A Modified Nonlinear Grey Bernoulli Model Used for Water Consumption Prediction

WANG Yu-lu, YUAN Yan-bing, YUAN Xiao-hui , ZHANG Miao

***Abstract*—**Residential water consumption in cities has typical sequence characteristics of randomness, fluctuation and discreteness, which lead to low accuracy in predicting the medium and long term data. In order to solve this problem, a modified nonlinear grey Bernoulli model was proposed. In this model, a fractional order was introduced for the transformation of raw data to improve the fitting degree; a self-adaptive artificial fish swarm algorithm (SAFSA) was used to seek the best power exponent and time action parameters, so that to identify the oscillation characteristics in the original data; by metabolic method, the interference caused by the old information was avoided, thereby reducing the prediction accuracy loss. The time series data of Wuhan's residential water consumption between 2004 and 2014 were used to verify the effectiveness of the optimized model in predicting water consumption. The results demonstrate that the modified model can show higher prediction accuracy than several kinds of traditional grey models. For further direction, the optimized model, which provides a new method in predicting the mid-and-long term water consumption, has important theoretical significance and practical values in water resource allocation.

***Index Terms*—**NBGM (1, 1); Fractional order; SAFSA; Metabolic; Water Consumption Prediction;

I. INTRODUCTION

Water consumption prediction is the precondition and foundation of the reasonable water resources management. The results directly affect the reliability and practicability of the decision-making with scheduling water. In recent years, rapid economic development and expanding industry scale result in the water demand increase while the improvement of technology level, water saving measures, rated water consumption and stepwise surcharge for extra use of water lead to a downtrend. Therefore, water consumption shows a certain volatility and randomness.

Methods for water consumption prediction are various, including regression analysis [1], water quota method [2] neural network [3] grey prediction method [4], etc. Many foreign scholars prefer using multiple regression and neural network method to forecast water consumption. Although the efficiency of these methods has been verified, they ask for a large amount of supporting data and prophase investigation. In the process of practical application, data acquisition was difficult. Therefore, domestic scholars put forward that the grey system could be applied to forecast water consumption [5].

Grey System, put forward by Ju-Long Dun in 1980s [6], was a method which can solve problems of small samples, poor information and uncertainty. As one of core contents of the grey prediction, GM (1, 1) model has been widely applied in many fields like economics, management and engineering because of its simple modeling process, small amount of required data and simple equations. However, in the actual establishment of the model, the GM (1, 1) model shows a low fit dealing with non-linear sequences. For this reason, Chun-I Chen [7] proposed a nonlinear grey model based on Bernoulli equation, with variable fixed powers. The adjustable parameters in the model can effectively identify the oscillation characteristics in the original data, which greatly improved the model prediction accuracy, was applied to various fields. Many scholars have improved the model with practical applications [8]-[11] The optimization of the NGBM (1,1) model is mainly based on the parameters and residuals, and there is little research on the optimization of the gray system. The grey sequence is an important part of the grey system, its generation technology is also the key to improve the prediction precision. Professor Liu [12] proposed the concept of buffer operator and established the equation. On this basis, Dang, etc [13] constructed several improved buffer operators. However, for the generation of gray sequence, there was accumulating generation operator (AGO) besides the buffer operator. The existing grey forecasting models are mostly modeled by the first order AGO, then the predicted value is obtained. This undoubtedly omits the grey information existing in the decimal places. In this study, we introduce the fractional order into the NGBM (1, 1) model to optimize the gray sequence of the model and improve the prediction precision.

As the adjustable parameters determine the modeling accuracy, the way to select parameter values plays another important role. So far, the most commonly used parameter selection method is the particle swarm optimization algorithm (PSO) [14]. However, Local optimal solution is likely to occur in PSO due to its higher speed of convergence. In this study, a self-adaptive artificial fish swarm algorithm (SAFSA) is applied to select parameter optimization in the study. This algorithm has the advantages of overcome the local extremum, high convergence speed, flexible in use, strong adaptability robustness, etc.

