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Modeling of Monthly Runoff Prediction Based on VMD-APSO-BiLSTM Model

Jianming Zhang[#,*], Shubo Zhang[#], Kelin Wang[#], Jiahao Bai[#], Ran Tao[#]

School of Architecture and Engineering, Nanchang University, Nanchang, China, 330031
[*]Corresponding author: 18381915636@163.com
[#]These authors contributed equally.

Abstract: *Runoff forecasting is crucial for water resources management, flood risk assessment, and ecological protection, as accurate basin runoff prediction can provide a scientific basis for the rational allocation of water resources and advance flood prevention. This study aims to improve the accuracy of monthly runoff prediction by proposing a novel method based on the combination of variational modal decomposition (VMD) and adaptive particle swarm optimization bi-directional short-term and long-term memory network (APSO-BiLSTM), addressing the limitations of traditional models. By analyzing data from the Beibei Hydrological Station of the Jialing River, this study compared the performance of four models: VMD-APSO-BiLSTM, VMD-APSO-LSTM, APSO-BiLSTM, and APSO-LSTM. The results demonstrate that the VMD-APSO-BiLSTM model outperforms the other models during both the training and testing periods, achieving Nash-Sutcliffe efficiencies (NSEs) of 0.95 and 0.93, and root mean square errors (RMSEs) of 516.75 and 992.15, respectively. These findings indicate that the proposed model effectively captures the nonlinear characteristics and long-term dependencies of hydrological data, highlighting its potential for enhancing runoff forecasting accuracy.*

Keywords: *Runoff Forecasting; Variational Modal Decomposition; BiLSTM Network*

1. Introduction

Runoff forecasting holds significant scientific value and practical importance in water resources management, flood risk assessment, and ecological conservation [1]. With the intensification of global climate change and human activities, the runoff processes in river basins are exhibiting more complex nonlinear and non-stationary characteristics, posing new challenges to traditional prediction methods [2]. Existing research shows that linear models such as Autoregressive Integrated Moving Average (ARIMA) have notable limitations in handling complex hydrological processes, often failing to meet practical accuracy requirements [3]. Although machine learning methods like Artificial Neural Networks (ANN) have improved nonlinear modeling capabilities to some extent, they still fall short in capturing the multi-scale features and long-term dependencies of runoff sequences [4-5].

To address these issues, this study proposes an innovative approach that integrates Variational Mode Decomposition (VMD) with an Adaptive Particle Swarm Optimization Bidirectional Long Short-Term Memory network (APSO-BiLSTM)[6-7]. This method uses the VMD algorithm to decompose runoff sequences into multiple scales, effectively extracting hidden features of hydrological processes. Meanwhile, it employs an improved Adaptive Particle Swarm Optimization algorithm to optimize BiLSTM network parameters, enhancing the model's ability to simulate complex hydrological processes. The results demonstrate that the proposed VMD-APSO-BiLSTM model outperforms traditional methods in both prediction accuracy and stability, providing a new technical approach for hydrological forecasting in river basins.

To enhance the accuracy of monthly runoff forecasting, this study integrates the Variational Mode Decomposition (VMD) algorithm for multi-scale data decomposition with a "decomposition-prediction-reconstruction" framework, enabling more effective extraction of intricate patterns inherent in hydrological time series. The optimized VMD-APSO-BiLSTM model demonstrates significant improvements in mitigating boundary effects commonly associated with conventional approaches, thereby enhancing both predictive stability and accuracy during the testing phase. Future investigations could extend this framework by incorporating advanced data processing techniques, such as Spectral Clustering, to further improve the model's robustness and generalizability across diverse hydrological datasets and scenarios[10].

