APPLICABILITY OF ARTIFICIAL NEURAL NETWORK MODEL FOR SIMULATION OF MONTHLY RUNOFF IN COMPARISON WITH SOME OTHER TRADITIONAL MODELS

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ABSTRACT: *Artificial Neural Network (ANN) model along with Back Propagation Algorithm (BPA) has been applied in many fields, especially in hydrology and water resources management to simulate or forecast rainfall runoff process, discharge and water level - time series, and other hydrological variables. Several researches have recently been focusing to compare the applicability of ANN model with other theory-driven and data-driven approaches. The comparison of ANN with M5 model trees for rainfall-runoff forecasting, with ARMAX models for deriving flow series, with AR models and regression models for forecasting and estimating daily river flows have been carried out. The better results that were implemented by ANN model have been concluded. So, this research trend is continued for the comparison of ANN model with Tank, Harmonic, Thomas and Fiering models in simulation of the monthly runoffs at Dong Nai river basin, Viet Nam. The results proved ANN being the best choice among these models, if suitable and enough data sources were available.*

Key words: *artificial neural networks (ANNs); simulation; rainfall runoff model; monthly runoff; Tank model; Harmonic model; Thomas and Fiering model; Dong Nai river basin.*

1. INTRODUCTION

Many available techniques for time series analysis assume linear relationships among variables. In the real world, however, temporal variations in data do not exhibit simple regularities and are difficult to analyze and predict accurately. It seems necessary that nonlinear models such as artificial neural networks, which are suited to complex nonlinear systems, be used for the analysis of real-world temporal data [1]. There are numerous applications of ANNs in the field of water resources: application of ANN for deriving the rainfall-runoff relationship [2, 3, 4]; for rainfall forecasting [5]; for river runoff forecasting [6]; for flood forecasting at the upper reach of the Red river basin, North Vietnam [7]. Other applications of ANNs include regional flood frequency analysis [8], regional drought analysis [9], and so on. Hsu [10] compared ANNs with traditional methods to model rainfall-runoff process. Chibanga [11] compared the performance of ANNs with that of multivariate ARMA model in application to the monthly inflow forecast and to historical record of river flow time series. Campolo [12] applied an ANN to forecast the flooding behaviour of the river Tagliamento using rainfall and water level as the only inputs. In continuity of this trend, in this paper, the simulation of monthly runoffs at Tri An and Phuoc Hoa stations, in Dong Nai river basin, Viet Nam were implemented by using ANN models and then the results were compared with those from Tank, Harmonic and Thomas & Fiering models.

2. THREE- LAYER FEEDFORWARD ARTIFICIAL NEURAL NETWORK MODEL

Where processes to be modeled are complex enough to be described mathematically, neural networks are considered to outperform the conventional, deterministic models most of the time (www.stowa-nn.ihe.nl/Applications_Fuzzy _Logic.htm). And in other view of Kolmogorov's theorem [13] and Funahashi's work [14], it is now universally held that a three-layered ANN can serve as any continuous function approximator for as long as a sufficient number of hidden neurons is used. Given a training set of input-output data, the most common learning rule for multi-layer perceptrons is the back-propagation algorithm [1]. So, here, three-layer ANN with ten hidden nodes, using BPA method with multi-input variables, one output variable has been used to simulate the runoff process (Fig. 1). Details concerning to Back Propagation Neural Network can be obtained in reference [2].

In hydrology, the values of input can be causal variables such as rainfall, temperature, evaporation, water level, discharge, etc. at the previous or same period of output variable; at the various locations within the considered rivers or basin. The values of output can be hydrological responses such as runoff, water level, etc. The numbers of input nodes have strictly to be satisfied with that of causal input variables in relation to output targets. The relations between the output target variables and input variables in quantitative and causal qualitative have to be selected as appropriate as possible based on the physical meanings and relations of the problem to reduce the waste of computational and search time in training process [2].

The procedure for application of three-layer ANN model for generation of the monthly runoff at a station within the basin follows these steps:

- Select the input set of causal variables related to the target, monthly runoff, based on the physical meaning of the real world and/or using the correlation matrix for the study catchment area [11].
- Search for the appropriate structure of ANN: number of input variables, number of nodes in hidden layer, and the connection weights and biases by using the trial method and depending on the basis of the standards for statistic performances for training and testing stages.