On this basis, the model only considers the data before the real time (t=n), the old information will produce disturbance, which makes the prediction accuracy descend, when facing the passage of time or dealing with long time prediction. In this

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WANG Yu-lu is with the School of Resources and Environment Engineering, Wuhan University of Technology, Wuhan, Hubei 430070, P.R.C

YUAN Yan-bing is with the School of Resources and Environment Engineering, Wuhan University of Technology, Wuhan, Hubei 430070, P.R.C

case, metabolic grey prediction has recently drawn great attention owing to its performance, which makes the grey prediction in dynamic systems. As is shown by the meaning of the word 'metabolic', these systems can input the latest data while remove the oldest ones to form an new dynamic sequence. Thus, it can track the data fluctuation quickly and enhance the precision of predicion.

Taking the deficiencies of NGBM (1, 1) model into account, this article applied fractional order to improve the grey generation of the model, based on the analysis of the fractional order intensity, using SAFSA to select the optimal parameters. As the past of tIime will bring the loss of precision model, metabolic method was introduced to fine-tune the data, build a dynamic model with time series, and apply it in residential water consumption predicting. Finally, verified the feasibility and effectiveness of the optimized model by the fitting and forecasting results.

II. Method and Model

A. Modified Nonlinear Grey Bernoulli Model

A modified NGBM (1, 1) model was proposed to predict the water consumption with better performance. The optimization of the NGBM (1, 1) model involved the following steps:(1) AGO determines the trend of model fitting, the introduction of fractional order improved the limit of integer order in modeling process and improves the accuracy of modeling sequence; (2) SAFSA was used to find the best cumulative fractional order of the model, background value p and exponential value r in real-time, get a model with best fitting effect can reduce the interference of system behavior data; (3) metabolic method was applied to establish the dynamic model, avoided the model from losing of accuracy in prediction with the passage of time. The form of AF-MNBGM (1, 1) model is as follows:

Step 1: Assume the original data sequence

$$x^{(0)} = \left[x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right]$$

Step 2: Give the sequence a fractional order AGO. Let the order is s, then the equation is as follows：

$$x^{(s)}(k) = \sum_{i=1}^{k} \frac{\Gamma(s+k-i)}{\Gamma(k-i+1)\Gamma(n)} x^{(0)}(i), \quad (1)$$

where k =1,2,3,…, n is the original data point.

Step 3: Using differential equation, there is

$$\frac{\Delta x^{(s)}}{\Delta t} = \Delta x^{(s)}(k+\Delta t) - x^{(s)}(k) = x^{(0)}(k), \quad (2)$$

where Δt =1.

The $x^{(s)}(k)$ of Eq.(3) is approximated by

$$x^{(s)}(k) \approx p x^{(s)}(k) + (1-p) x^{(s)}(k-1) = z^{(s)}(k), \quad (4)$$

where k =2,3…, n, p is the background value.

Step 5: Establish the first-order differential

$$\frac{d_{x^{(s)}}}{d_t} + a x^{(s)} = b\left[x^{(s)}\right]^r, \quad (5)$$

where r determines the accuracy of the model and does not belong to the real number except 1.

Step 6: Substitute Eq.(a) into Eq.(6), the equation can be written

$$x^{(s)}(k) + a z^{(s)}(k) = b\left[z^{(s)}(k)\right]^r. \quad (6)$$

Step 7: Calculate [a, b] by the least-square method

$$[a,b]^T = \left[B^T B\right]^{1} B^T Y \quad . \quad (7)$$

Step 8: Establish the time response function of the s-order Accumulated Generated Sequence

$$x\_feorcast^{(s)}(k) = \left[\left[\left[x^{(0)}(1)\right]^{(1-r)} - \frac{b}{a}\right] e^{-a(1-r)(k-1)} + \frac{b}{a}\right]^{\frac{1}{1-r}}, \quad (8)$$

when s=1, r=0, p=0.5, Eq.(9) is the traditional GM (1, 1) model.

Step 9: Give the $x\_forecast^{(s)}$ a fractional order I-AGO, obtain the forecasting results with unknown parameters [s,r,p]

$$x\_forecast^{(0)}(k) = x\_forecast^{(s)-s}(k) = \sum_{i=1}^{k-1} (-1)^{i} \frac{\Gamma(s+1)}{\Gamma(s-i+1)\Gamma(i+1)} x\_forecast^{(s)}(k-i). \quad (9)$$

Step 10: Use SAFSA to select the optimal value of s, r and p； the objective function is as follows:

$$Y = \frac{1}{n-1} \sum_{i=2}^{n} \frac{\left|x^{(0)}(k) - x\_forecast^{(0)}(k)\right|}{x^{(0)}(k)} \quad . \quad (10)$$

The realization of the main process of AFSA will show in 2.2.

