Inflow forecasting using Artificial Neural Networks for reservoir operation

Case study: the multi-purpose Ubonratana reservoir in Thailand

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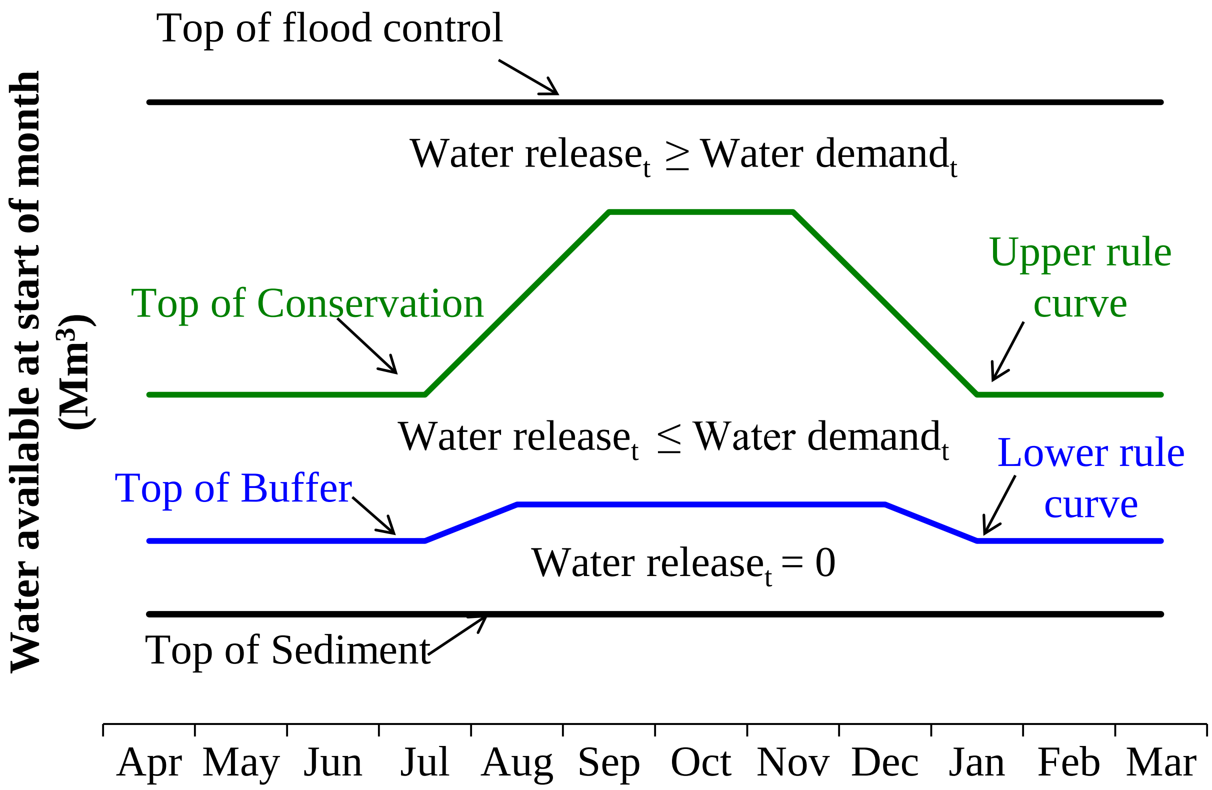
Schematic of rule curves for reservoir operation



For water allocation, water release is based on the amount of water available at the start of the month relative to the ordinates of the rule curves.

$$WA_t = S_t + Q_t$$

where

WA_t = Water available in month t.

S_t = storage at start of t.

Q_t = expected inflow during t.

Reservoir operation: Challenge

$$WA_t = S_t + Q_t$$

Known

Unknown

Reservoir operation: Challenge (Cont'd)

Several possible assumptions about Q_t:

(1) Equal to the historic flow for the month being considered (Type A)

(2) Equal to the 1-month ahead flow forecast (Type F)

(3) Equal to the historic mean flow for the month (Type M)

(4) Unknown with release decision only conditioned on S_t (Type N).

