

A Modified Semi-parametric Regression Model For Flood Forecasting

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ABSTRACT:

In recent years, inundation, one of natural calamities, occurs frequently and fiercely. We are sustained severe losses in the floods every year. Therefore, the development of control methods to determine, analyze, model and predict the floods is indispensable and urgent. In this paper, we propose a justified semi-parametric regression model for flood water levels forecasting. The new model has three components. The first one is parametric elements of the model. They are water level, precipitation, evaporation, air-humidity and ground-moisture values, etc. There is a complex connection among these parametrics. Several innovated regression models have been offered and experimented for this complicated relationship. The second one is a non-parametric ingredient of our model. We use the Arnak S. Dalalyan et al.'s effective dimension-reduction subspace algorithm and some modified algorithms in neural networks to deal with it. They are altered back-propagation method and ameliorated cascade correlation

algorithm. Besides, we also propose a new idea to modify the conjugate gradient one. These actions will help us to smooth the model's non-parametric constituent easily and quickly. The last component is the model's error. The whole elements are essential inputs to operational flood management. This work is usually very complex owing to the uncertain and unpredictable nature of underlying phenomena. Flood-water-levels forecasting, with a lead time of one and more days, was made using a selected sequence of past water-level values observed at a specific location. Time-series analytical method is also utilized to build the model. The results obtained indicate that, with a new semi-parametric regression one and the effective dimension-reduction subspace algorithm, together with some improved algorithms in neural network, the estimation power of the modern statistical model is reliable and auspicious, especially for flood forecasting/modeling.

Key words: semi-parametric model, regression, time-series, multi-variate, dimension-reduction, subspace, neural network, back-propagation method, cascade correlation algorithm, conjugate gradient, flood, water-level, forecasting, modeling.

1. INTRODUCTION

Vietnam is a tropical and temperate country. It is characterized by a strong monsoon influence, a considerable amount of sunny days, and with a high rate of rainfall and humidity. It's usually affected by the change of climate. Floods happen more and more with increasing frequency and devastation. To help people to subsist on floods, to reduce human and material losses to the minimum are the our main goal. Flood modeling or forecasting is a remedy for this problem. There are several techniques for modeling flood water levels. One of the most important prerequisites in operational flood management is predicted flood values in nealy real-time sense.

Historically, there are different methods for flood forecasting. A large number of rainfall-runoff models have been developed. These include conceptual models that try to conceptualize the physical process influencing the runoff, empirical models, and complex models that couple meteorologic and hydrologic models for flow forecasting – [1]. Recently, we have some modern models used for flood water level forecasting, such as: MARINE, SSARR, TANK, NAM, MIKE11, DIMOSOP, HYDROGIS,...Most of them are one-dimensional hydrolic, hydraulic or hydro-dynamic models, which apply St. Venant adequate simultaneous equations. They are still the most popular flood forecasting models. Nevertheless, Bertoni et al. - [1] - point out that the real-time forecasts obtained by modeling rainfall-runoff processes are less accurate than those obtained by empirical channel routing of a hydrograph observed at an upstream gauging observation point. Most of above-mentioned models are extremely complex and require considerable external information for their application that may not be available at all locations anytime. An alternative solution to solve this problem could be the use of a semi-

parametric regression model, in company with using neural networks, viz using modified back-propagation, cascade correlation algorithms, and altered conjugate gradient one, to create a new semi-parametric model for flood water levels modeling/forecasting.

This mathematical model has three components. The first one is parametric elements of the model. They are water level, precipitation, evaporation, air-humidity and ground-moisture values, etc. There is a multi-variate complex linear/ non-linear connection among these parametrics. Several innovated regression models have been offered and experimented for this complicated relationship.

The second one is a non-parametrical ingredient of our model, $g(z_i)$. This part has been used for local adjustment so that it is better to fit responses value. The Arnak S. Dalalyan et al.'s effective dimension-reduction subspace algorithm and some modified algorithms in neural networks have been applied to deal with it. The main method is Hristache et al.'s solutions (2001) and then many relative algorithms. Besides, training of the network was done with the help of some modified methods neural network, via data sets, to minimize the mean squared error. This action will help us to smooth the model's non-parametric constituent easily and quickly.

There are some advantages when using a neural network for flood water-level modeling and forecasting:

Neural networks are useful when the underlying problem is either poorly defined or not clearly understood.

