Prediction of Inflow to Reservoir in Namchon Reservoir Networks System in Thailand by ANN

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Abstract

Reservoir behavior depends on inflow, rainfall, water storage, etc. In particular, reservoir operations are closely associated with the inflow to the reservoir. The Khaohinson Royal Development Study Center located in Chachoengsao Province, Eastern Thailand. Due to the changing pattern of agriculture and popularity of agro-tourism, water demand of the royal study center is increasing. Therefore, it is crucial to aid the Namchon Reservoir Network (NRN) System's operation in the royal study center area, which calls for an appropriate technical approach to predict the inflow of the area and assess the reservoir operation. In this study, a data-driven model was developed based on the Artificial Neural Network (ANN) method, which was verified and used to predict the monthly inflow of the 2nd Namchon reservoir, the upstream reservoir of the royal study center. The optimal convergence of hydrological variable input for the 2nd Namchon reservoir consists of inflow during the month (I_t), lagged rainfall of one-month (R_{t-1}) and water storage during the month (S_t). Inflow prediction of the NRN System used three hydrological variable inputs to predict water inflows into the royal study center by ANN. They are regarded as the best convergence to predict one-month ahead inflow of the NRN system, compared with the observation data from 2009 to 2018. The predicted values from ANN well match the measured values. Inflow prediction shows precise results.

Keywords: inflow prediction, Artificial Neural Network, Khaohinsorn Royal Development Study Center, Namchon reservoir networks system.

1. Introduction

The investigation territory is the Khaohinsorn Royal Development Study Center, which was established in 1979 to reflect His Majesty King Bhmibol's wisdom in agriculture development to help villagers achieve sustainable and economic self-sufficiency. The royal study center activities rely on water from the Namchon reservoir network (NRN) system, a form of water management using multiple reservoirs linked together by the diversion of excess water from the 2nd Namchon reservoir to the 8th Namchon reservoir and the small-scale reservoirs in the royal study center, respectively (Fig.1).

