Research Paper

ARTIFICAL NEURON NETWORK FOR FLOOD FORECASTING AS INFLOW OF PLEIKRONG RESERVOIR IN POKO RIVER

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ARTICLE HISTORY

Received: April 12, 2018; Accepted: May 08, 2018

Publish on: December 25, 2018

ABSTRACT

In Vietnam, modern and small hydropower reservoirs play an important role in socio-economic development. However, the effective operation of such reservoirs based on the argument of the release function and expected future inflow is one of the most important variables that the operators will reply on to control such release. In other words, to attenuate floods, the operators have to release water in advance, so to create an empty volume (flood volume) in the reservoir, into which the excess in flow can be accommodated during the flood events. Therefore, the predicted periods should be as long as possible to create a sufficient large flood volume in the reservoir, while releasing a flow that is not so high to mitigate the impacts on downstream. Nevertheless, predicting the future inflow is still a big challenge for the local hydrologists due to the lack of information and technology. This paper proposes a method to predict the inflow of Pleikrong hydropower reservoir which located in downstream of Poko river, a second tributary of SeSan River and the observation data is insufficient and incorrect. This method uses MIKE NAM to construct the inflow then the Artificial Neuron Network to predict the inflow based on the availability of data. The result is surprising when R^2 for 6 hourly forecasted inflow is about 0.97 and for 12 hourly forecasted is about 0.79 which correspond to the catchment concentrat-ion time of 9 hours. The results of this study will hopefully be an example to apply on many case studies in Viet Nam and other ungauged stations system.

Keywords: *Reservoir management, flood forecast, MIKE NAM, ANN, PleiKrong.*

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1. Introduction

Flood forecasting is an important and integral part of a multi-purpose reservoir management, and can help to provide early warning for efficiency operation (Guo, 2009). Various flood forecasting models, including data driven flood forecasting such as regression model, and more sophisticated real time catchment-wide integrated hydrological and hydrodynamic models such as using MIKE 11 module of DHI software may be adopted (Jain et al., 2012). These models provide forecasted flow and water level at the controling locations known as Forecast Points. The Forecast Points are usually located along major rivers or known as the inflow of reservoir and they will be operated for flood mitigation during a flood event (Socini, 2007). However, current reservoir operation does not fully realize and appreciate the benefits that accrue from the enhanced level of forecasting accuracy and the current innovative techniques (Castelletti, 2012). Forecasts about the discharge are calculated in real-time, by using the model to transform the input functions into a corresponding discharge function time.

The physical based models describe the hydrological processes occurring in a basin which are expected to have significant advantages over purely empirical models. The main advantages of these models are their accuracy and the potential for performing comprehensive sensitivity analyses. The parameters of these models have direct physical interpretation, and their values might be established through field or laboratory investigations (Sulafa HagElsafi et al., 2014). On the contrary, the data driven models as the black box showing the relationship between inputs and outputs are developed then using this function latter to simulate or forecast interest variables. Therefore, it requires less data and detailed information.

The stream flow modeling is a key tool in water resources management, early warning for flood hazards, and related impacts. Many advanced types of models exist, but they have been developed for a diverse range of climatic regions. The physical based models like hydrology and hydrodynamic models for this purpose have the capability of simulating a wide range of flow situations. However, these models require accurate river geometric and hydrological data, which may not be available at many locations. For forecasting purpose, the types of model use forecasted climate data for prediction which may cause more errors in the result. On the other hand, the data driven models for stream flow forecasting can be applied in the case study where there is not much data available. Among these models, Artificial Neural Network (ANN) provides a quick and flexible approach for data integration and model development. Therefore, this research used ANN models to forecast floodis to PleiKrong reservoir. It is anticipated that this work will provide baseline information toward the establishment of a flood warning system for the case study and other similar regions in the Central part of Viet Nam.

2. Study area

The Poko river is located in the Western part of Kon Tum province. It is the secondary tributary of SeSan river with the area of 3,210 km^2 and has 152 km long. The river originates from the high mountain of Chu Prong in Dak Glei district, flowing in the north-south direction. Frequent floods have caused serious damage in recent years. According to statistics, in the last 35 years, the basin has been suffered to severe flood events. In 1994, flood damage was 18 billion VND while it reached 2.6 billion VND in 1996, 7.5 billion VND in 2009 and 30 billion VND in 2009 (Song Tra ECCL, 2015). However, meteo-hydrologica stations are not sufficient for water related studies. There are only three rain stations including Dak Mot, Dak To and Dak Glei of which Dak Glei is not continuous to operate. For hydrological purpose, there is only one discharge station at Dak Mot and one water level station at Dak To (Fig. 1).

