Team Control Number

For office use only		Team Control Number	For office use only	
T1	________________	**50042**	F1	________________
T2	________________		F2	________________
T3	________________	Problem Chosen	F3	________________
T4	________________	**E**	F4	________________

2016 Mathematical Contest in Modeling (MCM) Summary Sheet

(Attach a copy of this page to each copy of your solution paper.)

Summary

To address the water scarcity issue, we firstly establish water carrying capacity coupling model comprising of two sub-models. One is designed for simulation and prediction utilizing 3-level **BP**(Back Popagation) structure, the other is for comprehensive evaluation by integrating as much information as possible. We choose 13 indexes like *total water resources amount, GDP, population* and so on. In this way the outcome can be transformed into an evaluation result by 5 levels. Then we utilize China's statistics to test our model and it is proved to be feasible for the absolute values of relative error are all within 1%.

Secondly, we choose Ukraine which was heavily exploited in 2002 to be our target. We use **PCA**(Principle Component Analysis) and select 8 indexes such as *total withdrawal, GDP, population, wastewater, industrial use, hydroelectricity, agricultural use, municipalities use* to conduct dynamic comprehensive evaluations. SPSS 22 figures out two significant indicators based on data we gathered, namely, *population and industry*. And the ranks of the final score F demonstrate that the overall trend is getting worse; however, situations started to bounce back from 2003 to 2005.

Thirdly, for the sake of minimizing errors, we optimize our model to the new **TGB** model consisting of triple-inputs, grey model and BP model after we apply Ukraine data into our BP model to complete predictions. The improved TGB model is designed by us and can provide better and more accurate figures. Our prediction results show that Ukraine's water stress issue would continue to deteriorate if no measure was taken.

Next, we propose to establish a desalination plant in southern coastal areas. To select the best cite for this construction, we use **AHP**(Analysis Hierarchy Process) method and finally choose Odessa considering four important criteria: *geography, local technological level, benefits and profits, and investments*. Apart from all the mentioned work, we also use **fitting** to simulate a possible clean water curve produced by desalination. In order to quantize its validity, we simply take the quotient of the mean value of annual produced desalination water in 15 years and the mean value of annual total water withdrawal in 15 years, which comes out to be 49.03%. This figure indicates that our intervention is effective. Last but not least, we evaluate our model in an objective way to help future work.

Slaking Ukraine's Thirst for Water Based on BP Model

Team # 50042

February 2, 2016

Summary

To address the water scarcity issue, we firstly establish water carrying capacity coupling model comprising of two sub-models. One is designed for simulation and prediction utilizing 3-level **BP**(Back Popagation) structure, the other is for comprehensive evaluation by integrating as much information as possible. We choose 13 indexes like *total water resources amount, GDP, population* and so on. In this way the outcome can be transformed into an evaluation result by 5 levels. Then we utilize China's statistics to test our model and it is proved to be feasible for the absolute values of relative error are all within 1%.

Secondly, we choose Ukraine which was heavily exploited in 2002 to be our target. We use **PCA**(Principle Component Analysis) and select 8 indexes such as *total withdrawal, GDP, population, wastewater, industrial use, hydroelectricity, agricultural use, municipalities use* to conduct dynamic comprehensive evaluations. SPSS 22 figures out two significant indicators based on data we gathered, namely, *population and industry*. And the ranks of the final score F demonstrate that the overall trend is getting worse; however, situations started to bounce back from 2003 to 2005.

Thirdly, for the sake of minimizing errors, we optimize our model to the new **TGB** model consisting of triple-inputs, grey model and BP model after we apply Ukraine data into our BP model to complete predictions. The improved TGB model is designed by us and can provide better and more accurate figures. Our prediction results show that Ukraine's water stress issue would continue to deteriorate if no measure was taken.

Next, we propose to establish a desalination plant in southern coastal areas. To select the best cite for this construction, we use **AHP**(Analysis Hierarchy Process) method and finally choose Odessa considering four important criteria: *geography, local technological level, benefits and profits, and investments*. Apart from all the mentioned work, we also use **fitting** to simulate a possible clean water curve produced by desalination. In order to quantize its validity, we simply take the quotient of the mean value of annual produced desalination water in 15 years and the mean value of annual total water withdrawal in 15 years, which comes out to be 49.03%. This figure indicates that our intervention is effective. Last but not least, we evaluate our model in an objective way to help future work.

Key Words: water stress; Back Propagation; TGB; Grey Prediction; PCA; AHP

1 Introduction

According to the survey conducted by the United Nations, one quarter of the world's population will suffer from water scarcity. Water use has been growing at nearly twice the rate of population over the last century. There's no denying that daily life requires water resources for industrial, agricultural, and residential purposes. Therefore, it is quite necessary and urgent to find out feasible solutions to solve water stress issues.

There are several popular methods to tackle prediction problems. Back Propagation(BP)[1] is an effective method characterized by extensive flexibility self-learning and mapping. It contains knowledge about Artificial Neural Network (ANN) and can approach almost any nonlinear function theoretically and therefore has satisfying results in the field of modeling and prediction of multi-variable nonlinear systems. We utilize this method to directly investigate the internal relationships so as to sheer away from those difficulties that would be met with by other quantization approaches. Hence, Back Propagation lies a solid foundation for researching water resources carrying capacity.

Our group dedicates to establish a model that can both accomplish qualitative and quantitative analysis to give prediction of water stress in 15 years.

2 Assumptions

In order to have a better study on this paper, we simplify our model by the following assumptions:

- There will be no droughts, floods, earthquakes and other strong natural disasters in 15 years.
- There will be no additional artificial water supply except our determined water strategy intervention in 15 years.
- The society will maintain steadily stable and related social policies are kept the same.
- Ecological conditions such as weather, climate, hydrology, etc. won't change in 15 years.
- Any intervention plan will be effectuated immediately in 2016.

Under the above and basic assumptions, we can set out to construct our model (show our approach in detail).

3 Establishment of Model

In order to depict the ability of a region to provide clean water to meet the needs of its population, we adopt an idea of water resources carrying capacity[2]. It is a prevalent idea defined as the ability to support social, economic and environmental development based on predictable level of technology and economy in the context of a certain historical stage. It follows the principle of sustainable development, takes the basic ecological need of water into consideration and requires both reasonable and optimal configurations.

3.1 Principles of Model

This model comprises of two sub-models. One sub-model is designed for simulation and prediction. It utilizes 3-level BP structure, where the input vectors are main factors ΔX while the output vector is water resources carrying capacity ΔY, and nodes of hidden layers are determined by a specific algorithm. The basic idea is to use known inputs ΔX_k and outputs ΔY_k to train this network so as to meet certain accuracy requirements. The well-trained network would be able to predict future vaules. The other sub-model is for comprehensive evaluation by integrating as much information as possible. In this way the outcome can be transformed into an evaluation result, easy for people to understand[3].

3.2 Structure of Model

(1)**Overall Structure** The overall model is shown as Figure 1.

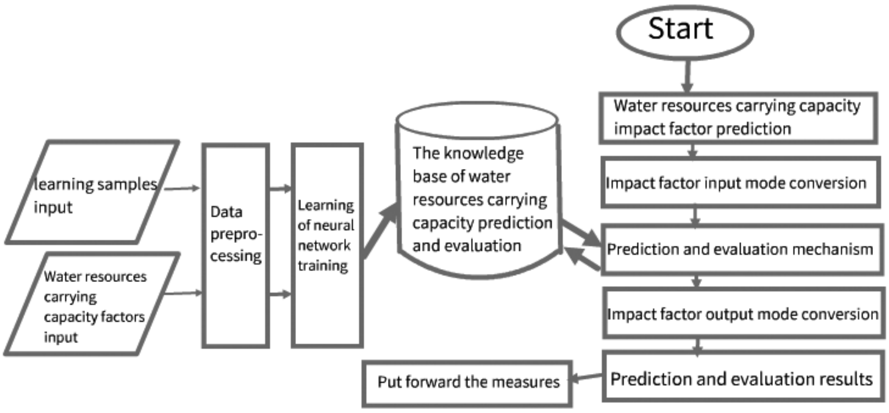


Figure 1: Structure of water carrying capacity coupling model based on ANN theory

(2)**Neural Network Structure** This model consists of the pre-process of data and the main BP network, shown in figure 2 [7]. Pre-process section manages data by some rules. BP network differs in layers, outputs, and nodes. We construct a 3-level BP network, namely, input layer, hidden layer, and output layer. The node number m inside this network is determined by the degree of inputs. If the output layer degree is n, then we can get to know the node number in the hidden layer is $L = \frac{m \times n}{2}$. The hidden layer output is Sigmoid function.

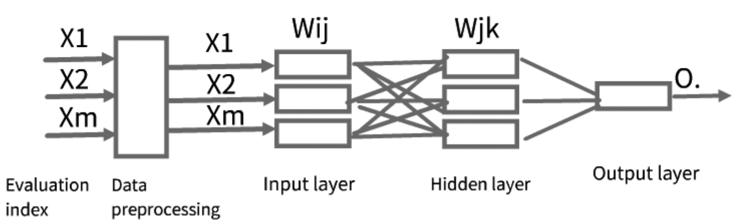


Figure 2: ANN topology structure of water carrying capacity model

3.3 Establishment of Evaluation Indicators System

We need to transform water resources carrying capacity into several specific indicators. Due to the fact that there are numerous factors affecting the prediction and evaluation of carrying capacity and therefore it is essential and critical to distinguish key factors from diverse and complicated causes. Generally speaking, indicators can be sundered into three groups. One group is related with the physical characters such as quality, quantity, etc., another group is about social interventions such as population, economy and policies. The third group is concerning ecological factors such as climates and forests. Considering these three groups, we establish our indicators system shown in figure 3[4].

