Demand estimation of water resources via bat algorithm

Xiangdong Pei*

Taiyuan Comprehensive Senior High School,
Taiyuan, China
Email: typxd@163.com
*Corresponding author

Youqiang Sun and
Yeqing Ren

Complex System and Computational Intelligence Laboratory,
Taiyuan University of Science and Technology,
Taiyuan, China
Email: Youqiang_sun@163.com
Email: 18435155956@163.com

Abstract: In the process of urban water resources planning, the demand estimation of urban water consumption is one of the important basic contents. In this paper, a hybrid model of linear estimation model and an exponential estimation model are proposed to forecast the water consumption. The bionic intelligent algorithms are widely used in industrial engineering, so, we use intelligent algorithms to solve the proposed model including Bat Algorithm (BA) and modified Bat Algorithm (FTBA). FTBA improves the global search capability, and the improvements increase the probability of solving the optimal value. In the simulation experiments, we use the data from Nanchang city during 2003 to 2015. The data from 2003 to 2012 are used to find the optimal weights, and the remaining data (2013–2015) are used to test the models. Simulation results show that the modified BA (FTBA) is superior to the standard algorithm and achieves higher accuracy in prediction.

Keywords: demand estimation; water resource; hybrid model; BA; bat algorithm.

Reference to this paper should be made as follows: Pei, X., Sun, Y. and Ren, Y. (2020) 'Demand estimation of water resources via bat algorithm', *Int. J. Wireless and Mobile Computing*, Vol. 18, No. 1, pp.16–21.

Biographical notes: Xiangdong Pei received his degree in Applied Mathematics from the Department of Mathematics, Shanxi University in July 1999. Currently, he is the Office Director of the Taiyuan Comprehensive Senior High School, a Senior Teacher of the Secondary School, an expert in information technology and curriculum integration teaching in Shanxi Province, and a high-level backbone teacher in Taiyuan City.

Youqiang Sun is an Academic Master of Computer Science and Technology from Taiyuan University of Science and Technology, China. His research interest includes computational intelligence and scheduling.

Yeqing Ren is an Academic Master of Computer Science and Technology from Taiyuan University of Science and Technology, China. Her research interest includes computational intelligence and makeup transfer.

1 Introduction

With the development and expansion of cities, the daily water consumption has become an important factor affecting urban development (Pulido-Calvo and Gutiérrez-Estrada, 2009). Through the prediction of urban water consumption, the allocation of water resources can also be carried out well in advance, and the economic benefits can be maximised. The prediction and estimation of water consumption plays an important role in urban construction planning and dispatching management of dispatching system (Zou et al., 2004). The rational use of water resources is the key to solving current urban water problems. Due to the number of city's residents, the nature of major industrial and mining enterprises, the scale of economic development, geographical location, natural conditions and other reasons, the water supply system in different cities varies greatly. Therefore, different prediction models for different cities can make the prediction more accurate.

The main research directions are divided into two categories: empirical prediction method and regression prediction analysis method based on predictive model for water consumption influence factors (Zou et al., 2004; Lou et al., 2013). The method of empirical prediction is usually to make a rough estimate of the future water consumption through the experience, which lacks theoretical basis and has low accuracy. And for regression prediction analysis method, it relies on the predicted amount of historical observation data and data patterns, through analysis, to find out the order of the law of change. This makes it easy to think of multivariate regression analysis, which is also used in current water forecasting.

Many efforts have been implemented. Nhu Do uses the Genetic Algorithm (GA) to solve the water distribution system model, and the simulation shows that the GA can achieve a well result on a 24-h period case (Do et al., 2017). Paulo proposes a double seasonal ARIMA model, and uses the Harmony Search Algorithm (HSA) to optimise that model. The simulation results show the effectiveness of this algorithm (Oliveira et al., 2017). Lou adopts Weighted Arithmetic Average (WAA) operator and Immune Genetic Algorithm (IGA) to fit the expert decision matrix. The experiment has yielded good results (Lou et al., 2013).

Yang (2010), Chakri et al. (2017) and Yammani (2016) proposed a new swarm intelligence algorithm, Bat Algorithm (BA). BA is widely used in industry, so this paper uses bat algorithm to solve the water resources prediction model. A large number of research results show that, compared to Particle Swarm Algorithm (PSO) (Cui and Zeng, 2005a; Eberhart and Kennedy, 2002), GA (Cui and Zeng, 2005b; Goldberg, 1989) and other swarm intelligent algorithms, BA can dynamically control the process of mutual conversion between local search and global search, so as to avoid falling into local optimal defects, with better convergence (Yang, 2011). At the same time, in order to enhance the global search performance of the BA, we improved the bat algorithm.

