Flood Flow Prediction Based on Neuro-fuzzy Networks

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Keywords: Neuro-fuzzy networks, back-propagation iterative algorithm, the first order gradient optimization algorithm, flood flow, membership function.

Abstract: To realize the accurate prediction for the flood flow, the prediction approach of the flood flow based on neuro-fuzzy networks is proposed. In recent years, the artificial intelligence has developed rapidly and applied in different fields widely. At first, the architecture of neuro-fuzzy networks is put forward in this paper, the parameters are adjusted by back-propagation iterative algorithm and the first order gradient optimization algorithm. For example, based on the measurement data at Nanning hydrological station in July 2001, the water level and the fluctuation rate are input into neuro-fuzzy networks, the flood flow is the output, the training and checking are performed by neuro-fuzzy networks, the results show that the neuro-fuzzy networks has high accuracy and low error in the prediction of flood flow.

1. Introduction

The hydrological prediction is an important basis for the rational allocation and utilization of water resources, flood prevention and drought resistance, and is studied by the scholars and hydrologists, which is the needs of modern hydrological development. The hydrological prediction models used currently include the runoff correlation model and the Xin'anjiang model, which are deterministic models [1], the determined prediction values are outputted to the user, and the dispatchers make corresponding decisions based on the prediction values. However, the model used today is not accurate enough, which is the simulation approximation of the hydrological process, and the structure and parameters of the model are inaccurate. In the face of uncertain hydrological changes and the hydrological prediction values expressed by the determination values, it is a common problem for dispatchers to handle reasonably the prediction values and make the optimal dispatch based on the hydrological prediction values when making decisions.

In recent years, Artificial Intelligence (AI) has been once again attracted great attention from the academic community, which draw lessons from the research achievements of neuroscience, and is a combination of biological science, information science, computer science, mathematics and other subjects. It has non-linearity, non-locality, non-constancy, self-adaptability and the powerful computing ability, which marks a new turning point for the development of Artificial Intelligence, and is widely applied in the field of hydrology and water resources prediction [2].

2. Literature Review

Many scholars have applied artificial neural network to hydrological prediction. For example, Xiangyang Li et al. proposed a bayesian probabilistic model for hydrological prediction based on BP neural network, which is proved that the prediction accuracy is significantly improved through experiments [1]; Bo Pang et al. established a real-time runoff prediction model based on the coupled linear response and error correction model of total runoff, and the experiment shows that this method has good applicability [3]; Chaoqun Li et al. applied artificial neural network to solve the problem of dimensional disaster and overtraining in hydrological prediction, and after comparing the random error superposition method, tolerance training method, penalty function method, early suspension method and mixed method, the mixed method had the best training effect [4]; Dong Wang et al. expounded the application and development trend of artificial neural network from the hydrological prediction, classification and identification, optimal operation and calculation, and environmental and water quality assessment, etc. [2]; Guangyuan Kan et al. established BK (BP-KNN) model by coupling BP neural network with k-nearest neighbor algorithm, and simulated the confluence process, the experimental results showed that this method had high accuracy [5]; Guanghua Qin et al. introduced forgetting factor and expectation factor and adjusted the weight value with exponential energy function, and built a neural network model with sensitive functions, which improved the prediction accuracy and avoided the oscillation phenomenon in the learning process [6]; Keming Huang et al. proposed a hydrological prediction classification method based on the idea of phase space dimension expansion of time series [7]; Manling Dong et al. used BP network, L-M network and RBF network to realize the hydrological prediction, which are compared, the results shows that L-M network and RBF network are more accurate than BP network [8]; Jing Yuan et al. established a neural network prediction model by applying the least square recursive method and forgetting factor, and tracked the changes of time-varying parameters for the model in real time, the experiment proved that the method had fast tracking ability and high identification accuracy [9]; Based on artificial neural network and semi-distributed hydrological model, Shuang Liu et al. constructed the runoff estimation model (P-NN-TOP) and optimized the global parameters with particle swarm optimization and calculated the runoff yield and concentration, and the experiment showed that this method improved the accuracy of runoff simulation [10]; Lixue Wang et al. proposed a hydrological prediction model based on grey system and RBF neural network, and the experiment showed that the model is simple to operate and has high prediction accuracy [11]; Shuqian Wang et al. proposed a fuzzy neural network hydrological prediction model based on rain intensity distance index, and the result showed that this method could improve the prediction accuracy of the model [12].