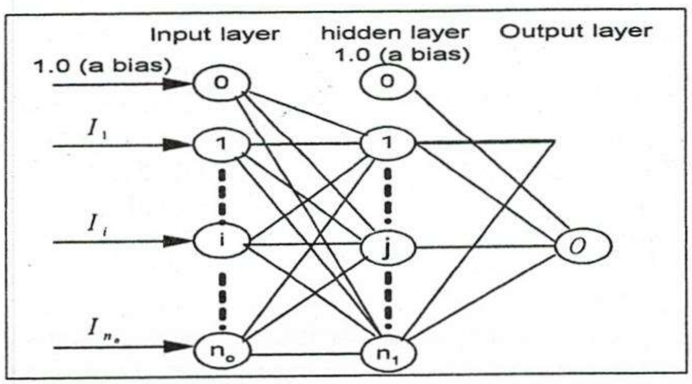

Fig 1. Three-layer feedforward ANN with one output variable

3. HARMONIC ANALYSIS MODEL

The periodicity of physical vibrations can commonly be found in natural phenomena. The water level in coastal river, seasonal rainfall and runoff, etc. may be thought as the illustrations. Actually, runoff in a river includes three principal components, namely *trend, periodicity* and *randomness*. The trend is due to human activity in their use of water such as diversion and/or extraction of water for irrigation, water supply etc., by the channel-construction, or deforestation within the basin. The trend component can be eliminated through adding the diversion to measured data. Then, the runoff can be investigated as a synthesis of periodicity and randomness. If the contributing level of randomness is not so high, then *harmonic analysis* through using the Fourier series can be applied to study the runoff phenomenon for generating the flow as described by the following equation:

$$Q_t = \frac{1}{T}\sum_{i=1}^{T} F_i + \sum_{k=1}^{N} C_k.Sin(\frac{2.\pi}{T_k}.t + \phi_k) \qquad (1)$$

Where, Q_t is the calculated monthly discharge; F_i is measured monthly discharge. The first term of RHS is the mean discharge; the second term of RHS describes the periodic sinusoidal vibrations of sub-harmonic components. The values of component number (N), period (T_k), amplitude (C_k) and phase (ϕ_k) of each sub-harmonic component have to be determined during the modeling process. Various search technique can be applied to obtain the fittest solution, such as Genetic Algorithm (GA), other local search approaches, or even the trial approach. The GA or other search techniques requires the setting-up of algorithm and programming. The trial approach usually takes time and effort to get the fittest solution. Therefore, in present study, a proposed approach was done for searching the solution. The search method is as follows:

(i) Introduction of a combination of N sub-harmonic component with given set of T_k was started out. During this process, the basic period of 12 months due to seasonal rainfall phenomenon should firstly be considered. The standard deviation of historic monthly runoff data could be used as the amplitude to this component at the starting point.

(ii)The process was continued by searching for C_k and ϕ_k such that the Root Mean Square Error (RMSE) of the simulated values compared with the measured data was minimum:

$$Min\left\{\sqrt{\frac{\sum_{i=1}^{T}(F_i - Q_i)^2}{T}}\right\} \qquad (2)$$

$$C_k \geq 0; \forall k = 1..N \qquad (3)$$

$$Q_i \geq Q_{\min}; \forall i = 1..T \qquad (4)$$

Constraints:

Where, Q_{min} being an absolutely minimum value of monthly runoff might occur at the considered station. This value being a positive number was assumed based on the historic monthly runoff series at that station (F_i) based on the statistical theory. The constraint (4) was added to avoid the calculated monthly runoff being negative (not reasonable due to the nature of monthly runoff) during the search process.

(iii) The combination of sub-harmonic component was changed step by step, by adding one more component of T_k. Then, the repetition of calculation process can be restarted from step (ii).

This repetitive calculation process would be stopped whenever the value of RMSE was not able to decrease anymore.

An MS EXCEL program has been written for convenient adjustment of the calculated curve to obtain the better fit to the recorded one. The *automatically graphical show* and the *value of Root Mean Square Error (RMSE)* for trial cases can be shown promptly during the solution search process.

4. THOMAS AND FIERING MODEL

The formula to simulate monthly runoff for Thomas and Fiering [15] model include two portions. The first is fixed portion. It is created from the historic data and their statistic characteristics. For monthly flow, the periodicity with basic period of year was considered. Then, the statistic characteristics of each month were used to create this fixed portion of the flow with zero value of normally distributed random number (u=0). The second portion of monthly runoff is the random one. It is used to describe the randomness of monthly runoff for each month whenever the generated monthly runoff is being calculated. The governing equation is as follows:

$$Q(i,j) = Q_{av}(j) + b(j).(Q(i,j-1) - Q_{av}(j-1)) + S(j)\{1-[r(j)]^2\}^{1/2}.t \qquad (5)$$

where, Q(i,j) is the discharge during the j th month of the i th water year in a generated sequence, reckoned from the start of synthesized sequence; $Q_{av}(j)$ is mean historic monthly discharge during the j th month (j: 1..12 for Jan. to Dec.); b(j) is the regression coefficient for estimating flow in the j th month from (j-1) th month; S(j) is the standard deviation of flows in the j th month; r(j) is the correlation coefficient with flow in preceding month; t is the standard normal variable which changes its value each time the equation is applied. In Eq. (5), values of j can be applied from 2 to 12. In the case j=1, then j-1 is taken by using month December (j=12) of the previous year. The statistic parameters can be found in reference [16].

5. TANK MODEL

Tank model was proposed by Prof. M. Sugawara, in Japan, in year 1956's for simulation of flood flow. It was modified and improved, thereafter and applied in many places in the world. The procedure of simple Tank model is presented in Fig. 2.