In 2003, PleiKrong reservoir was built in 14 km downstream of DakMot station for hydropower purpose and it went to operate in 2006 after two years of construction. In 2014, Thuy Loi University conducted a survey of longitude profiles and cross sections along Poko river and DakBsi river to simulate and analyze the inundation maps of the system. However as seen above, there is no controling points to calibrate and validate this system by using the hydrodynamic models. Therefore, it is necessary to find out a method to predict the inflow of the reservoir (PleiKrong inflow from now on) that cannot based on physical based models (hydrological model in combination with hydraulic model) using forecasted rainfall events if the data of the river cross sections is available. Other potential way is using only hydrological models with forecasted rainfall but there is a big gap in predicted future meteorological variables in Viet Nam due to the uncertainty of climate in the study case. the Artificial Neuron Network (ANN) is used for flood forecasting purpose.

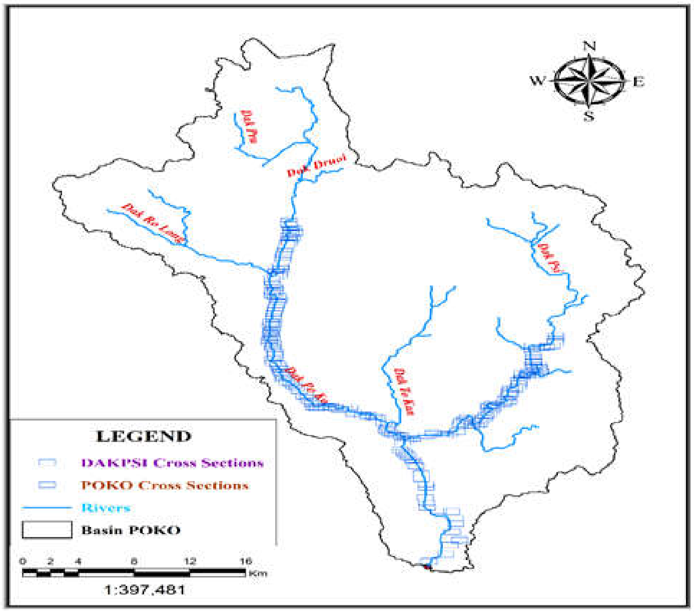

Fig. 1. PleiKrong reservoir catchment in Poko river

3. Methodology

Based on the available data, the proposed method here is using MIKE NAM to simulate the past inflow events in Pleikrong. This model is validated with the discharge time series observed at Dak Mot hydrological station then its parameter set will be transferred to PleiKrong catchment as a similar watershed (step 1 to step 3 in Fig. 2). In fact, Dak Mot catchment accounts for two-third area of PleiKrong and they are located in the similar climate region. That is why the set of parameters from the Dak Mot model was slightly modified on concentration time related parameters and applied in Pleikrong catchment). Then these estimated inflows will be used as the output of system while inputs can be any available information at previous time step for training an ANN network (Fig. 2). The main advantage of this method is the information used to predict the inflow is deterministic which should be known at predicted time by observation. The errors can be reduced by not using predicted information for flood forecasting. This method worked well in the case study and hopefully it will be useful when applying in other similar problems.

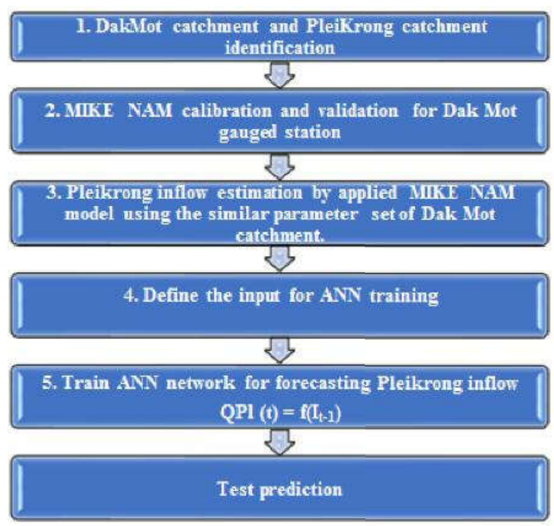

Fig. 2. The flood forecasting procedure of Pleikrong inflow $QPl_{(t)}$ where I_{t-1} can be any well known information at previous time step.

3.1 MIKE NAM model

MIKE NAM is a rainfall-runoff model contained in MIKE package that developed by DHI. This conceptual model simulates some hydrological processes that happened within the catchment including overland flow, interflow, base flow and recharge from groundwater. This is one of the most common hydrological models which were used in Viet Nam since 2000. The structure of the model is described in Fig.3.