The rest of this paper is organised as follows: in Section 2, we build the linear estimation model, exponential estimation model and hybrid model based on real data. Then, we introduce the flow of BA and FTBA algorithms in Section 3. The simulation experiments are tested in Section 4. Section 5 gives the conclusions and future work.

2 Estimation models on water resource

We focus on the water resource in Nanchang city, China (Wang et al., 2017). The consumption of water resources is related not only to the number of local residents, but also to economic development and local enterprises. Table 1 shows the composition of historical water consumption from 2003 to 2015, including industrial water use, agricultural water use, residential water use and ecological water use. Table 2 shows the relationship between water resources consumption, industrial production and agricultural production.

Table 1 Historical water use from 2003 to 2015 in Nanchang city $\left(10^8\text{m}^3\right)$

Year	*Total water use*	*Industrial water use*	*Agricultural water use*	*Residential water use*	*Ecological water use*
2003	24.21	9.81	11.55	2.53	0.32
2004	26.22	8.72	14.47	2.75	0.28
2005	28.14	8.30	16.92	2.60	0.32
2006	27.71	8.11	16.73	2.52	0.35
2007	32.55	7.51	21.27	2.92	0.85
2008	30.42	6.90	19.73	2.94	0.85
2009	33.42	6.57	20.15	3.21	3.49
2010	30.87	7.51	17.37	3.49	2.50
2011	31.26	8.97	17.70	4.03	0.56
2012	28.82	9.20	14.68	4.36	0.58
2013	32.62	9.35	18.23	4.45	0.59
2014	31.42	8.92	17.35	4.54	0.61
2015	30.64	9.17	16.21	4.64	0.62
Average	29.87	8.39 (28%)	17.10 (57%)	3.46 (12%)	0.92 (3%)

Table 2 The total water use, population, gross industrial, and gross agricultural production in Nanchang city from 2003 to 2015

Year	*Total water use*	*Population*	*Gross industrial production* (10^8 *yuan*)	*Gross agricultural production* (10^8 *yuan*)
2003	24.21	4,437,476	250.95	51.29
2004	26.22	4,469,671	306.08	99.11
2005	28.14	4,500,672	374.93	115.76
2006	27.71	4,530,776	448.15	124.58
2007	32.55	4,563,025	532.75	142.84
2008	30.42	4,597,936	676.61	171.14
2009	33.42	4,632,067	753.20	187.20
2010	30.87	5,042,567	952.75	204.66
2011	31.26	5,088,996	1223.72	229.35
2012	28.82	5,131,564	1290.93	249.35
2013	32.62	5,184,231	1398.63	266.12
2014	31.42	5,240,179	1500.70	283.63
2015	30.64	5,302,914	1619.50	296.92

It can be seen in Tables 1 and 2, agricultural and industrial water use reached 57% and 28%, respectively. But residential water use and ecological water use accounted for only 12% and 3%, respectively. Agricultural water accounts for most of it, but the gross production is not as high as the gross industrial production.

From the above analysis, we've considered different factors of water consumption and total economic, we according to the linear estimation model and exponential estimation model (Assareh et al., 2010), then propose a hybrid model.

Linear estimation model:

$$Y_l = x_1 \cdot W_1 + x_2 \cdot W_2 + x_3 \cdot W_3 + x_4 \tag{1}$$

Exponential estimation model:

$$Y_e = x_1 \cdot W_1^{x_2} + x_3 \cdot W_2^{x_4} + x_5 \cdot W_3^{x_6} + x_7 \tag{2}$$

In equations (1) and (2), the W_1, W_2 and W_3 are the population, gross industrial production, and gross agricultural production, respectively. $x_i \in [0, 1]$ are the weights for both of the equations. Y_l and Y_e are linear and exponential models, respectively. And the hybrid model is defined by

$$Y_h = x_1 \cdot Y_l + (1 - x_1) \cdot Y_e \tag{3}$$

The hybrid model can also be written as:

$$\begin{aligned} Y_h &= x_1 \cdot (x_2 \cdot W_1 + x_3 \cdot W_2 + x_4 \cdot W_3 + x_5) \\ &\quad + (1 - x_1) \cdot \left(x_6 \cdot W_1^{x_7} + x_8 \cdot W_2^{x_9} + x_{10} \cdot W_3^{x_{11}} + x_{12}\right) \end{aligned} \tag{4}$$

$x_i \in [0, 1]$ are the weights for hybrid model, Y_h represents the hybrid model, W_1, W_2 and W_3 are still represent the population, gross industrial production, and gross agricultural production, respectively.