Their applications do not require a prerequisite knowledge about the studied process. etc [2]

Owing to these reasons, neural networks are designed to recognize the a hidden pattern in the data in a similar way to that of the human brain. The details of their functions and applications could be given in various documents (e.g., refs. [1], [4], and [6]).

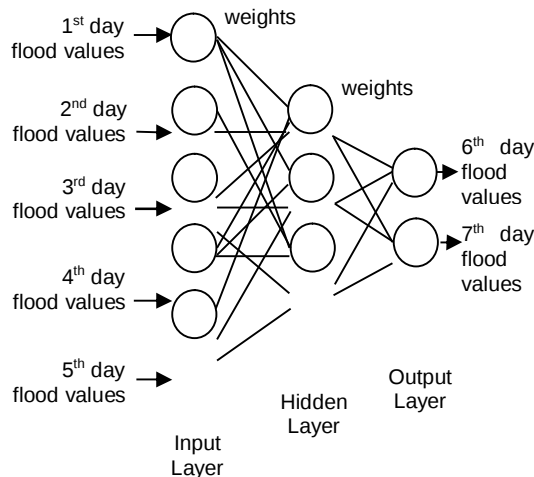


Figure 1. Three-layer feedforward neural network

The neural network is suitable for the particular application belongs to the feedforward type, as illustrated in Figure 1, that has the capacity for approximating any continuous function.

The following parts describe an effort to modify and develop the back-propagation, cascade correlation and conjugate gradient neural networks for flood water-level modeling or forecasting in a particular location.

The last component is the model's error. It represents the measurement errors such as counting and figures surveying errors.

The whole elements of the model are essential inputs to operational flood management. This work is usually very complex owing to the uncertain and unpredictable nature of underlying phenomena. The technique of multi-variate semi-parametric regression modeling and neural

networks therefore was applied to model it. Flood-water-levels forecasting, with a lead time of one and more days, was made using a selected sequence of past water-level values observed at a specific location.

2. CASE STUDY

2.1. Study area

The measured flood water-level data were available at the Chau Doc and Tan Chau gauging stations, in An Giang province, Vietnam. Tan Chau station is coded as 019803, located on upstream of Tien River, at longitude 105°13'' and latitude 10°45'. Chau Doc station is coded as 039801, located on upstream of Hau River. They are settled in Long Xuyen quadrangular basin, one of areas sustained heavy losses in the inundations in Mekong Delta every year. It is shown in Figure 2.

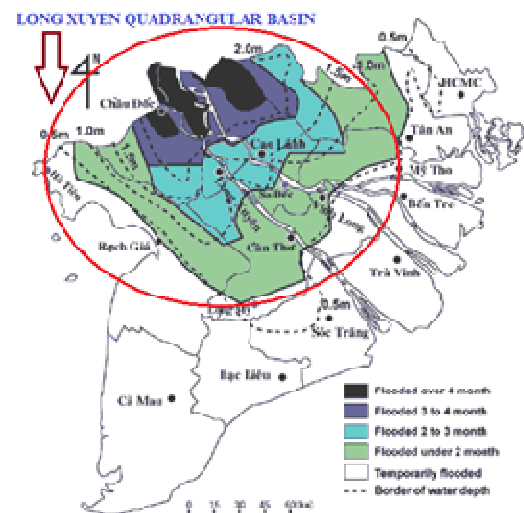


Figure 2. Catchment area plan

This catchment is approximately 489000 hectare natural area. The topography is sunken, even and flat with nearly from 0,4 m to 2,0 m altitude from the sea water level. Yearly, the flood season occurs from July to December. This studied basin is often inundated from 0,5 to 2,5 meter depth. The irregular change of upstream head-waters of Mekong River, especially from

the border between Cambodia and Vietnam, could lead into the fluctuations.

2.2. The data

Daily 24-hours flood water-level values in twelve years, from 1st January, 2000 to 31st December, 2011, were extracted from the weekly reports' records of the Regional Flood Management and Mitigation Centre, a division of Mekong River Commission. In each year, every seven successive days is gathered to form a group. In these groups, the 5 first daily values were the input values and two remaining ones were the output values. The first group, the third one, the fifth set...were used for training; and the others were applied for testing purposes. Thus, in all, 52704 input-output data records were used successively for training and 52704 data records were used for testing application.