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2. Methodology

2.1 VMD Model

Variational modal decomposition is an adaptive signal processing method based on the variational framework, which aims to decompose a complex signal into a series of modal functions with sparsity and band-limited properties. The core idea is to transform the signal decomposition into solving a set of modal functions with specific center frequency and bandwidth by constructing a constrained variational optimization problem. Given the original signal $f(t)$, the goal of VMD is to decompose it into$K$ modal functions $u_k(t)(k=1,2,\ldots,K)$, each of which is narrowly distributed around its center frequency ω_k[8-9]. The optimization problem of VMD can be formulated as follows:

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \tag{1}$$

The constraints are:

$$\sum_{k=1}^{K}u_k(t)=f(t) \tag{2}$$

Where ∂t denotes the time partial derivative, $\delta(t)$ is the Dirac function, $*$ is the convolution operation, and j is the imaginary unit. By introducing the quadratic penalty term α and the Lagrange multiplier $\lambda(t)$, the VMD uses the alternating direction multiplier method (ADMM) to solve the modal function $u_k(t)$ and the center frequency ω_k iteratively until it converges.The VMD is able to adaptively separate the different frequency components of the signal with high robustness and clear physical significance, which is suitable for the analysis and processing of non-stationary signals.

2.2 APSO-BiLSTM

Adaptive Particle Swarm Optimization Bidirectional Long Short-Term Memory Network is a hybrid approach combining optimization algorithms and deep learning models to enhance the performance of time series prediction. The core idea is to optimize the hyperparameters of the bi-directional long- and short-term memory network through the adaptive particle swarm optimization (APSO) algorithm, so as to enhance the prediction ability of the model. Given the time series data $\{x_t\}_{t=1}^{T}$, the goal of APSO-BiLSTM is to minimize the prediction error by optimizing the key hyperparameters (e.g., learning rate, number of hidden layer units, etc.) of BiLSTM[11].The optimization problem of APSO can be formulated as:

$$\min_{\boldsymbol{\theta}}\left\{\mathcal{L}(\boldsymbol{\theta})=\frac{1}{N}\sum_{i=1}^{N}\left(y_i-\hat{y}_i(\boldsymbol{\theta})\right)^2\right\} \tag{3}$$

The constraints are:

$$\hat{y}_i(\boldsymbol{\theta})=\mathrm{BiLSTM}(\boldsymbol{x}_i;\boldsymbol{\theta}) \tag{4}$$

Whereθ denotes the set of hyperparameters of BiLSTM;$\mathcal{L}(\boldsymbol{\theta})$ is the loss function, usually using the mean square error (MSE);y_i is the true value;$\hat{y}_i(\boldsymbol{\theta})$ is the predicted value of the BiLSTM model; and BiLSTM$(\boldsymbol{x}_i;\boldsymbol{\theta})$ denotes the predicted output of the BiLSTM model on the input x_i.

The APSO algorithm dynamically adjusts the velocity and position of particles to find the global optimal solution by simulating the searching behavior of the particle swarm in the solution space. Its position update formula is:

$$\begin{gathered}\boldsymbol{v}_i^{t+1}=\boldsymbol{w}\boldsymbol{v}_i^t+c_1r_1(\boldsymbol{p}_i^t-\boldsymbol{x}_i^t)+c_2r_2(\boldsymbol{g}^t-\boldsymbol{x}_i^t)\\ \boldsymbol{x}_i^{t+1}=\boldsymbol{x}_i^t+\boldsymbol{v}_i^{t+1}\end{gathered} \tag{5}$$

Where $\boldsymbol{v}_i^t$ and $\boldsymbol{x}_i^t$ denote the velocity and position of the i th particle at the iteration number$t$, respectively;$\boldsymbol{w}$ is the weighting coefficient;c_1 and c_2 are the learning factors;r_1 and r_2 are the random numbers;$\boldsymbol{p}_i^t$ is the individual particle's historical optimal position; and g^t is the population's historical optimal position. The optimized parameters and their ranges are shown in Table 1.

Table.1 Preferred Range of Parameters.