3 Bat algorithm and modified bat algorithm

3.1 The principle of bat algorithm (BA)

BA (Liu et al., 2018) is a heuristic intelligent algorithm that simulates the principle of echolocation used in bat predation. The single-objective unconstrained optimisation problem is considered in this paper as equation (5):

$$\min\ f(x),\ \left[x = (x_1, x_2, ..., x_k, ..., x_D) \in E\right] \tag{5}$$

Suppose there are n virtual bats, and the i-th bat: $(i = 1, 2, 3, ..., N)$ is represented as equation (6):

$$< x_i(t), v_i(t), fr_i(t), A_i(t), r_i(t) > \tag{6}$$

where $x_i(t) = (x_{i1}(t), x_{i2}(t), ..., x_{ik}(t), ..., x_{iD}(t))$ and $v_i(t) = (v_{i1}(t), v_{i2}(t), ..., v_{ik}(t), ..., v_{iD}(t))$ are the position and velocity of the i-th bat in generation t, respectively, with frequency $fr_i(t)$, loudness $A_i(t)$, and emission rate $r_i(t)$ as the three required parameters.

In the next generation, the velocity is updated as follows:

$$v_{ik}(t+1) = v_{ik}(t) + (x_{ik}(t) - p_k(t)) \cdot fr_i(t) \tag{7}$$

where $p(t) = (p_1(t), p_2(t), ..., p_k(t), ..., p_D(t))$ is the best position found thus far by the entire swarm. Equation (7) can be viewed as a combination of the inertia $v_{ik}(t)$ and the influence of $p(t)$. The frequency $fr_i(t)$ is calculated as follows:

$$fr_i(t) = fr_{\min} + (fr_{\max} - fr_{\min}) \cdot rand_1 \tag{8}$$

where $fr_{\max}$ and $fr_{\min}$ are the maximum and minimum frequency values, respectively, and $rand_1$ is a random number uniformly distributed within [0, 1].

To reflect the bat decision, the position changes with some randomness. Let $rand_2$ be a random number uniformly distributed within [0, 1]; if $rand_2 < r_i(t)$ is satisfied, then the ith bat will execute the following global search pattern:

$$x'_{ik}(t+1) = x_{ik}(t) + v_{ik}(t+1) \tag{9}$$

Otherwise, the following local search pattern is adopted:

$$x'_{ik}(t+1) = p_k(t) + \varepsilon_{ik} \cdot \bar{A}(t) \tag{10}$$

where ε_{ik} is a random number generated by a uniform distribution within [–1, 1], $\bar{A}(t)$ is the average loudness of all bats, and

$$\bar{A}(t) = \frac{\sum_{i=1}^{n} A_i(t)}{n} \tag{11}$$

After the $x'_{ik}(t+1) = (x'_{i1}(t+1), x'_{i2}(t+1), ..., x'_{ik}(t+1), ..., x'_{iD}))$ is obtained by equations (9) and (10), the new $x_i(t+1)$ can be updated as follows:

$$x_i(t+1) = \begin{cases} x'_i(t+1) & \text{if } rand_3 < A_i(t) \wedge f(x'_i(t+1)) < f(x_i(t)) \\ x_i(t) & \text{otherwise} \end{cases} \tag{12}$$

where $rand_3$ is a random number generated by uniform distribution within [0, 1]. Similar to Cuckoo Search (CS), equation (12) implies that the position is updated only when the following two conditions are met: (1) a better position is obtained; and (2) the probability $A_i(t)$ is satisfied. If the position of the ith bat is updated, then the corresponding loudness and emission rate $r_i(t+1)$ are replaced as follows:

$$A_i(t+1) = \alpha A_i(t) \tag{13}$$

$$r_i(t+1) = r(0) \cdot (1 - e^{-\gamma t}) \tag{14}$$

where $\alpha > 0$ and $\gamma > 0$ are two predefined parameters, and $A(0)$ and $r(0)$ are two initial values for the loudness and emission rate, respectively.