The objective was to model and forecast daily flood water-level values with lead time of 1 and 2 days. Since the main purpose of this paper is to furnish citizens with short-term or medium-term forecasted results, we do not carry out the algorithm for 3-days, 4-days and beyond. The final results received from the modified semi-parametric regression model, via dimension-reduction subspace algorithm and these artificial neural networks could be helpful basic information for model adjusting, extending and upgrading. In other words, even though a larger lead time of model or forecast would be more useful to issues the flood warnings well in advance, the smaller lead time can help in making emergency reservoir operations and also in cautioning the population at longer distances downstream or at many specific sites where a nearby river gauging station is not available.

As shown in Figure 1, a sequence of five preceding daily values was given as input to the network, so as to enable the network to learn the pattern of flood water-level in the preceding days

and make a prediction accordingly to the future event. We can see that this future event belonged to lead times of one and two days, videlicet the sixth day flood values and the seventh day flood ones. If the lead time changes, the weights of neural network will be updated. At that time, the input part of the training pattern remains the same, but the output value will be changed. The choice of this sequence was made on a trial basis. No significant improvement in the prediction was noted when the sequence length was increased or decreased beyond 5 days, 6 days or 7 days.

3. THE TRAINING ALGORITHM

The proposed semi-parametric regression model is shown as following formula:

$$Y_i = \beta_0^T Z_i + g(\theta_0^T X_i) + \varepsilon_i = \beta_0^T Z_i + g(H_i) + \varepsilon_i$$

$$= \beta_0^T Z_i + f(\vartheta_1^T H_i, \vartheta_2^T H_i, \dots, \vartheta_m^T H_i) + \varepsilon_i \quad (1)$$

Suppose the data consists of n subjects. For subject $(k=1,2,\dots,n)$, Y_i is the independent variable, X_i is the m vector of parameters which we mentioned above, and $H_i = \theta_0^T X_i$ is the p vector of gene expressions within a pathway. The outcome Y_i depends on X_i and H_i . Besides, Z_i is a weighted combination of many parameters which affect the model significantly; and β_0^T is a m vector of regression coefficients.

Moreover, $g(H_i)$ is an unknown centered smooth function, and the error ε_i are assumed to be independent and follow $N(0, \sigma^2)$. $\beta_0^T Z_i$ is the parametrical part of model for epitaxial forecasting. A solution for this part can be obtained by minimizing the sum of squares equation:

$$J(g, \beta^T) = \sum_{i=1}^n (y_i - \beta^T x_i - g(z_i))^2 + \lambda \int_a^b [g''(z_i)]^2 dt,$$

with $\lambda \geq 0$ (2)

where $\lambda \geq 0$, is a tuning parameter which controls the tradeoff between goodness of fitting and complexity of the model; $\beta^T x_i$ is the parametrical part of model for epitaxial forecasting. Its objective is to control the independent variable trend. When $\lambda = 0$, the model interpolates the gene expression data, whereas, when $\lambda = \infty$, the model reduces to a simple linear model without $g(\cdot)$ [11].

In our model, flood forecasting problem is far from simple due to water level, precipitation, evaporation, air-humidity and ground-moisture. In this paper, many linear regression models (stepwise multiple linear – SML, partial least square – PLS, multirecursive – MR) are used to capture flood characteristics, while three modified artificial neural network models and the effective dimension-reduction subspace algorithm which Arnak S. Dalalyan et al. supposed in 2008 [12], are capable of capturing nonlinear patterns in the model.

The neural network was created by using three different modified algorithms, namely, back-propagation, adjusted cascade correlation and altered conjugate gradient methods. Basically, the primary objective of training is to reduce the global error, E , to the minimum. This error is defined below:

$$E = \sum_{p=1}^N E_p / N \quad (3)$$

where N = total number of training patterns,

E_p = error for training pattern p .

$$E_p = \sum_{k=0}^n (o_k - t_k)^2 / 2 \quad (4)$$

We can see ref.[13] for more information.

We attempt to reduce this global error by adjusting the weights and biases.

3.1. Adjusted Back-Propagation Algorithm

This involves minimization of the global error using a steepest-descent or gradient-descent approach. The network weights and biases are adjusted by moving a small step in the direction of a negative gradient of the error function during each iteration. The iterations are repeated until a specified convergence or number of iterations are achieved.

