# Reservoir inflow modelling by Neuro Fuzzy and ANN models

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# Introduction

- **Time series modeling - planning and management of reservoirs.**
- **Monthly reservoir operation for managing reservoirs with agricultural allocation.**
- **Time Series Analysis**
  - **seasonality of the time series is to be preserved, and**
  - **correlation structure with the preceding months is to be incorporated**

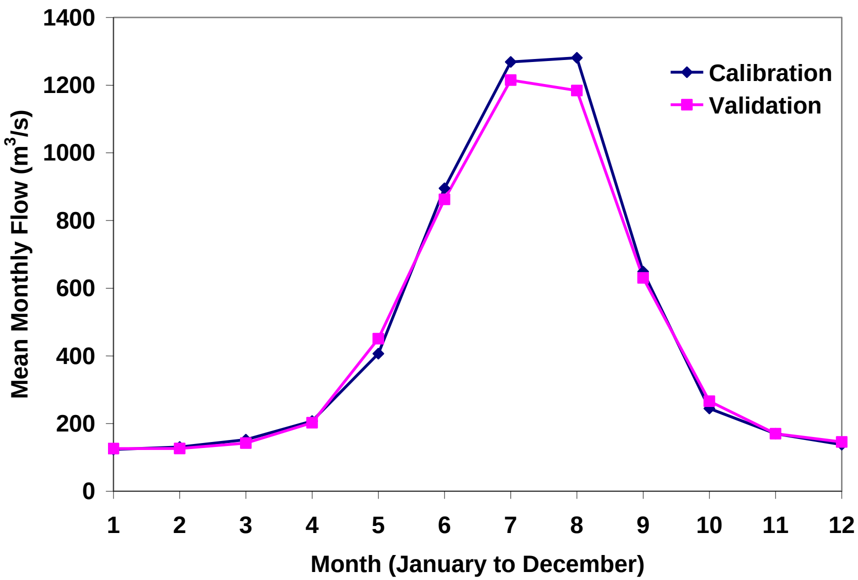
# OBJECTIVES

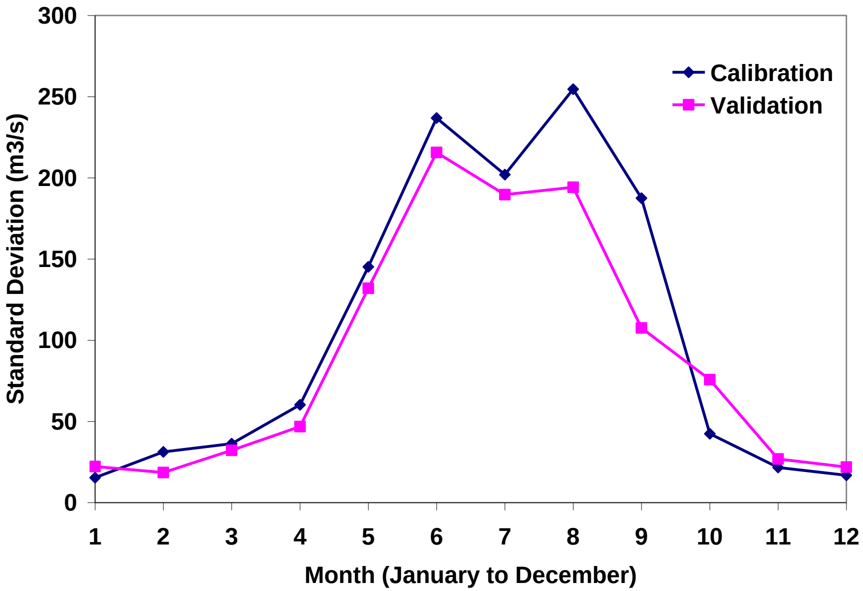
- **To investigate the potential of ANN and neuro-fuzzy systems in modelling hydrological time series.**
- **To apply the developed ANN and neuro-fuzzy models for simulating the time series of monthly flow data and compare it with Auto Regressive (AR) Model**

# Data Used

- Average Monthly inflow series of Bhakara Dam located in Sutlej River, India.
- 25 Years data for calibration and 15 Years data for validation
- The results obtained ANFIS models are compared against the results from back propagation algorithm based ANN and AR model.