Aim & Objectives

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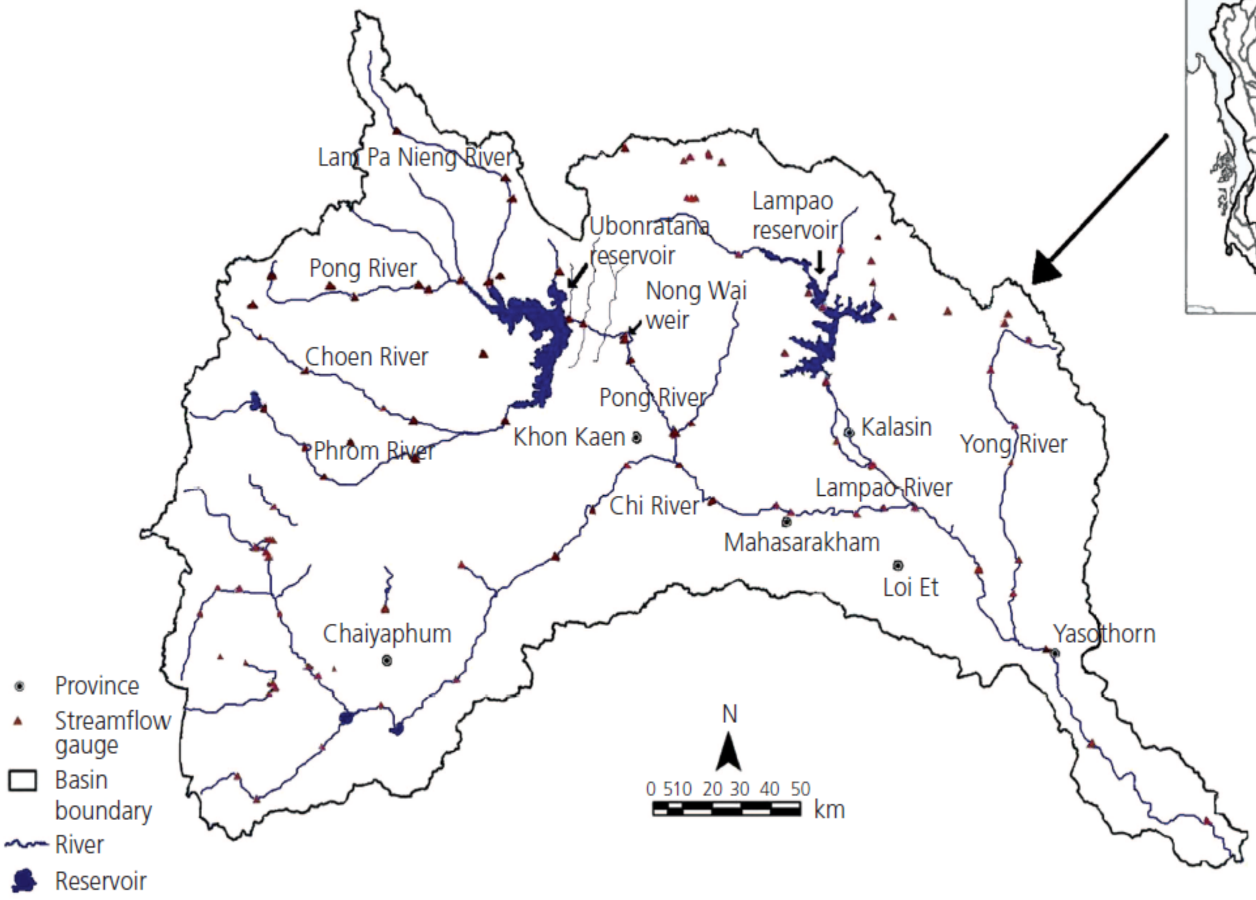
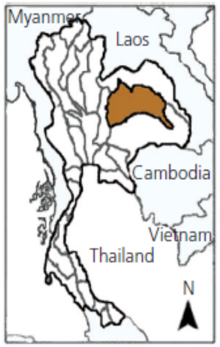
Aim: Investigate effect of different inflow knowledge situations, including forecasts, on reservoir operation performance.

Objectives are to :

- Select a suitable case study: the Ubonratana reservoir, Thailand
- Develop a multi-layer perceptron (MLP)-ANN model for one-month-ahead inflow forecasting.
- Perform reservoir simulations forced alternatively with each of the 4 inflow knowledge scenarios (see previous slide) and make recommendations.

