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RESEARCH ON SUITABLE TIME STEP TO FORECAST TRI AN RESERVOIR INLFOW IN DONG NAI RIVER BASIN USING ARTIFICIAL NEURAL NETWORK MODEL

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***Abstract*—Artificial Neural Network (ANN) model has been successfully being used to predict the river flow for rainfall-runoff process. The important question including how long the forecasting time step should be, which rainfall stations should be selected, which discharge and rainfall data at different time steps should be used for the input layer most suitably to forecast reservoir inflow with highest accuracy. Focusing these questions, hereinafter, ANN model was used to forecast inflow into Tri An reservoir in Dong Nai River Basin, Vietnam. Research results showed that six main rainfall stations including Bao Loc, Da Lat, Da Te, Di Linh, Dai Nga, Lam Dong; and the inflows into Tri An reservoir at current and previous time steps, directly affected forecasting inflow; and the appropriate time step to forecast the inflow into Tri An reservoir is from 7 days to 10 days. This is shown by the accuracy, Efficiency Index (EI) in network training period obtaining 90.83% and 89.65%, respectively; and in network testing phase obtaining 92.15% and 77.43%, respectively**

***Keywords*- artificial neural network model, forecasting reservoir inflow, Tri An reservoir inflow, Dong Nai River Basin, n-day-ahead inflow discharge, appropriate time step.**

I. Introduction

Chih-Chieh Young and Wen-Cheng Liu [1] studied predicts n-h-ahead runoff discharge in the Sandimen basin in southern Taiwan using a novel hybrid approach which combined a physically-based model (HEC-HMS) with an Artificial Neural Network (ANN) model. Hourly runoff discharge data (1200 datasets) from seven heavy rainfall events were collected for the model calibration (training) and validation (testing). Six statistical indicators (i.e. mean absolute error, root mean square error, coefficient of correlation, error of time to peak discharge, error of peak discharge and coefficient of efficiency) were employed to evaluate the performance. In comparison with the HEC-HMS model, the single ANN model, and the time series forecasting (ARMAX) model, the developed hybrid HEC-HMS–ANN model demonstrated improved accuracy in recursive n-h-ahead runoff discharge prediction, especially for peak flow discharge and time.

Forecasting of river discharge is crucial in hydrology and hydraulic engineering owing to its use in the design and management of water resource projects. The problem is customarily settled with data-driven models. Here, Xiao-yun Chen, et al. [2] have proposed a novel hybrid model which combines continuity equation and fuzzy pattern-recognition concept with artificial neural network for downstream river discharge forecasting in a river network at Yellow River, Georgia, USA. Time-varying water storage in a river station and fuzzy feature of river flow are considered accordingly. To verify the proposed model, traditional ANN model, fuzzy pattern-recognition neural network model, and hydrological modeling network model have been employed as the benchmark models. The root mean squared error, Nash–Sutcliffe efficiency coefficient and accuracy are adopted as evaluation criteria. Results indicated that the proposed hybrid model delivered better performance, which can effectively improve forecasting capability at the studied station. It was, therefore, proposed as a novel model for downstream river discharge forecasting because of its highly nonlinear, fuzzy and non-stationary properties.

In Taiwan, owing to the nonuniform temporal and spatial distribution of rainfall and high mountains all over the country, hydrologic systems are very complex. Therefore, preventing and controlling flood disasters is imperative. Nevertheless, water level and flow records are essential in hydrological analysis for designing related water works of flood management. Due to the complexity of the hydrological process, reliable runoff is hardly predicted by applying linear and non-linear regression methods. Therefore, S M Chen et al. [3] proposed a model for estimating runoff by using rainfall data from a river basin, and a neural network technique to recover missing data. For achieving the objectives, hourly rainfall and flow data from Nanhe, Taiwu, and Laii rainfall stations and Sinpi flow station in the Linbien basin were used along with the utilization of data records of 27 typhoons between the years 2005 and 2009. The Feed Forward Back Propagation (FFBP) network and Conventional Regression Analysis (CRA) were employed to study their performances. From the statistical evaluation, it has been found that the performance of FFBP exceeded that of regression analysis as reflected by the determination coefficients $R2$, which were 0.969 and 0.284 for FFBP and CRA, respectively.