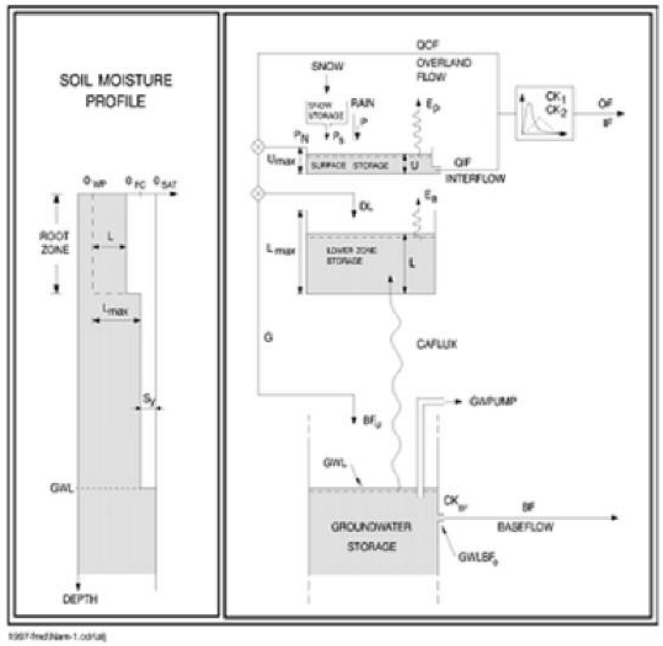

Fig. 3. Structure of MIKE NAM [5]

This structure is an imitation of the of the hydrological cycle in the continent. NAM simulates the rainfall-runoff process and the water content is divided into four different and mutually interrelated storages that represent different physical elements of the catchment including:

- Snow storage
- Surface storage
- Lower or root zone storage
- Groundwater storage

Based on the input data, NAM produces catchment runoff as well as information about other elements of the of the hydrological cycle, such as the temporal variation of the evapo-transpiration, soil moisture content, groundwater recharge, and groundwater levels. The catchment runoff is split conceptually into overland flow, interflow and base flow components (DHI, 2017).

3.2 ANN model

The ANN is a computer program that is designed to intimate the human brain and its ability to learn tasks. This program, acts as an expert system and is trained to recognize and generalize the relationship between a set of variable inputs and outputs (Sulafa HagElsafi et.al, 2014). There are two characteristics of the brain as primary features which are used in ANN: the ability to (1) "learn" and (2) generalize from limited information. The knowledge stored as the strength of the interconnecting weights (a numeric parameter) in ANNs is modified through a process called learning, using a learning algorithm. The more important information is the more weighted value is. Then the algorithmic function which based on back-propagation is used to modify the weights in the network. ANN network is "taught" to give an acceptable answer to a particular problem when the input and output values are sent to the ANN for "learning", initial weights to the connections in the architecture of the ANN are assigned, and the ANN repeatedly adjusts these interconnecting weights until it successfully produces output values that match the original values. The ANN maps the relationship between the inputs and outputs, and then modifies its internal functions to determine the best relationship that is represented by the ANN. The inner work and process of an ANN are often thought of as a "black box" with inputs and outputs. One useful analogy that helps to understand the mechanism occurring inside the black box is to consider the neural network as a super-form of multiple regression. Like linear regression resulting from the relationship that {y} = f{x}, the neural network finds some functions f{x} when trained. The most common type of artificial neural network consists of three groups, or layers, of units: (1) a layer of "input" units is connected to (2) a layer of "hidden" units, which is connected to (3) a layer of "output" units (Fig. 4).

In this study, ANN network was identified and trained with past flood events in the PoKo river from 2011 to 2013 and known as the inflow to PleiKrong. Later, this network is used to forecast the Pleikrong inflow as describe in step 5 of flood forecasting procedure in Fig. 3.

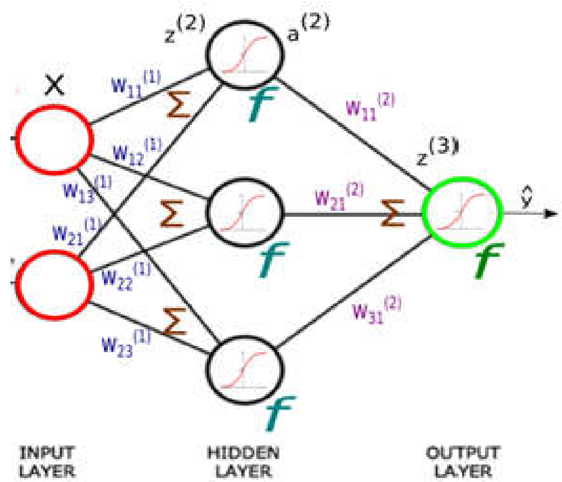

Fig. 4. An Example of a simple feed forward network, in which aj equals to the activation value of unit j, $w_{j,i}$ equals to the weight on the link from unit j to unit i, ini equals to the weighted sum of inputs to unit i, ai equals to the activation value of unit i (also known as the output value), and g equals to the activation function.