# Monthly mean and standard deviation of calibration and validation data



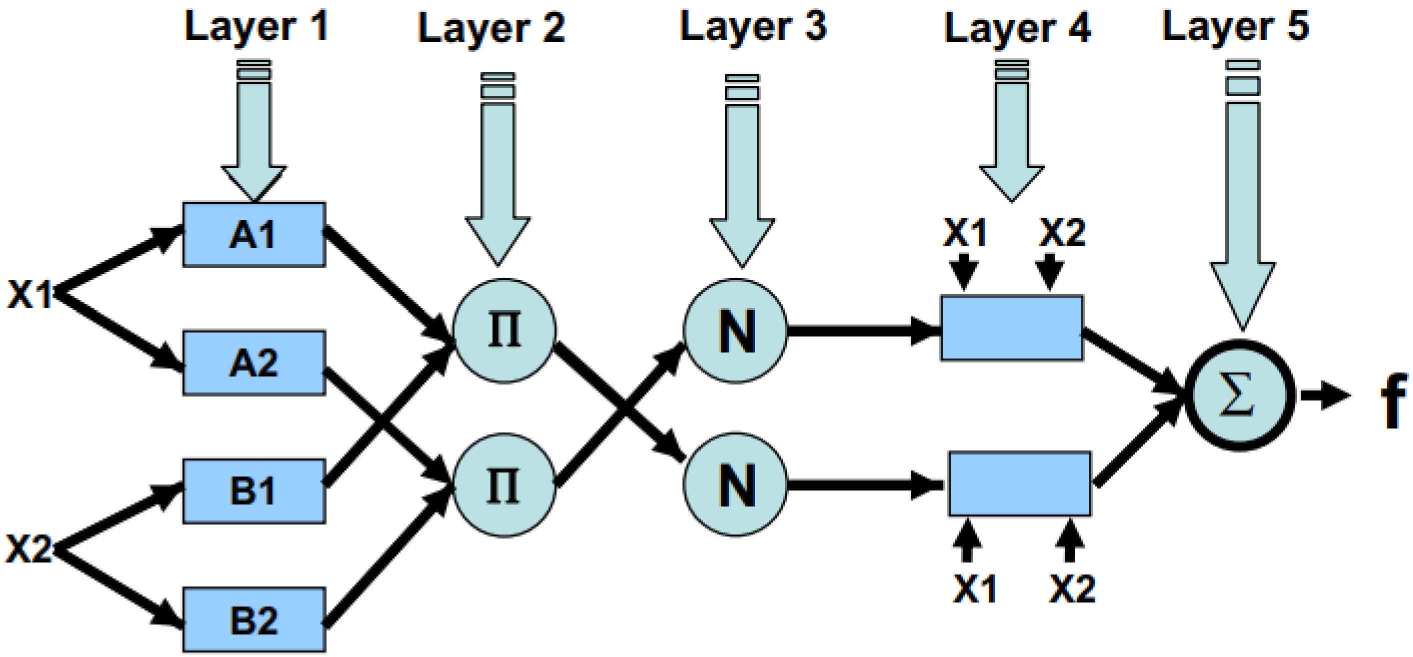
# Methodology

- Modelling of monthly Reservoir inflow series using
  - ANN Model
  - Neuro Fuzzy Model (ANFIS)
  - AR (autoregressive) model

# Methodology (ANFIS)

- **Determination of inputs for the system.**
- **Describing in detail the cause and effect action of the system with "*fuzzy rules*"**
- **Selection of FIS for designing an ANFIS**

# NEURO-FUZZY STRUCTURE FOR TIME SERIES MODELLING




Adaptive Neuro Fuzzy Inference System (ANFIS)

# ANN & ANFIS MODEL

**A. Considering only previous inflows in the input vector**

M1 $Q(t) = f(Q[t-1])$

M2 $Q(t) = f(Q[t-1], Q[t-2]])$

M3 $Q(t) = f(Q[t-1], Q[t-2], Q[t-3])$

M4 $Q(t) = f(Q[t-1], Q[t-2, Q[t-3], Q[t-4])$

(B) Considering previous inflows and cyclic term in the input vector:

M5 $Q(t) = f(Q[t-1], \cos[2\pi \cdot i/12], \sin[2\pi \cdot i/12])$
M6 $Q(t) = f(Q[t-1], Q[t-2], \cos[2\pi \cdot i/12], \sin[2\pi \cdot i/12])$
M7 $Q(t) = f(Q[t-1], Q[t-2], Q[t-3], \cos[2\pi \cdot i/12], \sin[2\pi \cdot i/12])$
M8 $Q(t) = f(Q[t-1], Q[t-2, Q[t-3], Q[t-4], \cos[2\pi \cdot i/12], \sin[2\pi \cdot i/12])$

# Time Series Modelling (AR ) Model

- If a hydrological time-series is represented by X1,X2,X3,...Xt; then symbolically the structure of the Xt is expressed by:
  - Xt [Tt;Pt;Et]
- Where Tt is the trend component, Pt is the periodic component and Et is the stochastic component.
- The first two components are specific deterministic features and contain no element of randomness.