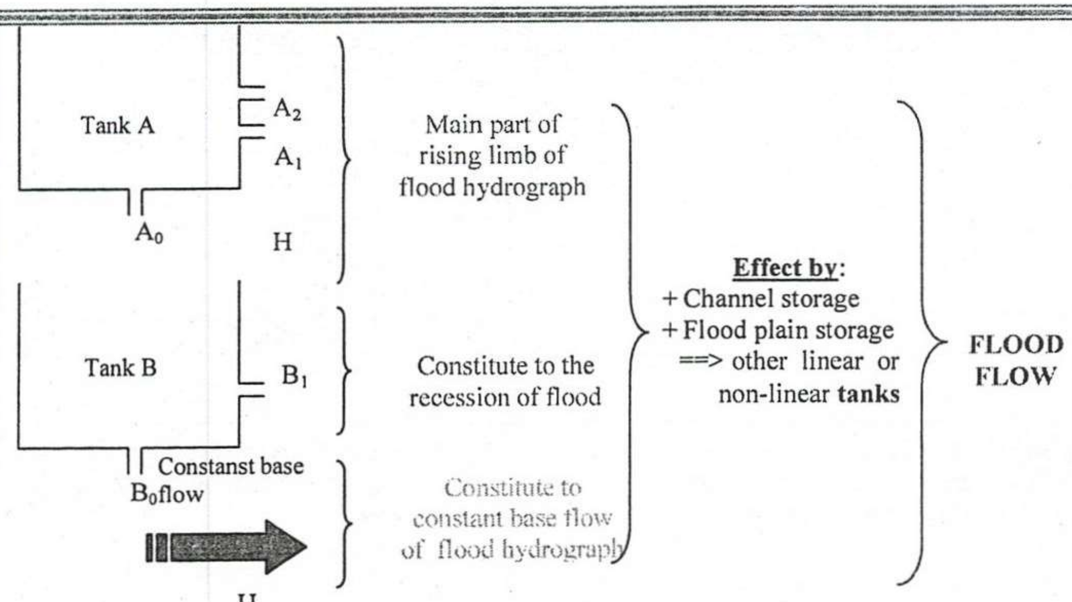

Fig 2. Sketch of Tank model

Due to deformation of the river, channel storage and over-bank flow, the output of Tank model should be modified by introducing another Tank (linear or non-linear) and even the consideration of channel storage and flood plain storage effects should be taken. It may be recognized that the input variables of Tank model include rainfall, evaporation. These are the variables that directly cause the runoff. Beside, Tank model also consider other physical factors, such as the infiltration, drainage area, base flow and a mechanism to simulate the physical phenomenon of rainfall runoff. The theoretical aspects of Tank model can be referred to Tank program [9, 17, 18, 19, 20].

6. APPLICATION OF RAINFALL-RUNOFF MODELS

6.1. Dong Nai river basin

Dong Nai River (DNR) basin is located in the South of Viet Nam. Its inland river system, with a total length of 635 km, is the largest in the nation. The catchment area of DNR basin is 37,400 km^2 and the average annual flow that drains into the sea, is 31 billions cubic meters. This area is in the tropical monsoon zone with two distinct wet and dry seasons in a year. The wet season is from May to October and the dry season is from November to April [21]. Two runoff stations at Tri An and Phuoc Hoa were studied in this river basin. Tri An runoff is the inflow source of the Tri An reservoir. Its mean monthly runoff and standard deviation during the year are shown in Fig. 3.b. Other statistic parameters are shown in Fig. 3a, as well. Phuoc Hoa monthly runoff is one of the main sources that supply water for Ben Than treatment plant, and for irrigation of Lower Dong Nai river basin through Sai Gon river. Its mean monthly runoff and standard deviation and other statistic parameters are shown in Fig. 4b and Fig. 4a, respectively.

Thereinafter, the above mentioned models were utilized to simulate the monthly runoffs at Tri An and Phuoc Hoa stations. Then the comparison and analysis of their simulated results are carried out. And, the conclusion on ANN model is finally conducted.

6.2. Availability and arrangement of data for simulation

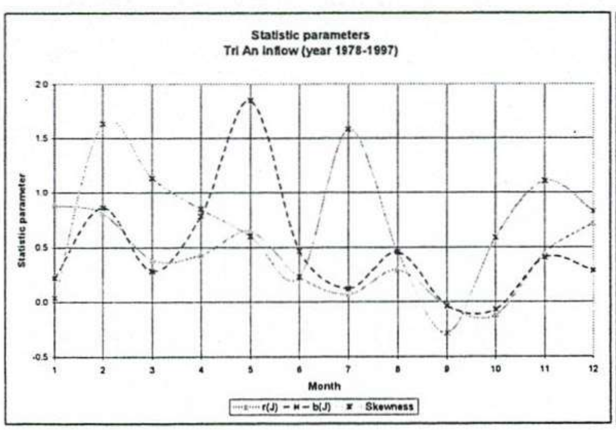

Fig 3a. Correlation coefficient, **r(j)**; coefficient of the regression, **b(j)**; and **skewness** of monthly runoff at Tri An station