Step 11: Substituting the optimal solution [s_1,r_1,p_1] into Eq.(10), the first prediction result is obtained, and new information can be extracted,

$$x\_new^{(0)}(k) = x\_forecast^{(0)}(k), \quad (11)$$

where $k=n+1, n+2, \ldots n+m$.

Step 12: Repeat Step 2 to Step11 to obtain the parameters [s_2,r_2,p_2] and establish the modified NGBM (1, 1) model

$$x\_feorcast2^{(s_2)}(k) = \left[\left[\left[x^{(0)}(1)\right]^{(1-r_2)} - \frac{b}{a}\right] e^{-a(1-r_2)(k-1)} + \frac{b}{a}\right]^{\frac{1}{1-r_2}}. \quad (12)$$

Step 14: Get the forecasting value of the modified NGBM (1, 1) model according to Step 10

$$x\_forecast2^{(0)}(k) = \sum_{i=1}^{k-1} (-1)^{i} \frac{\Gamma(s_2+1)}{\Gamma(s_2-i+1)\Gamma(i+1)} x\_forecast^{(s_2)}(k-i) \quad (13)$$

Step 15: Repeat Step 9 to Step11 until all the predicted values are got.

B. Self-adaptive Artificial Fish Swarm Algorithm (SAFSA)

Artificial fish algorithm put forward by Xiao-Lei Li [15]， was a kind of swarm intelligence optimization algorithm based on animal behavior. By simulating the fish foraging, following and randomness, this algorithm realizes the optimization in searching area. In the traditional artificial fish algorithm, the moving step length of each fish was fixed, making the algorithm converge slowly in the later period. In order to avoid this defectiveness, an optimized swarm intelligence algorithm [16], was introduced in this study, which can dynamically adjust the moving step length to select the parameter optimization of the model.

The following method is applied to realize the visual of artificial fish:

A virtual artificial fish's current position *Par*=[*s*,*r*,*p*], whose visual field is *Visual* and Par_v is the fish's viewpoint at one moment. If the objective function value at Par_v is lower than the current position, artificial fish will judge that this position has higher food concentration and move one step to Par_{next} toward this direction, or else continue looking for food. Algorithm will finish when iterative times exceed a given value GEN.

In the process of actual search, randomly initializing *N* number of *Par*, which can be denoted as$[s,r,p]_i$, $i=1,2,\dots,N$. The specific calculation process is as follows:

$$Par = Par_i^v = Par_{v_i} + rand(visual), \tag{14}$$

$$step = rand(|[r_v, p_v] - [r, p]|), \tag{15}$$

$$[r, p]_{next} = \frac{[r_v, p_v] - [r, p]}{\|[r_v, p_v] - [r, p]\|} * step, \tag{16}$$

where, rand() is a random number between [0, 1], moving step length denoted by *step*. The method by perceiving the companions' position to adjust themselves is similar to the method above, as the number of companions in the environment is limited.

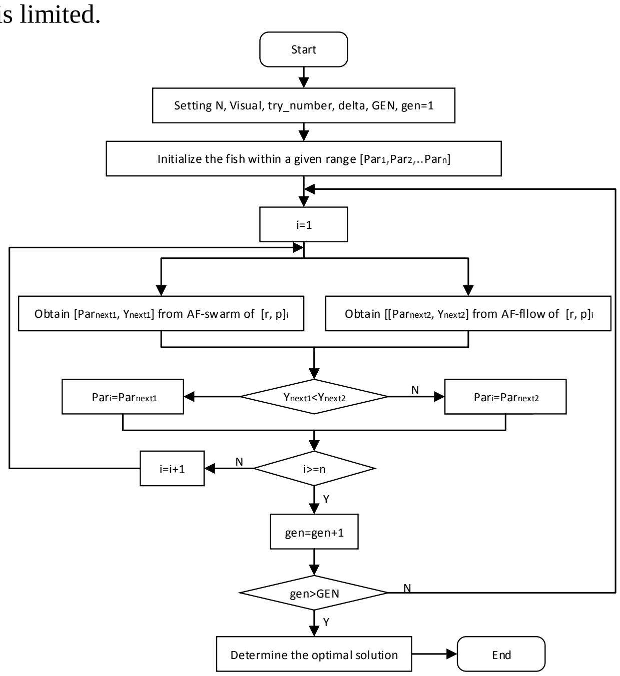

Fig. 1. The flow chart of AFSA

In Fig. 1 the degree of crowdedness of Pari is denoted by Delta, objective function is denoted by Yi obtains its value by Pari.