# Modeling of deterministic component

## – Nonparametric approach

Non-parametric method of separating periodicity can be expressed as follows:

$$Z_{t,\tau} = \frac{X_{t,\tau} - \overline{X}_\tau}{\sigma_\tau}$$

where $X_{t,\tau}$ is the original trend free series; $t$ represent year, $t = 1,2,3,\ldots n$; $n$ is the no. of years of records. $\tau$ represent month, $\tau = 1,2,3,\ldots \omega$; $\omega$ is no. of seasons in a year. $\overline{X}_\tau$ and $\sigma_\tau$ are sample mean and standard deviation of the $\tau$th month respectively.

## – Parametric approach

In parametric approach the removal of periodicity in mean and standard deviation is based on harmonic representation of seasonal parameters. The periodic component in any parameter $v$ may be approximated by $m$ harmonics of its basic period $\omega$ in the form.

$$v_\tau = v_x + \sum_{j=1}^{m}\left(A_j \cdot \cos\frac{2\pi j\tau}{\omega} + B_j \cdot \sin\frac{2\pi j\tau}{\omega}\right)$$

- **Removal of periodic component by parametric approach**

$$Z_{t,\tau} = \frac{X_{t,\tau} - \overline{X}_{\tau s}}{\sigma_{\tau s}}$$

where $X_{\tau s}$ is smoothened mean of τth month and $\sigma_{\tau s}$ is smoothened standard deviation of τth month.

- **Modeling of the stochastic component**
- **Dependent stochastic component**
  - **Modeled by autoregressive models**
- **Independent stochastic component.**
  - **Modelled by probability distribution.**

# Stochastic component

- Autoregressive models

$$z_t = a_1 z_{t-1} + a_2 z_{t-2} + \dots\dots\dots + a_m z_{t-m} + \varepsilon_t$$

$$r_k = a_1 r_{k-1} + a_2 r_{k-2} + \dots\dots\dots + a_m r_{k-m}$$

# Stochastic component

- AR(1)

$$a_1 = r_1$$

$$R_1^2 = r_1^2$$

# Stochastic component

- AR(2)

$$a_1 = \frac{r_1 - r_1 r_2}{1 - r_1^2}$$

$$R_2^2 = \frac{r_1^2 + r_2^2 - 2 r_1^2 r_2}{1 - r_1^2}$$

$$a_2 = \frac{r_2 - r_1^2}{1 - r_1^2}$$

# Stochastic component

- AR(3)

$$a_1 = \frac{(1-r_1^2)(r_1-r_3)-(1-r_2)(r_1 r_2-r_3)}{(1-r_2)(1-2r_1^2+r_2)}$$

$$a_2 = \frac{(1-r_2)(r_2+r_2^2-r_1^2-r_1 r_3)}{(1-r_2)(1-2r_1^2+r_2)}$$

$$a_3 = \frac{(r_1-r_3)((r_1^2-r_2^2)-(1-r_2)(r_1 r_2-r_3)}{(1-r_2)(1-2r_1^2+r_2)}$$

$$R_3^2 = (r_1^2+r_2^2+r_3^2+2r_1^3 r_3+2r_1^2 r_2^2 +2r_1 r_2^2 r_3-2r_1^2 r_2-4r_1 r_2 r_3-r_1^4 -r_2^4-r_1^2 r_3^2)/(1-2r_1^2-r_2^2+2r_1^2 r_2)$$

