

An Improved Long-Term Water Level Prediction Method for N-BEATS

Yilin Liu^{*}, Chenning Yuan, Xishi Chen

School of Computer Science, Yangtze University, Jingzhou, China

ABSTRACT

The water level of hydrological observatory has important reference significance in water resources utilization, drought and flood control and water supply and drainage. Aiming at the problem of poor accuracy and difficult training in long-term water level prediction, an improved time series model, WOA-N-Beats, is proposed, and the whale optimization algorithm is introduced to solve the problem of the model falling into local optimal solutions and the difficulty of finding optimal parameters. In the water level prediction of Wulong, Yichang, and Shashi stations in the next 512 days, the experiments show that compared with RNN and LSTM methods, WOA-N-Beats has the best MAE, MSE, and RMSE, and the enhancement effect is large, which realizes a more accurate prediction.

KEYWORDS

Water level prediction; Deep learning; Time series; N-BEATS; Whale optimization algorithm

1. INTRODUCTION

1.1. Research Significance

With the continuous improvement of industry and people's living standards in China, the demand for water is more vigorous, requiring more scientific and effective water use strategies. The ability to predict the change of water level is an important planning reference for the production and life of the city. At present, water level prediction through time series has been a common application. The traditional time series prediction methods based on statistics have matured, and Bai et al [1] realized the prediction of the fluctuation trend of groundwater level with differential integration of sliding average autoregressive model (ARIMA). However, essentially such methods can only capture linear relationships.

1.2. Related Research

In recent years, as neural networks are hot in various fields, in the field of hydrology, Guoliang Ji et al [2] have used Recurrent Neural Network (RNN) model for reservoir water level prediction, which is more convenient and effective. However, the RNN model is prone to gradient disappearance or gradient explosion when a certain number of neurons are reached on a long time series, which leads to the model cannot be trained or the final prediction is poor. Long-Short Term Memory (LSTM) introduces the gate mechanism for controlling the circulation and loss of features, and improves the shortcomings of RNN by using forget gate to decide whether to forget the previous neuron information or not. Li Shuangyu et al [3] used a variety of LSTM variants and combined several hydrological factors such as precipitation to achieve a more accurate prediction of the drainage system

flow. However, there are problems such as the network training speed is not fast enough, the generalization ability is weakened, and the prediction accuracy and efficiency are low.

The above study analyzes the prediction effect of recent years based on statistics and deep learning methods for water level as well as flow rate, both of which have their shortcomings, the author uses a new time series prediction model - N-BEATS [4], the specific principles of which are described in Chapter 1.2. multiple time series are trained together in parallel [5]. Finding the optimal parameters of N-BEATS through the whale optimization algorithm allows the model to reach the global optimal solution in less time.

2. MATERIALS AND METHODS

2.1. Data Sources

The dataset of this paper originates from the River Water Information Bulletin website in the data release section of the official website of Hubei Provincial Department of Water Resources, in which three sites, Wuhan Wulong, Yichang, and Shashi, Jingzhou, were selected, with a sampling frequency of days from January 1, 2012, to December 31, 2018, for a total of six years of data. Very few of the nulls were filled in using linear interpolation

2.2. Data Processing

Correlation analysis was performed using Pearson's coefficient (see equation 1) for all features of the dataset used in this paper . As shown in Table 1 (2 decimal places are reserved), according to the range of Pearson's coefficient, the water level shows a very strong correlation with the flow, a weak correlation with the than yesterday's rise and fall, and a very weak correlation with the water potential.

$$P = corr(X, Y) = \frac{cov(X, Y)}{\sigma_x \sigma_y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

Where x_i, y_j is the actual data value, X, Y , is the corresponding value of the corresponding model

2.3. N-BEATS Model

N-BEATS model is a deep neural structure based on forward and backward residual links and fully connected layer stacks. The model can be divided into three modules, a single block as the basic unit, a single stack formed by multiple blocks, and multiple stacks that are ultimately responsible for prediction. The structure is shown in Fig. 1.