Five ANN model versions were developed by Rafa H. Al-Suhili and Rizgar A. Karim [4] for the daily inflow forecasting to Dukan reservoir in Iraq. These models are dependent on the preceding days' lags (1, 2, 3, 4, and 5), respectively. The model versions forecasting correlation coefficients were found to be (94.6%, 94.6%, 95.2%, 95%, and 73%), respectively. The third model was used for forecasting and found capable of forecasting long term daily inflow series of the Dukan reservoir. And, it was found also capable of preserving the high and low persistence of this series in addition to the perfect simulation of the recession part and time to peak of the hydrograph.

Chuthamat Chiamsathit et al. [5] used multi-layer perceptron (MLP) artificial neural networks to forecast one-month-ahead inflow for the Ubonratana reservoir, in Thailand. To assess how well the forecast inflows have performed in the operation of the reservoir, simulations were carried out guided by the systems rule curves. As basis of comparison, four inflow situations were considered: (1) inflow known and assumed to be the historic (Type A); (2) inflow known and assumed to be the forecast (Type F); (3) inflow known and assumed to be the historic mean for month (Type M); and (4) inflow was unknown with release decision only conditioned on the starting reservoir storage (Type N). Reservoir performance was summarized in terms of reliability, resilience, vulnerability and sustainability. It was found that Type F inflow situation produced the best performance while Type N was the worst performing. This clearly demonstrated the importance of good inflow information for effective reservoir operation.

Faridah Othman and Mahdi Naseri [6] used ANN with 4 nodes in input layer and 5 neurons in hidden layer, and 1 node in the output layer to forecast the monthly inflow into Sultan Mahmud hydropower reservoir in Malaysia, using 21 years of historical monthly flow. The result showed that the Mean Squared Error (MSE) being 0.0188 and Correlation Coefficient (CC) being 0.7282 for training period; and MSE = 0.0283 and CC=0.7228 for testing period.

It is recognized that these researches mainly focused on demonstrating the usability of the ANN model for predicting and simulating the runoff flow originated from rainfall in a river basin; comparison between ANN model and other traditional models; coordinating it with the models having physical nature to improve forecasting efficiency. And clearly, each author applied the ANN model with different time steps: *hour, n-hour, day, month, etc*. The researches that concentrated on using ANN model to assess the accuracy of the flow forecast results that depended on the terrain conditions, geology of the basin, and the adequacy of the hydrometeorological stations as well as the time step, were found still a little. Therefore, in order to further raise awareness and appreciation of ANN model, hereinafter, this paper focuses on the accuracy of forecasting inflow into Tri An reservoir in Dong Nai River Basin, Vietnam, and its dependence due to time step.

Dong Nai River is the longest inland river in Vietnam, the second largest river basin in the South of Country, just behind the Mekong River basin. At upstream Tri An Reservoir, Dong Nai River flows through Lam Dong, Dak Nong, Binh Phuoc and Dong Nai provinces; and at downstream Tri An Reservoir, it passes through Binh Duong province and Ho Chi Minh City. Its length is of 586 km, computed from the head of the Da Dang River. Its whole catchment area is of 38,600 km²; and just 14,900 km^2, if computed to Tri An Reservoir. The mainstream of Dong Nai River in the upstream is called Da Rang River. The river originates from Lam Vien plateau, bending in the direction of the northeast - southwest from the mountainous region to the plateau of Ta Lai (Tan Phu District, Dong Nai province). The river is the natural boundary between Dak R Lap (Dak Nong, Province) and Bao Lam-Cat Tien (Lam Dong Province), between Cat Tien and Bu Dang (Binh Phuoc Province) -Tan Phu, between Tan Phu and Da Te (Da Teh) [7].

Dong Nai River upstream is named Da Dung, after the confluence with Da Nhim River, the river is called Upper Dong Nai; from there to the confluence with Saigon River, the river officially named Dong Nai River. Dong Nai River, south of Truong Son Range of Mountains with peaks of over 2000m, such as Lam Vien: 2167 m, Bi Doup: 2287 m, etc. The river source has a slope of 20-25%, having coordinates 108^o.42'.10"E and 12^o.12'.10"N, the average height of the watershed area is about 1700 m. From the source to the mouth of Xoai Rap River, Dong Nai River has an average slope of about 2.8 ‰ [8].