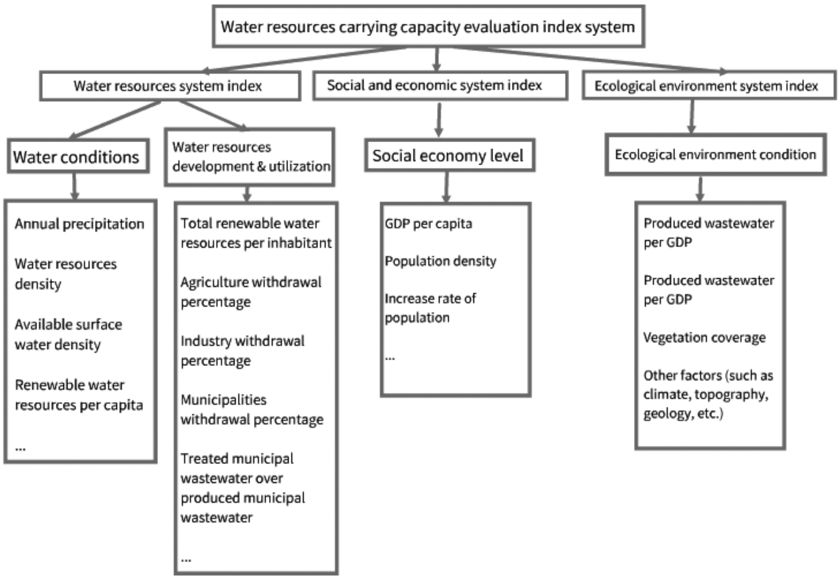


Figure 3: General evaluation indicators system of water carrying capacity

On the foundation of this general evaluation indicators system, we can actually use Principal Component Analysis (PCA) to ascertain specific evaluation indicators for a specific region if we know the comprehensive information. Considering the feasibility of modeling in limited time and finite archives that we have found, we select 15 of all factors that we can think of as the basic indicators. Below is the table of selected evaluation indicators (Table 1). After referring to the national water source evaluation criteria as well as research findings we found and considering the status quo, we divide indicators into 5 levels. Threshold values are demonstrated in Table 2.

4 Validation of Model

After establishing our model, the next step is to prove its validity. To best test the model, we decide to use available data about China to validate it because we find statistics relating to China more accessible than those of other regions.

4.1 Introduction about China

China is a sovereign state in East Asia. It is the world's most populous country, with a population of over 1.35 billion. Covering approximately 9.6 million square kilometers, China

Table 1: Selected indicators of water carrying capacity grade evaluation

Quantity of Water	anual precipitation	1
	water resources density	2
	available surface water density	3
	renewable water sources per capita	4
Exploition and Utilization	renewable water resources per inhabitant	5
	agricultural withdrawal percentage	6
	industrial withdrawal percentage	7
	municipalities withdrawal percentage	8
	treated municipal wastewater over produced municipal wastewater	9
Social Econimic Level	GDP per capita	10
	population density	11
	increase rate of population	12
Ecological Environment	produced wastewater per GDP	13
	produced wastewater per inhabitant	14
	vegetation coverage	15

Table 2: Thresholds of water resource carrying capacity evaluation indicators

Number	Equation	Level 1	Level 2	Level 3	Level 4	Level 5
1	$database$	≥ 1500	≥ 1200	≥ 1000	≥ 800	< 800
2	$\frac{total\ water\ resource}{territory\ area}$	≥ 80	≥ 60	≥ 40	≥ 20	< 20
3	$\frac{total\ water\ resource}{territory\ area}$	≥ 80	≥ 60	≥ 40	≥ 20	< 20
4	$\frac{total\ water\ resource}{population}$	≥ 5000	≥ 4000	≥ 3000	≥ 2000	< 2000
5	$\frac{total\ water\ withdrawal}{population}$	≥ 500	≥ 450	≥ 350	≥ 300	< 300
6	$\frac{agricultural\ withdrawal}{total\ withdrawal}$	≥ 40	≥ 30	≥ 20	≥ 10	< 10
7	$\frac{industrial\ withdrawal}{total\ withdrawal}$	≥ 40	≥ 30	≥ 20	≥ 10	< 10
8	$\frac{municipalities\ withdrawal}{total\ withdrawal}$	≥ 40	≥ 30	≥ 20	≥ 10	< 10
9	$\frac{treated\ municipal\ wastewater}{produced\ municipal\ wastewater}$	≥ 90	≥ 70	≥ 50	≥ 30	< 30
10	$\frac{GDP}{population}$	≥ 5	≥ 3	≥ 1	≥ 0.6	< 0.6
11	$\frac{population}{territory\ area}$	< 20	< 40	< 60	< 80	≥ 80
12	$database$	$< 1\%$	$\geq 1\%$	$\geq 3\%$	$\geq 5\%$	$\geq 7\%$
13	$\frac{produced\ wastewater}{GDP}$	≤ 10	≤ 15	≤ 25	≤ 30	> 30
14	$\frac{produced\ wastewater}{population}$	≤ 10	≤ 15	≤ 25	≤ 30	> 30
15	$\frac{vegetation\ area}{territory\ area}$	≥ 40	≥ 30	≥ 20	≥ 10	< 10
others	$database$	A	B	C	D	E

is the world's second-largest country by land area, and either the third or fourth-largest by total area, depending on the method of measurement.

There are many rivers and lakes in China, but they mainly belong to the Pacific Ocean water system, which determines the basic trend of the water flow to the East. Precipitation varies greatly across China, the general trend is decreasing from the southeast coast to the northwest inland, southeast coastal areas more than 1600 mm of precipitation, the Northwest has large areas of annual rainfall in 50 mm or less.China forest area of over square kilometers, the forest coverage rate is 20.36%. China's climate is mainly affected by the monsoon circulation, due to the changing terrain and the formation of a complex climate.

2014 China's GDP per capita was 7595 USD, in 2013 China's GDP per capita was 6264 USD, while in 2012 and 2011 were 6995 USD and 5577 USD, respectively. The proportion of Chinese agriculture accounted for 13.1%, the proportion of industry accounted for 46.2%, the proportion of service industry rose to 40.7%.

4.2 Application and Validation

4.2.1 Data needed in modeling

According to China's statistical archives since 2000, we have got three important factors to be inputs and select another two factors to be outputs to validate this model. What we do is to use statistics from 2000 to 2011 (12 sets training data) to train the network and use this model to "predict" the conditions in the year of 2012 and 2013. By doing so, we can compare these two sets of outputs with real figures so as to make comments on the model's validity. Table 3 shows the inputs and outputs we selected for China. Meanwhile, Table 4 provides details that are needed for validation.

Table 3: Water carrying capacity forecast indicators of BP model

Inputs	Surface Water Resources	I_1
	Groundwater Resources	I_2
	Duplicated Measurement Between Surface Water and Groundwater	I_3
Outputs	Total Amount of Water Resources	O_1
	Water Resources Per Capita	O_2

4.2.2 Results

After training the network using 12 set data, we get the predicted values. Below demonstrates the comparison between estimated values and real values (Table 5, Appendix A). To see the whole process clearly and vividly, we use Matlab 2015a to plot two curves to show the results. The figure is shown in Figure 4(Appendix B).

We can easily see that the relative errors are all smaller than 1%, which indicates a good prediction and the validity of our model. Through this validation test, our model is proved to be effective and accurate to tackle water resources carrying capacity.

Table 4: Statistics used to validate the model

Year	I_1 $\times 10^9 m^3$	I_2 $\times 10^9 m^3$	I_3 $\times 10^9 m^3$	O_1 $\times 10^9 m^3$	O_2 $m^3/person$
2000	26561.9	8501.9	7363.0	27700.8	2193.9
2001	25933.4	8390.1	7455.7	26867.8	2112.5
2002	27243.3	8697.2	7679.2	28261.3	2207.2
2003	26250.7	8299.3	7089.9	27460.2	2131.3
2004	23126.4	7436.3	6433.1	24129.6	1856.3
2005	26982.4	8091.1	7020.4	28053.1	2151.8
2006	24358.1	7642.9	6670.8	25330.1	1932.1
2007	24242.5	7617.2	6604.5	25255.2	1916.3
2008	26377.0	8122.0	7064.7	27434.3	2071.1
2009	23125.2	7267.0	6212.1	24180.2	1816.2
2010	29797.6	8417.0	7308.2	30906.4	2310.4
2011	22213.6	7214.5	6171.4	23256.7	1730.2
2012	28371.4	8416.1	7260.6	29526.9	2186.1
2013	26839.5	8081.1	6962.7	27957.9	2059.7

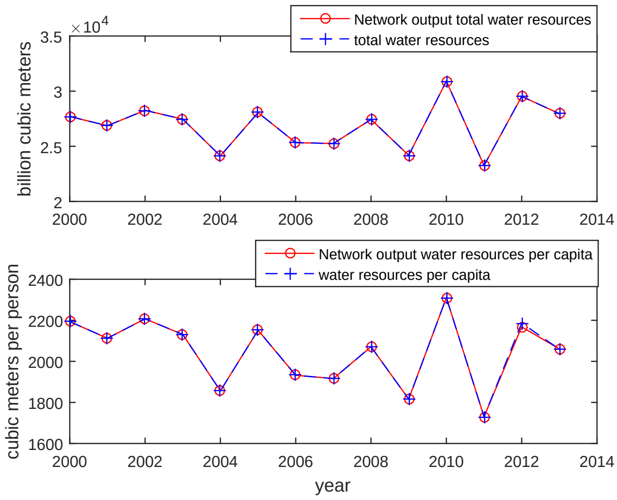


Figure 4: Plot of testing results of BP model

Table 5: Testing Result of BP model

Year	2012		
	Real Values	Estimated Values	Absolute Value of Relative Error/%
O_1	29526.9	29518.0	0.03%
O_2	2186.1	2168.0	0.8%
Year	2013		
	Real Values	Estimated Values	Absolute Value of Relative Error/%
O_1	27957.9	27966.0	0.03%
O_2	2059.7	2061.0	0.6%

5 Investigation

By looking through the UN water scarcity map, we finally chose Ukraine whose water resources are heavily exploited (Figure 5).