# Stochastic component

- Selection of order of AR model

AR(1) $R_2^2 - R_1^2 \leq 0.01 \text{ and } R_3^2 - R_1^2 \leq 0.2$

AR(2) $R_2^2 - R_1^2 \succ 0.01 \text{ but } R_3^2 - R_2^2 \leq 0.01$

AR(3) $R_2^2 - R_1^2 \succ 0.01 \text{ and } R_3^2 - R_1^2 \succ 0.01$

# Performance Evaluation

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Q_{oi} - Q_{pi})^2}{N}}$$

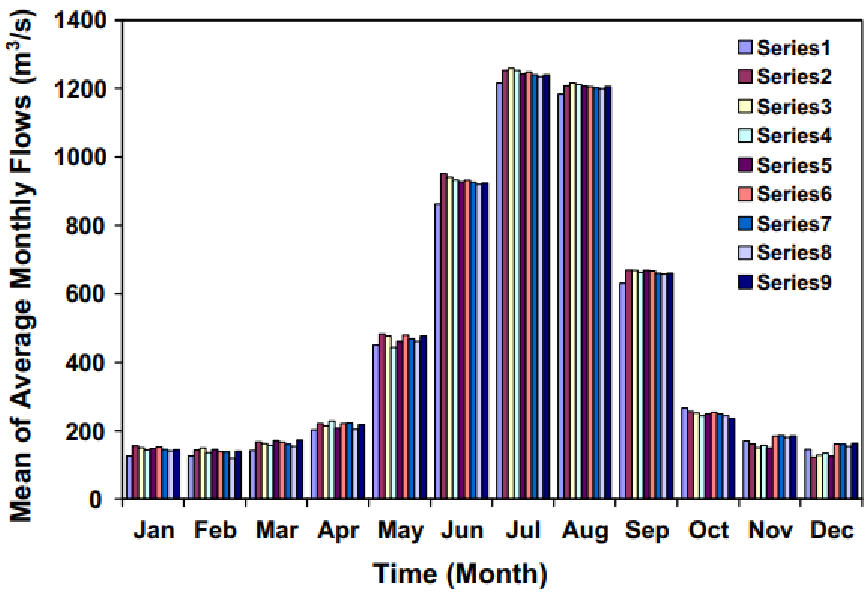
$$Efficiency = \left[ 1 - \frac{\sum_{i=1}^{N} (Q_o - Q_p)^2}{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2} \right]$$

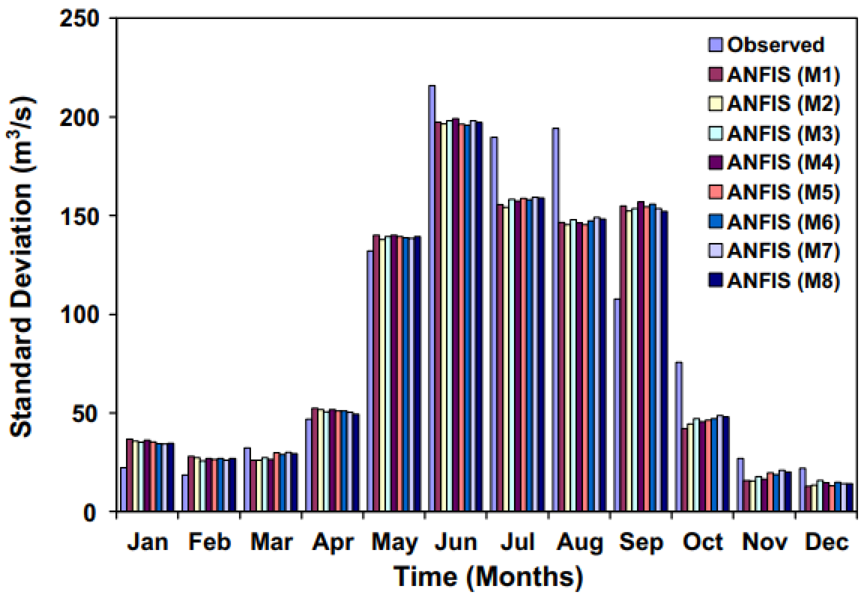
$$R = \frac{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)(Q_p - \overline{Q}_p)}{\sqrt{\sum_{i=1}^{N} (Q_o - \overline{Q}_o)^2 \sum_{i=1}^{N} (Q_p - \overline{Q}_p)^2}}$$

# AR MODEL RESULTS

- For the smoothening of parameters, **six harmonics** have been selected on the basis of $P_{max}$-$P_{min}$.
- Using the parametric approach, periodicity from the time series have been removed.
- Using the AR model selection criteria, **AR(2)** model has been selected for inflow forecasting.