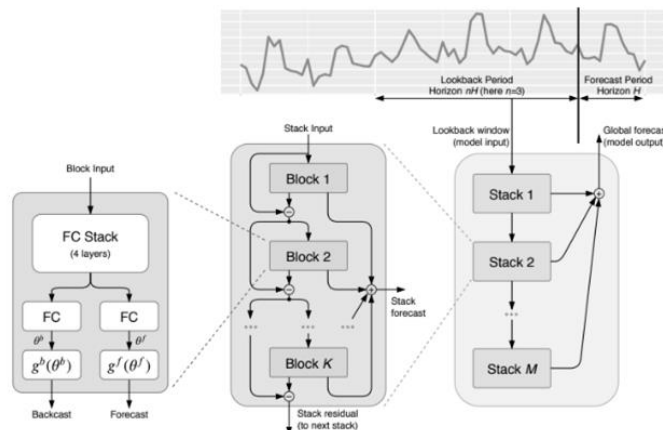


Figure 1. The network architecture of N-BEATS

The classical residual network architecture adds the inputs of a layer stack to its outputs and then passes the result to the next stack [6]. The DenseNet architecture extends this principle by introducing additional connections from the output of each stack, to the inputs of every other subsequent stack. The above approaches have demonstrated significant advantages in improving the trainability of deeper architectures [7]. N-BEATS, on the other hand, uses a dual residual residual structure, as shown in the middle and right 2 parts of Fig. 1, which has two residual branches, one running on the backcast prediction at each layer, and the other on the forecast branch at each layer, to better utilize the advantages of residual networks. Its operation is described by equation 2.

$$\begin{cases} \mathbf{x}_\ell = \mathbf{x}_{\ell-1} - \hat{\mathbf{x}}_{\ell-1} \\ \hat{\mathbf{y}} = \sum_{\ell} \hat{\mathbf{y}}_\ell \end{cases} \quad (2)$$

To summarize the structure and principle of N-BEATS as follows: each block outputs a partial prediction, which is first aggregated at the stack level and then aggregated at the whole network level to provide a hierarchical decomposition. The final prediction is the sum of all partial predictions.

2.4. Contrasting Models

The RNN model and the LSTM model have been cited numerous times in the time series and have been introduced in the citation section, so they will not be repeated here. Only their principle structures are given here, see Figures 2-3.