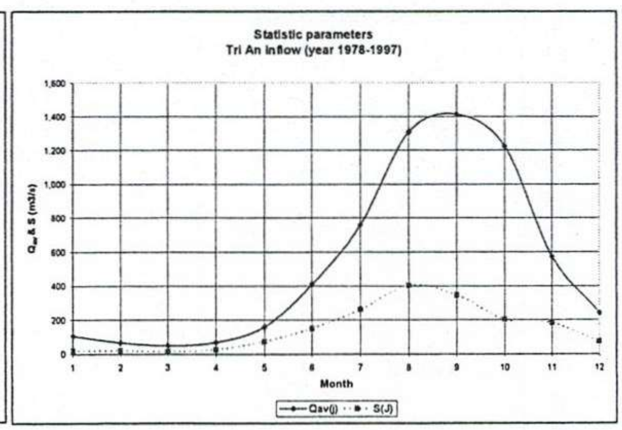

Fig 3b. Mean, **Q_{av}(j)** and standard deviation, **S(j)** of monthly runoff at Tri An station

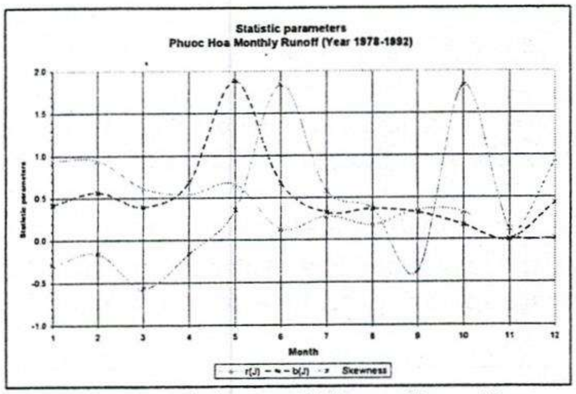

Fig. 4a. Correlation coefficient, **r(j)**; coeffient of the regression, **b(j)**; and skewness of monthly runoff at Phuoc Hoa station

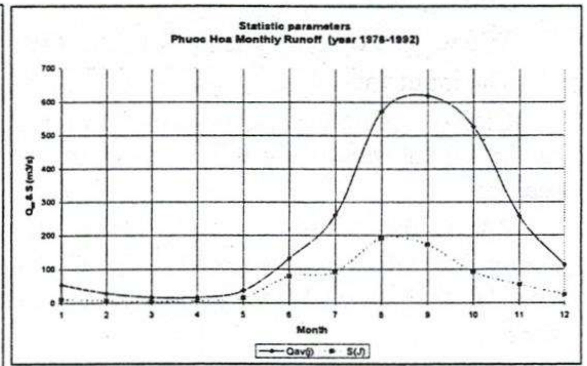

Fig.4b. Mean, $\mathbf{Q_{av}(j)}$ and standard deviation, **S(j)** of monthly runoff at Phuoc Hoa station

6.2.1. Measured data

At Tri Ân runoff station: available data from 1/1978 to 12/1986, and from 1/1989 to 12/1997.

At Phuoc Hoa runoff station: available data from 1/1978 to 12/1992

6.2.2. Simulated monthly runoff using Tank model by Jica

At Tri An station: simulated data is available from 1/1978 to 12/1986

At Phuoc Hoa station: simulated data is available from 1/1978 to 12/1992

6.3. Segmentation of time periods for monthly runoff simulation

6.3.1. Calibration stage

The 108 months from 1/1978 to 12/1986 for both Tri An and Phuoc Hoa stations were used for training phase to search for the suitable structure of ANN model, including appropriate input set and reasonable connection weights and threshold values. This period was also used for calibrating phases for Harmonic and Thomas and Fiering models.

6.3.2. Validation stage

At Tri An runoff station: including 36 months from 1/1989 to 12/1991

At Phuoc Hoa runoff station: including 72 months from 1/1987 to 12/1992.

These data were used for testing phase after the structure of ANN model had been completely trained. And, they were also used for Harmonic and Thomas & Fiering models for validation.

6.4. ANN model

Using trial method to search for the best combination of input set by comparing the performance of various alternatives based upon the statistic parameters. Finally, the input set of ANN model at two runoff stations were obtained.

6.4.1. Tri An monthly runoff

Qta(t) = f[Qta(t-1), Rdg(t), Rtt(t), Rdp(t), Rpl(t), Rdat(t), Rbl(t), Rdl(t), Rlk(t), Rdla(t), Rdd(t), Rtp(t), Rxl(t)] (6)

Where, The output variable: Qta(t) is the monthly discharge in month t, at Tri An station;

The input variables:

Qta(t-1): monthly discharge in month t-1, at Tri An station. This previous monthly runoff of the output variable was used here to simulate the base flow in month t during the dry seasons.