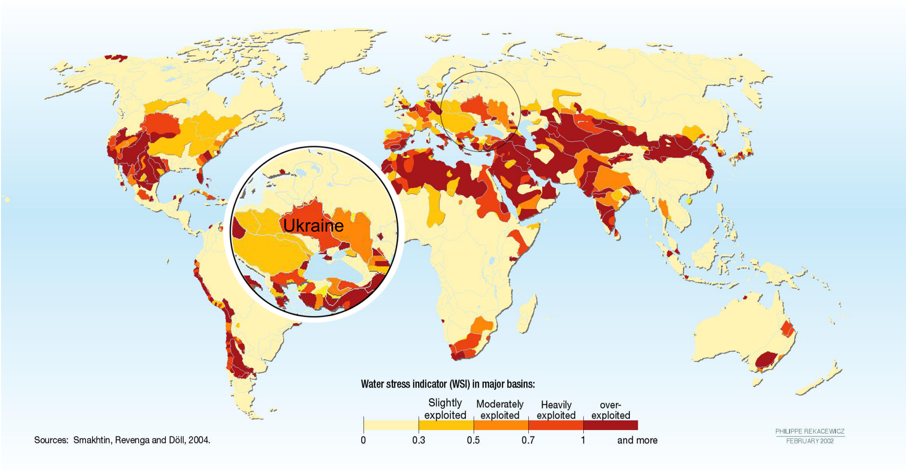


Figure 5: Water stress indicator in major basins (Ukraine zoomed in)

5.1 Water Resources in Ukraine

The country can be divided into seven major river basins, all of them discharging into the Black Sea except the Western Bug which flows towards the Baltic Sea:

- **The Dnipro (called Dnieper in Belarus) basin:** covering about 65 percent of the country. The Dnipro river rises in the Russian Federation, then flows into Belarus before entering Ukraine. Its main affluents in Ukraine are: the Desna river (on the left bank) and the Pripyat river (on its right bank).
- **The Dniester (called Nistru in the Republic of Moldova) basin:** covering 12 percent of the country. It flows into the Republic of Moldova before re-entering Ukraine some 50 km before its mouth in the Black Sea.
- **The Danube basin:** covering 7 percent of the country. The Danube is the river with the largest number of riparian countries in the world. Some affluents of the Danube rise in Ukraine in the Carpathian mountains, flow into neighbouring countries, and then join the mainstream of the Danube before its mouth in the Black Sea.
- **The coastal basin:** covering 7 percent of the country. It groups all the small rivers that flow directly into the Sea of Azov and the Black Sea, including all the Crimean rivers.
- **The Donets basin:** covering 4 percent of the country. It rises in the Russian Federation, and flows through Ukraine for about 450 km in its eastern part before re-entering the Russian Federation.
- **The Southern Bug (Pivdennyi Buh in Ukrainian) basin:** covering 3 percent of the country. It is an internal river basin.

- **The Western Bug (Zakhidnyi Buh in Ukrainian) and San basins:** covering 2 percent of the country. The Western Bug river rises in Ukraine, flows to the north, forming the border with Poland and then the border between Poland and Belarus, and finally flows into the Narew river in Poland, a tributary of the Vistula river.

IRSWR are estimated at 50100 million m^3/year (Figure 6) and incoming RSWR at 120180 million m^3. Therefore, the total RSWR are estimated at 170280 million m^3/year.

Name of basin	% part of country area	Internal RSWR	Inflow		Total RSWR	Outflow to:
		million m³/year	million m³/year	from	million m³/year	
Dnipro (Dnieper)	65	20 400	24 700 *	Belarus; Russian Fed.	45 100	Black Sea
Dniester	12	9 200	10 120	Republic of Moldova	19 320	Black Sea
Coastal	7	3 100	110	Republic of Moldova	3 210	Black Sea
Danube	7	9 400 **	84 050 ***	Border with Romania	93 450	Black Sea
Donets	4	2 700	1 200	Russian Federation	3 900	Russian Fed.
Southern Bug	3	3 400	-		3 400	Black Sea
Western Bug+ San	2	1 900	-		1 900	Poland
Total	**100**	**50 100**	**120 180**		**170 280**	

* *Dnieper from Belarus: 24 500 = 31 900 minus 7 400 of Pripyat, which enters already from UKR to BLR*
Dnieper from Russian Federation: 200 (Desna, branch of Dnieper)
** *Cisa + Prut*
*** *Total flow of border river 168 100, accounted 50 percent = 84 050*

Figure 6: Ukraine renewable surface water sources by major river basin

Renewable freshwater resources:			
Precipitation (long-term average)	-	565	mm/year
	-	341 000	million m³/year
Internal renewable water resources (long-term average)	-	55 100	million m³/year
Total renewable water resources	-	175 280	million m³/year
Dependency ratio	-	69	%
Total renewable water resources per inhabitant	2014	3 900	m³/year
Total dam capacity	2015	55 500	million m³

Figure 7: Ukraine renewable water sources

Internal renewable groundwater resources are estimated at 22000 million m^3/year. Artesian wells are found at an average depth of 100-150 m in the north of the country and at 500-600 m in the south. The overlap between surface and groundwater resources has been estimated at 17000 million m^3/year, which brings the total renewable water resources to 175280 million m^3 (170280+22000-17000) (Figure 7).

5.2 Water Use in Ukraine

Water use details are shown in Table 6 [5].

Table 6: Ukraine water use in 1998-2005 (unit:$\times 10^8 m^3$)

Year	1998	1999	2000	2001	2002	2003	2004	2005
Total Withdrawal	190.27	197.48	182.82	175.77	162.99	150.39	146.94	150.83
Total comsumption	139.35	144.68	132.22	124.82	119.01	114.03	98.27	98.74
Municipalities	34.81	34.59	33.00	34.21	33.50	32.50	30.82	30.36
Industrial	76.52	71.00	67.26	64.89	60.54	55.28	51.07	51.27
Agricultural	37.02	39.09	31.96	25.77	24.97	26.25	16.38	17.11

5.3 Causes of Water Scarcity

5.3.1 Modeling to find key factors

Based on the data that we gathered about Ukraine, we found 8 different types of statistics. To better understand the internal relationships amongst these figures, we apply Principal Component Analysis (PCA)[6] to conduct dynamic comprehensive evaluations. Suppose X_1:Total withdrawal, X_2:GDP, X_3:Population, X_4:Wastewater, X_5:Industrial use, X_6:Hydroelectricity, X_7:Agricultural use, X_8:Municipalities use. Data are shown in Table 7.

Table 7: Statistics of water resources and economy of Ukraine

Year	X_1 $\times 10^8 m^3$	X_2 $\times 10^8 USD$	X_3 $\times 10^6$	X_4 $\times 10^8 m^3$	X_5 %	X_6 %	X_7 $\times 10^8 m^3$	X_8 $\times 10^8 m^3$
1998	190.27	418.83	50.28	50.92	54.91	9.3	37.02	34.81
1999	197.48	315.81	49.89	52.80	49.07	8.7	39.09	34.59
2000	182.82	312.62	49.47	52.60	50.87	6.4	31.96	33.00
2001	175.77	380.09	48.67	50.95	51.99	6.9	25.77	34.21
2002	162.99	423.93	48.23	43.98	50.87	5.6	24.97	33.50
2003	150.39	501.33	47.79	36.36	48.48	5.0	26.25	32.50
2004	146.94	648.81	47.46	48.67	51.97	6.6	16.38	30.82
2005	150.83	828.81	47.09	52.09	51.92	6.5	17.11	30.36

After using SPSS 22 to process the data, we get correlation coefficients matrix of driving force factors (Table 8). We can conclude from Table 8 that selected factors are correlated, which is the vital basis to continue using PCA.

Table 8: Correlation coefficients matrix of driving force factors

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	1							
X_1	-0.779	1						
X_1	0.961	-0.809	1					
X_1	0.550	-0.072	0.411	1				
X_1	0.764	-0.285	0.745	0.671	1			
X_1	0.922	-0.811	0.950	0.223	0.643	1		
X_1	0.849	-0.874	0.867	0.122	0.542	0.868	1	
X_1	0.957	-0.789	0.985	0.403	0.745	0.930	0.908	1

Table 9 shows that first two dominant components have contributed 92.766%. Therefore, these two components can effectively reflect the water resources carrying capacity. Besides, from component matrix in Table 10, we know that the first dominant component is positively related to X_1, X_3, X_4, X_5, X_6, X_7, X_8 while it is negatively related to X_2. To recap, industry and population are major factors.

Table 9: Eigen values and squared loading of the principal components

Component	Total	% of Variance	Cumulative %
1	6.072	75.900	75.900
2	1.349	16.866	92.766

Table 10: Component matrix

Component	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
1	0.984	-0.818	0.988	0.441	0.759	0.946	0.905	0.987
2	0.102	0.466	-0.014	0.833	0.539	-0.180	-0.323	-0.020

Table 11 shows that F_1 and F_2 are scores of dominant component, F refers to the final score. The higher the scores is, the better the water resources carrying capacity will be, and vice versa. The ranks demonstrate that the overall trend is getting worse; however, from 2003 to 2005, situations started to bounce back.