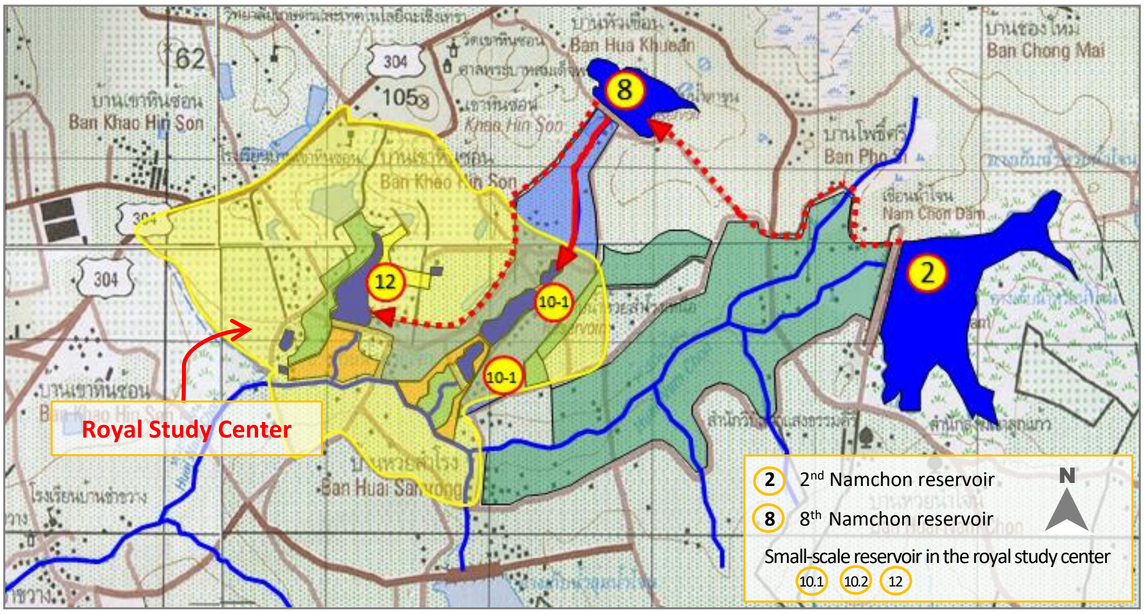

Figure 1 *Location of Khaohinsorn Royal Development Study Center*

Now the area serves as a model and an example for development for other areas, experiments in agriculture as well as demonstration plots are available to visitors and farmers looking to learn. The aforementioned endeavors have brought the center proven achievements, which are "Distinguished" Thailand Tourism Award 2002 in the agro-tourism attraction category and "Excellence" Thailand Tourism Award 2002 in the agro-tourism attraction category (ORDPB, 2012), resulting in increased water demand every year. Therefore, it is necessary to manage the reservoir not only inside the royal study center but also outside for the effective of the royal study center by Namchon reservoir networks (NRN) system.

Therefore, it is a great concern to the reservoirs of the NRN system to ensure providing water. Through the model for prediction of inflow, the study will help for future water management of the NRN system.

2. Objectives of the study

The objective of this study is to develop numerical models to support the water resource management of Namchon reservoir network (NRN) system. ANN-based model was developed to predict the inflow to the 2nd Namchon reservoir. The best convergent model was trained by selecting appropriate hydrological variable input to predict the inflow of the NRN system.

3. Literature Review

A prediction of hydrological variables is the estimation of future states of hydrological phenomena which are essential for the efficient operation of water infrastructure and the mitigation of natural disasters such as floods and droughts. For reservoir operation, inflow is important variables to estimate of discharge. Monthly inflow observation of a reservoir is the main data series for reservoir operation (Ismali, 2018). It is better to be able to use these data to model and predict the inflows of reservoir, which could assess how well the forecast inflows perform in the operation of the reservoir. The use of artificial neural networks (ANN) for predicting data can approximate a non-linear relationship between input and output data sets without considering physical processes and the corresponding equations of the system. Also, ANN model is much faster than a physically based model (Thair et al., 2012). Artificial neural network (ANN) is a mathematical computational method that imitates the biological neuron capability. A main feature of ANNs is to learn a pattern and apply the knowledge to similar patterns (Hussain et al., 2011). Many researches have applied ANN methods to model different complex hydrological processes. Neelakantan and Pundarikanthan (2000) applied ANN to improve the policies for reservoir operation. The results indicate that the solution performs satisfactorily as compared to the conventional simulation-optimisation model. Solomatine and Avila (1996) used ANN to approximate the hydrodynamic part of the MIKE 11 river model in optimizing reservoir operation. The ANN was trained based on the water levels given by the MIKE 11 model. Liong et al. (2000) demonstrated the use of the ANN for river stage forecasting in Bangladesh and showed the improved results. Considering the above advantages, in this study, artificial neural networks (ANN) have been applied to forecast one-month-ahead inflow to establish the prediction model and assess how well the forecast inflows have performed in the operation of the NRN system.

4. Methodology

The study expects one-month ahead inflow as output and assumes input data from the reservoir variable from the reservoir behavior simulation employed the mass balance equation, three types of variable inputs were considered: monthly inflow, monthly rainfall and monthly water storage. From Figure 2, a set of inputs in the form of input vector X is received by each unit and weights leading to the node form a weight vector W. The inner product of X and W is net and the output of the node is f(net) (Menhaj et al., 2010) as given by Eq. (1) and (2).