Through the above literature summary, it is concluded that the artificial neural network has extraordinary ability in hydrological prediction, especially through the improvement of traditional artificial neural network or the fusion of algorithms, which greatly improves the prediction accuracy of artificial neural network in the field of hydrology and water resources. In this paper, the Neuro-Fuzzy Networks (NFN) formed by the combination of neural network and Fuzzy Logic System (FLS) are applied to realize the accurate prediction of water flow in a certain basin.

3. Neuro-Fuzzy Networks

Both neural networks and fuzzy logic systems can be used independently to solve a problem (such as model prediction, pattern recognition or density estimation). However, the independent usage has some disadvantages compared with the combined usage: Neural network is only suitable for solving problems represented by a large number of training data, and the empirical knowledge of this problem is not needed. On the contrary, the fuzzy logic system needs synthesize rules rather than training data as prior knowledge. Therefore, the input and output variables need to be described semantically, if the semantic rules are incomplete, incorrect or contradictory, the fuzzy logic system needs to be fine-tuned by heuristic algorithm. The combination of neural network and fuzzy logic system forms the neuro-fuzzy networks [13], which inherits the advantages when used alone and abandons its disadvantages.

3.1.Neuro-Fuzzy Networks Architecture

The architecture of neuro-fuzzy networks is showed in Figure 1, which is a 5-layers neural networks. Compared with the traditional neural networks, there is an input at a node of any layer. The node performs an operation on the input to form an output (the function of input parameters) [14], the connection weight and membership function of the neuro-fuzzy networks are very different.

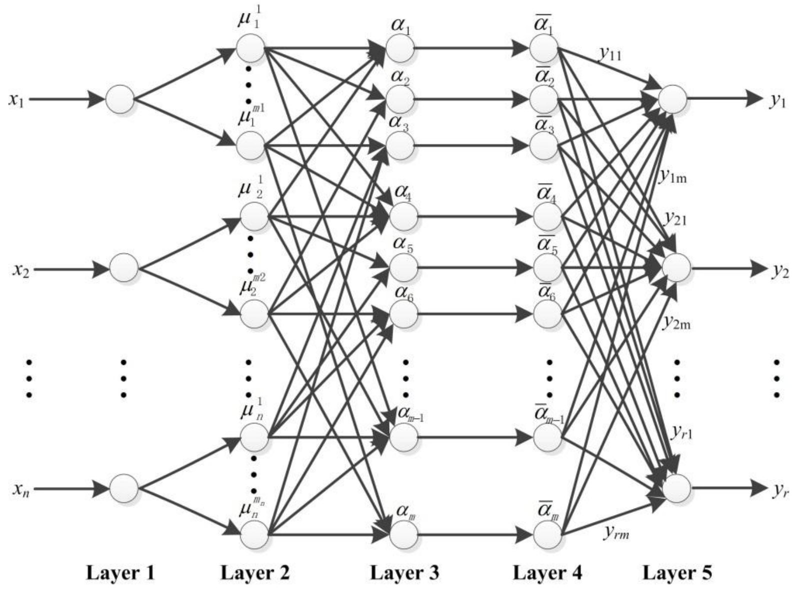

Figure 1: An architecture of neuro-fuzzy networks.

Layer 1: The node function of this layer transfers input variables directly to the next layer. For example, given the input variable $x = [x1, x2, x3..., xn]$, the number of nodes in this layer is n.

Layer 2: This layer contains input membership function nodes, which convert input numeric variables into a fuzzy sets (semantic labels), that is:

$$\mu_i^j = \mu_{A_i^j}(x_i) \tag{1}$$

where, i is the dimension of the input variable, $i = 1, 2, 3... , n$, j is the number of fuzzy segmentation of input variable xi, $j = 1, 2, 3... , m_i$. For example, if the Gaussian bell-shaped function is used as the membership function, namely:

$$\mu_i^j = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}} \tag{2}$$

where, c_{ij} is the central value of the membership function, σ_{ij} is the width of the membership function, and the number of nodes in this layer is $\sum_{i=1}^{n} m_i$.