Table 11: Scores of water resources carrying capacity in 1998-2005

Year	F_1	F_2	F	Rank
1998	1.27993	0.43103	1.044164	1
1999	1.25846	0.30825	1.007161	2
2000	0.54080	-0.5651	0.315157	3
2001	0.29376	-0.5776	0.125546	4
2002	-0.26058	-1.00844	-0.36786	5
2003	-0.78978	-1.76171	-0.89657	8
2004	-1.08912	0.69091	-0.71011	7
2005	-1.23347	1.45422	-0.69093	6

After analysing available data, we draw a conclusion that Ukraine mainly suffers from physical scarcity rather than economic scarcity.

5.3.2 Causes

Reasons for **physical scarcity** mainly contains the following environmental drivers:

- water resources per capita shortage
- water dependence
- uneven temporal and spatial distribution of water resources

In 2005, water resources per capita in Ukraine is about 1100 m^3 and less than 1700 m^3, which is the international water shortage warning line standard. Another fact that needs special attention is that the European average figure is 9089 m^3, way higher than Ukraine. Therefore, this bare fact implies that Ukraine belongs to water shortage countries.

What's more, from Figure 7 we notice a significant value, that is "Dependency ratio". Ukraine's dependency ratio is 69%. This figure illustrates to what extent this country relies on water inflows from contiguous countries. This indicates that Ukraine suffers from water dependence, which can also answer to the water stress issue.

Besides, temporal and spatial distribution of water resources in Ukraine is quite uneven. Generally speaking, water resources are abundant in the north and northwest while water resources are scarce in the south. Additionally, water mainly flows in spring, accounting for roughly 60% and 90% of the annual water resources in northern and southern areas respectively.

As for economic scarcity, based on the statistics, people in Ukraine have convenient access to clean water (access intex is 96% for total population, shown in Figure 8).Hence, we speculate that the infrastructure to provide water in Ukraine is, comparatively, comprehensively constructed.

Access to improved drinking water sources:			
Total population	2015	96	%
Urban population	2015	96	%
Rural population	2015	98	%

Figure 8: Access of water in Ukraine in 2010

Reasons for **social factors** mainly contains the following drivers:

- excessive consumption per capita
- water-consuming industrial structure

According to the results that we have found, the daily water consumption per capita in Ukraine is as high as 320 liters while the average level in western Europe is 100-200 liters. Figures are even higher in busy cities like Odessa and Kiev. This value shows that inhabitants in Ukraine use water extravagantly and lack of water saving consciousness.

Additionally, results produced by PCA conspicuously show that industrial withdrawal is always the dominant consumers (shown in Figure 9)and it has similar trend with total withdrawal curve. Hence, we can conclude that industrial withdrawal affects total withdrawal the most. When we compare this ratio with other countries, we find that Ukraine's percentage is relatively bigger, indicating the many industries in Ukraine is water-consuming.

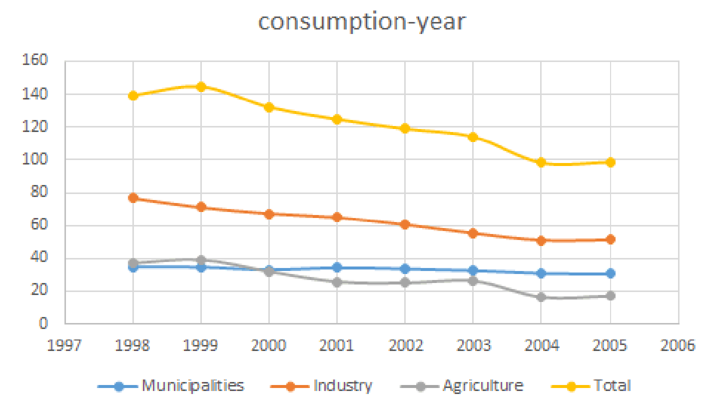


Figure 9: Ukraine water consumption in 1998-2005

6 Model Application to Ukraine

By using data that we have found plus the model that we have established, we get the predicted values for the following 15 years. Table 12 demonstrates the overall figures.

However, when we compare predicted values in 1998-2005 with real values, we calculated residual δ and found that the absolute value of residual $|\delta| = 0.3128$ (Appendix C), which is a little large. It indicates that the current model may be not precise enough to predict the future conditions when doing long-term estimation. Hence, we have to optimize our model to ensure its reliability.

Table 12: Predicted total water withdrawal in Ukraine in 1998-2030 using BP model

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006
Value	190.256	197.342	182.939	175.709	161.469	149.526	146.948	150.797	151.391
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015
Value	151.506	151.549	151.578	151.599	151.615	151.627	151.635	151.639	151.64
Year	2016	2017	2018	2019	2020	2021	2022	2023	2024
Value	151.638	151.633	151.626	151.616	151.603	151.589	151.571	151.552	151.53
Year	2025	2026	2027	2028	2029	2030			
Value	151.506	151.479	151.45	151.418	151.385	151.348			

6.1 Optimization of Model

6.1.1 Introduction of improved model

This improved model can be represented by TGB (Triple-inputs Grey Back Propagation model).

- **T**:triple-inputs. Three inputs are derived from GM(1,1), DGM(2,1), and Grey Verhulst model[9] accordingly. They are used as inputs of BP model. GM(1,1) refers to Grey Forcasting Model, and (1,1) represents first order differential equations with sole variable. Similarly, DGM(2,1) refers to Discrete Grey Forecasting Model. and Grey Verhulst Model is designed to describe the process to approach final values.
- **G**:grey model. Grey prediction conducts association analysis by system identifying the similarity of system factors to generate the law of the system change. By generating data sequence of strong regularity, one can establish the corresponding differential equation model, to predict the trend.
- **B**:BP model.This is exactly what we have established before improvement.

The structure of this new TGB model[8] can be represented by Figure 10.

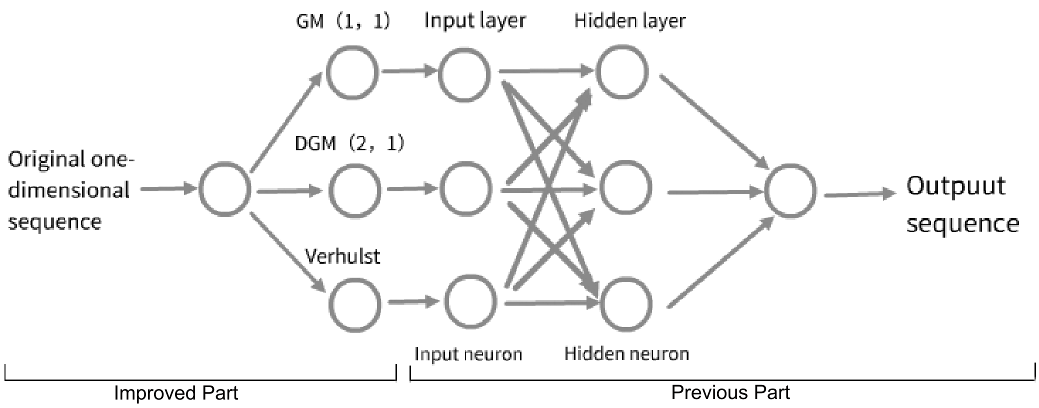


Figure 10: Structure of TGB model

6.1.2 Establishment of TGB Model

Let m be the original sequence length, n be the predicted sequence length.
Step 1: Use GM(1,1) (Appendix D), DGM (Appendix E), and Verhulst (Appendix F) model to figure out m simulation values and n predicted values.
Step 2: Utilize m simulation values to train the network until the precision meets the standard (Appendix G).
Step 3: Apply n predicted values to be inputs into the network, and the outputs are what TGB model finds out.

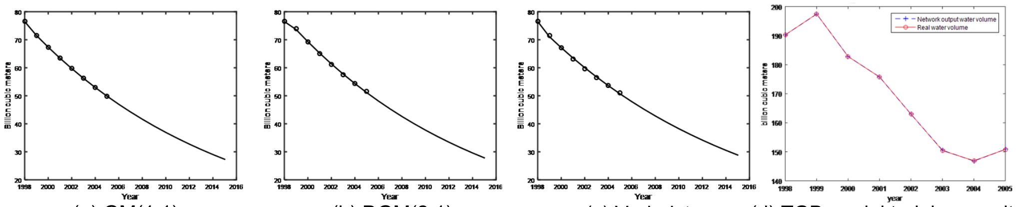
Three models have their own advantages with respect to different types of data. Table 13 (Appendix H) shows the advantage of TGB model compared to a single GM(1,1), DGM and Verhulst model. We can clearly see that TGB model has the smallest absolute of residual and therefore, has the best prediction.

Table 13: Comparison of 4 models

Model	Absolute Value of Residual$\lvert\delta\rvert$	Relative Error
GM(1,1)	0.0271	0.1606
DGM(2,1)	0.0071	1.25×10^{-5}
Verhulst	0.0115	5.0×10^{-5}
TGB	0.0039	2.39×10^{-5}

6.2 Prediction results

Applying the new TGB model, we get the following outputs. Figure 11 (a)(b)(c)demonstrates 3 processed inputs using GM(1,1), DGM(2,1) and Verhulst. Figure 11 (d) shows the training results of TGB model, and Figure 12 (Appendix I)shows the final predicted value of total water withdrawals. Detailed values are in Table 14 (Appendix 9).



