 2003-2011

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011
PCWR	127.80	194.43	182.64	171.56	161.15	151.37	142.18	133.56	125.50

Table 4: Beijing per capita water resources (cu.m/person) from 2012-2025

Year	2012	2013	2014	2015	2016	2017	2018
PCWR	117.84	110.69	103.97	97.66	91.74	86.17	80.94
Year	2019	2020	2021	2022	2023	2024	2025
PCWR	76.03	71.42	67.09	63.01	59.19	55.60	52.23

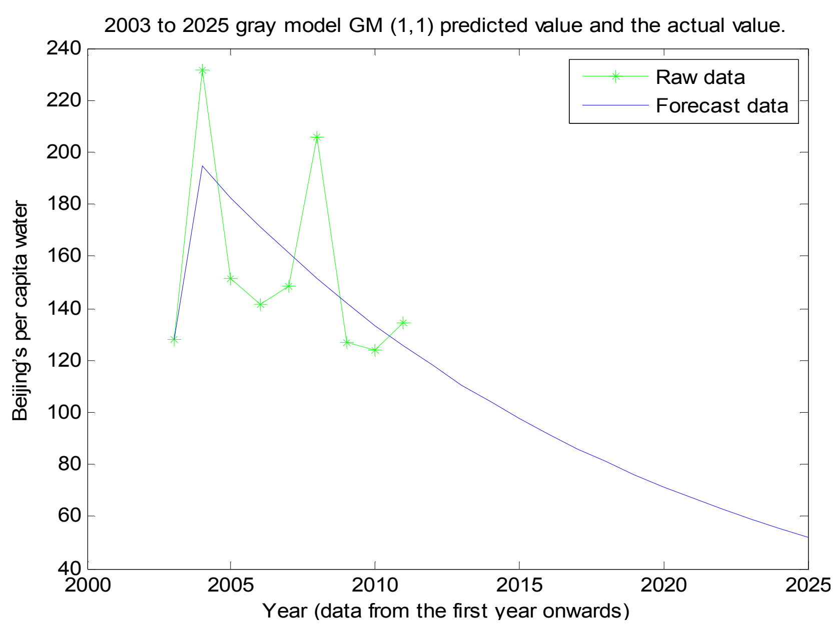

Fig. 1: Comparison of actual population quantity and the forecast 2003-2025

Now we use Beijing as an example to illustrate the water resource variable situation in the future 13 years. In Table 3 and 4, we give the actual and predictive values of Per Capita Water Resources (cu.m/person) (PCWR) for Beijing from 2003 to 2011 and 2012-2025.

At the same time we also concluded that 2003 to 2025 the actual data and predicted data comparison is shown in Fig. 1.

From the Table 2 we can know in 2025, the first ten serious water resource shortage provinces are respectively Ningxia, Shanghai, Tianjing, Beijing. Hebei, Jiangsu, Shandong, Henan, Shanxi, Gansu. Prediction results show that the first ten regions is a serious shortage of water resources, which should draw high attention. Liaoning, Guangdong and Inner Mong are in the edge of water resource shortage by compared with the criteria which the per capita water resources of less than 3,000 m^3 is the mild water shortage.

CONCLUSION AND RECOMMENDATIONS

According to China's 31 provinces and cities in the past nine years (2003-2011 years), Gray prediction model GM (1, 1) is used to predict water amount of China's 31 provinces and cities by 2025 the 14 years (2012-2025 years) and according to the amount of water resources in the shortage of water resources occupancy of the degree of the corresponding ranking, from China's top ten water provinces are respectively Ningxia, Shanghai, Tianjing, Beijing. Hebei, Jiangsu, Shandong, Henan, Shanxi, Gansu. Prediction results show that the ten regions is a serious shortage of water resources, which should draw high attention. Many water resource pans have been proposed (Alipour *et al*., 2010; Goodman and Edwards, 1992; Chen *et al*., 2011). According to the results of this study and the practice of China, some policy suggestions are proposed as follows:

- China's coastal cities such as Shanghai, Tianjin using desalination to solve the water shortage problem.
- Raise the price of water to the utilization of water resources in moderation, rational use of water resources and the realization of water resources effective.
- For the region which the water resources reproducible ability is weak, can recycle of water resources and sewage. Urban rainwater collection storage used for urban non-potable water direct water, or used as building inside and outside of the flushing water, green water spray, when necessary, also for industrial water, in a certain extent can alleviate the pressure of water supply for the city.
- Encourage seawater desalination, rainwater utilization and reuse of wastewater treatment, a city of optimal allocation of water resources and the whole society conservation new situation.
- Precipitation through the construction of reservoirs and dams, artificial recharge of ground measures impoundment to use of water resources.

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