Layer 3: Each node in this layer is thought as a fuzzy rule, which performs a minimum-maximum fuzzy operation on the input of the node. The fitness of each rule is calculated as follows:

$$\alpha_j = min(\mu_1^{i_1}, \mu_2^{i_2}, \cdots, \mu_n^{i_n}) \tag{3}$$

or

$$\alpha_j = \mu_1^{i_1} \mu_2^{i_2} \cdots \mu_n^{i_n} \tag{4}$$

where, $i_1 \in \{1, 2, 3, \ldots, m_1\}$, $i_2 \in \{1, 2, 3, \ldots, m_2\}$, …, $i_n \in \{1, 2, 3, \ldots, m_n\}$; $j = 1, 2, 3, \ldots, m$; $m = \prod_{i=1}^{n} m_i$, the number of nodes in this layer is m.

Layer 4: The nodes in this layer perform normalization operations, that is:

$$\overline{\alpha}_j = \alpha_j / \sum_{i=1}^{m} \alpha_i \tag{5}$$

where, $j = 1, 2, 3, \ldots, m$, the number of nodes in this layer is m.

Layer 5: The nodes of this layer perform defuzzification and calculate the outputs, and each rule is:

$$y_{ij} = p_{j0}^{l} + p_{j1}^{l} x_1 + \cdots + p_{jn}^{l} x_n = \sum_{i=0}^{n} p_{ji}^{l} x_i \tag{6}$$

where, p_{ji}^{l} is the connection weight coefficient, $l = 1, 2, 3, \ldots, r$; $j = 1, 2, 3, \ldots, m$; $i = 0, 1, 2, 3, \ldots, n$; r is the number of output values, $x_0 = 1$ is a constant, the number of nodes in this layer is m, and the output of neuro-fuzzy networks is:

$$y_i = \sum_{j=1}^{m} \overline{\alpha}_j y_{ij} \tag{7}$$

where, $i = 1, 2, 3 \ldots r$, y_i is the weight sum of all the rules.

3.2.Neuro-Fuzzy Networks Learning Algorithm

Learning parameters of the NFN include p_{ji}^{l}, c_{ij} and σ_{ij}. These parameters are calculated and fine-tuned using the error back-propagation iterative algorithm and the first order gradient optimization algorithm. The ultimate goal of the algorithm is to minimize the error E, which is defined as:

$$E = \frac{1}{2} \sum_{i=1}^{r} (t_i - y_i)^2 \tag{8}$$

where, t_i is the actual output value and y_i is the predicted output value.

The connection weight coefficient p_{ji}^{l} is fine-tuned using the following formula:

$$\frac{\partial E}{\partial p_{ji}^{l}} = \frac{\partial E}{\partial y_l} \frac{\partial y_l}{\partial y_{lj}} \frac{\partial y_{lj}}{\partial p_{ji}^{l}} = -(t_l - y_l) \overline{\alpha}_j x_i \tag{9}$$

$$p_{ji}^{l}(k+1) = p_{ji}^{l}(k) - \beta \frac{\partial E}{\partial p_{ji}^{l}} = p_{ji}^{l}(k) + \beta (t_l - y_l) \overline{\alpha}_j x_i \tag{10}$$

where, $i = 1, 2, 3... , n; j = 1, 2, 3... m; l = 1, 2, 3... r$; β is the learning rate.

After the correlation coefficient p_{ji}^{l} is fine-tuned, it becomes a constant. The parameters c_{ij} and σ_{ij} are as follows:

$$\delta_i^{(5)} = t_i - y_i \tag{11}$$

where, $i = 1, 2, 3... , n$.

$$\delta_j^{(4)} = \sum_{i=1}^{r} \delta_i^{(5)} y_{ij} \tag{12}$$

where, $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, m$.

$$\delta_j^{(3)} = \delta_j^{(4)} \sum_{\substack{i=1 \\ i\neq j}}^{m} \alpha_i \Big/ \left(\sum_{i=1}^{m} \alpha_i\right)^2 \tag{13}$$

where, $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, m$.