Case study:
Ubonranata Reservoir, Thailand





Hydrometeorological data	
Catchment area (km²)	12,000
Rainfall (mm/y)	1,200
Inflow (MCM/y)	2,604
The gross water requirements (MCM)	28,952
Municipal and Industrial demand (MCM/y)	11.8
Irrigation (MCM/y)	727
Downstream Control and other (MCM/y)	226

Reservoir physical data	
Reservoir capacity (MCM)	2,431
Active storage (MCM)	1,850
Dead storage (MCM)	581
Max.WL (m msl)	186
NWL (m msl)	182
Min.WL (m msl) for Hydropower	175
Min.WL (m msl) for Irrigation	168

- The reservoir information and water demand data of 384 months (1980-2012) provided by EGAT

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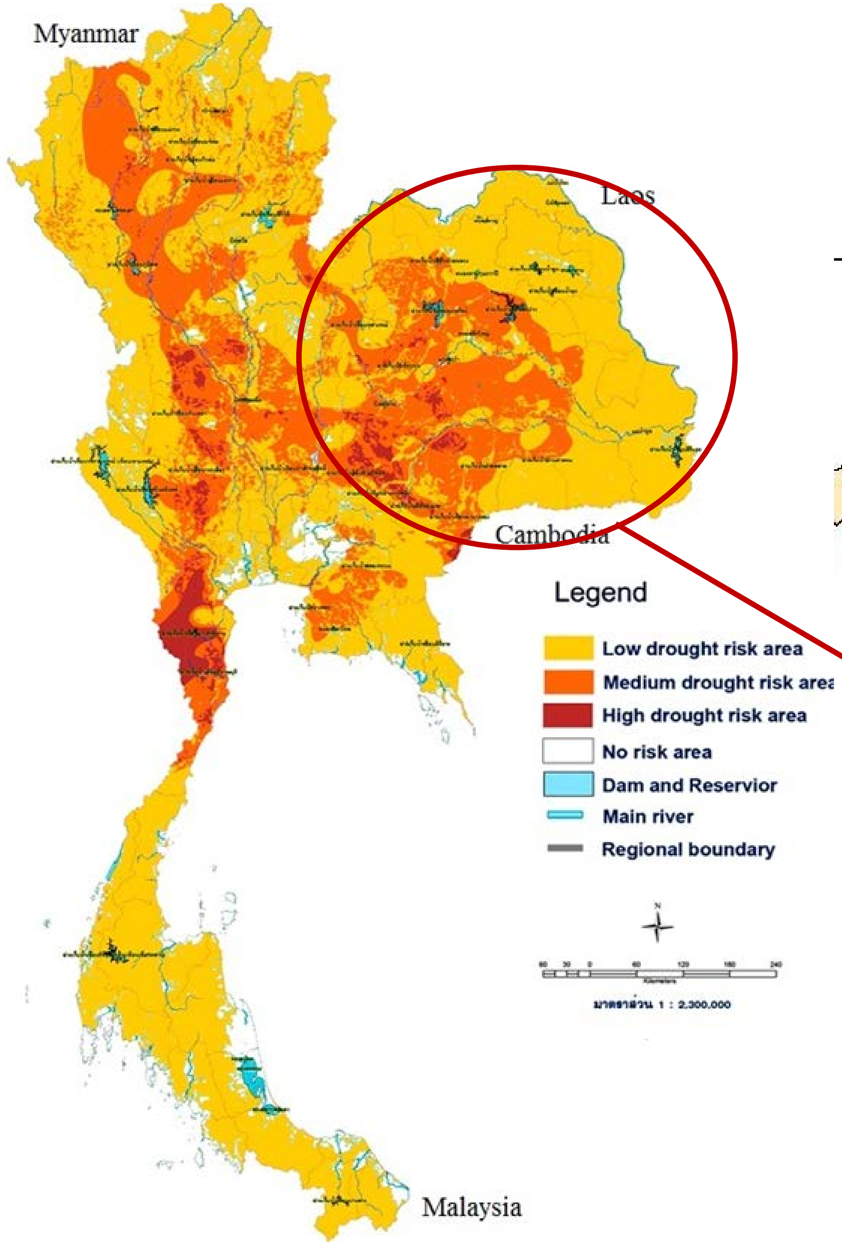
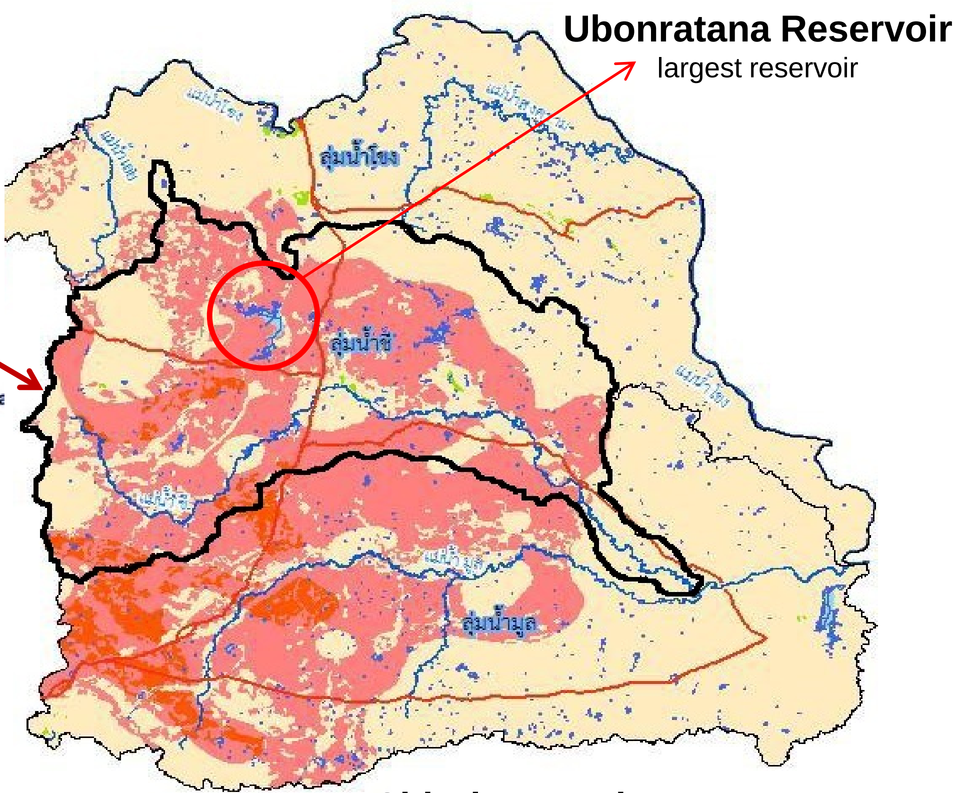
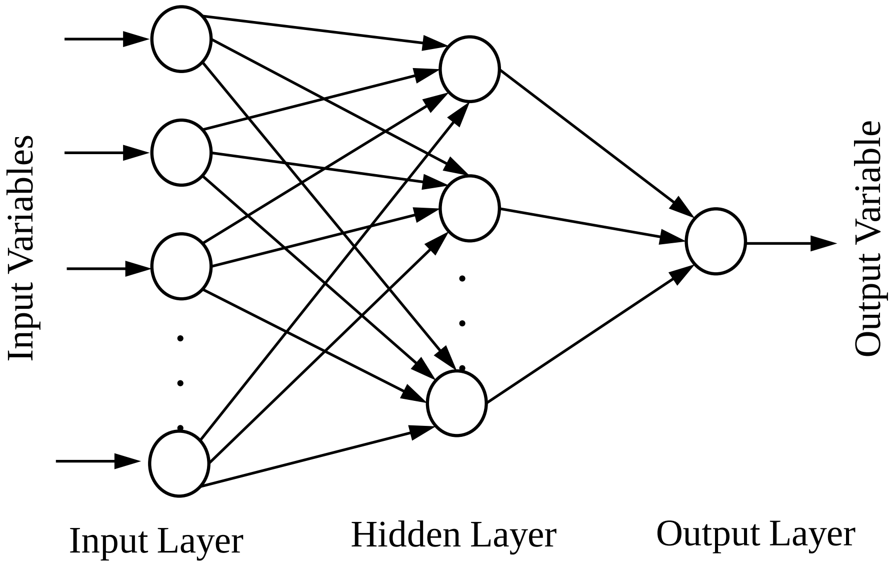
Northeastern Thailand





Inflow forecasts: Using ANN



The structure of ANN comprises an input layer, an output layer and one or more hidden layers.

The layers contain nodes or neurons which are connected by weights.

The number of nodes in the output layer is fixed by the problem, e.g. in the current work, it is the 1-month ahead inflow forecast.