Parameter Name	Explanation	Parameter Type	Value Range
Learning Rate	Initial rate for model training	float	[0.0001, 0.01]
LSTM Units	Number of neurons in LSTM layer	int	[10, 150]
Max Epochs	Maximum number of iterations	int	[30, 300]

2.3 Data Sources

The Jialing River is one of the important tributaries of the upper reaches of the Yangtze River, originating at the southern foot of the Qinling Mountains in Shaanxi Province, flowing through Shaanxi, Gansu, Sichuan and Chongqing, and finally joining the Yangtze River in Chongqing Municipality. Its basin area is vast and its hydrological characteristics are complex, which is an important part of the water resources of the Yangtze River basin. Beibei Hydrological Station, located in Beibei District, Chongqing, is one of the important hydrological monitoring stations of the lower reaches of the Jialing River. It undertakes the task of observing the water level, flow rate and other hydrological elements of the Jialing River, which provides important data support for the management of water resources in the river basin, flood prevention and disaster mitigation, and ecological protection[12].

In this study, the hydrological data from Beibei Hydrological Station of Jialing River from January 1, 2010 to December 1, 2021 were selected as the incoming water data on the first day of each month of each year. Among them, the data from January 1, 2010 to May 1, 2019 is used as the model training period for constructing and optimizing the prediction model, and the data from June 1, 2019 to December 1, 2021 is used as the model prediction period for verifying the prediction performance of the model. By analyzing the long-series hydrological data from the Beibei hydrological station of the Jialing River, we aim to reveal its incoming water pattern and provide a scientific basis for the management of water resources and flood forecasting in the basin.

2.4 Comparison of Programs and Evaluation Indicators

NSE (Nash-Sutcliffe Efficiency) and RMSE (Root Mean Square Error) are two commonly used metrics for evaluating the performance of hydrological models. NSE measures the degree of fit between model predictions and observed values, with a range from negative infinity to 1. A value closer to 1 indicates better predictive performance of the model. RMSE quantifies the error between predicted and observed values, where a smaller value signifies higher prediction accuracy of the model. The combined use of these two metrics provides a comprehensive assessment of the model's accuracy and stability.

In this study, four schemes (VDM-APSO-BiLSTM, VDM-APSO-LSTM, APSO -BiLSTM, VDM-APSO-LSTM, APSO and APSO- LSTM) were comparatively analyzed to evaluate the effectiveness of the proposed VDM-APSO-BiLSTM model. In particular, the data from January 1, 2010 to May 1, 2019 is used as the training period for model construction and parameter optimization, and the data from June 1, 2019 to December 1, 2021 is used as the testing period for model performance validation. By comparing the NSE and RMSE values in the training and testing periods, we aim to comprehensively analyze the prediction accuracy and stability of the models, and provide a scientific basis for hydrological prediction in the basin.

3. Results

3.1 VMD Decomposition Results

In the process of variational modal decomposition (VMD), the selection of the modal number$K$ has an important impact on the decomposition results. In order to determine the optimal number of modes, this study systematically evaluates different values of K by manual debugging method, combining the spectral characteristics of the signal and the physical significance of each mode after decomposition. After several tests and verifications,$K = 6$ is finally determined as the optimal number of modes. This value can effectively balance the center-frequency separation and bandwidth sparsity of the modal functions, and ensure that the decomposed modal functions can fully capture the multi-scale

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characteristics of the original signals, while avoiding the phenomenon of over-decomposition or under-decomposition. This choice provides a reliable basis for the subsequent VMD-based signal analysis and modeling, and the decomposition results are as shown in Figure 1.