$$\delta_{ij}^{(2)} = \sum_{k=1}^{m} \delta_k^{(3)} s_{ij} e^{-\frac{\left(x_i - c_{ij}\right)^2}{\sigma_{ij}^2}} \tag{14}$$

where, $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, m_i$; $k = 1, 2, 3, \ldots, m$. If the rule is calculated by formula (3), then $s_{ij} = 1$, otherwise $s_{ij} = 0$. If the rule is calculated by formula (4), then $s_{ij} = \prod_{\substack{j=1 \\ j\neq i}}^{n} \mu_j^i$, otherwise $s_{ij} = 0$. Parameter c_{ij} and σ_{ij} are fine-tuned as follows:

$$\frac{\partial E}{\partial c_{ij}} = -\delta_{ij}^{(2)} \frac{2\left(x_i - c_{ij}\right)}{\sigma_{ij}} \tag{15}$$

$$\frac{\partial E}{\partial \sigma_{ij}} = -\delta_{ij}^{(2)} \frac{2\left(x_i - c_{ij}\right)^2}{\sigma_{ij}^3} \tag{16}$$

$$c_{ij}(k+1) = c_{ij}(k) - \beta \frac{\partial E}{\partial c_{ij}} \tag{17}$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - \beta \frac{\partial E}{\partial \sigma_{ij}} \tag{18}$$

where, $i = 1, 2, 3, \ldots, n$; $j = 1, 2, 3, \ldots, m_i$; $k = 1, 2, 3, \ldots, m$; β is the learning rate, and the learning process is repeated until the minimum error is reached.

4. Case Analysis

Taking the flood water level and flow data monitored by Nanning hydrological station in July 2001 as an example [15], the prediction effect of the neuro-fuzzy networks was tested. Nanning hydrology station is located in the upper reaches of Yu river (Xixiangtang, Nanning city), where the left and right rivers meet in Song village, bordering Vietnam in the southwest, Yunnan in the west, and Guizhou in the northwest. Affected by the NO.3 typhoon in July 2001, heavy rain fell on the left and right river basins, and causing the river water level to rise sharply. Nanning hydrology station reached the highest water level (77.80 m) and maximum flow (13,400 m^3/s) since 1938 at 12:00 on July 8, 2001 [16].

Normalized operation is carried out for the monitored water level and water level fluctuation rate (△Z/△t, that is the ratio of water level increment △Z and time △t), which is the input of NFN, and the output is the predicted flood flow. Firstly, the training data set is input to the first layer of the NFN model, and the water level and water level fluctuation rate are transmitted to the network as input variables. In the second layer, the numerical data are fuzzified by the bell membership function. In the third layer, the initial Fuzzy Inference System (FIS) structure is generated with the method of subtraction clustering. Then, the error back-propagation iterative algorithm and the first order gradient optimization algorithm are used to fine tune the learning parameters. In the fourth layer, the rules gained form normalization form the early part of the rules; In the fifth layer, the output is defuzzized and the weight of the global output for NFN is calculated.

The distribution of membership functions of the first input variable (water level) before and after the training is shown in Figure 2, the x axis for the normalized data of water level variables y said membership degree, water level variables with 5 membership functions, according to the similarity of the aggregated data set, membership functions after build, using fuzzy minimum - maximum operation rule, rule number for a total of $N(x_1)\cdot N(x_2)\cdot\ldots\cdot N(x_n)$, where $N(x_n)$ is the number of membership functions of the n^{th} input variable. In this paper, n = 2, a total of 25 rules are formed.

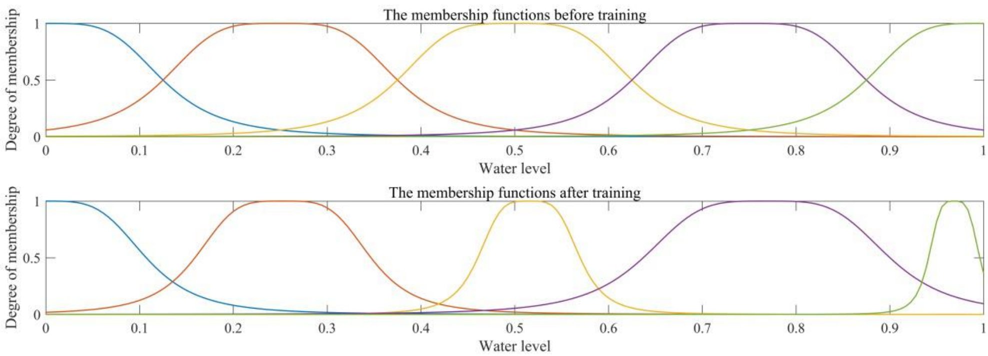

Figure 2: Membership function distribution of water level variable before and after training.