The pseudo code of the standard BA is listed in Algorithm 1:

Algorithm 1 Standard bat algorithm

Begin
For each bat, initialise the position, velocity, and parameters;
While (stop criterion is met)
Randomly generate the frequency for each bat with equation (8);
Update the velocity for each bat with equation (7);
If $rand_2 < r_i(t)$
Update the temp position for the corresponding bat with equation (9);
Else
Update the temp position for the corresponding bat with equation (10);
End
Evaluate its quality/fitness;
Re-update the position for the corresponding bat with equation (12);
If the position is updated
Update the loudness and emission rate with equations (13) and (14), respectively;
End
Rank the bats and save the best position;
End
Output the best position;
End

3.2 Fast BA with triangle-flipping strategy (FTBA)

Cai et al. (2018) compared to all the triangle flip modes, the performance of Bat Algorithm with Hybrid Triangle-Flipping Strategy (BAHTFS) is superior than others in CEC2013 data set.

As for evolutionary algorithm, it should dynamic balances the global and local search capability, in the early period, the algorithm should focus on the global search, so that the global optimal is possible to be found. And later period of the optimisation should improve the accuracy of solutions. From this perspective, the BAHTFS divides the algorithm into two stage:

If $t < \lambda \cdot largest\ Generation$
Using the random triangle-flipping strategy;
Else
Using the special directing triangle-flipping strategy as follows:

$$v_i(t+1) = \left(p(t) - x_m(t)\right) \cdot fr_i(t) \tag{15}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{16}$$

End

where in the equations (15) and (16), the v_i, p and x are the velocity, the optimal position and the present location, respectively.

Algorithm 2 Bat algorithm with triangle-flipping strategy

Begin
For each bat, initialise the position, velocity, and parameters;
While (stop criterion is met)
Randomly generate the frequency for each bat with equation (8);
Update the velocity for each bat with different triangle-flipping strategy (directing, random and hybrid);
If $rand_2 < r_i(t)$
Update the temp position for the corresponding bat with equation (9);
Else
Update the temp position for the corresponding bat with equation (10);
End
Evaluate its quality/fitness;
Re-update the position for the corresponding bat with equation (12);
If the position is updated
Update the loudness and emission rate with equations (13) and (14), respectively;
End
Rank the bats and save the best position;
End
Output the best position;
End

For convenience, we refer to the BAHTFS as fast BA with Triangle-Flipping Strategy (FTBA), and the algorithm flow as Algorithm 2 shows.

4 Evaluation criteria

4.1 Normalisation of data

The data of the water resource in Nanchang city from 2003 to 2015 are inconsistent data, for ease of calculation and decrease the influences of the different units of data, the normalised method is used. The total water use, population, gross industrial production and gross agricultural production are normalised as follow equation:

$$W^* = \frac{W - W_{\min}}{W_{\max} - W_{\min}} \tag{17}$$

where the W^* is the normalised value, W is the value that need to normalize, and the $W_{\max}$ and $W_{\min}$ are the maximal and minimum values in corresponding attributes, respectively.

4.2 Fitness evaluation function

The data of water resource from 2003 to 2015 are divided into two part, the data of 2003 to 2012 are used to train the weights in models, and the others (2013–2015) are used to test the trained model. To evaluate the trained weights, we use the Sum of Squared Errors (SSE) as fitness function.

$$f(x) = \sum_{i=1}^{m} \left(Y_{pre} - Y_{act}\right)^2 \tag{18}$$

where the Y_{pre} and Y_{act} are the predicated value and actual value, respectively. And the m is the number of the training samples.

4.3 The performance measure

In order to measure the quality of the fitness value, we use the Relative Error (RE) and Mean Relative Error (MRE) to measure the performance of algorithms.

$$RE = \left| \frac{Y_{pre} - Y_{act}}{Y_{act}} \right| \tag{19}$$

$$MRE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{Y_{pre}(i) - Y_{act}(i)}{Y_{act}(i)} \right| \tag{20}$$

where the $Y_{pre}(i)$ and $Y_{act}(i)$ are the predicted value and actual value of water consumption in the *i*-th sample.

We also use the Standard Deviations (Std.) to measure the accuracy of data.