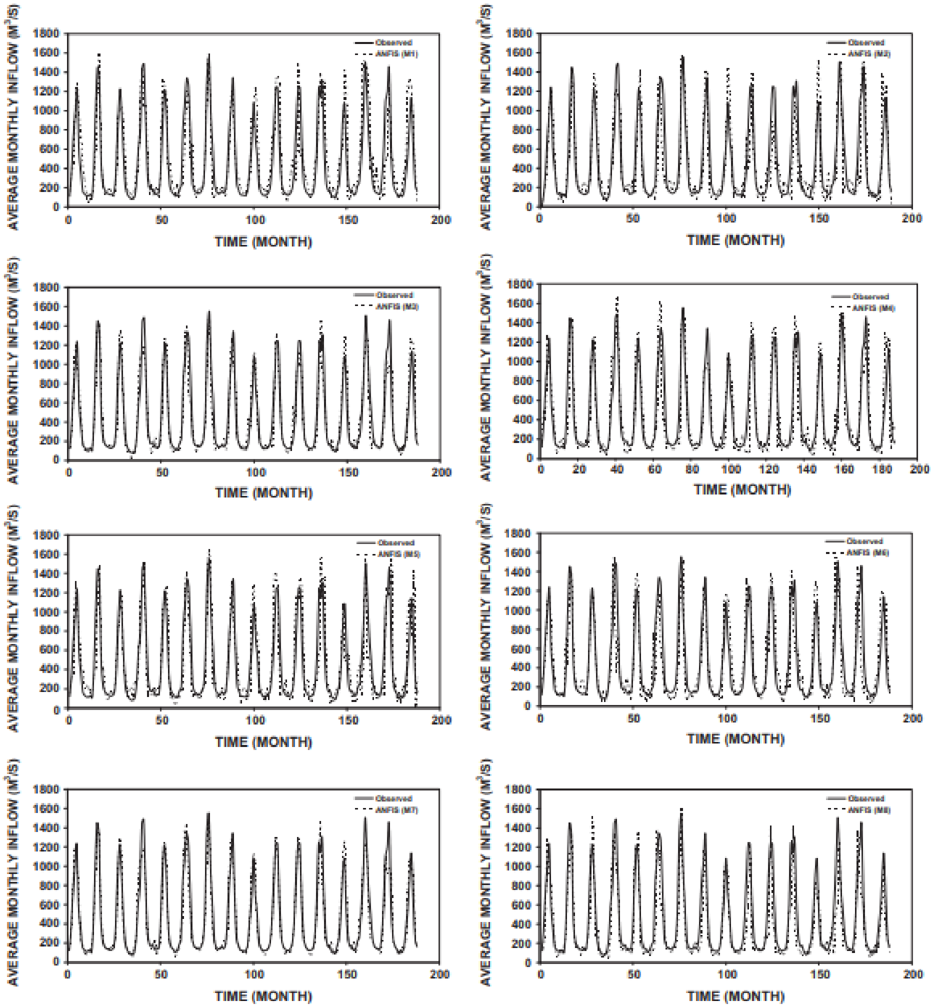
# ANFIS MODEL RESULTS




**Mean Monthly inflow and standard deviation statistics of observed and forecasted inflows- ANFIS Model**

# Time series of monthly mean inflows ANFIS model-validation results



# Performance indices of ANN models during calibration and validation

| Model | No. of rules | Calibration | | | Validation | | | AIC | BIC |
|---|---|---|---|---|---|---|---|---|---|
| | | RMSE ($m^3/s$) | NS coefficient | Coefficient of correlation | RMSE ($m^3/s$) | NS coefficient | Coefficient of correlation | | |
| MI | 7 | 188.10 | 0.6696 | 0.796 | 256.30 | 0.6768 | 0.818 | 1.818 | 2.057 |
| M2 | 7 | 184.40 | 0.6852 | 0.812 | 251.40 | 0.6900 | 0.824 | 1.813 | 2.063 |
| M3 | 7 | 178.30 | 0.6924 | 0.816 | 244.10 | 0.6984 | 0.827 | 1.804 | 2.065 |
| M4 | 7 | 182.30 | 0.6828 | 0.815 | 245.70 | 0.6864 | 0.829 | 1.814 | 2.088 |
| M5 | 9 | 174.70 | 0.6864 | 0.802 | 252.20 | 0.6852 | 0.826 | 1.797 | 2.057 |
| M6 | 9 | 171.40 | 0.6984 | 0.816 | 247.30 | 0.6924 | 0.832 | 1.792 | 2.064 |
| M7 | 9 | 168.60 | 0.7044 | 0.818 | 241.70 | 0.7020 | 0.837 | 1.789 | 2.072 |
| M8 | 9 | 169.30 | 0.7008 | 0.815 | 242.10 | 0.6864 | 0.828 | 1.818 | 2.057 |