After NFN is trained, test data are input into the network to predict flood flow. For new inputting data set, when the new fuzzy rules can not match any existing rule, the new rules will be replaced by similar rules, which causes the error to be carried into the final result, therefore, a large amount of data is used to train NFN, to ensure the comprehensive for training rules. When a new data set is available, NFN is trained again. The input/output characteristic curve of the NFN is shown in Figure 3, and the water level and water level fluctuation rate are the input variables, the flow rate is the output variable.

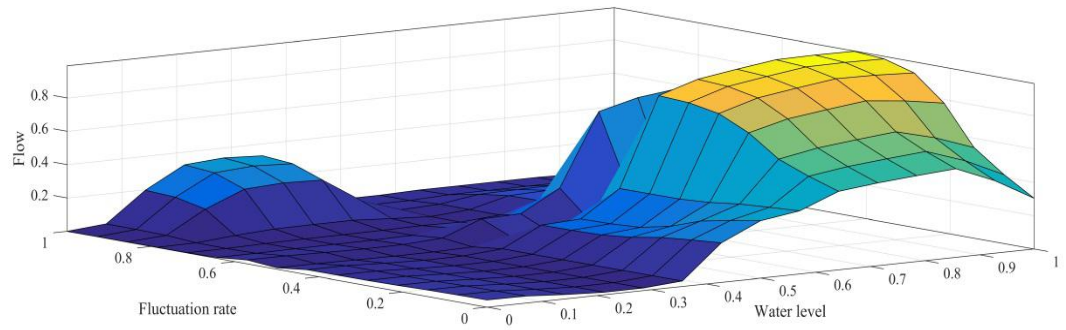

Figure 3: Input/output characteristic surface of neuro-fuzzy networks.

There are 5 membership functions for each input variable in NFN, which are bell-shaped functions, the initial fuzzy inference system structure is realized by mesh segmentation (genfis1), the error back-propagation iterative algorithm and the first order gradient optimization algorithm are adopted to optimize parameters, the training number is 200, the initial step length is 0.01, the step length decreasing rate is 0.9, the increasing rate is 1.1. After NFN is trained, the same training data is thought as test data, which is input into the network to verify system prediction effect, the actual measured value and predicted output value curve for NFN is shown in Figure 4, where the actual measured value of the flow is highly consistent with the predicted value of the NFN, and the error is 2.96666×10^{-7}.

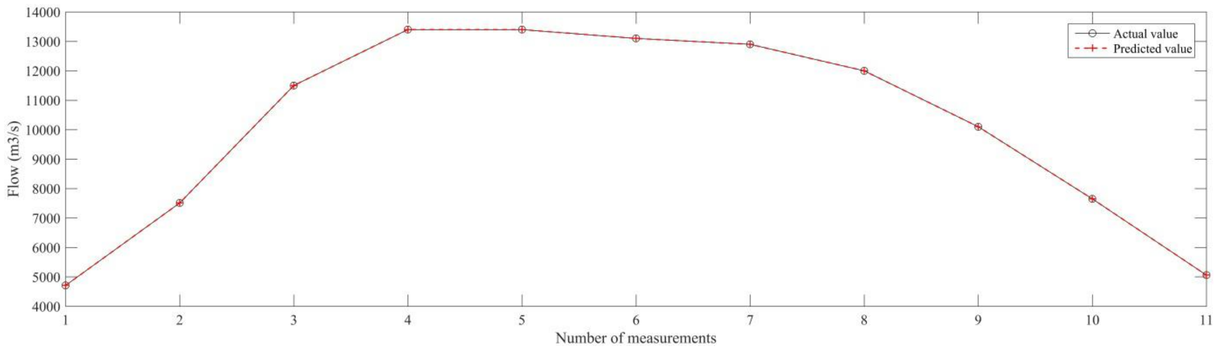

Figure 4: The output curve for actual measurement and prediction.