(a) GM(1,1) (b) DGM(2,1) (c) Verhulst (d) TGB model training results

Figure 11: TGB model results

Table 14: Predicted total water withdrawal in Ukraine in 1998-2030 using TGB model

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006
Value	190.272	197.482	182.822	175.777	162.994	150.395	146.945	150.834	149.925
Year	2007	2008	2009	2010	2011	2012	2013	2014	2015
Value	149.049	148.963	148.364	147.946	147.34	146.55	145.079	144.309	144.162
Year	2016	2017	2018	2019	2020	2021	2022	2023	2024
Value	144.232	146.041	147.957	149.93	151.913	153.862	155.74	157.52	159.181
Year	2025	2026	2027	2028	2029	2030			
Value	160.71	162.103	163.359	164.484	165.484	166.369			

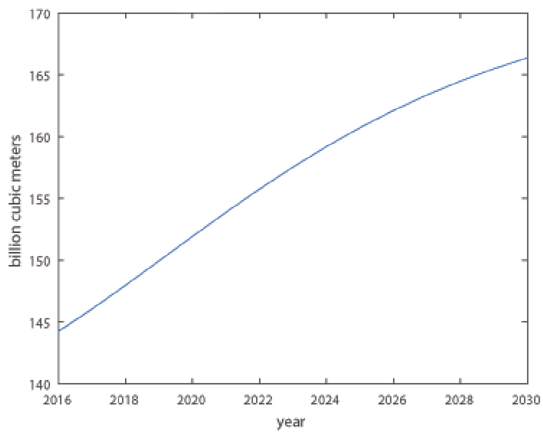


Figure 12: Ukraine predicted water withdrawal in 2016-2030

6.3 Analysis of Prediction

Our prediction results of total withdrawal is basically monotonic and will increase with time passing by. However, this figure seems to remain steady from the year of 2030. In other words, water stress in Ukraine is going to deteriorate, which seems to be an identical result with World Resource Institute(WRI)[14]. Figure 13 and Figure 14 shows the projected water demand and overall water stress in Ukraine conducted by WRI. Hence, Ukraine government has to intervene this water stress issue before it is too late.

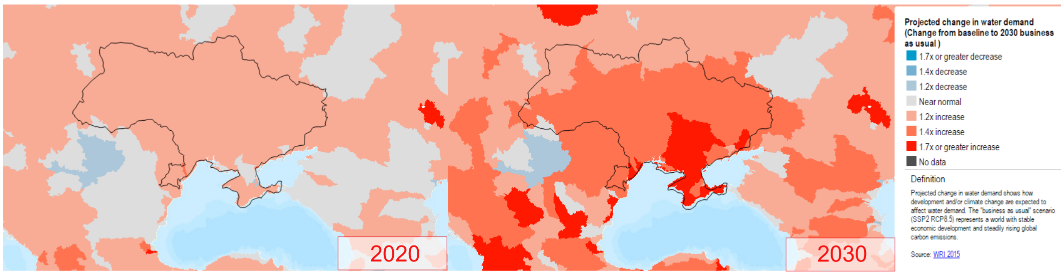


Figure 13: Ukraine projected change in water demand (WRI)

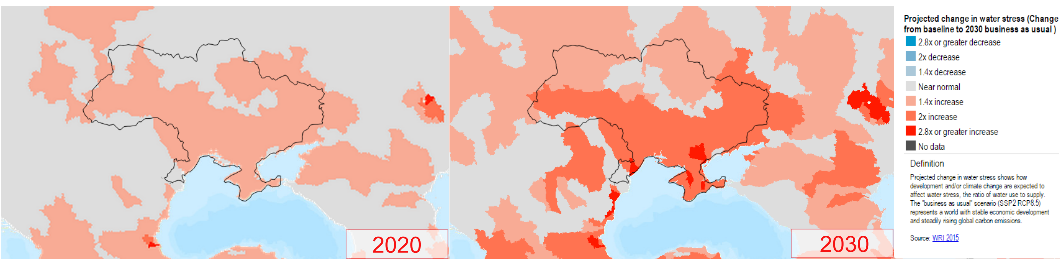


Figure 14: Ukraine projected change in water stress (WRI)

7 Intervention plan

There are some feasible approaches to tackle the water stress that would occur in Ukraine. Based on the fact that Ukraine is a coastal country and southern places suffer more from water stress, construction of desalination plants is an ideal approach. In recent years people have already acquired many novel and innovative methods to implement desalination, therefore this method is ensured by technology.

7.1 AHP modeling

By searching for geological information combined with our analysis, we select 4 potential locations to construct a desalination: Odessa, Kherson, Simferopol, and Berdyansk. These four places are marked in red dots in the following figure 15. In order to determine the location,

Figure 15: 4 potential locations of desalination plants

we apply Analytic Hierarchy Process(AHP)[12]. AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It has particular application in group decision making [12], and is used around the world in a wide variety of decision situations.

We establish our AHP hierarchy shown as figure 16. To obtain the pairwise comparison matrix, we need to compare the influence of C_1,C_2,...,C_n to the upper level. We follow the comparison scales proposed by Saaty, namely, to use 1-9 to depict the relative influence. Detailed information is shown in Table 15.

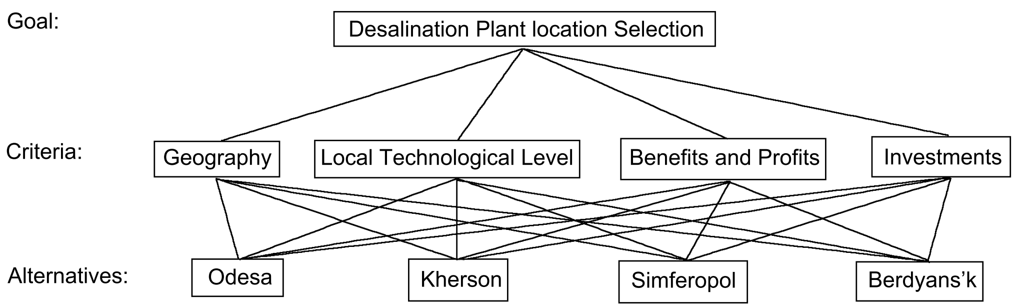


Figure 16: AHP hierarchy

Table 15: 1-9 scalea_{ij} definition

Scale	Definition
1	C_i and C_j have identical influence
3	C_i has a little bigger influence than C_j
5	C_i has greater influence than C_j
7	C_i has an evidently greater influence than C_j
9	C_i has a dominant influence compared to C_j
2,4,6,8	the influence of C_i over C_j is between the stated scale
1,1/2,...1/9	the influence of C_i over C_j is the opposite number of stated scale

Considering the status quo, we define pairwise matrix A.

$$A = \begin{pmatrix} 1 & 3 & \frac{1}{3} & 2 \\ \frac{1}{3} & 1 & \frac{1}{9} & 1 \\ 3 & 9 & 1 & 6 \\ \frac{1}{2} & 1 & \frac{1}{5} & 1 \end{pmatrix} \tag{1}$$

Again, we adopt consistency check approach designed by Saaty, namely **coincidence indicator**

$$CI = \frac{\lambda - n}{n - 1} \tag{2}$$

We can conclude that A is a consistent matrix if *CI*=0; the greater *CI* is, the more likely A to be inconsistent. For the purpose of evaluating the tolerance of inconsistency, we also need to find another criterium to judge *CI*. Saaty introduced **random indicator**. The process to calculate is to randomly construct matrix A', and then calculate *CI*. Finally the mean value of these *CI* is random indicator. The *RI* table is shown as Table 7.1.

Table 16: *RI* values versus n

n	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

It is clearly seen that $RI = 0$ when $n = 1, 2$. This is owing to rank 1 or 2 matrix is always consistent. As for $n \geq 3$, the **coincidence ratio** is defined as

$$CR = \frac{CI}{RI} \tag{3}$$

If $CR < 0.1$, we say it passes consistency check and this matrix can be applied.

According to our matrix, we calculate the eigen value and eigen vector by Matlab:

$$\lambda = 4.0752 \tag{4}$$

$$\mathbf{w} = (0.2061, 0.0768, 0.6184, 0.0987)' \tag{5}$$

Applying equation 2, $CI = \frac{0.0752}{3} = 0.0251$. We can find *RI*=0.9 from Table 7.1. Hence, follow equation 3 we get $CR = \frac{0.0251}{0.9} = 0.0279 < 0.1$. It passes the consistency check.

Next thing, determine the priority factors. In this cite selection issue, we have already got the ratio vector from criteria level to goal level. We need the factors from alternatives level to criteria level. Based on geography of Ukraine, we determine the following matrixes.

$$B_1 = \begin{pmatrix} 1 & \frac{1}{2} & 3 & 1 \\ 2 & 1 & 6 & 2 \\ \frac{1}{3} & \frac{1}{6} & 1 & \frac{1}{3} \\ 1 & \frac{1}{2} & 3 & 1 \end{pmatrix}, B_2 = \begin{pmatrix} 1 & 1 & 3 & 2 \\ 1 & 1 & 2 & 1 \\ \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{2} \\ 1 & 1 & 2 & 1 \end{pmatrix}, \tag{6}$$

$$B_3 = \begin{pmatrix} 1 & 1 & 2 & 2 \\ 1 & 1 & 2 & 1 \\ \frac{1}{2} & \frac{1}{2} & 1 & 1 \\ \frac{1}{2} & \frac{1}{2} & 1 & 1 \end{pmatrix}, B_4 = \begin{pmatrix} 1 & 2 & 3 & 3 \\ \frac{1}{2} & 1 & 2 & 2 \\ \frac{1}{3} & \frac{1}{2} & 1 & 1 \\ \frac{1}{3} & \frac{1}{2} & 1 & 1 \end{pmatrix} \tag{7}$$

where b_{ij} in $B_k(k = 1, 2, 3, 4)$ relates to the priority scale between A_i and A_j considering criterium C_k. Again, we calculate the ratio vectors and eigen values shown in Table 17.