Figure 1: Tri An Reservoir, Dong Nai River Basin & Rainfall Stations

II. The ANN model structure used for forecasting inflow into Tri An reservoir

In this paper, ANN model with Back Propagation Neural Network (BPNN) algorithm is applied for training to predict the inflow into Tri An reservoir. Time period from February 1978 to November 1987 is applied for this phase. To assess the effectiveness of the model, data from February 1989 to November 1991 were used to test the trained network. The source of historical hydrometeorological data were taken from document [9]. To compare the predictive efficiency of ANN model with respect to time step, five time-steps: 1-day, 7-day, 10-day, 15-day and 1-month were proposed for examination.

For each time step, different ANN structures (Alternative, ALT) were used for training and testing the network in order to select the most efficient structure. These structures were described as follows:

QTriAn(t+1) = f[QTriAn(t), QTriAn(t-1), .., QTriAn(t-k), R_Baoloc(t), R_Dalat(t), R_DaTe(t), R_DiLinh(t), R_DNga(t), R_LDong(t)]

Where, $k \in [0..5]$.

This means the input layer always included the current time's rainfall (t) of 6 rainfall stations in Dong Nai River basin namely, Bao Loc, Da Lat, Da Te, Di Linh, Dai Nga and Lam Dong; and the inflow into Tri An reservoir at current time step (t); and those with previous time steps including (t-1), (t-2),... (t-k) as shown in Table 1.

The algorithm consists of two phases: forward computation and back propagation. Criteria for evaluating the accuracy of forward phase is:

$$E_p = \frac{1}{2}\sum_{j=1}^{n_L}\left(t_j - O_{j,L}\right)^2 \qquad (1)$$

Here, n_L is the number of nodes in the output layer, t_j is the target value at node j, in output layer L, and $O_{j,L}$ is the computed value at node j, in output layer L; E_p is a half of sum of squared error between the computed value and the target value for a computed sample.

Thus, the total sum of the squared errors for all samples (p) is calculated as:

$$E = \sum_p E_p \qquad (2)$$

Suitable structure of ANN model for prediction is found when:

$$E < \varepsilon \qquad (3)$$

Here, ε is the allowable sum of the squared errors, and is taken as 0.0001.

Algorithm describes two phases of forward and backward computation for BPNN can be referenced in Duc [9].

The ANN structure, used in this study, is as follows:

1. *Input layer*: 6 rainfall stations at present time; the inflow into Tri An Reservoir at present time, and the inflows into Tri An reservoir at other previous time steps;

2. *Hidden layer*: 2 layers: with (5 + 5) nodes;

3. *Output layer*: 1 node is the inflow into Tri An reservoir at next time step: Q_{TrAn} (t + 1)

The detail of the inflow discharges into Tri An reservoir at current and various preceding time steps for 6 Alternatives are shown in Table 1. In all alternatives, the rainfall at present time step, namely R_BaoLoc(t), R_Dalat(t), R_DaTe(t), R_DiLinh(t), R_DNga(t), and R_LDong(t) were included in the input layer.

Table 1: Alternatives (ALT) and list of preceding time-step discharges in the input layer of ANN model

ALT	INPUT LAYER					
1	QTrAn(t)					
2	QTrAn(t)	QTrAn(t-1)				
3	QTrAn(t)	QTrAn(t-1)	QTrAn(t-2)			
4	QTrAn(t)	QTrAn(t-1)	QTrAn(t-2)	QTrAn(t-3)		
5	QTrAn(t)	QTrAn(t-1)	QTrAn(t-2)	QTrAn(t-3)	QTrAn(t-4)	
6	QTrAn(t)	QTrAn(t-1)	QTrAn(t-2)	QTrAn(t-3)	QTrAn(t-4)	QTrAn(t-5)