Rdg(t), Rtt(t), Rdp(t), Rpl(t), Rdat(t), Rbl(t), Rdl(t), Rlk(t), Rdla(t), Rdd(t), Rtp(t), Rxl(t): are respectively monthly rainfall at Dau Giay, Tuc Trung, Dong Phu, Phuoc Long, Date, Bao Loc, Di Linh, Lien Khuong, Da Lat, Don Duong, Ta Pao, Xuan Loc stations within DNR basin.

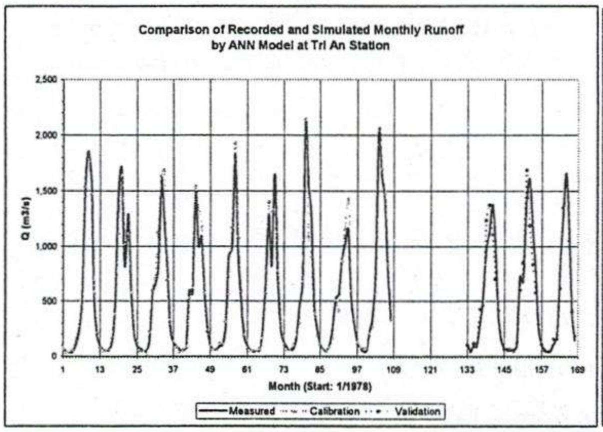

Fig 5a. Calibrated and validated monthly runoff by ANN model at Tri An station

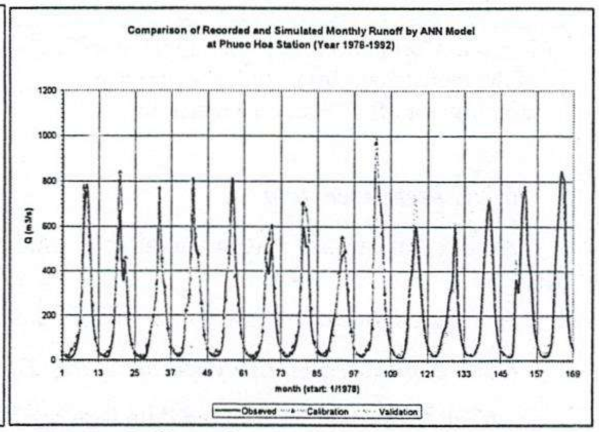

Fig 5b. Calibrated and validated monthly runoff By ANN model at Phuoc Hoa station

So, there are 165 connection weights required to be trained to describe the structure of ANN model to simulate suitably the rainfall runoff phenomenon at Tri An station.

6.4.2. Phuoc Hoa monthly runoff

Qph(t) = f[Qph(t-1), Qpl(t), Rpl(t), Rdp(t), Rbil(t)] (7)

Where, The output variable: Qph(t) is the monthly discharge in month t, at Phuoc Hoa station;

The input variables:

Qph(t-1): monthly discharge in month t-1, at Phuoc Hoa station to simulate the base flow in month t during the dry seasons.

Qpl(t): monthly discharge during the same month (t) at Phuoc Long station, upstream of Phuoc Hoa station, was included in the input set to describe the correlation of monthly discharge between two stations in the same month and the same river.

Rpl(t), Rdp(t), Rbil(t) are respectively monthly rainfall at Phuoc Long, Dong Phu and Binh Long stations within the Be river catchment area.

Therefore, there were 71 connection weights needed to be trained to describe the structure of ANN model to simulate suitably the rainfall runoff phenomenon at Phuoc Hoa station. The comparison between recorded monthly runoff and simulated results for training and testing stages at Tri An and Phuoc Hoa stations are presented in Fig. 5a and Fig. 5b. The values of RMSE, Root Mean Square Error Mean (RMSEM), Mean Absolute Deviation (MAD), RMSES

(Root Mean Square Error over Standard Deviation) and Efficiency Index (EI) for training and validation stages for both stations obtained by ANN are shown in the Table 1, 2, 3 and 4.

6.5. Tank model

The simulated monthly runoffs at Tri An and Phuoc Hoa stations, that were calculated using Tank model by Jica, were used for comparison with the results from other models.

Briefly, Tank model configuration used by Jica included 4 columns in horizontal direction. In each column, there were 4 tanks. Each tank, there were two holes, one for side and one for bottom to allow the water drain out to next tank or lower tank for simulation of runoff (including overland flow and infiltration). There almost were 64 parameters used to describe this model scheme, here. The simulated monthly runoffs by TANK model [21] for Tri An and Phuoc Hoa stations are presented in Fig. 6a and Fig. 6b. The statistic parameters for simulation by Tank model are also shown in the Table 1, 3 and 4.