Table 17: Alternative level calculation results

k	1	2	3	4
	0.2308	0.3541	0.3483	0.4554
w_k	0.4615	0.2639	0.3033	0.2628
	0.0769	0.1180	0.1742	0.1409
	0.2308	0.2639	0.1742	0.1409
λ_k	4	4.2361	3.8708	4.0104
CI_k	0	0.0787	0.0431	0.0035

What needs to be clarified is that all the *CI*s have passed the check. Lastly, we combine all of the priority factors to achieve the final priority index, which is simply the product of two priority vectors: (7.1) and Table 17. By multiplying these two vectors we get

$$w_f = [0.3351, 0.3289, 0.1465, 0.1895]' \tag{8}$$

We can tell from the results that we pick Odessa to be the best cite to build desalination plants.

7.2 Intervention Advantages and Weaknesses

Like any model,the one present above has its strengths and weaknesses. Some of the major points are presented below.

7.2.1 Advantages

- **Alleviating the water stress in the south**
  One of the most significant strengths is to drastically alleviate the water stress issue by providing the country more fresh water from Black sea. Since the South is the most serious place in Ukraine, and by establishing a desalination plant here in a coastal city, people can utilize water from the ocean, taking advantage of technology to transform salty water to edible clean water. This method can increase total available water resources.

- **Renewable**
  The raw materials of desalination plants are mainly seawater which is renewable. This coincides with the idea of sustainable development.

- **Providing more employment opportunities**
  The plan to establish desalination plants can produce many employment opportunities. Workers, constructors, technical workers, supervisors, etc. are abundantly needed in the region. Therefore, it can also alleviate the social instability caused by high unemployment rate.

7.2.2 Weaknesses

- **Gigantic initial investments**
  Establishing desalination plants requires both advanced technology and gigantic capital.

- **Rising price of water**
  Compared to the normal water resources, water from desalination needs more efforts and therefore, has higher prices. To maintain the operation of plants, the price of water will rise which may lead to indignation of inhabitants.

- **Possible negative effects on the ocean**
  Desalination can have some side effects on the ocean ecological system. Those substances in the seawater will not disappear and since people only take water from the ocean, it may cause the imbalance of ion density.

8 Intervention Effectiveness

Just as mentioned above, desalination is an effective way to solve the water scarcity. According to survey conducted by International Desalination Association (IDA)[10], the world's desalination volume is increasing rapidly by 10%-30%. Up till now there are more than 130 countries are using this technology to get water. Interestingly, more than half of the desalination is in Middle East. The world's pie chart is shown in Figure 17 [11].

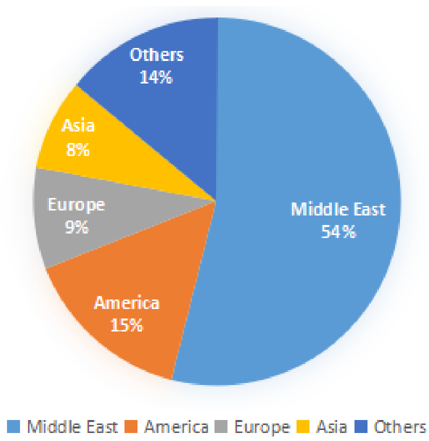


Figure 17: World's desalination distribution

Considering the similarities between China and Ukraine, we decide to transplant China's development goals to desalination, shown as Table 18.

Table 18: Desalination goals in Ukraine in 15 years

Year		2016	2020	2025	2030
Desalination	$\times 10^4 m^3/d$	3	100	300	800
Scale	$\times 10^4 m^3/d$	0.5	10	20-50	50-80
Tech-independency ratio	%	10	60	90	100
Investment	$\times 10^8 USD$	10	15	35	90

By this rough goal, we get possible curves of desalination shown in Figure 18. The line of best-fit is

$$f(x) = 0.3036x^3 - 1838x^2 + 3.71 \times 10^6 x - 2.496 \times 10^9 \tag{9}$$

The fitting residual is 6.457×10^{-11}, which indicates a great fitting (Appendix J).

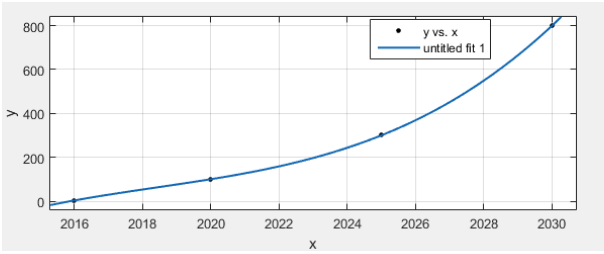


Figure 18: Fitting curve of desalination in Ukraine in 15 years

After doing some arithmetic calculations, we finally get that form 2016 to 2030, Ukraine can produce 115.177 billion m^3 clean water from desalination (Appendix K). Thus, the mean of these 15 years is 7.678 billion m^3. From the above Table 14, we know the mean of annual withdrawal water is 15.659 billion m^3. If we take the quotient of these two values, we get $\frac{7.678}{15.659} = 49.03\%$. Thus, from an average scale, we notice that desalination plants can effectively provide clean water to Ukraine.

9 Conclusions

Based on our model results, we find that Ukraine will experience more severe water stress in next 15 years. For one thing, geologically speaking, Ukraine is a country that suffers from renewable water resources. Water resources per capita in Ukraine less than the international water shortage warning line standard; temporal and spatial distribution of water resources in Ukraine is quite uneven; and Ukraine's water dependency ratio is very high. For another, Ukraine's social factors account for this issue as well. The daily water consumption per capita in Ukraine as well as the large amount of industrial withdrawal has made this country even more vulnerable. In a nutshell, this water use pattern is leading Ukraine to a rather serious situation.

For the purpose of addressing this issue, we propose to build a desalination plant in Odessa, which is located in southern coastal area. This method can effectively alleviate the water stress in the region. Besides, it coincides with the idea of sustainable development. However, it may need large amount of investments and might intrigue the rise of water price.

10 Evaluation of Model

Like any other model, the one presented above has its strengths and weaknesses. Some of the major points are presented below.

10.1 Strengths

- **Broad application**
  This model can be used for many countries, not only for Ukraine, as long as we have enough data of other countries. Therefore, this model can be transplanted to adapt to many situations.
- **Comprehensive and Systematic**
  This model can contain various kinds of data to complete prediction, and by taking as many as data into consideration as possible, the prediction will be more comprehensive and systematic, more likely to be achieve accurate estimation.
- **Excellent generalization ability**
  The core of this model is Back Propagation. BP ensures excellent generalization ability (the ability to adapt to new training samples). The model can respond correctly in spite of some noisy inputs.

10.2 Weaknesses

- **Inaccuracy for long-term prediction**
  Just like any prediction model, our model can't ensure its reliability for long-term prediction either. This is because of the bare fact that the model can no longer rectify its error for the lack of real values.
- **Fluctuation on results**
  TGB model's output can vary from time to time, yet within an acceptable range. This fluctuation may be magnified with the length of prediction period. That is to say, this model cannot give high-precision accurate quantitative values.

References

[1] Shashi Sathyanarayana. "A Gentle Introduction to Backpropagation", 2014: 4-13.

[2] Wang, Shuo, et al. "Multi-scale analysis of the water resources carrying capacity of the Liaohe Basin based on ecological footprints", Journal of Cleaner Production, 2013: 158-166.

[3] Wengao Lou, Suiqing Liu. "On Assessment of Sustainable Development Level of Regional Water Rsource Using Artificial Neural Networks", System Sciences and Comprehensive Studies in Agriculture, 2003: 114-119.

[4] Qingwen Min, et al. "Fuzzy-based Evaluation of Water Resources Carrying Capacity and its Application", 2004: 14-16.

[5] Liyu Han. "Development and utilization of water resources in Ukraine", China Academic Journal Electronic Publishing House, 2009: 61-66.

[6] Lang Xu. "Study on the water resources carrying capacity in Jiangsu Province based on principal component analysis", Resources and Environment in the Yangtze Basin, 2011: 1468-1474.

[7] Xiangui Xue, Lu Li. "Evaluation of water resources carrying capacity in Guizhou based on BP neural network", Fujian Computer, 2015: 8-9.

[8] Shitang Ke, et al. "Prediction on Wind Effects of Large Cooling Towers Based on Grey-Neural Network Joint Model", Journal of Nanjing University of Aeronautics and Astronautics, 2014: 652-658.

[9] Jianyong Liu, et al. "Forecasting model for development cost of equipment based on artificial neural network and grey Verhulst algorithm", Journal of PLA University of Science and Technology, 2008: 335-338.

[10] El-Dessouky H T, et al. "Multi-stage Flashi Desalination", Present and Future Outlook, 1999: 173-190.

[11] Junhong Wang, et al. "Development and application of seawater desalination", Industrial Water Treatment, 2008: 6-9.

[12] Qiyuan Jiang. Mathematical Model(4th Edition).