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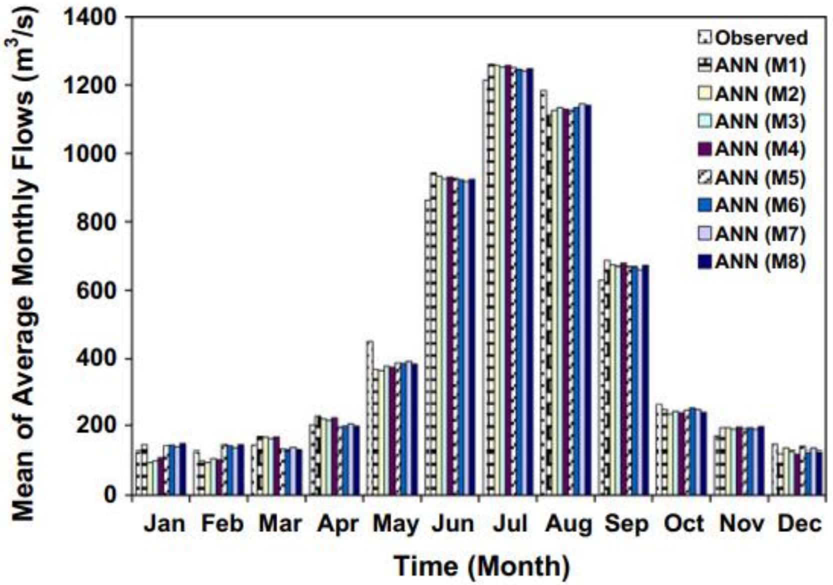