4. Results and discussion

In this study, it is necessary to clarify 2 subcatchments: Dak Mot catchment that is Poko basin up to Dakmot station and Pleikrong catchment that is Poko basin up to the Pleikrong reservoir. MIKE NAM model was calibrated and validated used the hourly recorded discharge time series. The weights of the rainfall at the gauging stations was estimated by Thiessen polygon method using data of Dak Mot and Dak To stations as presented in Fig. 5 and Table 1.

Table 1. Catchment area and its weighted values.

Period	Calibration	Validation	
Year	2003	2009	2011
NASH	0.89	0.91	0.93

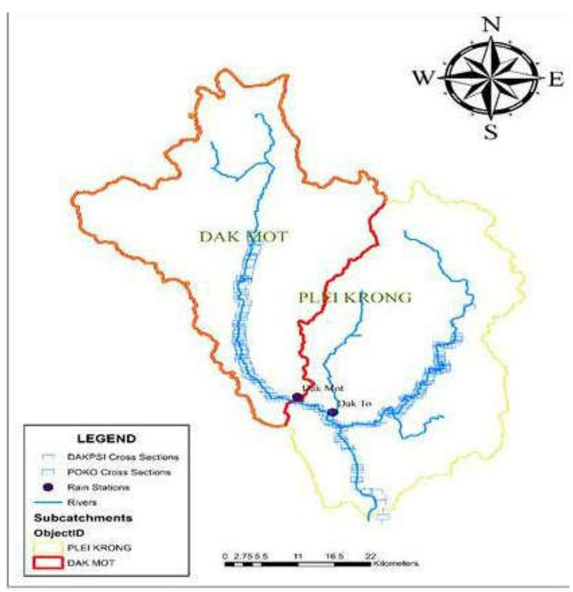

Fig. 5. Subcatchment and rain gauges in the Poko river basin

4.1 MIKE NAM Calibration and Validation for Dak Mot gauged station

In this research, MIKE NAM simulated very well the discharge at Dak Mot station. The values of evaluated criteria NASH for calibration and validation are acceptable as shown in Table 2 and the observed and estimated water discharge matched very well for calibration and validation (Fig. 6).

Table 2. NASH coefficients of calibrated and validated Dak Mot models

Period	Calibration	Validation	
Year	2003	2009	2011
NASH	0.89	0.91	0.93

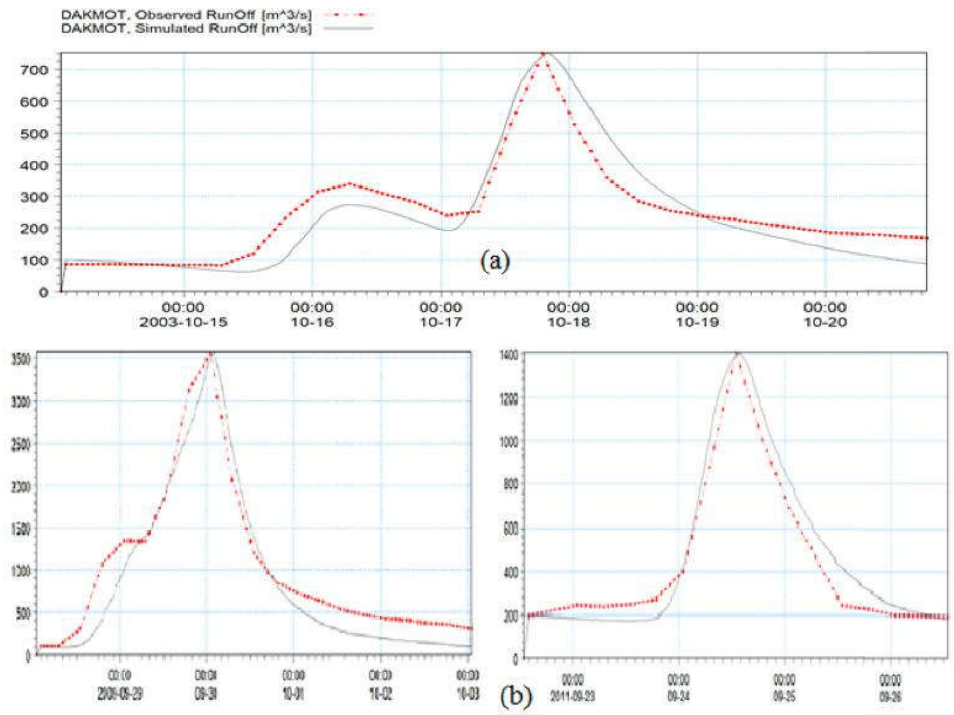

Fig. 6. Calibration and Validation of water discharge at Dak Mot

Therefore, it can be concluded that MIKE NAM model can be effectively used to simulate the water discharge in the Poko river with the set of validated parameters in Table 3.