[13] AQUASTAT. Food and Agriculture Organization of the United Nations. FAO Water Resources. http://www.fao.org/nr/water/aquastat/water_res/index.stm

[14] World Resource Institute. http://www.wri.org/

[15] http://www.latexstudio.net/

[16] http://www.chinatex.org/

Appendices

Appendix A

```
function main()
clc                 %clearing the screen
clear all;          %clearing memory in order to speed up the operating process
close all;          %closing all current figures
SamNum=12;          %the size of  input samples is 12
TestSamNum=12;      %the size of testing samples is also 12
ForcastSamNum=2;    %the size of predicting samples is 2
HiddenUnitNum=8;    %the size of middle layer hidden nodes is 8, one more than
                    %toolkit programs
InDim=3;                      %3-dimensional network input
OutDim=2;                     %2-dimensional network input

%original data
%surface water resources amount
sqrs=[26561.9 25933.4 27243.3 26250.7 23126.4 26982.4 24358.1 24242.5 ...
    26377.0 23125.2 29797.6 22213.6];
%groundwater resources amount
sqjdcs=[8501.9 8390.1 8697.2 8299.3 7436.3 8091.1 7642.9 7617.2 8122.0 ...
    7267.0 8417.0 7214.5];
%repeated amount of surface water and groundwater
```

```
sqglmj=[7363.0 7455.7 7679.2 7089.9 6433.1 7020.4 6670.8 6604.5 7064.7...
    6212.1 7308.2 6171.4];
%total water resources
glkyl=[27700.8 26867.8 28261.3 27460.2 24129.6 28053.1 25330.1 25255.2 ...
    27434.3 24180.2 30906.4 23256.7];
%water resources per capita
glhyl=[2193.9 2112.5 2207.2 2131.3 1856.3 2151.8 1932.1 1916.3 2071.1 ...
    1816.2 2310.4 1730.2];
p=[sqrs;sqjdcs;sqglmj];  %input data matrix
t=[glkyl;glhyl];           %objective data matrix
[SamIn,minp,maxp,tn,mint,maxt]=premnmx(p,t); %initialization for original
                                             %samples(input and output)

rand('state',sum(100*clock))   %generating a random number on the basis
                               %of the system clock seed
NoiseVar=0.01;                    %the noise intensity is 0.01čĺadding noise
                                  %to prevent over- fitting phenomenončl'
Noise=NoiseVar*randn(2,SamNum);   %generating noise
SamOut=tn + Noise;                   %adding noise to output samples

TestSamIn=SamIn;                 %here input samples are the same
                                 %as testing samples because of small samples
TestSamOut=SamOut;        %making output samples and testing samples the same

MaxEpochs=50000;                     %the maximum of training times is 5000
lr=0.035;                                 %the learning rate is 0.035
E0=0.65*10^(-3);                          %the target error is 0.65*10^(-3)
W1=0.5*rand(HiddenUnitNum,InDim)-0.1;
%initializing weights between input layer and hidden layer
B1=0.5*rand(HiddenUnitNum,1)-0.1;
%initializing thresholds between input layer and hidden layer
W2=0.5*rand(OutDim,HiddenUnitNum)-0.1;
%initializing weights between output layer and hidden layer
B2=0.5*rand(OutDim,1)-0.1;
%initializing thresholds between input layer and hidden layer

ErrHistory=[];              %occupying memory for middle variables in advance
for i=1:MaxEpochs

    HiddenOut=logsig(W1*SamIn+repmat(B1,1,SamNum)); %hidden layer network output
    NetworkOut=W2*HiddenOut+repmat(B2,1,SamNum);    %output layer network output
    Error=SamOut-NetworkOut;
    %difference between the actual output and network output
    SSE=sumsqr(Error);               %energy function (error sum of squares)

    ErrHistory=[ErrHistory SSE];

    if SSE<E0,break, end
    %breaking out of learning loop if error requirement is fulfilled

    %core programs of BP network are as follows
    %they are weights(threshold) making dynamic adjustments according to
    %negative gradient descent principle of energy function
    Delta2=Error;
    Delta1=W2'*Delta2.*HiddenOut.*(1-HiddenOut);

    dW2=Delta2*HiddenOut';
    dB2=Delta2*ones(SamNum,1);

    dW1=Delta1*SamIn';
    dB1=Delta1*ones(SamNum,1);
    %correcting weights and thresholds between hidden layer and output layer
    W2=W2+lr*dW2;
```

```
    B2=B2+lr*dB2;
    %correcting weights and thresholds between hidden layer and input layer
    W1=W1+lr*dW1;
    B1=B1+lr*dB1;
end

HiddenOut=logsig(W1*SamIn+repmat(B1,1,TestSamNum));
%hidden layer carrys out final result
NetworkOut=W2*HiddenOut+repmat(B2,1,TestSamNum);
%output layer carrys out final result
a=postmnmx(NetworkOut,mint,maxt);   %restoring the result of output layer
x=2000:2011;                        %timeline scale
newk=a(1,:);                        %network outputs passenger capacity
newh=a(2,:);                        %network outputs freight volume
figure ;
subplot(2,1,1);plot(x,newk,'r-o',x,glkyl,'b--+')
%comparison diagram of total water resources
legend('Network output total water resources','total water resources');
xlabel('year');ylabel('billion cubic meters');
subplot(2,1,2);plot(x,newh,'r-o',x,glhyl,'b--+')
%comparison diagram of water resources per capita
legend('Network output water resources per capita','water resources per capita');
xlabel('year');ylabel('cubic meters per person');

%using the trained network to predict
%the corresponding processing should also be made when using the trained
%network to forecast the new data pnew
pnew=[ 28371.4 26839.5
       8416.1 8081.1
       7260.6 6962.7];         %related data in 2012 and 2013čż
pnewn=tramnmx(pnew,minp,maxp);
%using normalized parameters of original input data to normalize new datačż
HiddenOut=logsig(W1*pnewn+repmat(B1,1,ForcastSamNum));
%hidden layer carrys out predicted results
anewn=W2*HiddenOut+repmat(B2,1,ForcastSamNum);
%output layer carrys out predicted results

%restoring predicted data to original order of magnitudesčż
anew=postmnmx(anewn,mint,maxt)
```

Appendix B

```
%actual total water resources
glkyl1=[27700.8 26867.8 28261.3 27460.2 24129.6 28053.1 25330.1 25255.2 27434.3 ...
    24180.2 30906.4 23256.7 29526.9 27957.9];
%actual water resources per capita
glhyl1=[2193.9 2112.5 2207.2 2131.3 1856.3 2151.8 1932.1 1916.3 2071.1 1816.2 ...
    2310.4 1730.2 2186.1 2059.7];

%predicted total water resources
glkyl2=[27700.8 26867.8 28261.3 27460.2 24129.6 28053.1 25330.1 25255.2 27434.3 ...
    24180.2 30906.4 23256.7 29518.0 27966.0];
%predicted water resources per capita
glhyl2=[2193.9 2112.5 2207.2 2131.3 1856.3 2151.8 1932.1 1916.3 2071.1 1816.2 ...
    2310.4 1730.2 2168.0 2061.0];

figure ;
x=2000:2013;
subplot(2,1,1);plot(x,glkyl2,'r-o',x,glkyl1,'b--+')
%comparison diagram of total water resources
```

```
legend('Network output total water resources','total water resources');
xlabel('year');ylabel('billion cubic meters');
subplot(2,1,2);plot(x,glhyl2,'r-o',x,glhyl1,'b--+')
%comparison diagram of water resources per capita
legend('Network output water resources per capita','water resources per capita');
xlabel('year');ylabel('cubic meters per person');
```

Appendix C

```
%res0
pre=[190.255745110849,197.342256137325,182.939118533223,175.709243979758,...
    161.469365688413,149.525957485249,146.948262773806,150.797309789114];
real=[190.27 197.48 182.82 175.77 162.99 150.39 146.94 150.83];
146residual0=[];
relative_error0=[];
for i=1:8
    residual0(i)=pre(i)-real(i);
    relative_error0(i)=residual4(i)/real(i);
end
residual0                       %residual
relative_error0                 %relative_error

residual0_mean=abs(mean(residual0))
relative_error0_mean=abs(mean(relative_error0))
```

Appendix D

```
%GM(1,1) model
clc;
clear all;

x0 = [190.27 197.48 182.82  175.77  162.99  150.39  146.94  150.83];

n = length(x0);
% judging  to determine whether it is suitable for GM(1,1) model
lamda = x0(1:n-1)./x0(2:n);
range = minmax(lamda);
% judging whether it is suitable for GM(1,1) model
if range(1,1) < exp(-(2/(n+2))) | range(1,2) > exp(2/(n+2))
    error('stepwise ratio is out of the range of GM(1,1) model');
else
   % null string output
    disp('              ');
    disp('suit G(1čň1) model');
end

% AGO accumulation
x1 = cumsum(x0);
for i = 2:n
    % calculating mean with consecutive neighborsčňthat is white background value
    z(i) = 0.5*(x1(i)+x1(i-1));
end
B = [-z(2:n)',ones(n-1,1)];
Y = x0(2:n)';
% doing division to matrix,computing coefficient and grey action
u = B\Y;
% D represents derivative and dsolve function is used to solve symbolic ordinary
```

```
% differential equation in MATLAB
x = dsolve('Dx+a*x=b','x(0)=x0');
% subs function aims to replace elementsčňhere replacing a,b,x0 with specific
% values u(1),u(2),x1(1)
x = subs(x,{'a','b','x0'},{u(1),u(2),x1(1)});
forecast1 = subs(x,'t',[0:n-1]);
% digits and vpa functions are used to control the number of significant figures
digits(6);
% y is AGO(or cumulative)
y = vpa(x);
% continuous subtraction for AGO output
% diff is used to take a derivative of symbolic expression
% but it represents computed difference of adjacent elements if a vector is input
forecast11 = double(forecast1);
exchange = diff(forecast11);

disp('evaluating predicted value for known data')
forecast = [x0(1),exchange]   %evaluating predicted value for known data
```