$$\text{Node input: net} = Xi*Wi \qquad (1)$$

$$\text{Node output: out} = f(\text{net}) \qquad (2)$$

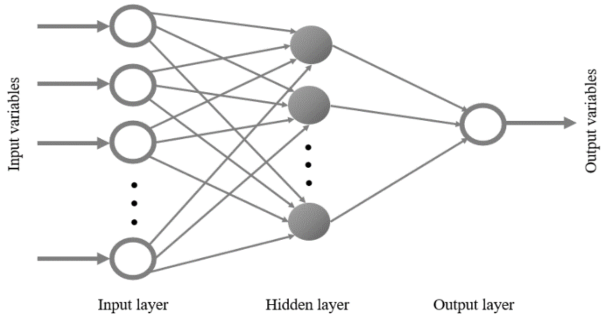

Figure 2 *Typical Structure of Artificial Neural Network*

The process of optimizing the connection weights is known as training. This is equivalent to the parameter estimation phase in conventional statistical models. Stopping criteria are used as early-stop-rule (ESR) to avoid over-fitting and decide when to stop the training process. After the training and stopping criteria of the model have been successfully accomplished, the performance of the trained model should be validated. The purpose of the model validation is to ensure that the model has the ability to generalize within the limits set by the training data. Testing also used to verify the effectiveness of the stopping criterion and to estimate the expected performance in the future. In this study, ANN was applied for the 2nd Namchon reservoir which is credible of hydrological data, located on Namchon sub-basin, Chachengsao Province, Eastern Thailand. About the ANN inputs, there are three types variable of the reservoir behavior, inflow during month in mcm, rainfall during month in mcm and reservoir storages during month in mcm. The output of the model is one-month ahead inflow forecast in mcm. The data set has a record length of 10 years covering between 2009 and 2018. The data are randomly divided into three sets (training, testing and validation). In total, 80% of the data are used for training, 10% of the data are used for testing and 10% of the data are used for validation, respectively. These subsets are also divided in such a way that they are statistically consistent and thus represent the same statistical population.

The input and output variables are pre-processed by scaling them between 0 and 1, to eliminate their dimensions and to ensure that all variables receive equal attention during training. The simple linear mapping of the variables extremes is adopted for scaling, as it is the most commonly used (Maier et al., 2010). In order to process the data, input and output data were standardized to avoid the model from being conquered by variables with large values (common in artificial intelligence models) in the table1. All data were standardized in the range of 0-1 by using the Eq. (3).

$$Z_i = \frac{y_i - y_{min}}{y_{max} - y_{min}} \tag{3}$$

where; z_i is the value after standardization, y_i is the value before standardization, y_{max} is the maximum value and y_{min} is the minimum value.

***Table 1**: Ranges of 2nd Namchon reservoir data used for the ANN model*

Model variables	Maximum value	Minimum value
Inflow, mcm	0.7498	0.0376
Rainfall, mcm	0.3080	0.0000
Water storage, mcm	60.8400	10.4280

Model structure improvement is important to limit vulnerabilities from model misspecifications and guarantee efficiency on the grounds that various predictions may have various necessities and essential items (Mohammad et al., 2005). The results of different patterns are estimated by the root-mean-square error (RMSE), the mean absolute error (MAE) and the correlation coefficient (R) or coefficient of determination (R^2) given by Eq. (4), (5) and (6), respectively.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_i^0)^2}{n}} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^0\right| \tag{5}$$

$$R = \frac{\sum_{i=1}^{n}(y_i^0 - y^0)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(y_i^0 - \bar{y}^0)^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{6}$$

where, y_i^0 and y_i are the observed and predicted monthly inflow, respectively; n is the number of the data; y^0 and y are the mean values of the precipitation and the simulated value.

5. Results and discussion

The study aims to evaluate the capability of ANN in the prediction of one-month ahead inflow of the 2nd Namchon reservoir, by considering the reservoir variables from the reservoir behaviors. Three types of variable inputs were considered: inflow during month, rainfall during month and water storage during month. Further, the comparison of the performance of inflow forecast into the 2nd Namchon reservoir using six functional forms is shown in Table 2. The best convergence was achieved for combination of inflow during month (I_t), lagged rainfall of one-month (R_{t-1}) and water storage during month (S_t) compare with Correlation Coefficient (R) was 0.9675, Mean Absolute Error (MAE) was 0.0733 and Root Mean Squared Error (RMSE) was 0.0937 for training data in Table 2.