Table 3. Validated parameters of MIKE NAM model for Dak Mot catchment

Parameter	Values
Lmax (mm)	100
Umax (mm)	10.2
CQOF	0.77
TOF	0.0296
TIF	0.0703
TG	0.953
CKIF (hours)	335.3
CK12 (hours)	25
CKBF	1585

4.2 Estimation of the outflow of Pleikrong catchment

The study made the comparison on the characteristics of Dak Mot and PleiKrong catchments. Because Dak Mot is a two-third part of PleiKrong, two catchments have similar characteristics. The concentration time of each catchment is the only parameter to be modified and the concentration time of Pleikrong should be higher than that of Dak Mot. Therefore, we keep the same value for all parameters except the concentration time. The set of parameters will be used to simulate the past flood events in 2011 - 2013 for PleiKrong when the data is available. These estimated discharges will be used to train ANN and test the model prediction.

4.3 Development of ANN network for PleiKrong inflow forecasting

a. Data set

The concentration time of PLeiKrong catchment is about 9 hours. Then the hydrological principle taught that PleiKrong inflow can be affected by 6 to 12 hourly rain in the system. In addition, it can be effective by the outflow of Dak Mot and PleiKrong catchments at the previous time steps. However, for more accurate estimation, Pleikrong inflow did not consider in the argument of prediction. In conclusion, there are 9 variables were considered as presented in Table 4.

Table 4. Variables for simulation of inflow at Pleikrong

No.	Variables	Time steps	Available period	Note
1	tnat	06 hour	02/06/2011 – 31/12/2013	Interval values from 1 to 365 days
2	$X_{ĐM\_6h}$	06 hour	02/06/2011 – 31/12/2013	6 hourly rain at Dak Mot station
3	$X_{ĐM\_12h}$	06 hour	02/06/2011 – 31/12/2013	12 hourly rain at Dak Mot station
4	$X_{ĐT\_6h}$	06 hour	02/06/2011 – 31/12/2013	6 hourly rain at Dak To station
5	$X_{ĐT\_12h}$	06 hour	02/06/2011 – 31/12/2013	12 hourly rain at Dak To station
6	$Q(ĐM)_{t-3}$	06 hour	02/06/2011 – 31/12/2013	Dak Mot discharge
7	$Q(ĐM)_{t-2}$	06 hour	02/06/2011 – 31/12/2013	Dak Mot discharge
8	$Q(ĐM)_{t-1}$	06 hour	02/06/2011 – 31/12/2013	Dak Mot discharge
9	$Q(ĐM)_{t}$	06 hour	02/06/2011 – 31/12/2013	Dak Mot discharge

b. ANN Inputs selection

To select the most effective inputs for ANN network, IIS (Galelli and Castelletti, 2013) was used and selected from three inputs. The Pleikrong inflow later is estimated as the function of $X(DM)_{6h}$; $X(DT)_{6h}$; $Q(DM)_{t-1}$ as shown in Equation 1.

$$Q(PL)_t = f[X(DM)_{6h}; X(DT)_{6h}; Q(DM)_{t-1}] \quad (1)$$

c. Set up ANN network

The network was described by 10 neurons as the total neurons should not be lower then the number of variables used for inputs and outputs and must not be very large for saving computation time. Two third of time series will be used for training and the remaining of one third will be used for validation and testing.

d. Training ANN network

The relevant data from 1/6/2011 - 30/11/2012 was used to train the ANN network. The predictands are advanced 6, 12, 18 and 24 hourly Pleikrong inflows and the predictors are the presented 6 hourly rain at Dak Mot, Dak To and the presented discharge at Dak Mot station. The result is presented in Fig. 7 to Fig. 10.