Appendix E

```
%DGM(2,1) model
clc;
clear all;

x0=[190.27 197.48   182.82  175.77  162.99  150.39  146.94  150.83];
%original data sequence
n=length(x0);
a_x0=diff(x0)';%calculating first forward difference
B=[-x0(2:end)',ones(n-1,1)];
disp('using least square method to fit parameter')
u=B\a_x0  %using least square method to fit parameter
disp('working out symbolic solution of differential equation')
x=dsolve('D2x+a*Dx=b','x(0)=c1,Dx(0)=c2');
%working out symbolic solution of differential equation
x=subs(x,{'a','b','c1','c2'},{u(1),u(2),x0(1),x0(1)});
yuce=subs(x,'t',0:n-1);
%calculating predicted value of first forward difference for known data

x=vpa(x,6)
disp('calculating predicted value for known data')
x0_hat=double( [yuce(1),diff( double(yuce) )] )
%calculating predicted value for known data
```

Appendix F

```
%Verhulst model
clc;
clear all;

x0=[190.27 197.48   182.82  175.77  162.99  150.39  146.94  150.83];
%original data sequence
n=length(x0);

x1=diff(x0);
x1=[x0(1),x1]
for i=2:n
```

```
z1(i)=0.5*(x0(i)+x0(i-1));
end
z1
B=[-z1(2:end)',z1(2:end)'.^2]
Y=x1(2:end)'
abhat=B\Y %estimating parameters a and b
x=dsolve('Dx+a*x=b*x^2','x(0)=x1'); %solving ordinary differential equation
x=subs(x,{'a','b','x1'},{abhat(1),abhat(2),x0(1)}); %using values of paramaters
yuce=subs(x,'t',0:n-1) %calculating first forward difference

x=vpa(x,6)
disp('calculating predicted value for known data')
x0_hat=double( [yuce(1),diff( double(yuce) )] )
%calculating predicted value for known data

forecast=x0_hat;
for i=1:n-1
    forecast(i+1)=forecast(i)+x0_hat(i+1);
end

disp('calculating predicted value for known data')
forecast                %calculating predicted value for known data
```

Appendix G

```
clc
clear
syms a b;
c=[a b]';
A=[190.2700  193.7160  183.9220  174.6210  165.7910  157.4100  149.4500  141.8900];
%input the forecast values from the results of program GM1~3
B=cumsum(A);  % accumulation for original data
n=length(A);
for i=1:(n-1)
    C(i)=(B(i)+B(i+1))/2;  % generating accumulation matrix
end
% calculating value of coefficient
D=A;D(1)=[];
D=D';
E=[-C;ones(1,n-1)];
c=inv(E*E')*E*D;
c=c';
a=c(1);b=c(2);
% predicting subsequent data
F=[];F(1)=A(1);
for i=2:(n+25)
    F(i)=(A(1)-b/a)/exp(a*(i-1))+b/a ;
end
G=[];G(1)=A(1);
for i=2:(n+25)
    G(i)=F(i)-F(i-1); % getting predicted data
end
t1=1998:2005;
t2=1998:2030;
G
plot(t1,A,'ko', 'LineWidth',2)
hold on
plot(t2,G,'k', 'LineWidth',2)
xlabel('Year', 'fontsize',12)
ylabel('Billion cubic meters','fontsize',12)
```

```
set(gca,  'LineWidth',2);

residual=[a b]';
relative_error=[a b]';
for i=1:n
    residual(i)=G(i)-A(i);
    relative_error(i)=residual(i)/A(i);
end
residual                     %residual error
relative_error               %relative error
```

Appendix H

```
%res1~3
residual1=[0 -0.0416 -0.0387 -0.0338 -0.0299 -0.0288 -0.0251 -0.0191];
relative_error1 =[0 -0.2150 -0.2104 -0.1934 -0.1803 -0.1830 -0.1679 -0.1349];

residual2=[0 1.2653 -0.0277 -0.8269 -1.1067 -0.8386 0.0085 1.4690];
relative_error2 =[0 0.0067 -0.0002 -0.0046  -0.0063 -0.0049 0.0001 0.0093];

residual3=[0 0.4786 -0.0565 -0.3482 -0.4173 -0.2844 0.0300 0.5058];
relative_error3 =[0 0.0026 -0.0003 -0.0020 -0.0025 -0.0018 0.0002 0.0034];

residual1_mean=abs(mean(residual1))
relative_error1_mean=abs(mean(relative_error1))

residual2_mean=abs(mean(residual2))
relative_error2_mean=abs(mean(relative_error2))

residual3_mean=abs(mean(residual3))
relative_error3_mean=abs(mean(relative_error3))

%res4
pre=[190.271684715879,197.482192372527,182.822476118608,175.7773509548315,...
    162.993762767777,150.394842643418,146.945399451505,150.833539421809];
real=[190.27    197.48   182.82   175.77   162.99   150.39   146.94   150.83];

residual4=[];
relative_error4=[];
for i=1:8
    residual4(i)=pre(i)-real(i);
    relative_error4(i)=residual4(i)/real(i);
end
residual4                     %residual
relative_error4               %relative_error

residual4_mean=abs(mean(residual4))
relative_error4_mean=abs(mean(relative_error4))
```

Appendix I

```
%TGB model
clc;
clear all;
%original data
%output data
data=[190.27 197.48 182.82  175.77  162.99  150.39  146.94  150.83];
```

```
%GM11 predicted total water withdrawal
GM11 =[190.2700  193.7160  183.9220  174.6210  165.7910  157.4100  ...
    149.4500  141.8900];
%DGM predicted total water withdrawal
DGM=[190.2700  188.3733  184.3634  180.0079  175.2771  170.1386  ...
    164.5572  158.4949];
%Verhulst predicted total water withdrawal
Verhulst=[190.2700  184.6402  178.9621  173.2493  167.5153  161.7741 ...
    156.0396  150.3257];

b=[GM11;DGM;Verhulst];  %input data matrix
c=[data];          %output data matrix

%bp neuron simulation
[pn,minp,maxp,tn,mint,maxt]=premnmx(b,c);
%normalizing the input matrix b and the output matrix c
dx=[-1,1;-1,1;-1,1];
%the minimum value is -1 amd the maximum is 1 by normalization

net=newff(dx,[3,7,1],{'tansig','tansig','purelin'},'traingdx');
%establishing a model and using the gradient descent method  to train it
net.trainParam.show=100;         %executing 100 loops to show a result
net.trainParam.Lr=0.05;          %the learning rate is 0č605
net.trainParam.epochs=50000;     %the maximum of training times is 50000
net.trainParam.goal=0.00001;     %the MSE is 0č600001
net=train(net,pn,tn);            %starting to train itčňpn is used as an
                                 %input sample while tn is output
                                 %using data which has been normalized

an=sim(net,pn);                  %using the trained model to simulate
a=postmnmx(an,mint,maxt);
%dealing with the net-output an=sim(netčňpn) as follows after training

%drawing, and comparing to simulation results
x=1998:2005;
newk=a(1,:);
figure (3);
plot(x,newk,'b--+',x,data,'r-o')
title('Combination water volume forecast')
legend('Network output water volume','Real water volume');
xlabel('year');ylabel('billion cubic meters');

%the corresponding processing should also be made when the trained network
%is used to forecast the new data pnew
%GM11 predicted total water withdrawal
GM11 =[190.2700  193.6744  183.8833  174.5872  165.7611  157.3812  149.4249 ...
    141.8709  134.6987  127.8891  121.4238  115.2853  109.4571  103.9236  ...
    98.6698   93.6817   88.9457   84.4491   80.1798   76.1264   72.2779   ...
    68.6239   65.1547   61.8609   58.7335   55.7643   52.9452   50.2686   ...
    47.7273   45.3145   43.0236   40.8486   38.7836];
%DGM predicted total water withdrawal
DGM=[190.2700  189.6386  184.3357  179.1810  174.1704  169.3000  164.5657 ...
    159.9639  155.4907  151.1426  146.9161  142.8078  138.8144  134.9327 ...
    131.1594  127.4918  123.9266  120.4612  117.0927  113.8183  110.6355  ...
    107.5418  104.5345  101.6114   98.7699   96.0080   93.3232   90.7136 ...
    88.1769   85.7112  83.3144   80.9846   78.7200];
%Verhulst predicted total water withdrawal
Verhulst=[190.2700  185.1188  178.9056  172.9011  167.0980  161.4897  ...
    156.0696  150.8315  145.7692  140.8767  136.1485  131.5790  127.1628...
    122.8948  118.7701  114.7839  110.9314  107.2082  103.6100  100.1325  ...
    96.7718   93.5239   90.3849   87.3514   84.4196   81.5862   78.8480  ...
    76.2016   73.6441   71.1723  68.7836   66.4750   64.2439];
```

```
pnew=[GM11;DGM;Verhulst];
pnewn=tramnmx(pnew,minp,maxp);
anewn=sim(net,pnewn);
anew=postmnmx(anewn,mint,maxt)
```

Appendix J

```
clc                    %clearing the screen
clear all;             %clearing memory in order to speed up the operating process
close all;             %closing all current figures

figure;
x=[2016 2020 2025 2030];
y=[3 100 300 800];
plot(x,y);             %the chart of desalination capacity's predicted trend
title('Desalination capacity');
xlabel('year');ylabel('ten thousand cubic meters');

cftool                 %fitting curve
```

Appendix K

```
clc                   %clearing the screen
clear all;            %clearing memory in order to speed up the operating process

p1 =      0.3036;
p2 =       -1838;
p3 =    3.71e+06;
p4 =  -2.496e+09;

syms x
f=p1*x^3 + p2*x^2 + p3*x + p4;
int(f, x, 2016, 2030)    %calculating the integral
```