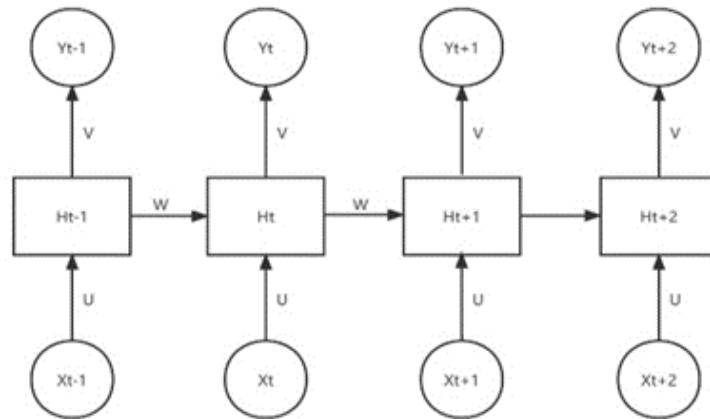


Figure 2. RNN structure diagram

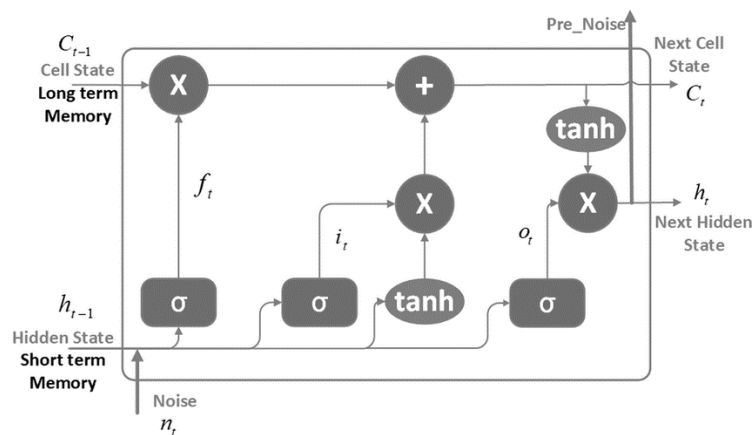


Figure 3. LSTM structure diagram

2.5. Whale Optimization Algorithm

Whale Optimization Algorithm (Whale Optimization Algorithm) is a natural heuristic optimization algorithm inspired by humpback whales' feeding behavior by Mirjalili in 2016 to simulate their group hunting behavior with an algorithmic model[8]. Its biggest feature is to use random individuals or optimal individuals to simulate the hunting behavior of humpback whales, and to use spirals to simulate the bubble net attack mechanism of humpback whales, so as to achieve the effect of global optimization.

2.6. Experimental Process Design

Experimental environment: python3.7-based deep learning library pytorch was used to build the model. The configuration of the experimental computer is AMD Ryzen 4800H CPU + Nvidia GeForce GTX3060 according to different models to set parameters and hyperparameters.

The key parameters such as block, stack, batch-size and learning rate in N-BEATS have a large impact on the final prediction effect, so WOA is used to find out the optimal parameters. The specific flow is shown in Fig. 4