Inflow forecasting with ANN: Model structure identification

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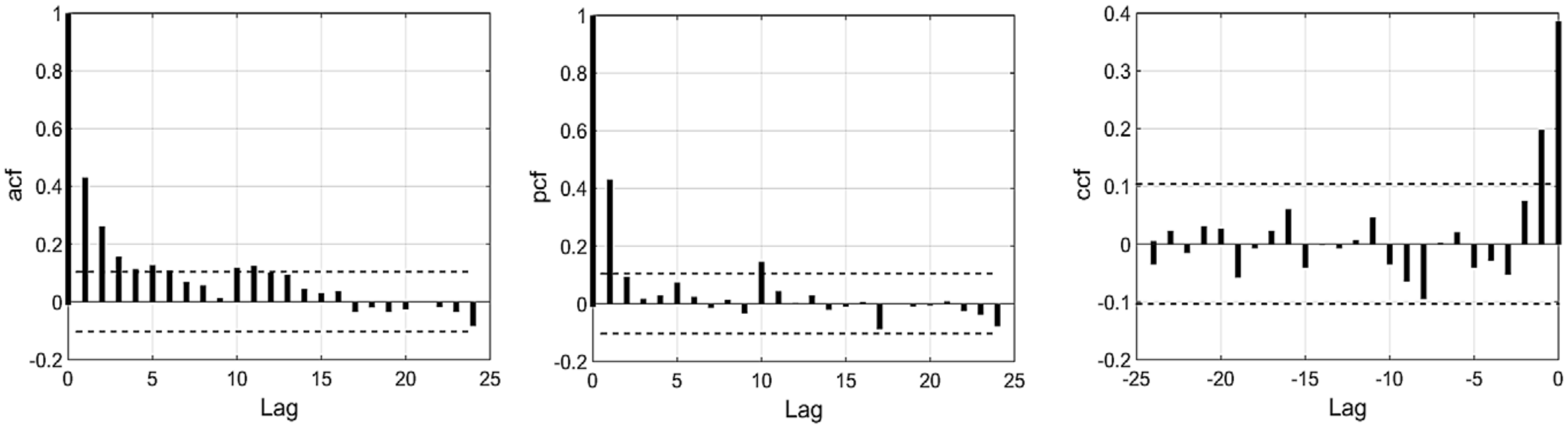
- Input variables: examination of the auto-correlation function (acf), partial-autocorrelation function (pcf) and cross-correlation function (ccf)
- Hidden layer: 1 layer; nodes by trial and error training
- Out put layer: 1 node (1-month ahead forecasts)

ANN model structure:
acf, pcf, ccf

acf pcf ccf



- The acf shows infinite attenuation with only the first three lags of inflow being significant.
- The ccf indicates that the first two lags of the rainfall are significant.

ANN inflow forecasts:
Models structure

$$Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3}, R_{t-1}, R_{t-2}, \overline{Q}_t)$$

where

Q_t is the one-month ahead inflow forecast;

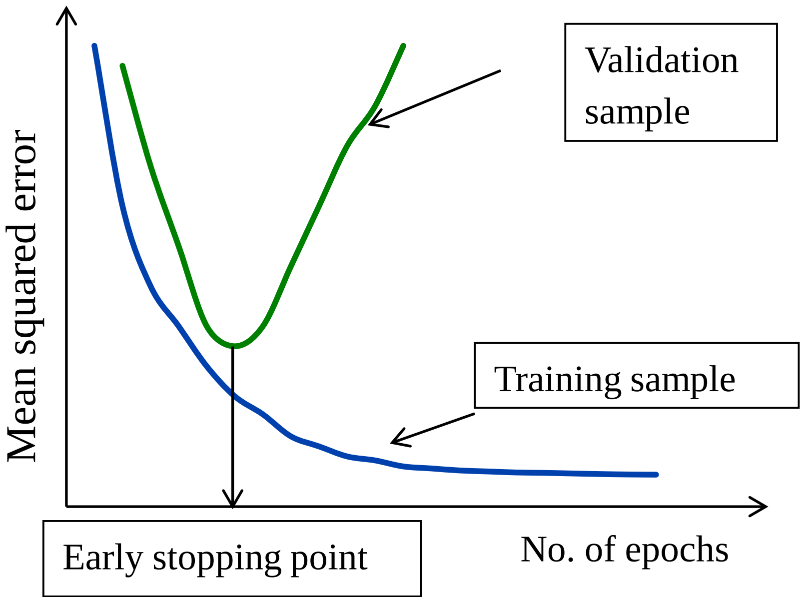
Q_{t-1}, Q_{t-2} and Q_{t-3} are lagged inflows of one-month, two-month and three-month, respectively;

R_{t-1} and R_{t-2} are lagged rainfall of one-month and two-month, respectively;

$\bar{Q}_t$ is historic mean inflow for the current month.