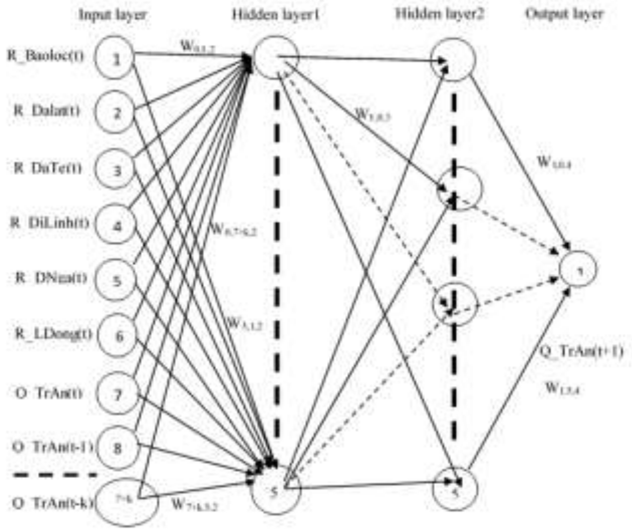

Figure 2: The ANN structure for forecasting inflow into Tri An reservoir

Here, $W_{ji,m}$ is the weight link from the node (i) in the layer (m-1), with node (j) in the next layer (m). And, 1st layer is input layer; 2nd layer is first hidden layer; 3rd layer is second hidden layer; and 4th layer is output layer.

III. Computed results and analysis

A. *Evaluation criteria*

1) *Mean Absolute Deviation*:

$$\textbf{MAD} = \frac{1}{T}\sum_{i=1}^{T}\left|Q_i - F_i\right| \qquad (4)$$

Where, Q_i: recorded discharge; F_i: Forecasting discharge.

2) *Root Mean Square Error*:

$$\textbf{RMSE} = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(Q_i - F_i\right)^2} \qquad (5)$$

3) *Root Mean Square Error Mean*:

$$\textbf{RMSEM} = \frac{RMSE}{Q_{av}} \qquad (6)$$

Where, Q_{av}: Average recorded discharge.

4) *Root Mean Square Error Over Standard Deviation*:

$$\textbf{RMSES} = \frac{RMSE}{S} \tag{7}$$

Where,

$$S = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(Q_i - Q_{av})^2} \tag{8}$$

5) *Efficiency Index [10]*

$$\textbf{EI} = \frac{SST - SSE}{SST} \tag{9}$$

Where,

$$SST = \sum_{i-1}^{T}(Q_i - Q_{av})^2 \tag{10}$$

$$SSE = \sum_{i=1}^{T}(Q_i - F_i)^2 \tag{11}$$

B. *Computed results*

1) *The time step of 1-DAY*:

Table 2: The computed results for forecasting 1-DAY inflow into Tri An reservoir during the training phase, from January 5, 1978 to November 30, 1987

ALT	Q (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
4	534.56	91.596	161.872	30.282	136.771	28.990
5		97.289	91.928	17.197	67.145	16.464
6		89.215	183.371	34.304	154.032	32.841

Table 2a: The computed results for forecasting 1-DAY inflow into Tri An reservoir during the Testing phase, from February 1, 1989 to November 30, 1991

ALT	Q (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
4	544.41	79.809	239.601	44.011	201.283	44.935
5		87.548	188.163	34.563	141.198	35.288
6		73.969	272.052	49.972	238.876	51.021

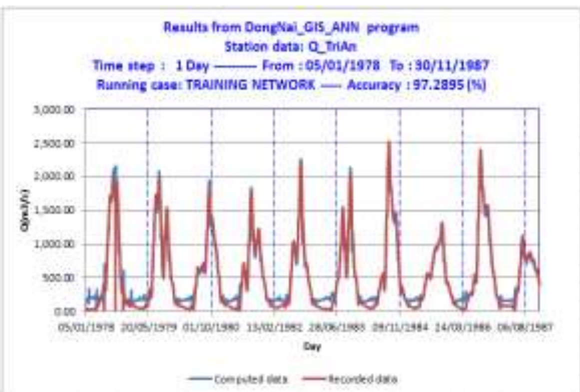

Figure 3: Forecast DAILY inflow into Tri An Reservoir by ANN program, **TRAINING PHASE**

Figure 3a: Forecast DAILY inflow into Tri An Reservoir by ANN program, **TESTING PHASE**

2) *The time step of 7-DAY*:

Table 3: The computed results for forecasting 7-DAY inflow into Tri An reservoir during the training phase, from January 5, 1978 to October 22, 1987

ALT	Q (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
3	538.886	83.956	222.989	41.380	174.276	40.054
4		79.301	253.281	47.001	166.705	45.496
5		90.828	168.604	31.288	107.441	30.286
6		83.201	228.177	42.342	139.704	40.986

Table 3a: The computed results for forecasting 7-DAY inflow into Tri An reservoir during the Testing phase, from 05/01/1989 to 24/10/1991.