***Table 2**: Result of ANN training for reservoir operation*

Different Functional form	Correlation Coefficient (R)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
$Q_{t+1} = f(Q_t, R_t, S_t)$	0.9478	0.0643	0.0831
$Q_{t+1} = f(Q_{t-1}, R_t, S_t)$	0.9684	0.0720	0.0951
$Q_{t+1} = f(Q_t, R_{t-1}, S_t)$	0.9675	0.0733	0.0937
$Q_{t+1} = f(Q_t, R_t, S_{t-1})$	0.9542	0.0682	0.0901
$Q_{t+1} = f(Q_{t-1}, R_{t-1}, S_t)$	0.9362	0.0681	0.0896
$Q_{t+1} = f(Q_{t-1}, R_t, S_{t-1})$	0.9484	0.0701	0.0910

where, Q_t is inflow during month; Q_{t-1} is lagged inflow of one-month; R_t is rainfall during month; R_{t-1} is lagged rainfall of one-month; S_t is water storage during month; S_{t-1} is lagged water storage of one-month

The results of ANN for the training, validation and testing were compared with the observed data. The predicted values from ANN matched the measured values very well. Figure 3 shows the trained validation and testing result of predicted valued by ANN with observed data of inflow in mcm from 2nd Namchon reservoir. Figure 3 shows training, validation and testing results of forecasting data and observation data of inflow. Figure 4 shows the comparison of forecasting data and observation data of inflow.

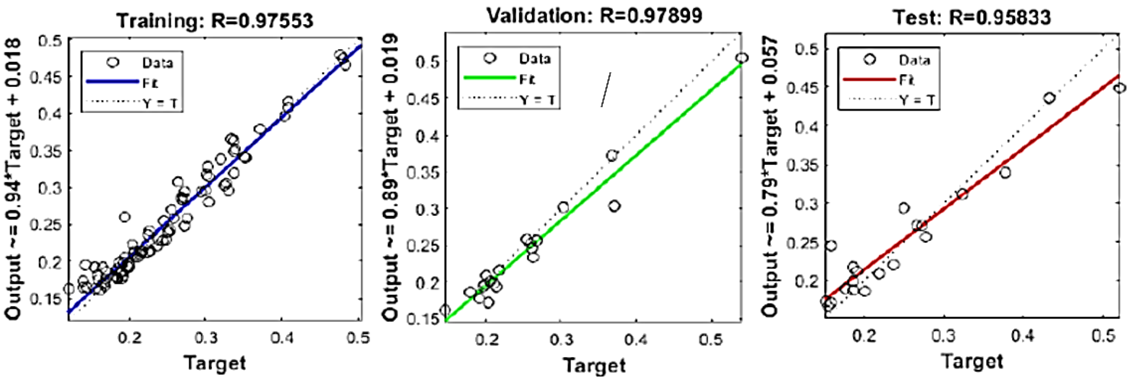

Figure 3 *Training, validation and testing results of forecasting data and observation data of inflow*