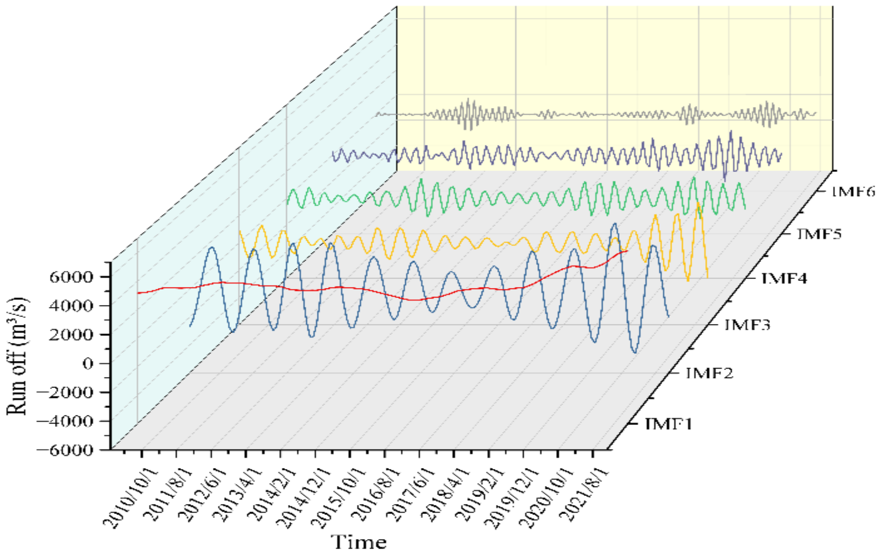

Figure1. Result of the variational mode decomposition

3.2 Forecast results and their analysis

To comprehensively evaluate the predictive performance of each model, this study employs a dual approach combining graphical analysis and quantitative metrics. Initially, scatter plots were generated to visualize the relationship between observed values and model-predicted values during the prediction period, providing an intuitive representation of model performance. Subsequently, two widely accepted statistical metrics—the Nash-Sutcliffe Efficiency (NSE) coefficient and Root Mean Square Error (RMSE)—were calculated for both the training and prediction periods to quantitatively assess model accuracy and stability. The NSE, ranging from -∞ to 1, serves as a measure of model fit, with values closer to 1 indicating superior predictive capability. Similarly, RMSE, a measure of prediction error, reflects model accuracy, with lower values denoting higher precision. By integrating the insights from scatter plot visualization with the quantitative evaluation provided by NSE and RMSE metrics, a robust comparative analysis of model performance was conducted. This comprehensive evaluation framework not only facilitates the identification of performance disparities among competing models but also provides a systematic basis for model selection. The results of this analysis are presented in Figure 2, offering a clear and detailed comparison of model performance across the evaluated criteria.

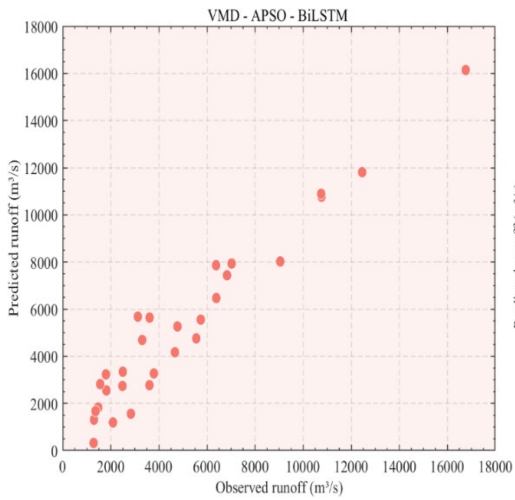

Figure2(a) VMD - APSO - BiLSTM Scatter Plot

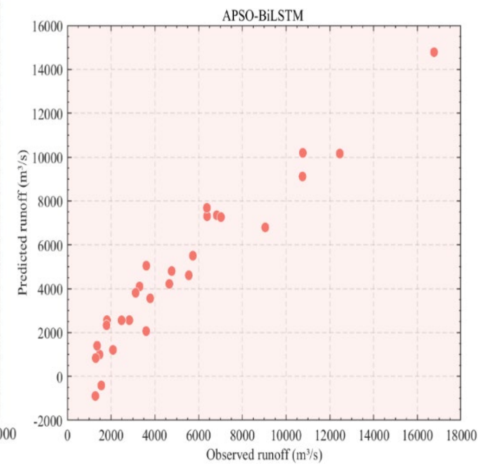

Figure2(b) APSO - BiLSTM Scatter Plot

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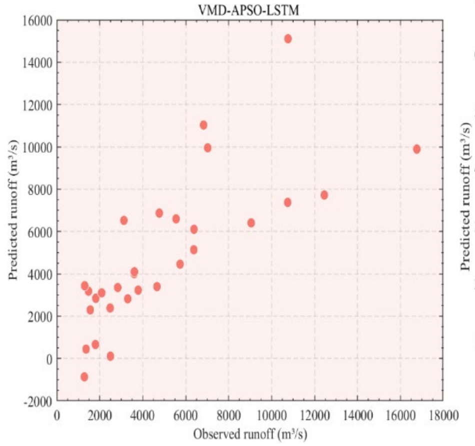