The gradient descent is defined by

$$W_{k+1} = W_k - mg_k \quad (5)$$

where W_{k+1} = vector of weights at the $(k+1)$ th iteration index,

W_k = vector of weights at the k th iteration index,

m = step size (given by the user),

g_k = error gradient vector at k th iteration index, $= \nabla f(W_k)$,

$f(W_k)$ = error function E for the weight vector W_k .

The preceding error-gradient approach is simple to use. Nonetheless, it converges slowly and may exhibit oscillatory behaviour due to the fixed step size. So, we could change some parameters from $f(W_k)$, modify the iteration step flexibly rely on typical characteristics of each data set. We could also alter the threshold for normalizing the input values, if these values exceed the given threshold. These actions would diminish separately the error for each training pattern. Since that time, the global error could be reduced to minimum. In other words, the global error is close to zero. These changes abovementioned will be stopped when a specified convergence is achieved.

There are some notes for this algorithm.

Firstly, the input layer has five nodes. The hidden layer has three nodes, and the output layer has two others.

Secondly, the standard threshold of our network is 420 (cm) for Tan Chau gauging station and 350 (cm) for Chau Doc one. These values are chosen because if water levels equal or overcome it, floods or inundations situations will occur. However, if one of five normalized input values for a specific operation is more than or equal to 1, the threshold (or the milestone) of our global network will be added 50 centimeters. We will repeat this action (add 50 cm for the current global threshold) if one of five normalized input values for a specific operation is still more than or equal to 1. This 50-centimeter gap is chosen because it is the gap between three flood danger-alarm levels at these gauging stations.

This alteration causes some unprecedented and flexible change for our neural network. It means that the output values of the neural network will be gotten better and better if we use the suitable threshold. Besides, our model is not influenced by any input value.

Thirteenthly, the transfer function as sigmoidal function, which we use, is given by

$$\mathbf{O}_{Oq} = (-1)^m / \left[1 + e^{-\lambda(I_{Oq} - \theta_{Oq})} \right] \quad (6)$$

where $\mathbf{O}_{Oq}$ is the output of the q th output neuron,

I_{Oq} is the input of the q th output neuron,

θ_{Oq} is the threshold of the q th neuron.

$m = 0$ if the normalized output value is greater than zero, otherwise $m = 1$.

This is also a creative point of our neural network. The choice of signs contributes to reduce errors for training patterns. Note that we only choose the minus signal if the normalized output value is not greater than zero.

However, if the resulting size of the network is too small, it gives rise to inadequate learning of the problem. On the other hand, lack of generalization and convergence difficulties may arise if the network is huge. The training modified algorithm of cascade correlation is directed toward eliminating these inconveniences.

3.2. Modified Cascade Correlation Algorithm

This algorithm begins a minimal network, i.e without any hidden node, then automatically trains and adds new hidden unit one-by-one in a cascading manner. Scilicet, if the variance between the realized output and the targeted one is not low, it adds one hidden node [7], [8]. This candidate node is connected to all input nodes and previous added hidden units, i.e to all other nodes except the output nodes. Weights associated with hidden units are optimized by a gradient-descent method in which the correlation between the hidden unit's output and the residual error of the network is maximized. If S_C is an overall sum of such correlations,

$$S_C = \sum_{i=1}^m \left| \sum_{p=1}^{Np} (z_{n+2,p} - \overline{z_{n+2}})(E_{ip} - \overline{E_i}) \right| \quad (7)$$

We can see ref [13] for more details.

Strictly speaking, S_C is actually a covariance, not a true correlation because the formula leaves out some of the normalization terms.

There are several new points for this algorithm. Firstly, we have the standardized way for input and output values, as mentioned above. Secondly, we propose some sigmoidal functions for hidden units [13].

Results which we received from these different sigmoidal functions show that they are trustworthy and reliable for constructing neural

network models, especially for flood water-levels forecasting.

3.3. Ameliorated Conjugate Gradient Algorithm

This technique differs from the previously mentioned error back-propagation in gradient calculations and subsequent corrections to weights and bias.

Here, a search direction d_k is computed at each training iteration k , and the error function $f(\bar{X})$ is minimized along it using a line search.

The gradient descent does not move down the error gradient as in the preceding back-propagation method but along a direction that is conjugate to the preceding step. The change in gradient is taken as orthogonal to the preceding step with the advantage that the function minimization, carried out in each step, is fully preserved due to lack of any interference from subsequent steps.