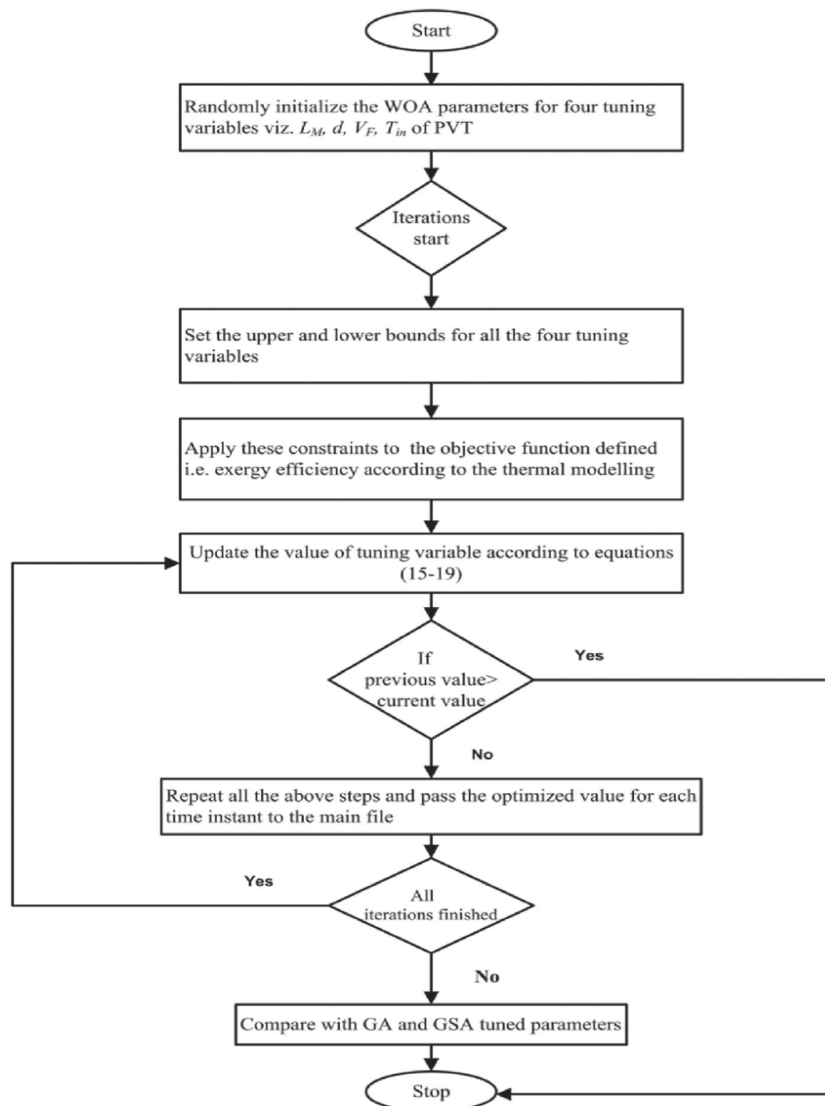


Figure 4. WOA-N-BEATS implementation process

3. RESULTS AND ANALYSIS

3.1. Evaluation Indexes

In this paper, three evaluation indexes are used to evaluate the prediction effect of the model, which are Mean absolute Error (MAE), Mean Square Error (MSE), and Root-Mean Square Error (RMSE). MAE is to find the difference between the predicted value and the real value squared, while MSE solves the defect that the error of MAE is related to the sample, and RMSE is sensitive to the larger error, and the smaller value of the three indexes represents the better. While MSE solves the defect of MAE's error related to the sample, RMSE is sensitive to larger errors, and the smaller value of the three indicators represents the better. The specific calculation of the indicators is shown in Equation 3.

$$\begin{cases} MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \\ MSE = \frac{1}{n} \sum_{i=1}^n (y_{test}^i - \hat{y}_{test}^i)^2 \\ RMSE = \sqrt{\frac{\sum_{i=1}^n (y_t - \hat{y}_t)^2}{n}} \end{cases} \quad (3)$$

Where in Eq. 15 n is the total number of samples, y is the actual value, and \hat{y} is the predicted value.

3.2. Parameter Optimization of the Model

The WOA is used to globally search for the key parameters that are optimal for N-BEATS, and the loss function values are recorded during the training of the model, and the results are shown in Fig. 5.



Figure 5. Line chart of training loss

From Fig. 5, it can be seen that under the optimization of WOA, the global optimal solution is reached in less than 500 iterations. That is, the optimal parameters of the N-BEATS model are found to minimize the loss function.

3.3. Analysis of results

It can be seen that WOA-N-BEATS performs best compared to both RNN and LSTM in predicting the water level in the next 512 days on the test set. Taking the Wulong site as an example, the MAE of WOA-N-BEATS is reduced by 33.1% compared to RNN, 74.3% compared to LSTM, and in MSE and RMSE: 42.8%, 86.8% and 23.5%, 63.6% respectively. The enhancement is smaller compared with N-BEATS.

Prediction effect analysis: The prediction effect of the four models is shown in Figs. 5-7. After WOA optimization, N-BEATS shows better prediction performance in long-term water level prediction at different stations, with better fitting effect, faster finding of optimal solution, smaller deviation from the actual value, and solving the outlier problem of the original N-BEATS in prediction.

Table 1. Comparison of model evaluation indexes

Model	WOA-N-BEATS			RNN			LSTM			N-BEATS		
Mark	MAE	MSE	RMS E	MAE	MSE	RMS E	MAE	MSE	RMS E	MAE	MSE	RMS E
Wulong	1.03	2.34	1.53	1.54	4.02	2.00	4.00	17.68	4.20	1.27	2.92	1.71
Yichang	0.83	0.980	0.99	1.19	2.75	1.66	1.70	2.62	1.90	0.96	1.45	1.21
Shashi	1.40	3.04	1.70	2.10	5.64	2.37	1.43	2.61	1.62	1.51	3.22	1.75