5 Simulation experiments and results

For the effectiveness of the simulation, we set the parameters of the two algorithms to the same. And the simulation runs on MATLAB 2016. The simulation environment is set as follows:

Table 3 The parameters of the BA and FTBA

Parameters	*Values*
Search domain	$[0,1]^D$
Frequency	[0.0, 5.0]
Initial $A_i(0)$	0.95
Initial $r_i(0)$	0.9
α	0.99
γ	0.9
Dimension D	12
Independent operation times	50
Fitness value evaluation times	3000
Population size	100

From the Table 4, the predictions of water resource of BA are 32.1125, 32.3516 and 32.5997; compare to the actual data, the FTBA predicts the water resources usage are closer to actual values. So the improved BA can achieve a better prediction, basically close to the actual value. The average RE of BA and FTBA are 0.9844 and 0.1247, obviously lower RE value are better, RE can better reflect the credibility of predicted value. And Table 5 compares the RE in 2013–2015, the FTBA is superior than BA in all of the RE values. In test set, from Table 6, all of the MRE results are preferable in FTBA from 2013–2015. It shows that the average performance of FTBA is better than that of BA on this model. And the standard deviations in these experiments are also show that the FTBA is more stable than BA. Not only the best MRE and mean MRE are better than BA, but even worse MRE is also better than BA.

Table 4 The prediction of water resource $\left(10^8\,\mathrm{m}^3\right)$ during 2013–2015

Year	*Actual*	*BA*	*FTBA*
2013	32.62	32.1125	31.6588
2014	31.42	32.3516	31.8058
2015	30.64	32.5997	31.9658
average	…	0.9844	0.1247

Table 5 The RE of prediction water resource during in BA and FTBA during 2013–2015

Year	*BA RE*	*FTBA RE*
2013	0.6120	0.1143
2014	0.9845	0.0535
2015	1.3566	0.2062
Average	0.9844	0.1247

Table 6 The MRE of hybrid model in BA and FTBA

Algorithm	*Best MRE*	*Mean MRE*	*Std.*	*Worse MRE*
BA	0.0603	0.1648	0.1260	0.3048
FTBA	0.0535	0.1247	0.0769	0.2062

In Table 7, FTBA consumes more time than BA, because of the hybrid triangle-flipping strategy. A little bit of time consumption in exchange for a significant increase in accuracy is worthwhile. The optimal weights are shown in Table 8, and the best fitness shows that the FTBA is superior to BA. From the above experimental data, as for we proposed hybrid model, the FTBA is more effective than BA. After our improvement, the new bat algorithm has better global search ability than the standard bat algorithm.

Table 7 The MRE of hybrid model in BA and FTBA

Time cost	*BA*	*FTBA*
Time (seconds)	267.4497	314.7908

Table 8 The weights and best fitness of hybrid model in BA and FTBA

Algorithm	*BA*	*FTBA*
x1	0.0184	0.0000
x2	0.4229	0.1163
x3	0.5599	0.3403
x4	0.2943	0.7248
x5	0.2781	0.5853
x6	0.0270	0.0000
x7	0.0073	0.0562
x8	0.6826	0.8421
x9	0.3694	0.2295
x10	0.1711	0.0000
x11	0.3307	0.5139
x12	0.0181	0.0000
Best fitness	0.3878	0.3600

6 Conclusion and future work

In this paper, we combine the linear estimation model and exponential estimation model, and propose the hybrid estimation model. We use the hybrid model in the water resource of Nanchang city from 2003 to 2015. Then we divide the data into two parts, training set (2003–2012) and test set (2013–2015), the training set to solving optimal weights in hybrid model, and test set for verify the validity of weights. The standard BA and modified BA (FTBA) are used in the model. Although BA can solve the estimation of water resources according to the model, the FTBA is superior to the standard BA.

In our future work, we will enhance the authenticity of the model, and consider more factors in predicting. For a better result, the algorithm also should be further improved. Moreover, the model can also be used for other city water resources, to solve the problem of water resources allocation and scheduling.

Acknowledgements

This work is supported by the National Natural Science Foundation of China under Grant No. 61806138, No. U1636220 and No. 61663028, Natural Science Foundation of Shanxi Province under Grant No. 201601D011045, PhD Research Start-up Foundation of Taiyuan University of Science and Technology under Grant No. 20182002.