For each iteration k , we determine the constant α_k which minimizes the error function $f(\bar{X}_k + \alpha_k d_k)$ by a line search, where d_k is the search direction at iteration k . Then, we choose a new direction vector $d_{k+1} = -g_{k+1}$ if it is an integral multiple of N , where N is the dimension of $\bar{X}$. Otherwise, $d_{k+1} = -g_{k+1} + \lambda_k d_k$ (8), where $\lambda_k = (q_k - n\alpha_k d_k)' g_{k+1} / d_k' q_k$ (9)

with n is the number of iteration steps.

This is a altered conjugate gradient equation.

The modified conjugate gradient algorithm based on this equation possesses the property of quadratic termination. This is proved by the fact that for a given quadratic function $f(x)$ and a

perfect line search, the direction generated by the new method is identical to the one obtained by Fletcher-Reeves conjugate gradient and the DFP methods.

4. RESULTS AND DISCUSSION

The modified model was trained with the help of 52704 input-output data records by using some modified methods which are mentioned above. In this work, various parameters of the model, some ameliorated algorithms in neural network, the number of iterations, the initial normalized values for the input layer, etc., were tested. The configuration of the model, the number of iterations to archive an overall mean square error of the 10^{-31} , and the CPU time required for this on a laptop, with Intel core i5 processor, are given in Table 1 for warning time of 1 and 2 days.

Table 1. Training details for back-propagation algorithm

Year	Network configuration			Iteration s	Time (s)
	I	O	H		
2009	5	3	2	35100	1053
2010	5	3	2	52920	1587,6
2011	5	3	2	48600	1458

Table 2. Training detailsfor modified cascade correlation algorithm

Year	Network configuration			Iteration s	Time (s)
	I	O	H		
2009	6	2	2	8775	263,25
2010	6	2	2	11760	352,8
2011	6	2	2	10125	303,75

Besides, the maximum error (ME1), minimum error (ME2), the average value of errors (AE), the normalized maximum and minimum values (ME3 and ME4), the maximum and minimum values of η (ME5, ME6) and α (ME7, ME8) are also given in Table 2.

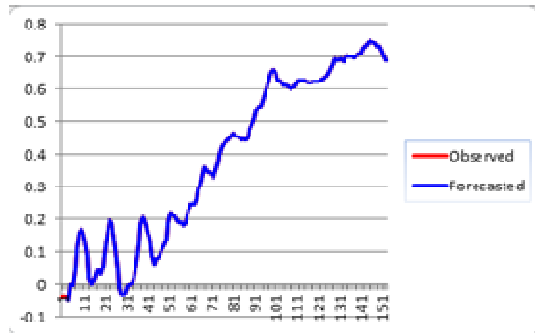


Figure 3. One and two days-ahead flood water level forecast in 2010 via back-propagation algorithm

The network outputs of models and forecasts with lead time of one day were compared with the actual observation. Figure 3 shows time-history comparisons for different warning times in 2010 via back-propagation algorithm. Figure 4 is carried out such comparisons in 2009 by using the modified cascade correlation algorithm.

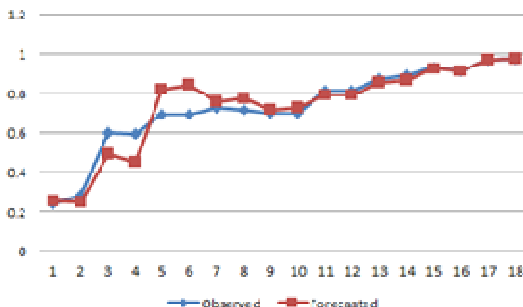


Figure 4. One and two days-ahead flood water level forecast in 2009 via modified cascade correlation algorithm.

The observations and predictions for flood water levels in 2009, 2010 and 2011 are plotted continuously in these figures for plotting convenience, through in actual fact they occurred with time gaps.

Besides, via the scatter diagrams, these observations were further confirmed by noticing the values of the correlation coefficient R

between actual and computed flood water levels, calculated using the following equation:

$$R = \left(\frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \right) \quad (10)$$

The values of R were approximate to 1. All of global error values were less than 10^{-31} . So, the convergence in the global error is satisfied.