III. Result and Discussion

A. Data

To verify the superiority of the model, the study used the residential total water consumption data in 2004-2014 in Wuhan Statistical Yearbook as an example. Data of 2004-2011 were basic data which was used to model and fit effect analysis and data of 2011-2014 were used to effect analysis of the model prediction. The experimental data are shown in Table.1.

TABLE I: The residential total water consumption in Wuhan City

Year	2004	2005	2006	2007
Water consumption ($*10^3m^3$)	42445	42450	35654	37100
Year	2010	2011	2012	2013
Water consumption ($*10^3m^3$)	40173	44625	47385	48211.69

B. Strength analysis of fractional order

In order to find the effect of different grey sequences on the modeling results, we took a specific NGBM (1, 1) model with r = p = 0.5 as an example, the minimum mean absolute percentage error (MAPE) between the predicted values and the actual values of the model fitted by the AGO under different fractional orders were obtained and the comparison results were shown in Fig.2.

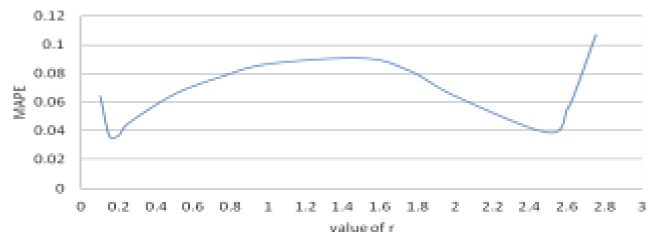

Fig. 2. MAPE for model prediction under different fractional orders

It can be seen from Fig. 2 that the fitting accuracy of the model varies with the r-value under the condition that the exponent r and the background value p do not change. In the case of the actual $r\in(0,3)$, its course of changes was not difficult to find the minimum was in decimal places. This indicated that the fractional order played a positive role in the improvement of prediction accuracy.

However, from the practical point of view, the change of the fractional orders made the model have multi - extreme values. In order to obtain the minimum error in these extreme values, we need to expand the r-value search domain, find a suitable search method. In this article, SAFSA was used to select the r value, and the best target result could be obtained from the global point of view, with the fastest speed and the minimum operation complexity.

C. Optimal parameters based on SAFSA

SAFSA is used to find the optimal value of the key parameters [*s*,*r*,*p*] and to decide the shape of the model. With the ultimate goal of obtaining the MAPE, objective function is established as Eq. (11).The basic parameter settings of SAFSA are as Table.2.

TABLE II: Parameter Settings

Parameter	N	GEN	Try_num	Delta	Visual
Value	100	200	100	0.01	0.1

The realization of the modeling is operated in MATLAB. Y value of each iteration is shown in Fig.3.

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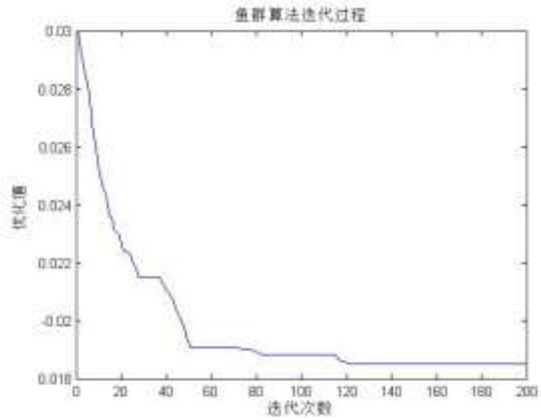

Fig. 3. The AFSA iterative results of 200 times

From above operation results, the study could obtain the optimal value [*s,r,p*] and minimum MAPE of the first prediction were as follows：

TABLE III: ALGORITHM RUNNING RESULTS

Parameter	s	r	p	Y
Optimal value	1.4091	0.06041	0.43507	0.01852

D. Modified NGBM (1, 1) Model and Analysis

With the results above, we could get the grey sequence $x^{(s)}$=[42445.00,102259.25,167513.53,241259.30,323942.96,414349.85,511689.99,619509.35], developmental quotient a=-0.08404 and constant b=27309.97143.