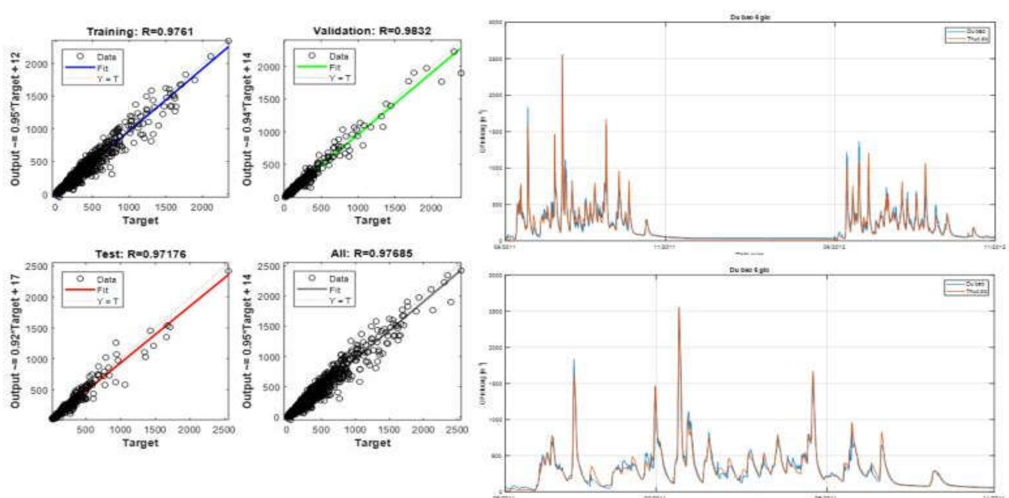

Fig. 7. Advanced 6 hourly predicted Pleikrong inflow: result and evaluation.

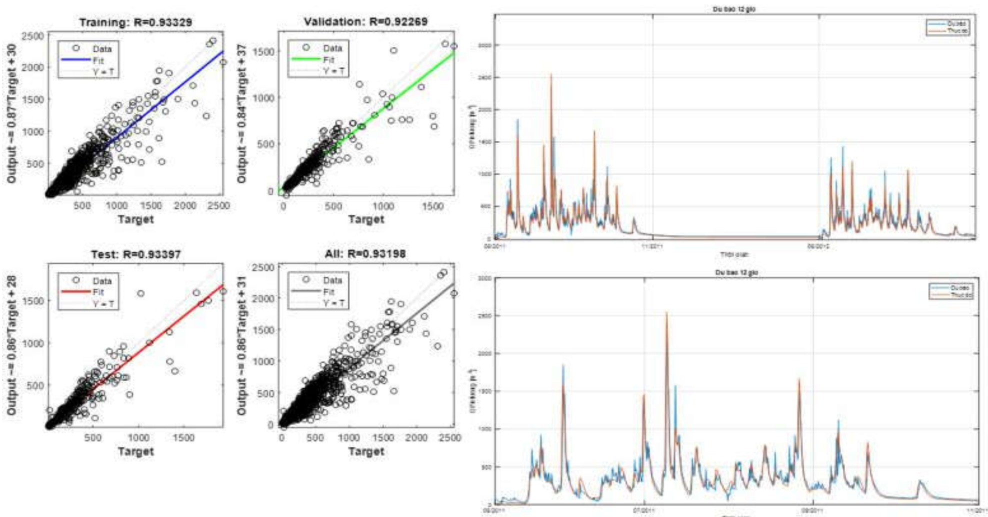

Fig. 8. Advanced 12 hourly predicted Pleikrong inflow: result and evaluation.

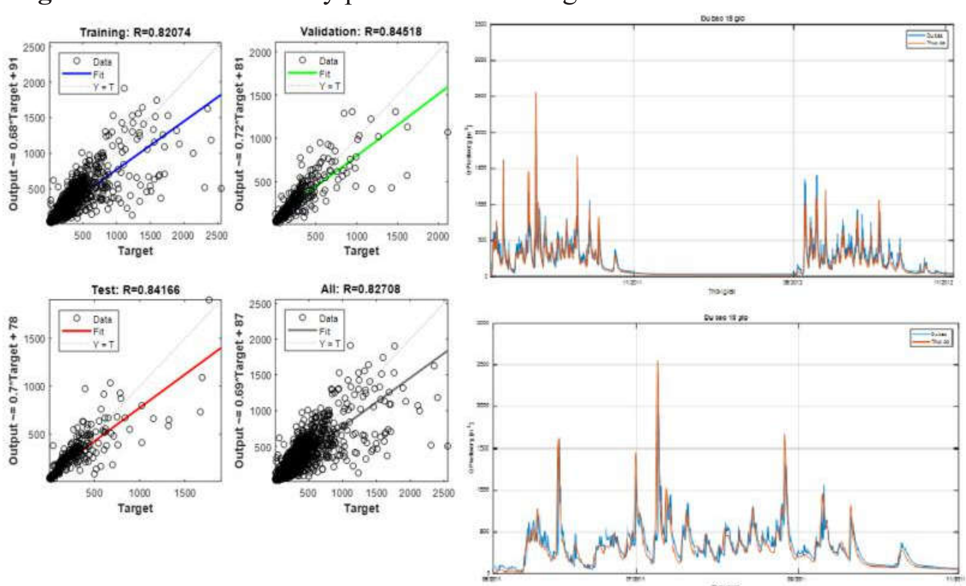

Fig. 9. Advanced 12 hourly predicted Pleikrong inflow: result and evaluation.