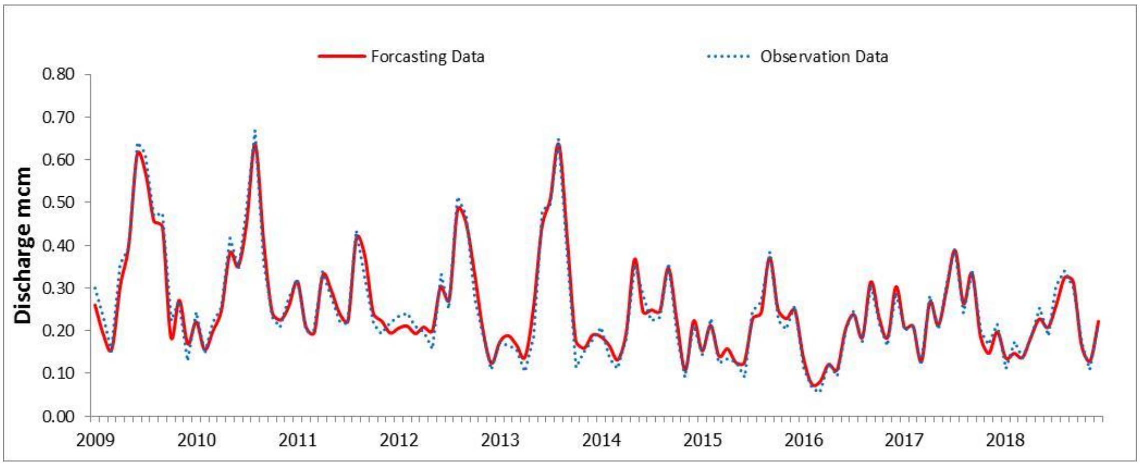

Figure 4 *Comparison of forecasting data and observation data of inflow*

Namchon Reservoir Networks (NRN) System is extremely important for water support in the activities of the royal study center, which is carried out by the diversion of excess water from one reservoir to fill the reservoir with water storages. The NRN System consists of (1) the 2nd Namchon reservoir, (2) the 8th Namchon reservoir and (3) the small-scale reservoirs in the royal study center (the 10.1th Namchon reservoir, the 10.2th Namchon reservoir and the 12th Namchon reservoir). The NRN system has inflow from both the Namchon canal and 2 tributaries of the Namchon canal, the Samrong canal and the Jek canal. The inflow from the Namchon main canal flows into the 2nd Namchon reservoir, while the inflow from the Samrong canal and Jeak canal flows into the 8th reservoirs and the 12th Namchon reservoirs within the royal study center area, respectively (Fig.5).