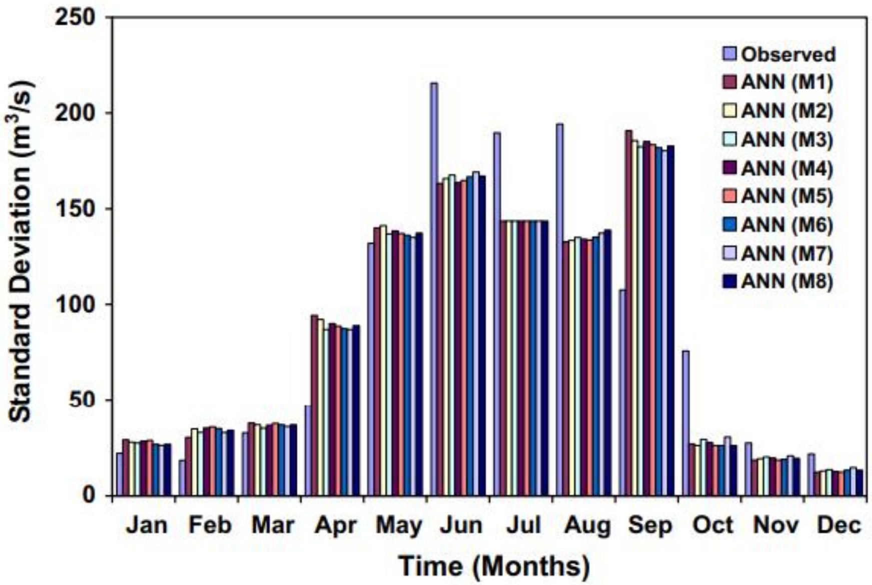

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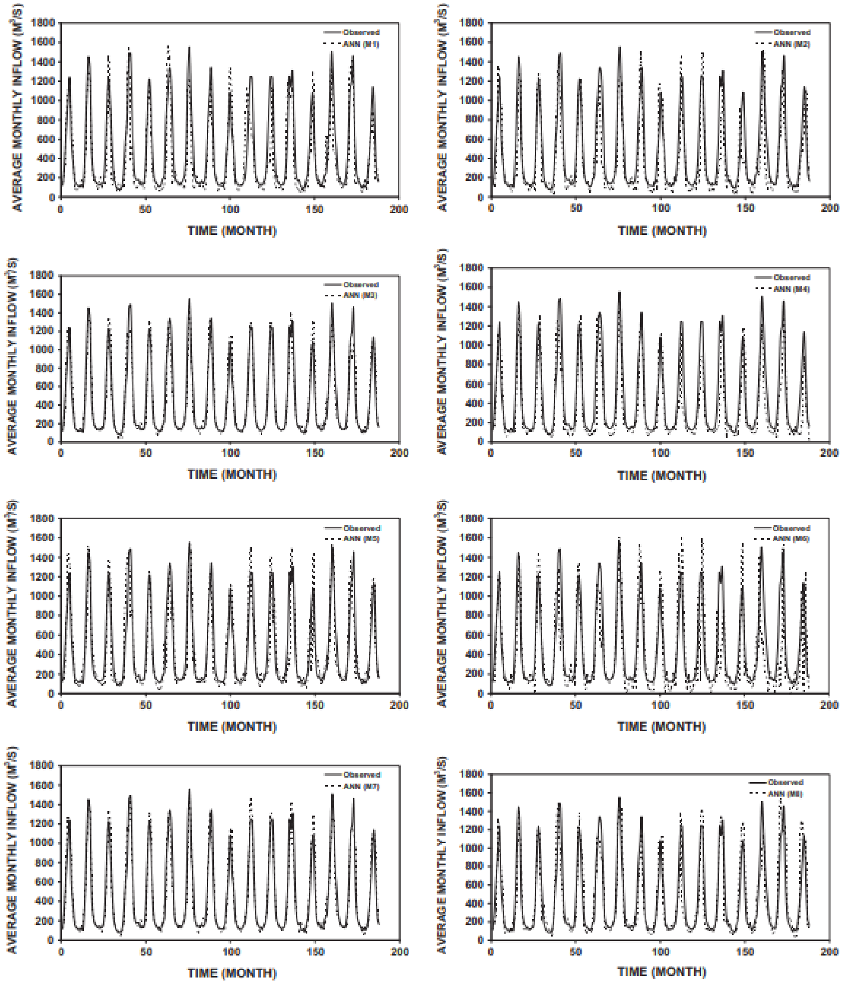

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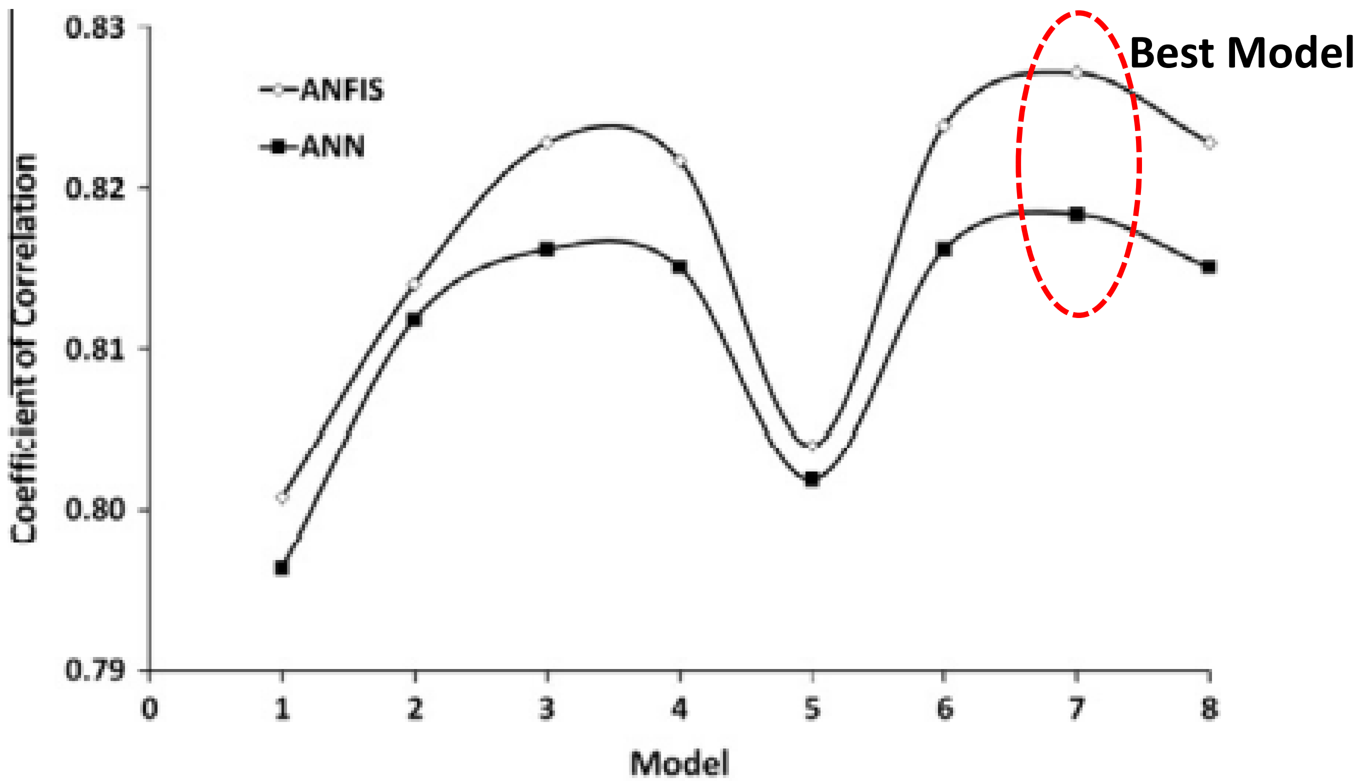
# Comparison of coefficient of correlation of ANN and ANFIS models