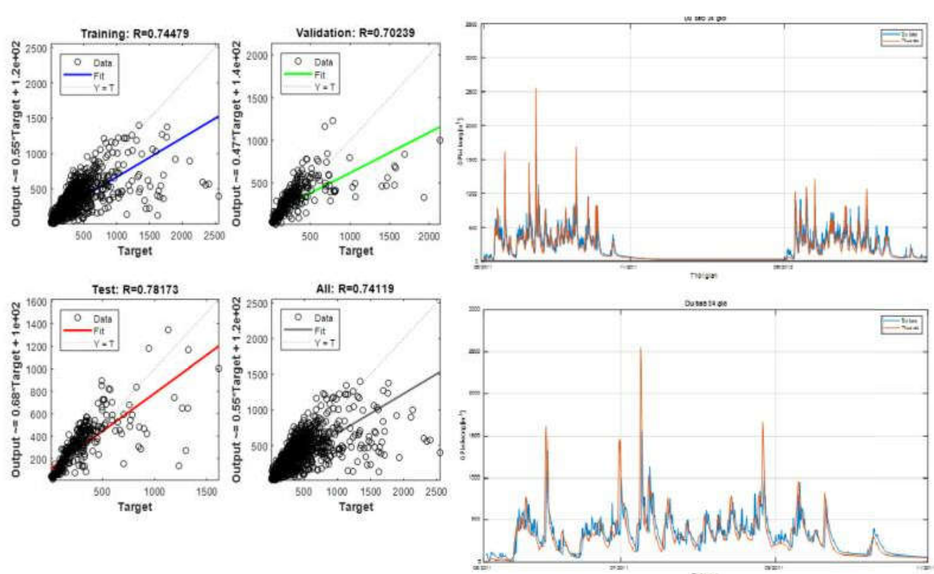

Fig. 10. Advanced 18 hourly predicted Pleikrong inflow: result and evaluation

Table 5. Evaluation of ANN training for flood forecasting to Pleikrong reservoir

Criteria	6hr	12hr	18hr	24hr
R^2	0.98	0.93	0.86	0.74

The results show the good prediction of Pleikrong inflows with NASH coefficients larger than 0.7 for 6 hours, 12 hours, even for 18 hours and 24 hours predicted time as shown in Table 5. Then the network was accepted for predicted test using past event in September to November, 2013.

e. Predicted test for the period from September to November, 2013

Using the validated ANN network to test the predicted inflow in the period from September to November, 2013. The visualized result is presented in Fig. 11.

In addition, there are three criteria which were used to evaluate the efficiency of the predicted alternatives: determination coefficient R^2, S/σ ratio in which S is the deviation of predicted error time series and σ is the deviation of predictor time series and correlation coefficient . Beside them, the time and magnitude of peaks, and the matching of observed and predicted time series were also considered as the evaluation criteria.