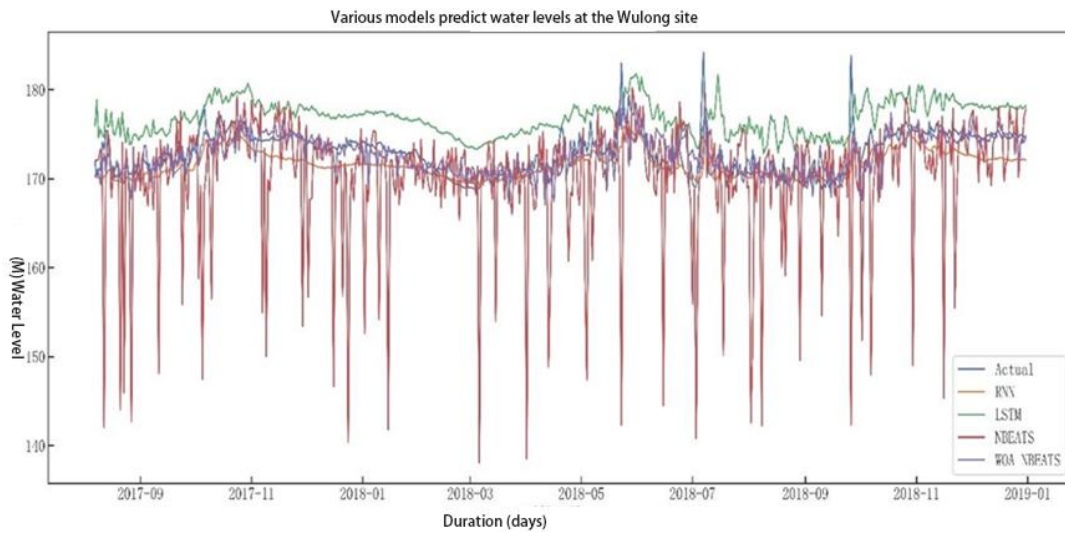


Figure 6. Comparison of predictions of various models at Wulong station

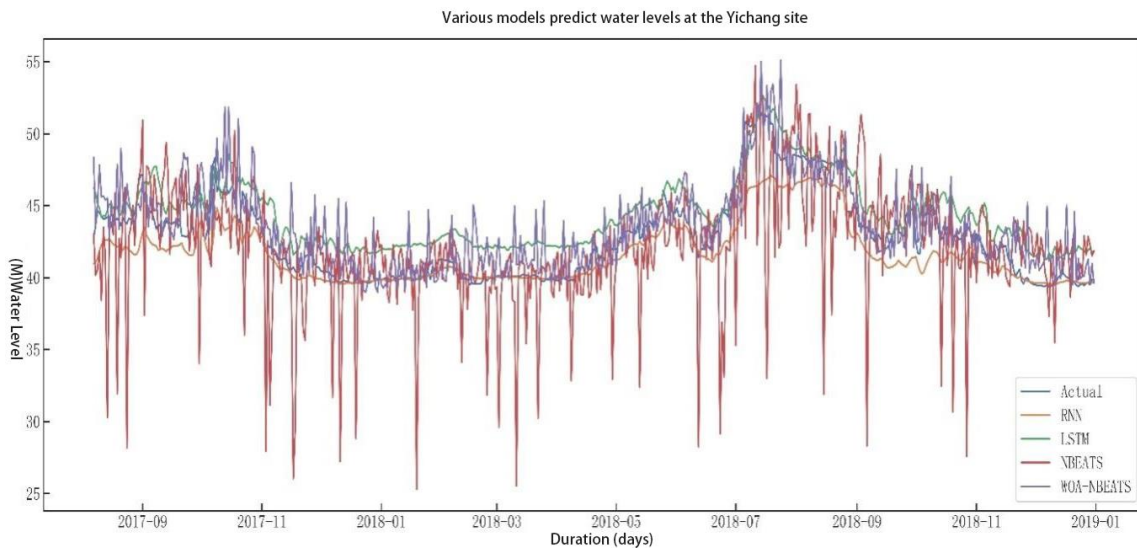


Figure 7. Comparison of predictions of various models at Yichang station

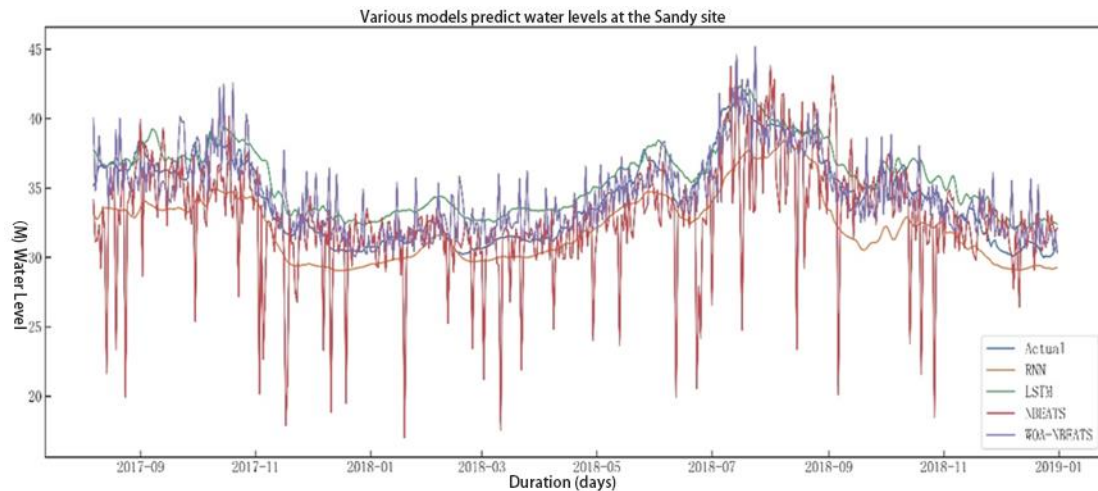


Figure 8. Comparison Of Predictions Of Various Models At Shashi Station

4. SUMMARY

In this study, an improved N-BEATS model for long-term water level prediction is proposed, and the main conclusions are as follows.

- (1) In the process of constructing the model, multiple hydrological factors are used as time series and downsampled into multiple sub-time series, which are added into N-BEATS to form parallel training of multiple time series data, which improves the speed of model training.
- (2) The introduction of WOA solves the problem of discrete values in N-BEATS during long-term time series, and realizes more stable and accurate long-term water level prediction, which provides a reference for the development of more scientific water supply and drainage strategies.

REFERENCES

- [1] Xiao, B., Kai, B., & Yalin, J. (2019). Numerical simulation of karst groundwater and dynamic prediction based on Modflow and ARIMA model in Fengfeng mining area. *Science Technology and Engineering*, 19(17), 85-90. <https://doi.org/10.3969/j.issn.1671-1815.2019.17.011>