6.6. Harmonic analysis

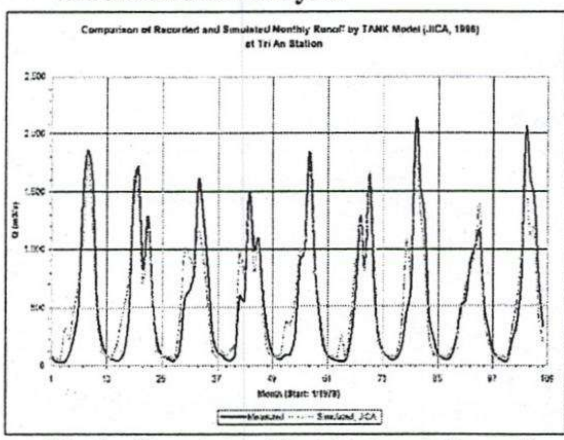

Fig. 6a. Recorded and Simulated monthly runoff by TANK model (JICA, 1996) at Tri An station

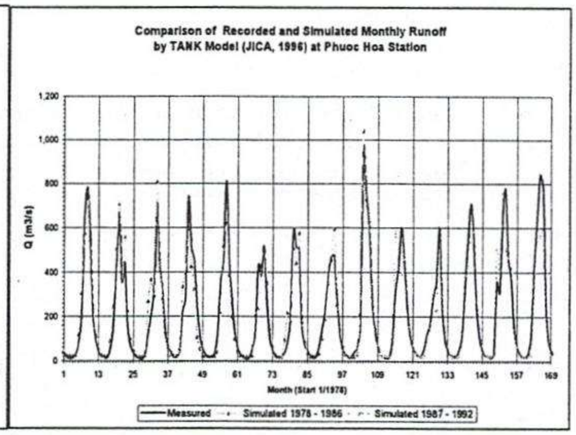

Fig. 6b. Recorded and Simulated monthly runoff by TANK model (JICA, 1996) at Phuoc Hoa station

6.6.1. The simulation results at Tri An station

The Q_{av} stands for the first term, $\frac{1}{T}\sum_{i=1}^{T} F_i$ in the RHS of Eq. 1 that is the average of historic monthly runoff, 542.01 m^3/s. After searching, all the sub-harmonic components were reached, and the simulated monthly runoff was shown in Fig. 7a. The bottom and middle levels of monthly runoff curves at these stations strongly have the characteristic of periodicity, during period of the dry season. The characteristic of periodicity and less randomness during these months is also revealed in Fig. 3b. During this period, the values of standard deviation of monthly runoff are very low. The top portions of monthly runoff curves depend on the rainfall. Therefore, they strongly have the characteristic of randomness during the rainy season. So, if the trial increases in amplitude of sub-harmonic components were implemented to catch these top portions of curves, then the values at the bottom will not satisfy the constraint (4), and even they may become negative, not reasonable.

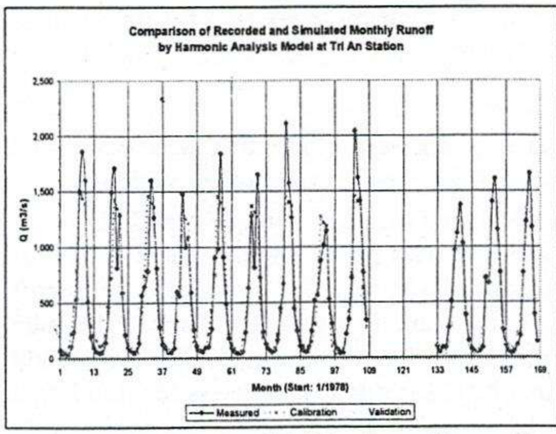

Fig. 7a. Calibrated and Validated monthly runoff By Harmonic Analysis model at Tri An station

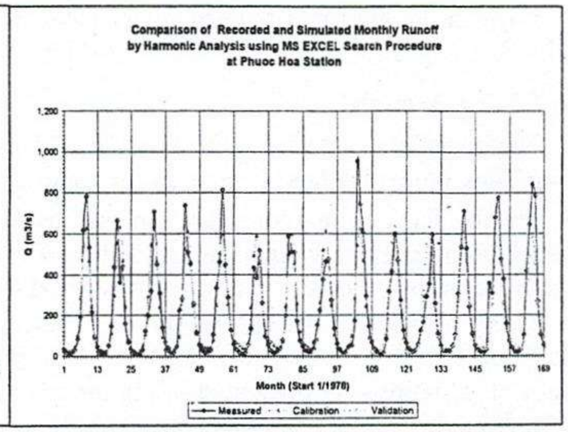

Fig. 7b. Calibrated and Validated monthly runoff By Harmonic Analysis model at Phuoc Hoa station

6.6.2. The simulation results at Phuoc Hoa station

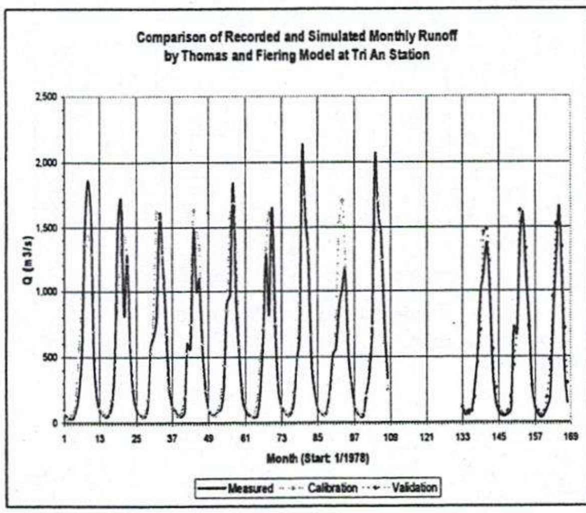

Fig. 8a. Calibration and validation of simulated Monthly ff by Thomas & Fiering model at Tri An station