ANN inflow forecasts:
Training algorithm

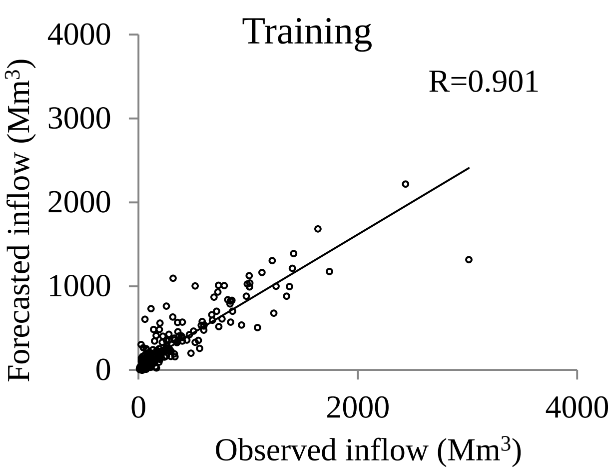
The early-stopping rule (ESR) was used for the ANN training and for the 360 months (April 1982-March 2012) of data were split into three (90:5:5) for training, validation and testing, respectively.

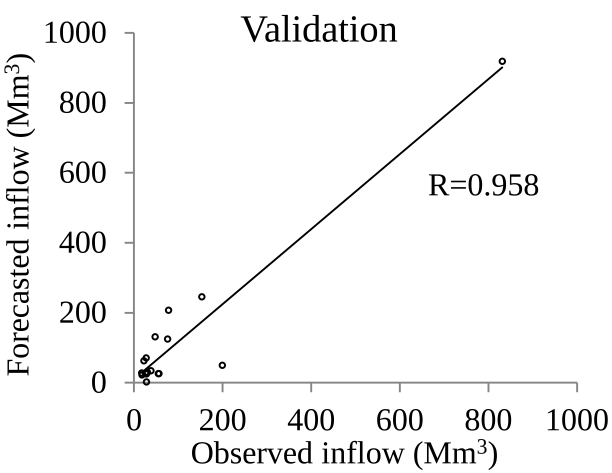


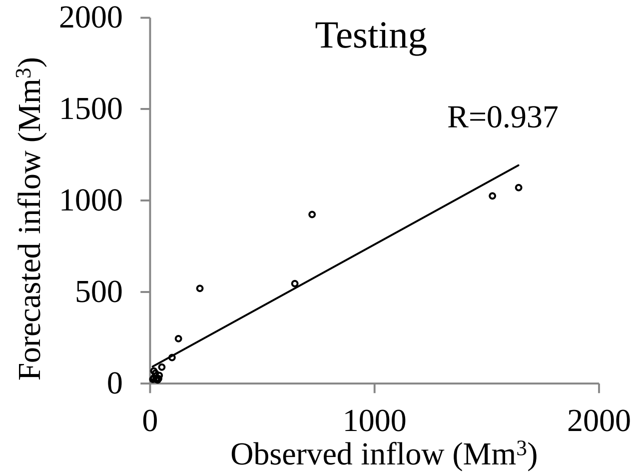
(i) a training set, used to determine the network weights and biases,
(ii) a validation set, used to estimate the network performance and decide when the training should be stopped, and
(iii) a test set, used to verify the effectiveness of the stopping criterion and to estimate the expected performance in the future.

ANN inflow forecasts: Hidden neurons

- Trail-and-error: varied between 1 and 35
- Best architecture had 33 neurons in the hidden layer.