5. CONCLUSIONS

The major aim of the work is to study, test, explore and demonstrate the potential of semi-parametric regression model, together with artificial neural networks, for modeling and forecasting flood water levels. It can be noticed that the adjustment of the synaptic weights was quicker in the smaller network, with the mean square error dropping sharply until it reached the maximum value acceptable, defined by the user. It is interesting to observe that, like occurred in this case, the performance sometimes is not improved when the number of neurons is increased. For this reason, it is interesting to test the network several times if a solution is not found on the first training exercise. when we use suitable sigmoidal functions for hidden units, the speed of computation is raised up rapidly. As can be easily noticed, the neural networks usually fit the experimental data with high accuracy and sensibleness.

Furthermore, simulation is a widely accepted tool in systems design and analysis. Because its basic concepts are easily understood, it has become a powerful decision-making instrument. The results have shown that a semi-parametric regression model, along with artificial neural network models, is capable of modeling and forecasting the flood water levels, especially for low warning times. The precision of the estimates will depend on the quality of the information used to train the model. It is possible to create flexible and non-linear models that have

better adherence to experimental data than traditional models. Moreover, it is possible to acquire and store knowledge in a dynamic configuration, creating models that can be constantly updated for different situations. In short, the simulations carried out, using real data from various tests, demonstrated that a semi-

parametric regression model, together with artificial neural network, can be very useful tools for modeling and forecasting spatio-temporal flood water levels. The new semi-parametric regression model will be continued to develop and apply in our real world, emphasized in the studied area.

Một mô hình hồi quy bán tham số có hiệu chỉnh cho bài toán dự báo lũ lụt

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TÓM TẮT:

Trong những năm gần đây, lũ lụt, một trong các hiện tượng thiên tai, xảy ra ngày càng nhiều và khắc nghiệt. Hàng năm, con người luôn phải gánh chịu hậu quả do lũ lụt gây ra. Bởi thế, việc phát triển các phương pháp quản lý nhằm giúp cho ta xác định, phân tích, mô hình, và dự báo lũ lụt là việc làm hết sức cấp bách và cần thiết. Trong phạm vi bài báo này, chúng tôi đề xuất một mô hình hồi quy bán tham số có hiệu chỉnh cho bài toán dự báo mực nước lũ. Mô hình mới sẽ có ba thành phần. Thứ nhất là thành phần tham số của mô hình. Chúng bao gồm thông số về độ cao mực nước, lượng mưa, lượng nước bốc hơi,... Các tham số này có mối quan hệ ràng buộc

với nhau khá phức tạp. Nhiều mô hình hồi quy mới đã được đề xuất và thử nghiệm. Thành phần thứ hai là thành phần phi tham số của mô hình. Chúng tôi sử dụng thuật toán cải tiến hiệu quả cho không gian con suy giảm số chiều do Arnak S. Dalalyan và các cộng sự đã đề xuất, cùng với một vài thuật toán cải biên trong công nghệ mạng nơ ron để giải quyết thành phần thứ hai này. Các thuật toán đó là: giải thuật lan truyền ngược, phương pháp tương quan liên kế, và đạo hàm gradient liên hợp có cải tiến. Các mô hình khác nhau được thử nghiệm, lựa chọn, nhằm giúp cho việc làm trơn cục bộ của thành phần phi tham số được nhanh chóng để dàng. Thành

phần thứ ba là sai số của mô hình. Tất cả yếu tố này là thông tin đầu vào thiết yếu cho bài toán quản lý và kiểm soát lũ lụt. Việc làm này cũng thường được áp dụng khi ta gặp phải những vấn đề phức tạp và các hiện tượng thiên tai khó dự báo. Mục nước dự báo được tiến hành dựa trên dữ liệu thu được trước đó, cho phạm vi một ngày, hai ngày sắp tới, tại một vị trí cụ thể. Phương pháp phân tích chuỗi thời gian cũng được xem xét khi

xây dựng mô hình. Những kết quả thu được cho thấy rằng với mô hình hồi quy bán tham số mới này, cùng với thuật toán cải tiến hiệu quả cho không gian con suy giảm số chiều, và một số giải thuật cải biên của công nghệ mạng nơ ron, đã cho ta thấy tính linh động, khả thi, đáng tin cậy, của mô hình thống kê hiện đại, nhất là trong việc xây dựng bài toán dự báo lũ lụt.

Từ khóa: mô hình bán tham số, hồi quy, chuỗi thời gian, đa biến, không gian con suy giảm số chiều, mạng nơ ron, phương pháp lan truyền ngược, thuật toán tương quan liên kế, đạo hàm gradient liên hợp, mực nước lũ, mô hình hóa, dự báo.

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