Figure2(c) VMD - APSO - LSTM Scatter Plot

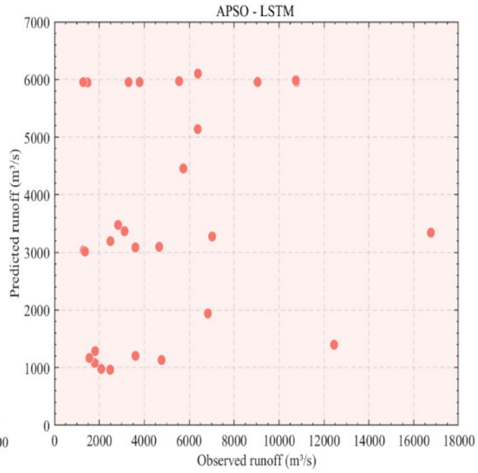

Figure2(d) APSO - LSTM Scatter Plot

Figure 2. Scatter plot for prediction results of each model.

The relevant accuracy indicators, namely Table 2 below, are provided for further analysis.

Table 2. Comparison of NSE and RMSE of Different Models in Training and Testing

Model	NSE in Training Period	RMSE in Training Period	NSE in Testing Period	RMSE in Testing Period
VMD - APSO - BiLSTM	0.95	516.75	0.93	992.15
VMD - APSO - LSTM	0.93	587.15	0.91	1138.89
APSO - BiLSTM	0.69	1255.77	0.57	2482.16
APSO - LSTM	- 0.55	2811.27	- 0.32	4334.82

As can be seen from Table 2, the Nash efficiency coefficients (NSE) of the VMD-APSO-BiLSTM model are 0.95 and 0.93 in the training and testing periods, respectively, and the root mean square errors (RMSE) are 516.75 and 992.15, which are significantly better than the other compared models (VMD - APSO-LSTM, APSO-BiLSTM and APSO-LSTM). This indicates that the VMD-APSO-BiLSTM model performs well in capturing the nonlinear features and long-term dependence of the hydrological time series, and has high prediction accuracy and stability. In contrast, the APSO-LSTM model has negative NSE values (-0.55 and - 0.32) and high RMSE values (2811.27 and 4334.82) in both the training and testing periods, indicating that it has poor predictive ability and fails to fit the actual data effectively. In summary, the VMD-APSO-BiLSTM model shows superior performance in both the training and testing periods, which verifies its effectiveness and reliability in the prediction of water inflow and provides an efficient method for hydrological prediction in the basin.

4. Conclusions

In conclusion, the present study proposes a novel hybrid framework for monthly runoff forecasting by integrating Variational Mode Decomposition (VMD) with Adaptive Particle Swarm Optimization (APSO) and Bi-directional Long Short-Term Memory (BiLSTM) networks. The proposed VMD-APSO-BiLSTM model was applied to runoff data from the Beibei Hydrological Station in the Jialing River Basin, demonstrating superior predictive performance compared to traditional methods and other machine learning models. This conclusion is supported by higher Nash-Sutcliffe Efficiency (NSE) values and lower Root Mean Square Error (RMSE) metrics. The VMD algorithm effectively decomposes complex hydrological time series into intrinsic mode functions, enabling the extraction of underlying patterns, while the APSO-optimized BiLSTM architecture captures long-term dependencies and non-linear characteristics in the data. The results highlight the robustness and accuracy of the proposed model, establishing it as a reliable tool for improving runoff forecasting. This advancement offers significant potential for enhancing water resource management and flood prediction systems, providing a valuable contribution to the field of hydrological modeling.

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