References

Assareh, E., Behrang, M.A., Assari, M.R. and Ghanbarzadeh, A. (2010) 'Application of PSO (particle swarm optimization) and GA (genetic algorithm) techniques on demand estimation of oil in Iran', *Series Application of PSO (Particle Swarm Optimization) and GA (Genetic Algorithm) Techniques on Demand Estimation of Oil in Iran*, Vol. 35, No. 12, pp.5223–5229.

Cai, X., Wang, H., Cui, Z., Cai, J., Xue, Y. and Wang, L. (2018) 'Bat algorithm with triangle-flipping strategy for numerical optimization', *International Journal of Machine Learning and Cybernetics*, Vol. 9, No. 2, pp.199–215.

Chakri, A., Khelif, R., Benouaret, M. and Yang, X-S. (2017) 'New directional bat algorithm for continuous optimization problems', *Series New Directional Bat Algorithm for Continuous Optimization Problems*, Vol. 69, pp.159–175.

Cui, Z. and Zeng, J. (2005a) 'A modified particle swarm optimization predicted by velocity', *Proceedings of the 7th Annual Conference on Genetic and Evolutionary Computation*, Washington DC, USA, ACM, pp.277–278.

Cui, Z. and Zeng, J. (2005b) 'A new organizational nonlinear genetic algorithm for numerical optimization', *Advances in Natural Computation,* Berlin, Heidelberg, Springer Berlin Heidelberg, Vol. 3612, pp.255–258.

Do, N., Simpson, A., Deuerlein, J. and Piller, O. (2017) 'Demand estimation in water distribution systems: solving underdetermined problems using genetic algorithms', *Series Demand Estimation In Water Distribution Systems: Solving Underdetermined Problems Using Genetic Algorithms*, Vol. 186, pp.193–201.

Eberhart, R. and Kennedy, J. (2002) 'A new optimizer using particle swarm theory', *Proceedings of the 6th International Symposium on Micro Machine and Human Science*, pp.39–43.

Goldberg, D.E. (1989) 'Genetic algorithms in search, optimization and machine learning', *Series Genetic Algorithms in Search, Optimization and Machine Learning*, Vol. xiii, No. 7, pp.2104–2116.

Liu, Q., Wu, L., Xiao, W., Wang, F. and Zhang, L. (2018) 'A novel hybrid bat algorithm for solving continuous optimization problems', *Series A Novel Hybrid Bat Algorithm for Solving Continuous Optimization Problems*, Vol. 73, pp.67–82.

Lou, S., Wang, H., Niu, W. and Yejun, X.U. (2013) 'Optimization of multi-stage group decision making for water resource allocation', *Series Optimization of Multi-Stage Group Decision Making for Water Resource Allocation*, Vol. 35, No. 3, pp.111–119.

Oliveira, P.J., Steffen, J.L. and Cheung, P. (2017) 'Parameter estimation of seasonal arima models for water demand forecasting using the harmony search algorithm', *Series Parameter Estimation of Seasonal Arima Models for Water Demand Forecasting Using the Harmony Search Algorithm*, Vol. 186, pp.177–185.

Pulido-Calvo, I. and Gutiérrez-Estrada, J.C. (2009) 'Improved irrigation water demand forecasting using a soft-computing hybrid model', *Series Improved Irrigation Water Demand Forecasting Using a Soft-Computing Hybrid Model*, February, Vol. 102, No. 2, pp.202–218.

Wang, H., Cui, Z., Wang, W., Zhou, X., Zhao, J., Lv, L. and Sun, H. (2017) 'Firefly algorithm for demand estimation of water resources', *Series Firefly Algorithm for Demand Estimation of Water Resources*, Vol. 10637, pp.11–20.

Yammani, C. (2016) 'A multi-objective shuffled bat algorithm for optimal placement and sizing of DGs with load variations', *IEEE Region 10 Conference (TENCON*, Elsevier, Vol. 79, pp.120–131.

Yang, X. (2011) 'Bat algorithm for multi-objective optimisation', *Series Bat Algorithm for Multi-Objective Optimisation*, Vol. 3, No. 5, pp.267–274.

Yang, X.S. (2010) 'A new metaheuristic bat-inspired algorithm', *Series A New Metaheuristic Bat-Inspired Algorithm*, Vol. 284, pp.65–74.

Zou, G.Y., Wang, H.F., Wang, D.W. and Zhang, G.X. (2004) 'Urban water consumption forecast based on neural network model', *Series Urban Water Consumption Forecast Based on Neural Network Model*, June, Vol. 33, No. 3, pp.364–368.