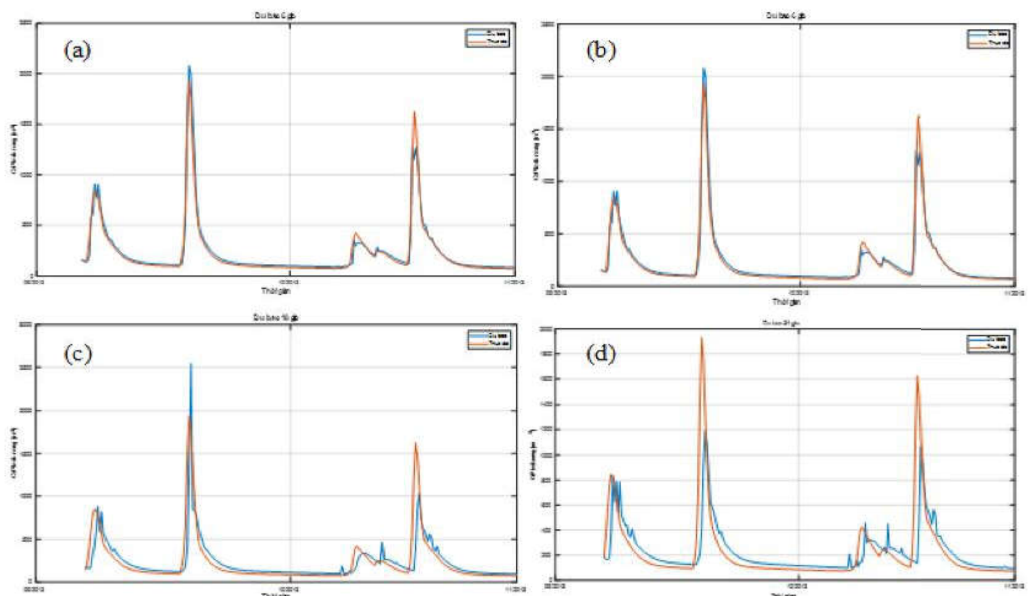

Fig. 11. Predicted (green) and observed (red) values of Pleikrong inflow in advance of 6 hourly (a), 12 hourly (b), 18 hourly (c) and 24 hourly (d)

Table 6. Evaluation of the testing results during September to November, 2013

Criterial	6hr	12hr	18hr	24hr
R^2	0.97	0.79	0.66	0.47
S/σ	0.19	0.35	0.6	0.72
η	0.90	0.81	0.65	0.62

From Fig.11 and Table 6 one can be seen that 6 hours forecasting give a very good result. The peaks' time of observed and predicted flows matches perfectly and the different between the peak values are in the acceptable limit (smaller than 10% of observed one). In addition, R^2, S/σ ratio and η get very good values. For 12 hours forecasting, the value of evaluation criteria still has good values as shown in column 2 of Tab.6 which are in their acceptable ranges. However, for 18 hours and 24 hours forecasting, the prediction are poor with the very bad values of evaluated criteria (column 3 and 4 in Table 6 respectively). This is due to the fact that the concentration time of the basin and also the time lag to convey flood from Dak Mot to Pleikrong are smaller than these periods. Then 18 hours and 24 hours forecasts in advance using rain data are not meaningful in the real world.

In conclusion, ANN can be used for flood forecasting of Pleikrong inflow in short duration like 6 hours and 12 hours ahead to predict the flood caused by heavy rainfall events in the system. It will be an importance advantage for Pleikrong reservoir operation and a reference for other similar studies.

5. Conclusion and Recommendation

With the limitation in data and information, flood forecasting for hazard mitigation and reservoir operation has a big gap for implementing in many regions over the world and especially in Vietnam. This research proposed the method using ANN to predict the Pleikrong inflow as an example of flood forecasting for limited gauges. The results showed that ANN can work well if it is trained with past flood events.

In addition, ANN can be better than physical based model in this situation due to the fact that it used the deterministic data to predict the flood that can reduce the error during forecasting process. However, it needs a long and representative time series of variables to give a good network or it will be difficult to predict the events that never happen in the past. For this limitation, synthesis data can be generated and used as training data set.

References

1. Castelletti, A., Galelli, S., Restelli, M. and Soncini-Sessa, R., 2012. Data-driven dynamic simulation modelling for the optimal management of environmental systems. *Environmental Modelling & Software*. 34(0): 30 - 43.

2. DHI (2014). *MIKE NAM user guide*.

3. Guo, S. et at., 2000. Reservoir Comprehensi ve and Automatic Control System. *Wuhan University of Hydraulic and Electrical Engineering Press*. Wuhan (in Chinese). η

4. Jain, S.K., Mani, P., Jain, S.K., Prakash, P., Singh, V.P., Tullos, D., Sanjay Kumar, S., Agarwal, S.P. and Dimri, A.P., 2017. A Brief review of flood forecasting techniques and their applications. *International Journal of River Basin Management*, UK.

5. Le Van Nghinh, Hoang Thanh Tung, Nguyen Ngoc Hai, 2015. Research on application of neural network in forecasting flood in rivers in Binh Dinh and Quang Tri.

6. Truong Van Anh et al., 2016. Estimating the foreign flow from China to Vietnam supporting water resources planning and management in Da river basin. *Meteorolical and Hydrological Journal*

7. Rodolfo, S.S., Weber, E., Castelletti, A., 2007. Integrated and Participatory Water Resources Management. *Elsevier publisher*.

8. Sulafa, HagElsafi et al., 2014. Artificial Neural Networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan, *Alexandria Engineering Journal*. Elsevier publisher.

9. Song Tra Energy Consultant Company Limited, 2015. *Dak Po Ko Hydropower Project.*

10. Xiao, Y., Guo, S.L., Liu, P., Yan, B.W. and Chen, L., 2009. Design Flood Hydrograph Based on Multicharacteristic Synthesis Index Method. J*ournal of Hydrologic Engineering Press, ASCE, USA.*