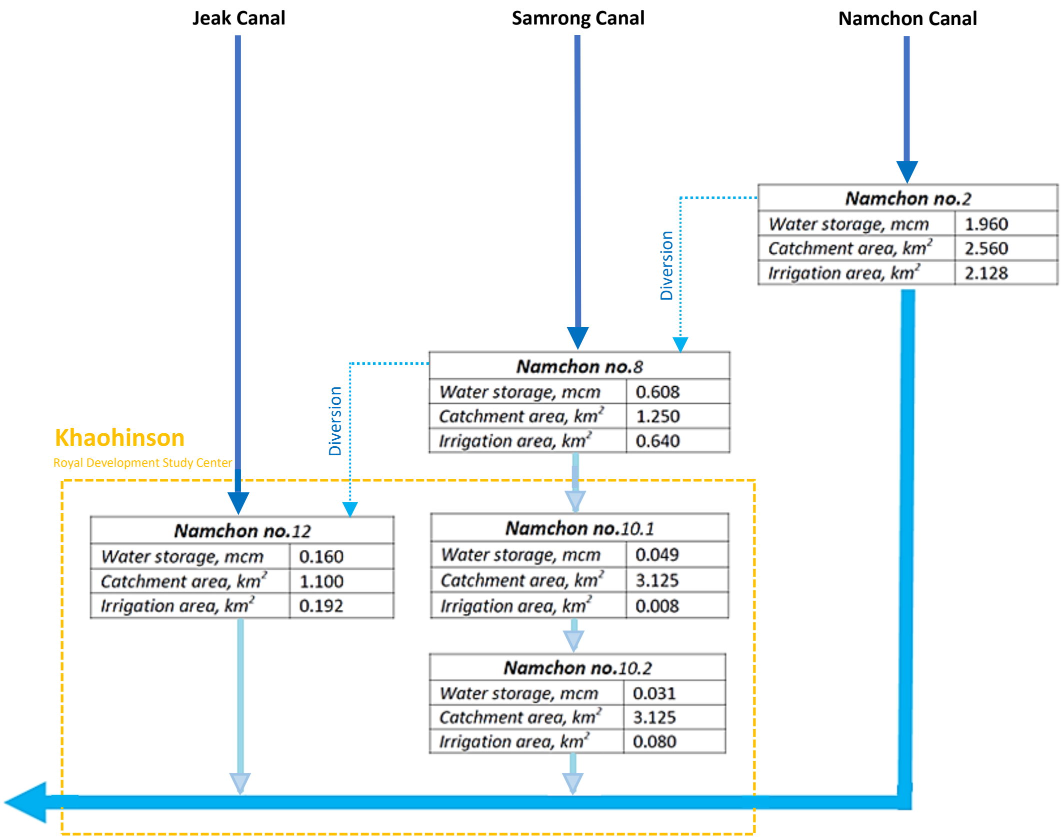

Figure 5 *Namchon Reservoir Networks (NRN) System*

Prediction of inflow to reservoir in the NRN system, ANN is used to predict water inflows from 3 canals into the NRN system, consisting of the inflow from the Namchon canal flow into the 2nd Namchon reservoir, the inflow from the Somrong canal flow into the 8th Namchon reservoir and the inflow from the Jeak canal flow into the 12th Namchon reservoir within the royal study center, to support the royal study center's activities.

Inflow prediction of the NRN System used appropriate hydrological variable inputs to ANN: inflow during month (Q_t), lagged rainfall of one-month (R_{t-1}) and water storage during month (S_t). They are regarded as the best convergence to predict one-month ahead inflow of the NRN system, compared with the observation data from 2009 to 2018. The predicted values from ANN well match the measured values (Fig. 6 and 7).