These parameters are applied to establish first modified NGBM (1, 1) model as follow:

$$x\_forecast^{(s)}(k) = \left[\left[\left[x^{(1)}(1)\right]^{1.537} + 1.444*10^{8}\right]e^{0.146(k-1)} - 1.444*10^{8}\right]^{0.651} \tag{16}$$

Obtained the fitting and forecasting results of 2004-2014 water consumption on the basis of Eq. (10), $x\_forecast^{(s)}$=[42445,37552.70,37100.01,38018.97,39704.99,41939.64,44630.13,47737.18,51248.68,55168.24].Comparing the actual values, the model fitted MAPE is only 1.85%, showing satisfactory. For the prediction, the relative errors with the true value [47385,48211.69,50073] are 0.74%, 6.3% and 10.17%, individually. Although the 2012 forecasting result had a relative error of 0.74%, the prediction lost its precision with the passage of time, increase of time interval and discrete rate, which could be verified by 2014 forecasting result, whose relative error went to 10.17%. In order to improve the forecasting precision and increase the value of the model in practical application, the metabolic method is introduced to further modify the NGBM (1, 1) model.

With the result of the $x\_forecast^{(s)}$, an equal dynamic sequence can be obtained $x\_m^{(0)}$=[42450,35654,37100,39031,39736,40173,44625,47737.18].

Establish the once metabolized modified NGBM (1, 1) model based on Eq. (16), the optimal value [*s,r,p*] obtained by SAFSA was as fallows:

TABLE IV: ALGORITHM RUNNING RESULTS

Parameter	s	r	p	Y
Optimal value	191172	0.41019	0.7095	0.01221

The time response function of the model is

$$x\_forecast2^{(s_2)}(k) = \left[\left[\left[x^{(0)}(2)\right]^{0.589} + 1.087*10^{4}\right]e^{0.038(k-1)} - 1.087*10^{4}\right]^{1.696} \tag{17}$$

The final prediction results are given in Table.5 according to EP (17).

Comparing pre - and post - metabolic modeling results, the modified NGBM (1, 1) model has satisfactory fitting precision as its MAPE is 1.21%, increase 0.64% than the original; its relative error of out-of sample forecasting result from 2013-2014 are 0.05% , 4.87% and 7.87%, which are 0.74%, 6.3% and 10.17% in the first prediction results. Thus, the predictive effect of the modified NGBM (1, 1) model is relatively superior.

The study also builds a traditional GM (1, 1) mode which can be expressed as follows:

$$x_{GM}^{(1)}(k) = \left[x^{(1)}(1) + 2.15*10^{6}\right]e^{0.017(k-1)} - 2.15*10^{6} \tag{18}$$

The study obtained the predicted values, relative error and fitting curves in order to compare and analyze these three models. These results are shown in Table.5 and Fig. 4.

TABLE V: THE PREDICTED VALUES AND RELATIVE ERROR

Year	Actual value	GM(1,1) model		NGBM (1, 1) model		Modified NGBM (1, 1)	
		values	Error(%)	values	Error (%)	values	Error (%)
2004	42445	42445	0	42445	0	42445	0
2007	37100	39125.07	5.46	36939.7	0.43	37330.48	0.00
2008	39031	39797.88	1.96	37677.92	3.47	38253.53	2.59
2009	39736	40482.26	1.88	39257.94	1.20	39909.25	0.08
2010	40173	41178.41	2.50	41451.19	3.18	42048.72	4.40
2011	44625	41886.54	6.14	44163.17	1.03	44564.96	0.01
MAPE (%)		5.25		2.14		1.21	
2012	47385	42606.83	10.08	47357.55	0.06	47409.42	0.05
2013	48211.69	43339.52	10.11	51028.1	5.84	50560.84	4.87
2014	50073	44084.80	11.96	55186.55	10.21	54012.53	7.87
MAPE (%)		10.72		5.37		4.26	