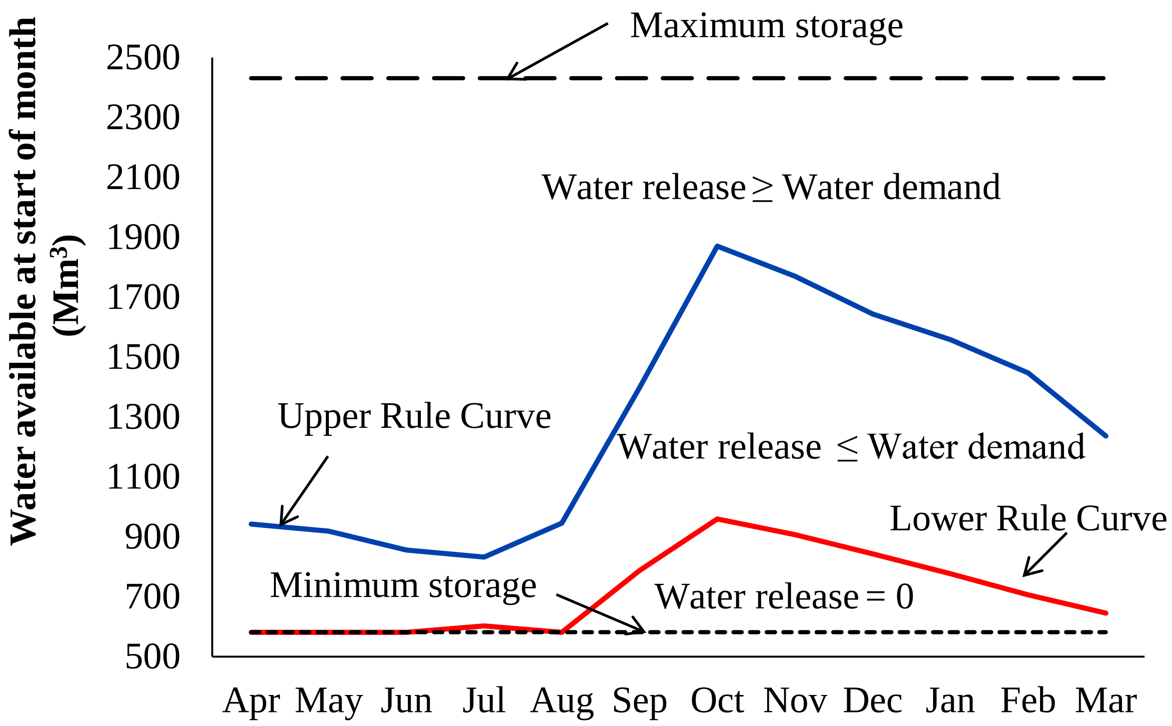






Reservoir operation

Rule curves of Ubonratana reservoir developed by Chiamsathit et al. (2014)



The original rule curves were provided by the EGAT; the improved versions of these developed by Chiamsathit et al. (2014) were used in the current study.

The upper rule curve (URC) : The maximum level for flood control purposes

The lower rule curve (LRC): The limit for conservation purposes

Chiamsathit, C., Adeloye, A. J. and Soundharajan, B. (2014) Assessing competing policies at Ubonratana reservoir, Thailand. Proceedings ICE (Water Management). 167(WM10). p.551 –560.

Reservoir performance simulation

Mass balance equation: $S_{t+1} = S_t + Q_t - D'_t - E_t$

Water available during *t*: $WA_t = S_t + Q_t$

Let the actual end-of-period storage be $S_{end,t}$, the relationships between this and S_{t+1} for each of the assumed inflow knowledge assumptions become:

(1) Type A: $WA_t = S_t + Q_t$ and $S_{end,t} = S_{t+1}$

(2) Type F: $WA_t = S_t + Q'_t$ and $S_{end,t} = S_{t+1} + Q_t - Q'_t$

(3) Type M: $WA_t = S_t + \overline{Q}_t$ and $S_{end,t} = S_{t+1} + Q_t - \overline{Q}_t$

(4) Type N: $WA_t = S_t$ and $S_{end,t} = S_{t+1} + Q_t$

where S_t and S_{t+1} are respectively storage at the beginning and end of time *t*; Q_t is the observed (correct) inflow during time *t*, ; E_t is the net evaporation (evaporation minus direct rainfall) in period t; D_t' is the total water release towards meeting the target demand of D_t during t. Q'_t is the corresponding forecast inflow, $\overline{Q}_t$ is the historic mean flow for the month of time t,

Reservoir performance simulation

With the available water determined, release then takes place guided by the rule curves as follows:

Case 1: For $WA_t \geq URC_m$ this is the excess operation case, i.e., $D'_t \geq D_t$

$$D'_t = S_t + Q_t - E_t - URC_m$$

$$Y_t = D'_t - D_t$$

Case 2: For $LRC_m < WA_t < URC_m$ this is the normal operation case, i.e., $D'_t \leq D_t$

$$Y_t = 0$$

If $WA_t - D_t \geq LRC_m, D'_t = D_t$

If $WA_t - D_t < LRC_m, D'_t = WA_t - LRC_m$

Case 3: For $WA_t \leq LRC_m$ this is the deficit operation case, i.e., $D'_t = 0$

(No water released)

where URC_m is the upper rule curve during month *m(=1, 2.,3,…,12)* of the year; LRC_m is the lower rule curve during month *m*; Y_t is the excess water released during period *t*. In general, t = 12(y-1) + m for years y = 1, 2, 3…., n, where n is the number of years in the data record.

Reservoir Performance Indices

- Time-based Reliability (R_t) $$R_t = N_s / N$$
- Volume-based Reliability (R_v) $$R_v = \sum_{t=1}^{N} D_t' \Big/ \sum_{t=1}^{N} D_t$$
- Resilience (φ) $$\varphi = \frac{1}{\left(\frac{f_d}{f_s}\right)} = \frac{f_s}{f_d}$$
- Vulnerability (η) $$\eta = \frac{\sum_{k=1}^{f_s} \left(\frac{\max(sh_k)}{D_k}\right)}{f_s}$$
- Sustainability index (λ) $$\lambda = \left(R_t \varphi (1-\eta)\right)^{1/3}$$
- Group sustainability index (λ_G) $$\lambda_G = \sum_{j=1}^{M} w_j \lambda_j$$ where $$w_j = \frac{D^j}{\sum_{j=1}^{M} D^j}$$

where Ns is the total number of months out of N that the demand was met; fs is the number of failure sequence; f_d is the total duration of the failures (months); max (shk) is the maximum water shortage in failure sequence k and Dk corresponding demand: λj is the sustainability for users category j; w_j is the weighting for user j; M is the total number of users sectors and D_j is the average annual water demand for users sector j.

Results:

Reservoir performance

Policy	Water user	Total water shortage (Mm^3)	Excursions of $S_{end,t}$ below LRC	f_d	f_s	Reliability (%) R_t	Reliability (%) R_v	φ	η	λ_{user}	λ_G
P-A	Domestic	0	8	0	0	100	100	-	0	1	0.557
	Downstream	0.5		1	1	99.72	99.99	1	0.026	0.99	
	Irrigation	309.4		15	3	95.83	98.58	0.2	0.626	0.415	
P-F	Domestic	0	14	0	0	100	100	-	0	1	0.655
	Downstream	0		0	0	100	100	-	0	1	
	Irrigation	244.5		10	4	97.22	98.88	0.4	0.591	0.542	
P-M	Domestic	0	16	0	0	100	100	-	0	1	0.464
	Downstream	0		0	0	100	100	-	0	1	
	Irrigation	166.8		6	1	98.33	99.24	0.167	0.853	0.289	
P-N	Domestic	3.2	4	6	5	98.33	99.09	0.833	1	0	0.543
	Downstream	132.7		10	9	97.22	98.04	0.9	0.77	0.586	
	Irrigation	1062.6		28	15	92.22	95.13	0.536	0.684	0.539	

- In terms of R_t and R_v, P-F was marginally better than using P-A and significantly better than P-N; P-F was, however, inferior to P-M.
- The net effect of such large releases (based on the upwardly-biased inflow forecasts) is the increased number of excursions of the end-of-period storage ($S_{end,t}$) into the region below the LRC
- P-F was superior to all others for the irrigation allocation

Results (Cont'd):

Reservoir performance

- In terms of the total amount of water released, P-A, P-F and P-M were significantly better than P-N.

- The group sustainability index for P-F was the highest

- The conservative nature of P-N resulted in the least number of excursions below the LRC. This is likely to benefit the hydro-power generation potential of the reservoir albeit at the expense of the water supply functions.

Summary

- Extensive testing of the ANN model showed that it was able to provide one-month-ahead inflow forecasts with reasonable accuracy.

- The performance of the ANN forecasts was tested against those of three other inflow scenarios and the reservoir simulation results showed that the ANN forecasts produced superior reservoir performance.

Summary Contd.

- The worst performing inflow situation was when there was complete lack of knowledge about the inflow and release decision was based on the starting storage alone.

- All this represents an objective demonstration of good inflow forecast knowledge for effective reservoir operation.

Questions?

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