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IMMUNE NETWORK ALGORITHM IN MONTHLY STREAMFLOW PREDICTION AT JOHOR RIVER

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ABSTRACT

This study proposes an alternative method in generating future stream flow data with single-point river stage. Prediction of stream flow data is important in water resources engineering for planning and design purposes in order to estimate long term forecasting. This paper utilizes Artificial Immune System (AIS) in modelling the stream flow of one stations of Johor River. AIS has the abilities of self-organizing, memory, recognition, adaptive and ability of learning inspired from the immune system. Immune Network Algorithm is part of the three main algorithm in AIS. The model of Immune Network Algorithm used in this study is aiNet. The training process in aiNet is partly inspired by clonal selection principle and the other part uses antibody interactions for removing redundancy and finding data patterns. Like any other traditional statistical and stochastic techniques, results from this study, exhibit that, Immune Network Algorithm is capable of producing future stream flow data at monthly duration with various advantages.

Keywords: immune network algorithm, artificial immune system, streamflow prediction.

INTRODUCTION

Streamflow forecasts is crucial to flood mitigation and water assets administration and arrangement. While transient expectation, for example, hour or every day guaging is essential for surge cautioning and resistance, long haul forecast focused around month to month, occasionally or yearly time scales is exceptionally helpful in store operations and watering system administration choices, for example, planning discharges, apportioning water to downstream clients, dry season moderation and overseeing stream bargains or executing conservative compliance [1].

A critical number of gauging models and approaches have been created and connected with this field because of the imperatives of hydrologic forecasting. These streamflow forecasting models can be categorized as process-driven methods and data-driven methods [2].

Linear models such as AutoRegressive (AR), AutoRegressive Moving Average (ARMA), AutoRegressive Integrated Moving Average (ARIMA), and Seasonal ARIMA (SARIMA) had made a great success in streamflow prediction[3]. Artificial Neural Networks (ANNs), Genetic Algorithms and Artificial Immune Systems (AIS) are some of streamflow prediction techniques which have grown popularity lately.

In this study the anticipated future streamflow information will be utilized for estimating of water assets arranging and operational frameworks. This anticipated streamflow information is extremely valuable for long haul guaging in the arranging and operation of the water assets administration. As an expansion, the utilization of the propose technique i.e Artificial Immune System will be another commitment to the field of hydrology in anticipating month to month streamflow information. The objective of this study is to develop and test the feasibility and accuracy of the monthly streamflow prediction model using an Artificial Immune System (AIS).

ARTIFICIAL IMMUNE SYSTEM

AIS was characterized as versatile frameworks, propelled by hypothetical immunology and watched resistant capacities, standards and models, which are connected to problem solving [4]. There are many conceptions and opinion that have been taken out from the biological immune systems to develop new set of computer instructions to apply as authentic world engineering and scientific quandaries solver.

The external microorganism is defended by the immune system from attacking the human bodies, as it is the main role of the immune system. [4]. Two types of immune system immunity, which is innate and adaptive immune system. Both systems are formed of two main lines of defense in the immune system[5]. It is capable to nearly recognize any pathogen or foreign or molecules and eliminate them from body [6]. The main applications of AIS that had been done before are data mining [7], pattern recognition [8], anomaly detection [9] and scheduling [10]. AIS has three main algorithms which are clonal selection algorithm (CSA), immune network algorithm (INA) and negative selection algorithm (NSA) [11][12][13].

INA for the most part connected to manage dynamic circumstance and improvement emergency where NSA generally fruitful applying its methodologies in abnormality identification [14]. Clonal Selection Principle is satisfactory in taking care of the issue with respect to scheduling and optimization [14]. This study uses INA in AIS to foresee month to month streamflow data[1]. © 2006-2015 Asian Research Publishing Network (ARPN). All rights reserved.

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IMMUNE NETWORK ALGORITHM

The model of Immune Network Algorithm used in this study is aiNet (Artificial Immune NETwork) proposed by de Castro & Von Zuben [5]. The aiNet is appearance kind of AIS inspired by immune network theory firstly proposed by Jerne in 1974.

The important role of the immune network is to put into use data compression, which followed by the clonal selection and affinity maturation principles. The immune network theory assumes the activities of immune cells, memory appearances and telling the differences between our own cells (known as self) and external invader (known as non-self) [16].

The aiNet model comprises of a gathering of cells, antibody interconnect by connections with related association quality. The ainet antibodies speak to the system inner pictures of pathogens (data example), to which they are uncovered.

The associations among these antibodies center their interrelations with giving a level of similitude among themselves in the given metric space. The closer the antibodies, the more comparative they are. This methodology brings about a neutralizer arrange that, can perceive the antigens (input data set) with a flexible simplification. Besides, the ainet is likewise a connectionist framework, in which a grid of association qualities is characterized to gauge the affinities among the network cells. The learning algorithm focuses on building a memory set that can perceive and characterize to the structural association of the training data. Particularly, the suppression threshold controls the specificity level of the cells, clustering accuracy, and in addition network plasticity [16].



Figure-1. Dynamics of the immune system.

STREAMFLOW PREDICTION MODELLIG

Streamflow prediction model based INA is illustrated in Figure-2.



Figure-2. INA modeling framework.

In initialization, a small number of elements randomly created. Antibody is represented by Ab and receives as input a set of antigens, Ag in the immune network. Each antigenic pattern is represented by the following functions:

$$Ab = [Ab1, Ab2, \dots Abn]$$
(1)

$$Ag = [Ag1, Ag2, \dots Agn]$$
(2)

There were many methods to calculate the affinity measurements and this study obtained the affinity by measuring the Euclidean distance, D using Equation (3) and the n highest affinity antibodies are selected.

$$D = \sqrt{\sum_{i=1}^{n} (Ab_i - Ag_i)^2} \tag{3}$$

Ab is antibodies Ag is antigen

Next, the n selected antibodies is going to proliferate (clone) and proportionally to their antigenic affinity; generating a set A of clones. Those cells that have a low affinity measure will go through metadynamics process where they will be replaced by new antibodies.