The training error and test error curve for NFN is shown in Figure 5, where the initial training/checking error decreases rapidly, when the training number reaches to the 12th time, error increases again, and then the error curve is wavy, when the training number reaches to the 110th time, the error curve appears arch, from the beginning of the 140th training, error remains consistent, until the end of the training.

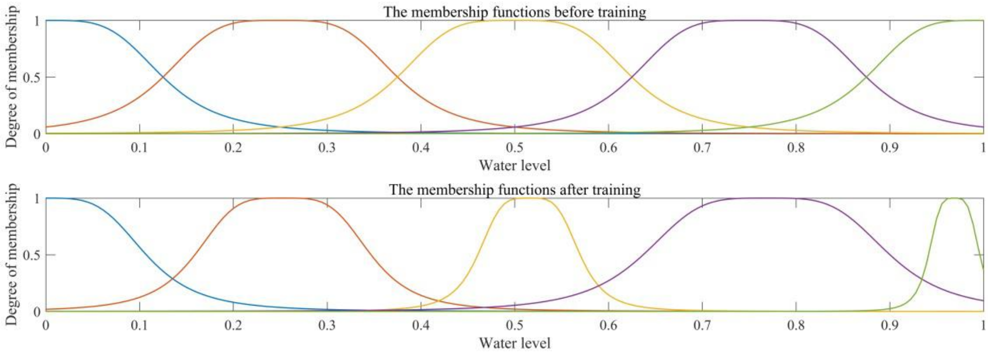

Figure 5: The training error and checking error curves for NFN.

The initial step size of NFN training is 0.01, and when the error decreases for 4 consecutive times, the step size increases. When the error changes and oscillates for 2 consecutive times (1 increase and 1 decrease alternately), the step size reduces. The step size change curve of NFN training process is shown in Figure 6.

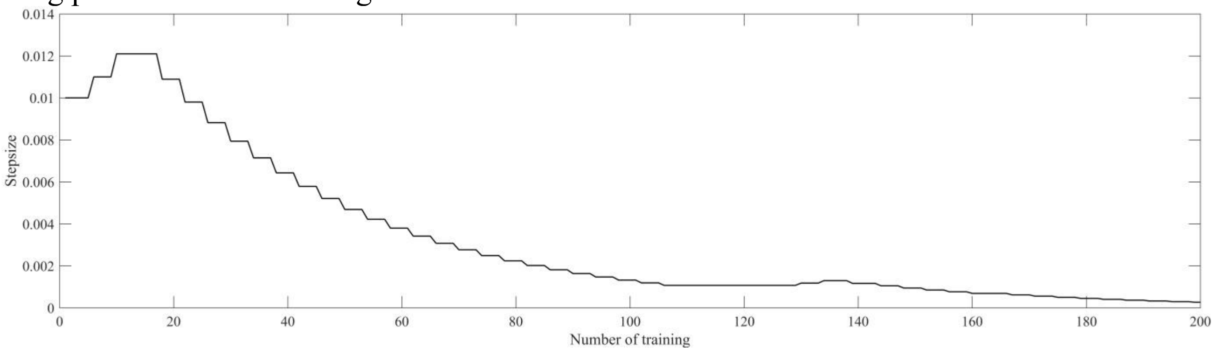

Figure 6: The change curve for training step size in NFN.

5. Conclusions

In this paper, a flood flow prediction method based on NFN is proposed to predict flood flow, including constructing a NFN model, and using back-propagation iterative algorithm and the first order gradient optimization algorithm to adjust parameters. Taking the flood water level and flow monitoring data of Nanning Hydrological Station in July 2001 as an example, the NFN model is tested. The results show that the method has high accuracy and low error value, new methods for hydrological monitoring of flood flow prediction is provided, the accuracy of flood flow prediction is improved, and the property losses caused by flood disasters is reduced.

Acknowledgments

This work was financially supported by the Water Conservancy Science and Technology Project of Guangxi Zhuang Autonomous Region (Grant NO. KY-201523), the Education Department Science and Technology Research Project of Guangxi Zhuang Autonomous Region (Grant NO. 2013YB302).

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