ALT	Q (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
3	554.804	77.934	250.845	45.213	217.538	46.974
4		86.241	198.079	35.703	167.675	37.093
5		92.152	149.598	26.964	107.247	28.014
6		83.755	215.235	38.795	163.895	40.306

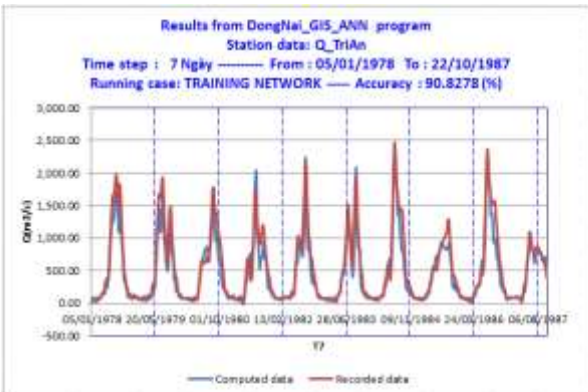

Figure 4: Forecast 7-days inflow into Tri An Reservoir by ANN program, **TRAINING PHASE**

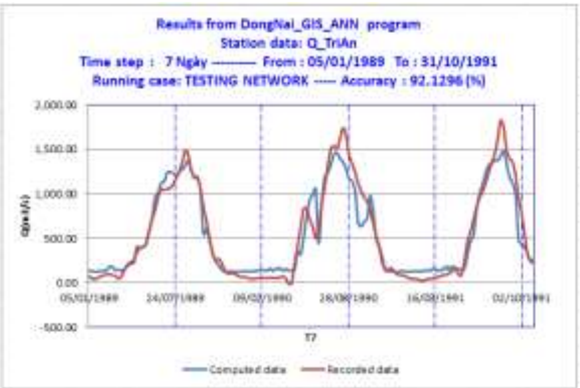

Figure 4a: Forecast 7-days inflow into Tri An Reservoir by ANN program, **TESTING PHASE**

3) *The time step of 10-DAY*.

Table 4: The computed results for forecasting 10-DAY inflow into Tri An reservoir during the training phase, from 04/01/1978 to 03/12/1987

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
3	533.813	62.687	337.960	63.311	226.502	61.084
4		80.896	241.826	45.302	148.922	43.708
5		72.745	288.841	54.109	174.849	52.206
6		89.648	178.013	33.347	119.366	32.175

Table 4a: The computed results for forecasting 10-DAY inflow into Tri An reservoir during the Testing phase, from 04/01/1989 to 10/11/1991

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
4	552.448	82.925	220.306	39.878	151.168	41.322
5		81.010	232.332	42.055	162.276	43.578
6		77.427	253.301	45.851	172.944	47.511

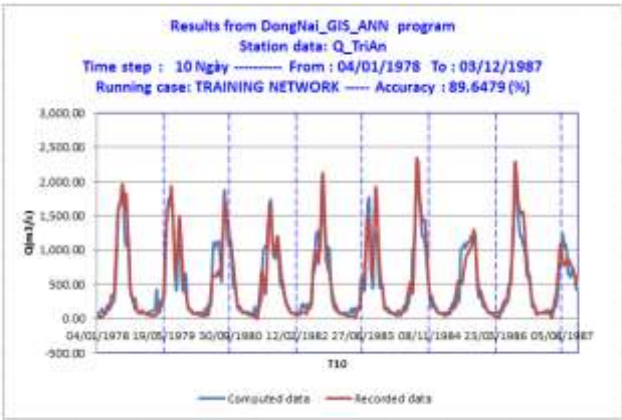

Figure 5: Forecast 10-days inflow into Tri An Reservoir by ANN program, **TRAINING PHASE**