The affinity among all the elements of the clonal memory set resolution in clonal interaction stage.

In the clonal suppression, those memory clones that are short of what the edge will be eliminated. In suppression stage, cell likeness gives a system in diminishing excess. At that point the remaining clones of the clonal memory fuse with all system antibodies structure system development.

Any comparable or non-empowered antibodies and antibodies that fall underneath the foreordained suppression limit will be removed in the network suppression. © 2006-2015 Asian Research Publishing Network (ARPN). All rights reserved.



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INA MODEL PERFORMANCE AND ANALYSIS

In this study, random data represent a set of antigen (Ag) while streamflow data represent a set of antibody (Ab). Streamflow data used in this study were in the form of monthly interval. In this study, monthly streamflow data were taken from JPS Ampang for Sg Johor station as the input data for simulation. The data is from May 1992 to April 2013.

The proposed model was trained using streamflow data (120 months) from Sg Johor station.

Validation stage of the model was carried out and new antigens were identified from the performance test. Lastly, new antigens were incorporated into the model for testing and prediction. This study uses MATLAB R2012a to design the structure of AIS algorithm. The performance of the model discussed as below.

INA model training

The proposed INA model was calculated through an RMSE of the Sg Johor station with ten iterations at each detector in streamflow data for 120 months. From the training, 600 numbers of detectors produced the lowest mean and the accuracy of the training results was 77.39%. The result was tabulated in Figure-3.



Table-1. Training results of aiNet.

Figure-3. Training of 10 runs RMSE for simulated data against a number of detectors.

INA model validation

At the training stage, the model was validated using 12 months from May-02 to April-03 for the Sg Johor station. The percentage of accuracy in the validation stage for the Sg Johor station is 97.19%. Based on the result, after identification of detectors is applied in the model, the validation results show an improvement of 20% accuracy of the output data.

The actual and predicted values are shown in Figure-4. From the graph it shows there is no huge difference between the predicted and actual values. The

minimum difference between the predicted and actual value is 0.170 while the maximum is 0.200.

Table-2. Validation results of aiNet.

Station	Sample	RMSE	Accuracy (%)
Sg Johor	12	0.233781	97.19



Figure-4. Validation performance for streamflow data in 12 months.

INA model performance testing

The Immune Network Algorithm Model is further investigated using the performance test such as R^2 , MAPE and RMSE indexes. As shown in Figure-5, the streamflow data of Sg Johor have recorded as 1. While RMSE and MAPE are found to be 0.0081 and 0.0617%, respectively.



Figure-5. Performance test obtained for streamflow data using proposed INA model.

In order to create new immune networks for prediction purposes, new antigens were obtained from the process of cross-validation. The proposed model went through cross-validation process from May-02 until April-03 (12 months). The results tabulated in Table-3. ©2006-2015 Asian Research Publishing Network (ARPN). All rights reserved.

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The simulated results were tested in 12 random trials to check the feasibility and accuracy of the proposed aiNet model.

 Table-3. Cross-validation of streamflow data for Sg Johor station.

No. of	Validation (May-02 to June-03) Average forecasting error		
trials			
1	0.294542		
2	0.201758		
3	0.176901		
4	0.203581		
5	0.181987		
6	0.209833		
7	0.160686		
8	0.181222		
9	0.163166		
10	0.172864		
11	0.139236		
12	0.181172		
Average	0.188912		

INA Model prediction testing

New antigens were recognized from model's training, performance test and cross-validation to predict future streamflow data. The new antigens are tabulated in Table-4 below.

Table-4. New antigen for streamflow prediction.

	Nonself
1	31.60
2	75.46
3	149.03
4	49.81
5	31.09
6	118.32
7	21.15
8	40.38
9	17.30
10	36.91
11	107.59
12	68.14

The new antigens were employed in the aiNet model and tested for streamflow data for 120 months (May-03 to April-13) as shown in Figure-6. The accuracy of the testing on Sg Johor is shown in Table-5. From the graph it shows there is no huge differences between the predicted and actual values. The minimum difference between predicted and actual value is 0.057 while the maximum is 0.064.



Figure-6. Actual and predicted streamflow data for Sg Johor station.

Table-5. Testing results of aiNet.

Station	Sample	RMSE	Accuracy (%)
Sg Johor	120	0.061669	92.60

The results show that the accuracy of the testing was more than 90%. The results show that the aiNet model developed was effective and capable to predict streamflow data for along time period.

INA model prediction

Figure-7 shows that the percentage of prediction for 10 years from January 2014 until December 2024. The adequacy of the AIS methodology show worthy results in streamflow prediction modelling which it has effectively made the best expectation strategy in demonstrating streamflow data at Sg Johor for more than 10 years.



Figure-6. Percentage of predicted streamflow data.

CONCLUSIONS

This paper proposed a new method for monthly streamflow prediction, Immune Network Algorithm (INA) which adapt from the biological immune system for one streamflow station which is a Sg Johor streamflow station. The result of the simulations shows the percentage of accuracy in the testing process between actual data and ©2006-2015 Asian Research Publishing Network (ARPN). All rights reserved.



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generated data in the range of 90%. This study has achieved its goal to develop and test the feasibility and accuracy of the monthly streamflow prediction model using an Artificial Immune System (AIS). In the future we will continue the same steps of prediction on another streamflow station and the percentage of accuracy will be calculated and compared.

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