For Table.5, by comparing the fitting results of NGBM (1, 1) model and modified NGBM (1, 1) model, the application of fractional order AGO makes the model closer to the original data. The main reason is that the modified NGBM (1, 1) model has weakened the error of NGBM (1, 1) model in the process of data mining, attested that the introduction of fractional order achieved the effect of optimizing the NGBM (1, 1) model. Comparing the MAPE of the traditional GM (1, 1) model, NGBM (1, 1) model and modified NGBM (1, 1) model which were 5.25%, 2.14% and 1.21%, respectively, the modified NGBM (1, 1) model has the lowest predicted error, which were

2.139%, 2.155%, 5.25%, and 17.72%, respectively, AF-NGBM(1,1) model has the lowest predicted error. Meanwhile, as shown in Fig. 4, for volatile data like 2005 and 2006, models established based on NGBM (1, 1) model has a good adaptability to the random sequence with fluctuation, the difference of MAPE is more than 6% with GM (1, 1) model. According to the analysis above, the modified NGBM (1, 1) model showed excellent capability when dealing with the sequence of randomness, fluctuation and discreteness, indicating a highly accurate fitting.

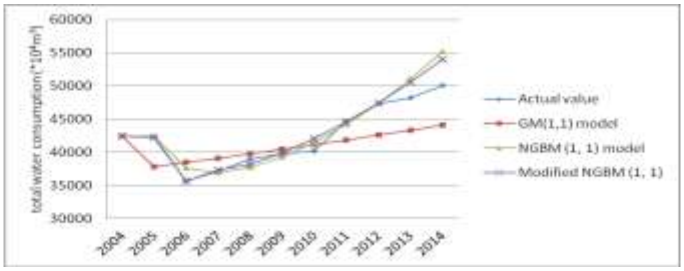

Fig. 4. The modeling trend using the three models

In the practical prediction, the relative errors of GM (1, 1) model were relatively stable, which were close to 10% and the MAPE is 10.72%. The NGBM (1, 1) showed its accuracy in forecasting compared with the traditional model, but has higher deviation than the modified NGBM (1, 1) model because of the old information. The joined of metabolic method provides NGBM (1, 1) model the effect of the dynamic evolution, enabling the model to adjust its shape continuously to be more timely and accurate with the passage of time. Modified MNGBM (1, 1) model built in this paper has the MAPE of 4.26% in predicting the water consumption from 2012 to 2014, which further proves the superiority of the model. The fitting and prediction effect of each model can also be seen more intuitively from Fig. 3.

In conclusion, when predicting the data with randomness, fluctuation and discreteness, the modified MNGBM (1, 1) model has its unique advantages. This model shows its high accuracy and good strain capacity fitting and prediction effect, at the same time, it realizes the dynamic change in time dimension, which provides a new method in predicting the mid-and-long term water consumption.

IV. Conclusion

Combination with the model parameter optimization method based on SAFSA, Compared with the classical NGBM (1, 1) model, the modified model improves the accuracy in fitting the original data, which makes it applicable in practical application. As the model can hardly keep its precision with the passage of time and increase of time interval and discrete rate, this article introduces the metabolic method to reduce the model accuracy loss. Based on the predicted data, the MAPE of the fitting using the optimized model is 1.21% and the MAPE of the prediction is 4.26%, which is significantly superior to the NGBM (1, 1) model.

In future studies, the model can be further optimized and applied to other industries. On the modeling parameters optimization method, we can further optimize the algorithm with mix of other algorithms. The differential equation and the boundary value of the model can also be further optimized. A GIS based visual-decision-supporting system can be constructed to improve the efficiency and level of water resource management and planning.

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WANG Yu-lu, born in Ningbo, Zhejiang Province, China, November 1991. She is now pursuing a master's degree in the School of Resources and Environmental Engineering, Wuhan University of Technology. The main research area is water resources allocation.

She had took part in the revision project for Wuhan Water Quota Standard in Major Industries, new rural planning project for Tongcheng County, research on spatial allocation of watershed sites based on hydrological characteristics (Supported by National Natural Science Foundation of China), ect.

WANG Yu-lu had won national third prize for National University Student Social Practice and Science Contest on Energy Saving & Emissions Reduction and national third prize for National Graduate Contest on Smart City Technology and Creative Design.