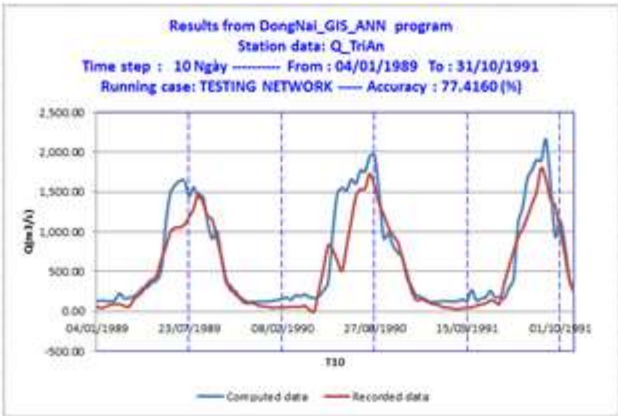

Figure 5a: Forecast 10-days inflow into Tri An Reservoir by ANN program, **TESTING PHASE**

4) *The time step of 15-DAY*.

Table 5: The computed results for forecasting 15-DAY inflow into Tri An reservoir during the training phase, from January 3, 1978 to January 26, 1988

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
1	528.438	41.738	416.644	78.844	332.422	76.329
2		65.180	322.080	60.950	191.250	59.000
3		72.782	284.773	53.890	171.243	52.171

Table 5a: The computed results for forecasting 15-DAY inflow into Tri An reservoir during the Testing phase, from January 3, 1989 to November 19, 1991

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
1	543.803	21.538	467.014	85.879	386.206	88.579
2		82.399	221.192	40.675	154.621	41.954
3		77.952	247.564	45.525	171.254	46.956

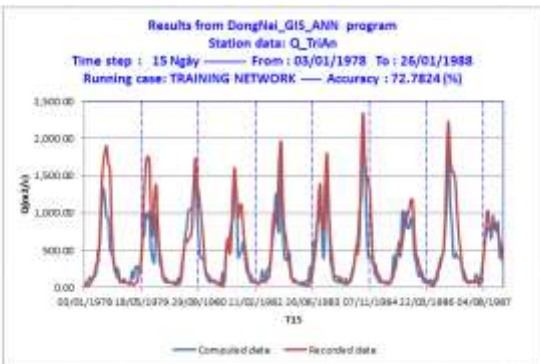

Figure 6: Forecast 15-days inflow into Tri An Reservoir by ANN program, **TRAINING PHASE**

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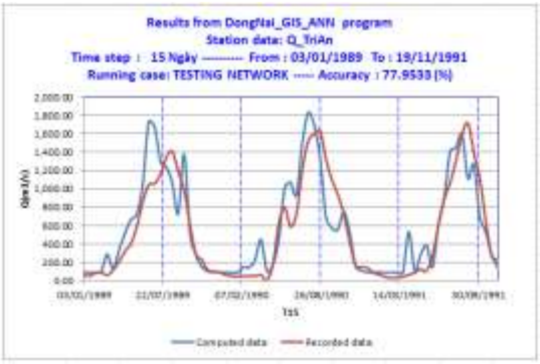

Figure 6a: Forecast 15-days inflow into Tri An Reservoir by ANN program, **TESTING PHASE**

5) *The time step of 1-MONTH*.

Table 6: The computed results for forecasting 1-MONTH inflow into Tri An reservoir during the training phase, from 02/1978 to 11/1987

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
1	535.484	56.892	21.558	4.026	214.977	65.657
2		79.547	244.849	45.725	162.190	45.225
3		74.095	275.558	51.460	170.616	50.897

Table 6a: The computed results for forecasting 1-MONTH inflow into Tri An reservoir during the Testing phase, 02/1989 to 11/1991

ALT	**Q** (m^3/s)	EI (%)	RMSE (m^3/s)	RMSEM (%)	MAD (m^3/s)	RMSES (%)
1	552.474	46.694	382.434	69.222	249.605	0.132
2		25.260	452.841	81.966	291.633	0.156
3		-3.449	532.763	96.432	282.385	0.184

Figure 7: Forecast MONTHLY inflow into Tri An Reservoir by ANN program, **TRAINING PHASE**