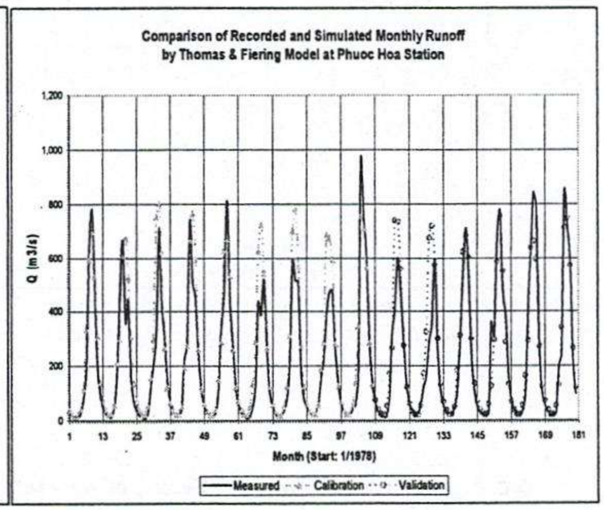

Fig. 8b. Calibration and validation of simulated Monthly runoff by Thomas & Fiering model at Phuoc Hoa station

The mean discharge at Phuoc Hoa station Q_{av} is 209.21 m^3/s. After using EXCEL program searching for the expected combinations of sub-harmonic components, satisfying two constraints (3) and (4) and trying to gain the RMSE value of simulated monthly runoff as low as possible, the parameters of these sub-harmonic components are finally obtained and the simulated monthly runoff are presented in Fig. 7b. Similar to the Tri An case, the characteristics of periodicity revealed on the bottom and middle levels, and the tops of the monthly runoff curves revealed the characteristic of randomness.

6.7. Thomas and Fiering model [15]

As seen in Eq. 5, the monthly runoff in month j, in year i depends on the mean monthly runoff in month j, $Q_{av}(j)$; the mean monthly runoff in month j-1, $Q_{av}(j-1)$; the regression coefficient of monthly runoff in month j with that in previous month, b(j); the standard deviation of monthly runoff in month j, S(j); the correlation coefficient of monthly runoff in month j with that in previous month, r(j). These values are constants for each historic time series data set. The simulated monthly runoff time series will depends on the starting monthly runoff and the random numbers, namely the standard normal variable, changing its value between 0 and 1. In this model, monthly rainfall data within the basin were not included.

Therefore, simulated monthly runoff may not follow closely recorded monthly runoff since the random characteristic of rainfall during the rainy season (from July to October) when standard deviation is high, as shown in Fig. 3b and Fig. 4b. Similar to Harmonic Analysis model, characteristics of periodicity revealed on bottom of monthly runoff curve during the dry season. So, its simulated values follow closely with the recorded ones. However, at top portions, its simulated values can not catch well with the recorded curve as shown in Fig. 8a and Fig. 8b.

6.8. Comparison and evaluation of simulated results of the ANN and other traditional model.

The performance statistics on resulting monthly runoffs by four models at both Tri An and Phuoc Hoa stations are shown in Tables 1, 2, 3 and 4. Compare these values and analyze the graphs in the above figures, the conclusions can be obtained as follows:

Table 1. Performance statistics on resulting monthly runoffs at Tri An, calibration stage

Kind of Model		EI	RMSE (m3/s)	RMSEM	MAD (m3/s)	RMSES
ANN		0.946	131.180	0.242	76.942	0.234
Tank (simulated by Jica)		0.833	197.947	0.365	145.486	0.353
Thomas & Fiering	*Min*	0.798	222.565	0.411	128.594	0.397
	Random	0.826	235.883	0.435	144.966	0.420
	Max	0.790	293.356	0.541	192.528	0.523
Harmonic Analysis		0.840	205.302	0.379	131.318	0.366

Table 2. Performance statistics on resulting monthly runoffs at Tri An, validation stage

Model		EI	RMSE (m3/s)	RMSEM	MAD (m3/s)	RMSES
ANN		0.902	155.498	0.294	104.069	0.295
Thomas & Fiering	*Min*	0.939	122.294	0.231	85.501	0.232
	Random	0.925	147.899	0.279	109.436	0.280
	Max	0.850	248.998	0.471	180.854	0.472
Harmonic Analysis		0.920	142.291	0.269	109.280	0.270

Table 3. Performance statistics on resulting monthly runoffs at Phuoc Hoa, calibration stage