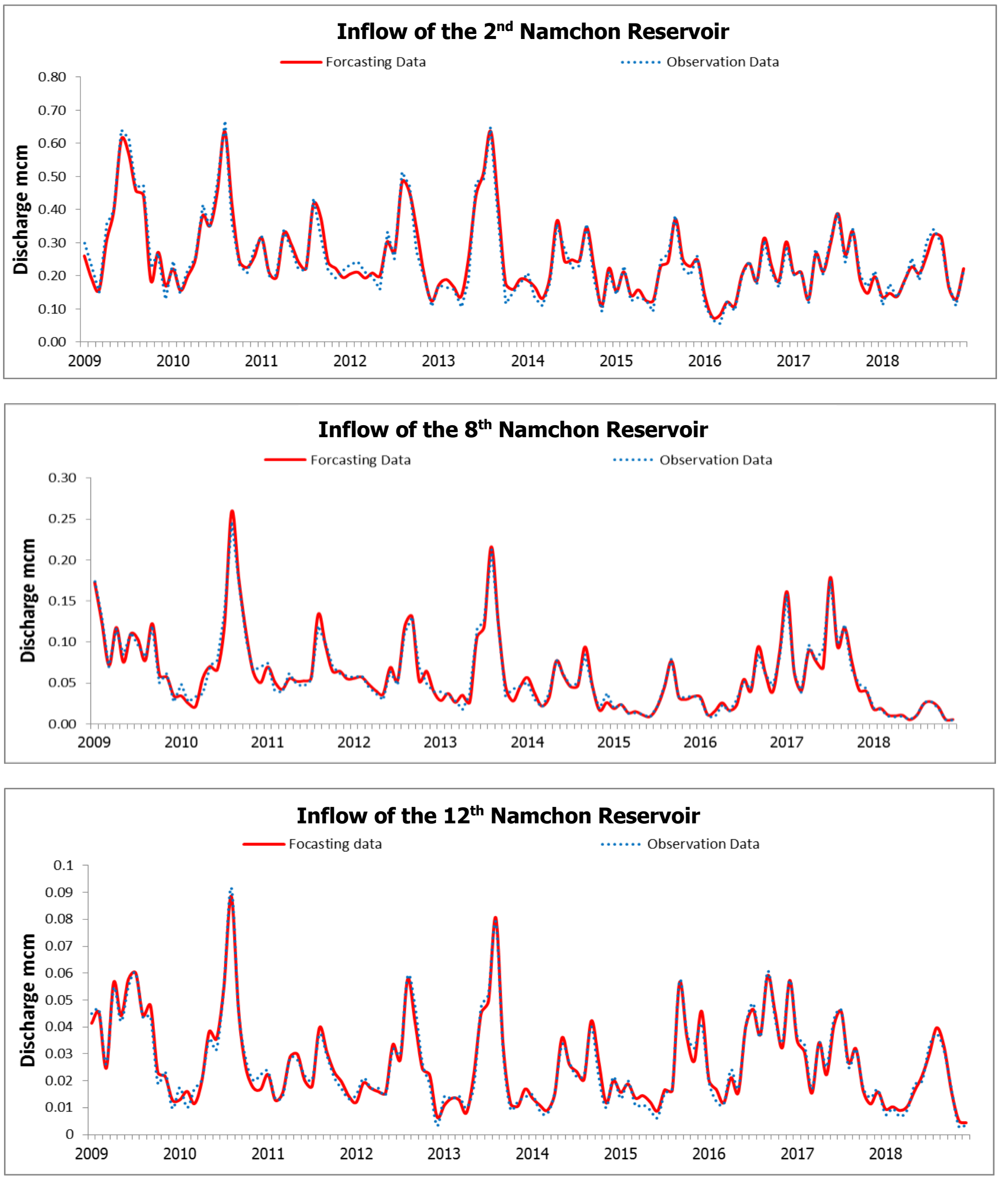

Figure 6 *Show comparison between forecasting data and observation data of Namchon reservoir networks (NRN) system inflow.*

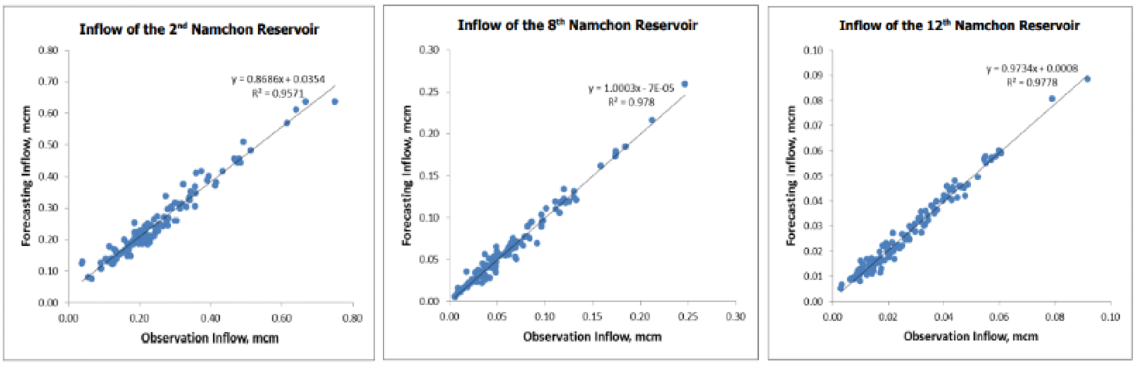

Figure 7 *Show comparison between forecasting data and observation data of NRN system inflow.*

5. Conclusion

In the present study, the artificial neural network (ANN) was used to study the inflow of NRN system. Current model was chosen because of their precise results in a shorter time frame with relatively simple inputs. It is necessary to find the best convergent hydrological variable input for appropriate predict for reservoirs, which have different geographic and climatic conditions and directly affect the hydrology variable of the reservoir. The best convergent hydrological variable input used to the 2nd Namchon reservoir is studied based on data recorded. Three types of variable inputs were considered (inflow, rainfall and water storage) to assess how well the inflow prediction has performed in the operation of the reservoir as a basis of comparison six input functional form. The best convergence of hydrological variable input for the 2nd Namchon reservoir consists of inflow during month (I_t), lagged rainfall of one-month (R_{t-1}) and water storage during month (S_t). Inflow prediction of the NRN System used three hydrological variable inputs to predict water inflows into the royal study center by ANN. They are regarded as the best convergence to predict one-month ahead inflow of the NRN system, compared with the observation data from 2009 to 2018. The predicted values from ANN well match the measured values. Inflow prediction shows precise results.

The findings of this study can be used to aid the NRN system water diversion/release decisions. Having unpredicted circumstances of the weather, the early decision of the reservoir water release is always a difficult decision. Information on the inflow prediction in advance is used as a guideline by reservoir operators to decide early water diversion/release.

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