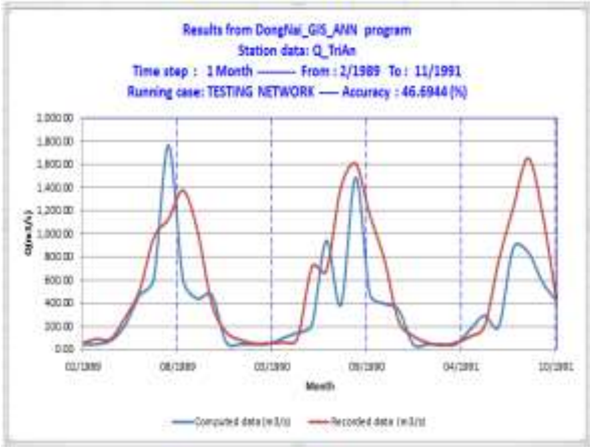

Figure 7a: Forecast MONTHLY inflow into Tri An Reservoir by ANN program, **TESTING PHASE**

The accuracy of forecast inflows into Tri An reservoir computed by ANN model due to time steps is shown in Table 7 and Figure 8.

Table 7: Accuracy of forecast inflow into Tri An reservoir computed by ANN model due to time step

CASE	**TIME STEP (DAYS)**				
	1	7	10	15	30
Training phase	97.29%	90.83%	89.65%	72.78%	56.89%
Testing phase	87.55%	92.15%	77.43%	77.95%	46.69%

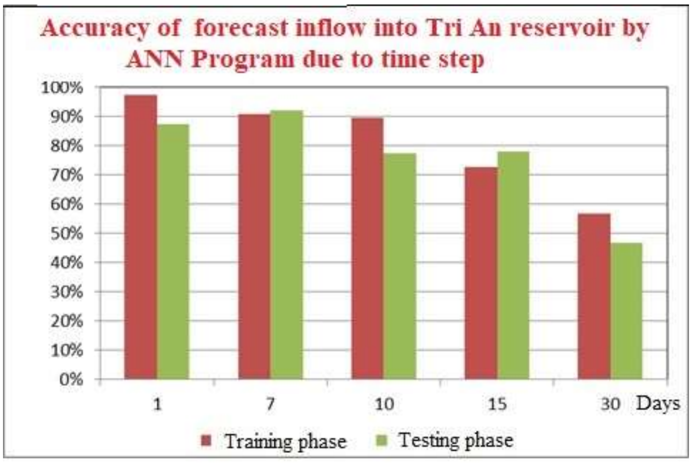

Figure 8: Accuracy of forecast inflow into Tri An reservoir computed by ANN Program due to time step.

IV. Conclusion

The ANN model using BPNN algorithm to forecast inflow into a reservoir has the following characteristics:

- Its structure has the important implications for the accuracy of forecast results;
- The time step also has an important impact on the accuracy of forecast results;
- The terrain and geology of the basin, the density and distribution of rainfall stations, as well as the

availability of data in the basin, in turn, affect to the ANN structure.

The infiltration, evaporation, the composition and distribution of vegetation cover on the soil surface in the river basin influence the level of preceding lag time step inflows.

Table 7 and Figure 8 show that just with 6 available rainfall stations: Dai Nga, Da Ta, Bao Loc, Di Linh, Dalat and Lam Dong, the ANN model can forecast rather accurately the inflow into Tri An reservoir. The higher the accuracy is, the shorter the forecasting time step used for ANN model is. Forecasting the daily inflow into Tri An reservoir can reach 97.29% of accuracy during the training phase, and 87.55% of accuracy during the testing phase. To ensure the accuracy not less than 90%, the forecasting time step should not exceed 7 days. If the forecasting time step is 10 days, the accuracy is around 77%; if the forecasting time step is 15 days, the accuracy is only about 70%. Predictability cannot be used for the time step taken up to 30 days, as its accuracy is below 46%.

From these results, we can conclude that:

- Each basin having particular properties, there will be just one most suitable forecasting time step as well as ANN structure that can be obtained to effectively forecast the reservoir inflow.
- The appropriate planning and action for initiative response to heavy floods can be timely done in order to avoid damage from flooding for the downstream of Tri An reservoir, Dong Nai-Saigon river region as well as ensuring the safety of Tri An reservoir in an active manner.
- As a result, this study results contributes to support the implementation of the Decision No. 471 / QĐ-TTg, dated 24 March 2016, and promulgates "The inter-reservoir operational process on Dong Nai river basin" by Prime Minister of Vietnam [11].

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More details