Model		EI	RMSE (m^3/s)	RMSEM	MAD (m^3/s)	RMSES
ANN		0.965	45.260	0.216	27.270	0.198
Tank (simulated by Jica)		0.924	62.114	0.297	40.934	0.272
Thomas & Fiering	*Min*	0.854	82.676	0.395	47.762	0.362
	Random	0.838	102.769	0.491	60.980	0.449
	Max	0.802	128.376	0.614	75.033	0.561
Harmonic Analysis		0.837	83.080	0.397	51.691	0.363

Table 4. Performance statistics on resulting monthly runoffs at Phuoc Hoa, validation stage

Model		EI	RMSE (m3/s)	RMSEM	MAD (m3/s)	RMSES
ANN		0.971	41.062	0.175	25.863	0.165
Tank (simulated by Jica)		0.825	90.456	0.385	55.808	0.364
Thomas & Fiering	*Min*	0.823	91.157	0.388	50.621	0.367
	Random	0.848	97.549	0.415	54.281	0.393
	Max	0.833	115.783	0.493	65.328	0.466
Harmonic Analysis		0.741	104.706	0.446	62.895	0.422

- The simulated monthly runoffs for all models showed the good fitness at the bottom and the middle of the monthly runoff curves. And, some large deviations at the top level occurred due to the randomness caused by rainfall during rainy season.

- For simulation of monthly runoff at Tri An and Phuoc Hoa stations, all models may be used. ANN obtained highest fitness to the measured monthly runoff curves, except at Tri An station, in validation stage from 1989 to 1991. For validation stage at Tri An station, the simulated results by ANN not better than other models may be due to some changes in the causal relations between output monthly discharge and input monthly rainfalls, such as the changes in ground surface plant covers, or some human activities within the basin: deforestation, dam construction, etc. within the period from 1987 to 1988, or due to other random variables that may not be included in the input layer of ANN model. The fitness for Tank model is ranked the second. However, Both ANN and Tank models required much more data including both monthly discharges and rainfalls at various stations within the basin.

- The fitness obtained by Harmonic and Thomas & Fiering approaches was somewhat lower than two above-mentioned models but they did not require so much data for simulation. Just historic monthly discharge data at considered station were included. No rainfall data within the basin were required. Therefore, in the case missing or not enough data, especially rainfall data, and reasonable accuracy required, Harmonic Analysis is preferred. However, it has to be supported by Search Procedure for obtaining the fittest solution. Thomas & Fiering model also obtained the necessary fitness to the measured data. However, it required more data than Harmonic Analysis because of the requirement of statistic calculation. Besides, the discharge time series simulated by Thomas & Fiering model depends on the randomness, each time it is created.

7. CONCULSION

Since limit on the available data and resources, this research has been conducted just for two runoff stations. However, following the recent research trends, this research proved that the ANN model may continuously be confirmed its value and role for simulation of monthly runoff. It is clearly better than other traditional models, namely Tank, Thomas & Fiering, and Harmonic models. In order to get rather general conclusions on the capability and efficiency of ANN model for monthly runoff simulation, more additional researches should continuously be implemented for the Dong Nai river basin.

ÁP DỤNG MÔ HÌNH MẠNG THẦN KINH NHÂN TẠO ĐỂ MÔ PHỎNG DÒNG CHẢY THÁNG VÀ SO SÁNH KẾT QUẢ VỚI CÁC MÔ HÌNH TRUYỀN THỐNG KHÁC

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TÓM TẮT: *Mô hình mạng thần kinh nhân tạo (ANN) dùng giải thuật lan truyền ngược (BPA) đã được áp dụng trong nhiều ngành, đặc biệt trong ngành thủy văn và quản lý nguồn nước, để mô phỏng hoặc dự báo tiến trình dòng chảy do mưa, chuỗi lưu lượng và mực nước theo thời gian và các biến thủy văn khác. Gần đây, một số nhà nghiên cứu tập trung so sánh năng lực áp dụng của mô hình ANN với những giải pháp dùng phương pháp lý thuyết hoặc phân tích dữ liệu khác. Nhiều nghiên cứu đã tiến hành so sánh mô hình ANN với mô hình cây M5 để dự báo dòng chảy do mưa, so sánh với mô hình ARMAX để tìm chuỗi dòng chảy, so sánh với mô hình AR và mô hình hồi quy để dự báo và thẩm đoán dòng chảy ngày ở các sông. Kết luận so sánh cho thấy mô hình ANN đạt được kết quả tốt hơn. Vì vậy, để tiếp tục xu hướng nghiên cứu này, bài báo đã thực hiện việc so sánh mô hình ANN với các mô hình Tank, Harmonic và Thomas & Fiering khi áp dụng để mô phỏng dòng chảy tháng ở lưu vực Sông Đồng Nai, Việt Nam. Kết quả cho thấy, mô hình ANN là một phương án chọn lựa tốt nhất nếu có nguồn dữ liệu đầy đủ và thích hợp.*

Từ khóa: *Mạng thần kinh nhân tạo (ANNs); mô phỏng; mô hình dòng chảy do mưa; dòng chảy tháng; mô hình TANK; mô hình điều hòa; mô hình Thomas và Fiering; lưu vực Sông Đồng Nai.*

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