- [2] Guo-liang, J. I., Man, Z. H. O. U., Tao, L. I. U., Teng-teng, H. U., & Yong, D. I. N. G. (2022). Predicting Water Level for Large Reservoirs Using Recurrent Neural Network. *Journal of Yangtze River Scientific Research Institute*, 39(3), 80. <https://doi.org/10.11988/ckyyb.20201266>
- [3] Zhu, W., Tao, T., Yan, H., Yan, J., Wang, J., Li, S., & Xin, K. (2023). An optimized long short-term memory (LSTM)-based approach applied to early warning and forecasting of ponding in the urban drainage system. *Hydrology and Earth System Sciences*, 27(10), 2035-2050. <https://doi.org/10.19853/j.zgjsps.1000-4602.2022.05.009>
- [4] Oreshkin, B. N., Carpov, D., Chapados, N., & Bengio, Y. (2019). N-BEATS: Neural basis expansion analysis for interpretable time series forecasting. arXiv preprint arXiv:1905.10437. <http://arxiv.org/abs/1905.10437>
- [5] Oreshkin, B. N., Dudek, G., Pelka, P., & Turkina, E. (2021). N-BEATS neural network for mid-term electricity load forecasting. *Applied Energy*, 293, 116918. <https://arxiv.org/abs/2009.11961>
- [6] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778). <https://doi.org/10.1109/CVPR.2016.90>
- [7] Yang, J. H., Park, S., Kim, S., Cho, Y., & Yoh, J. J. (2022). Accurate real-time monitoring of fine dust using a densely connected convolutional networks with measured plasma emissions. *Chemosphere*, 293, 133604. <https://doi.org/10.1016/j.chemosphere.2022.133604>
- [8] Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in engineering software*, 95, 51-67. <https://doi.org/10.1016/j.advengsoft.2016.01.008>