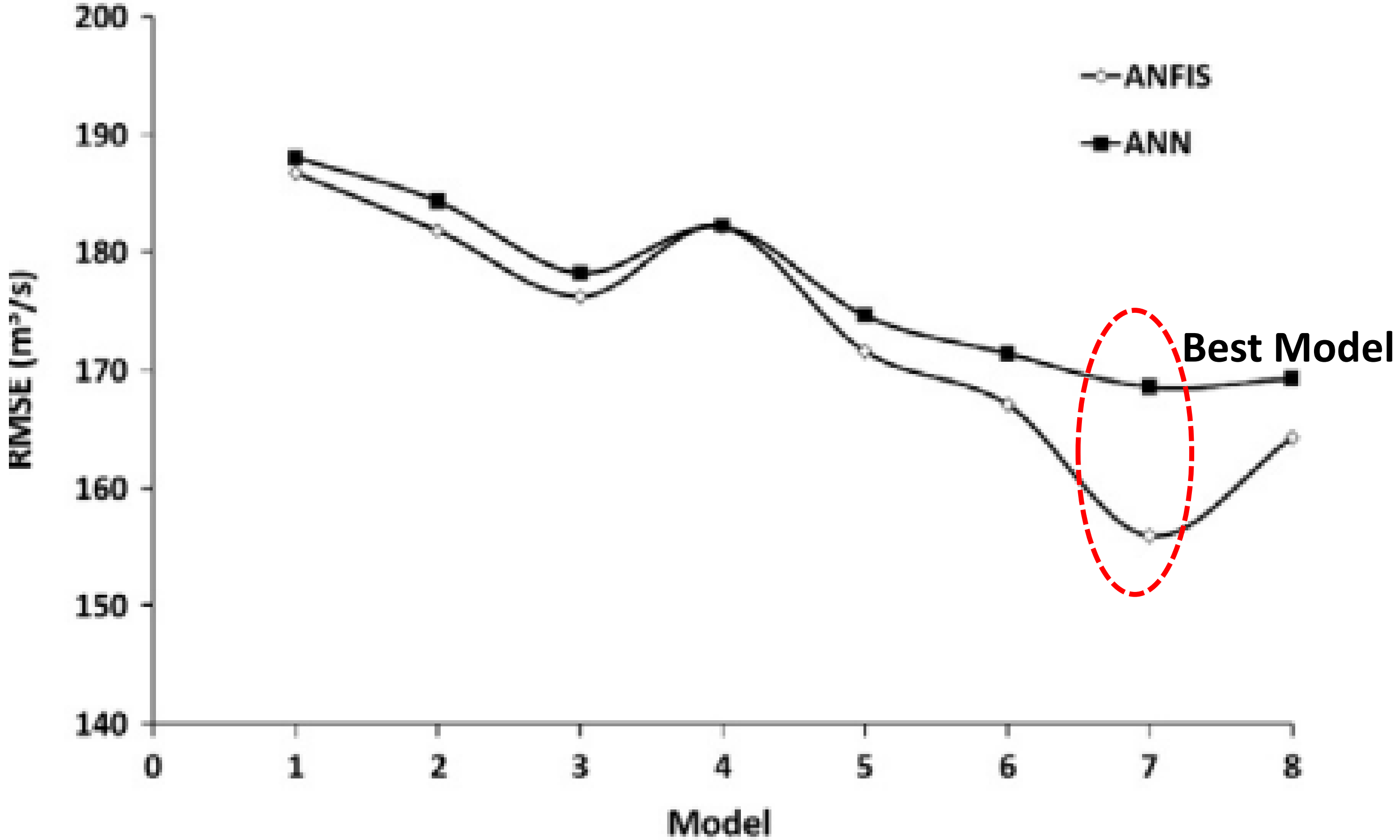
INCOLD
Indian National Committee on Large Dams

# INTERNATIONAL DAM SAFETY CONFERENCE

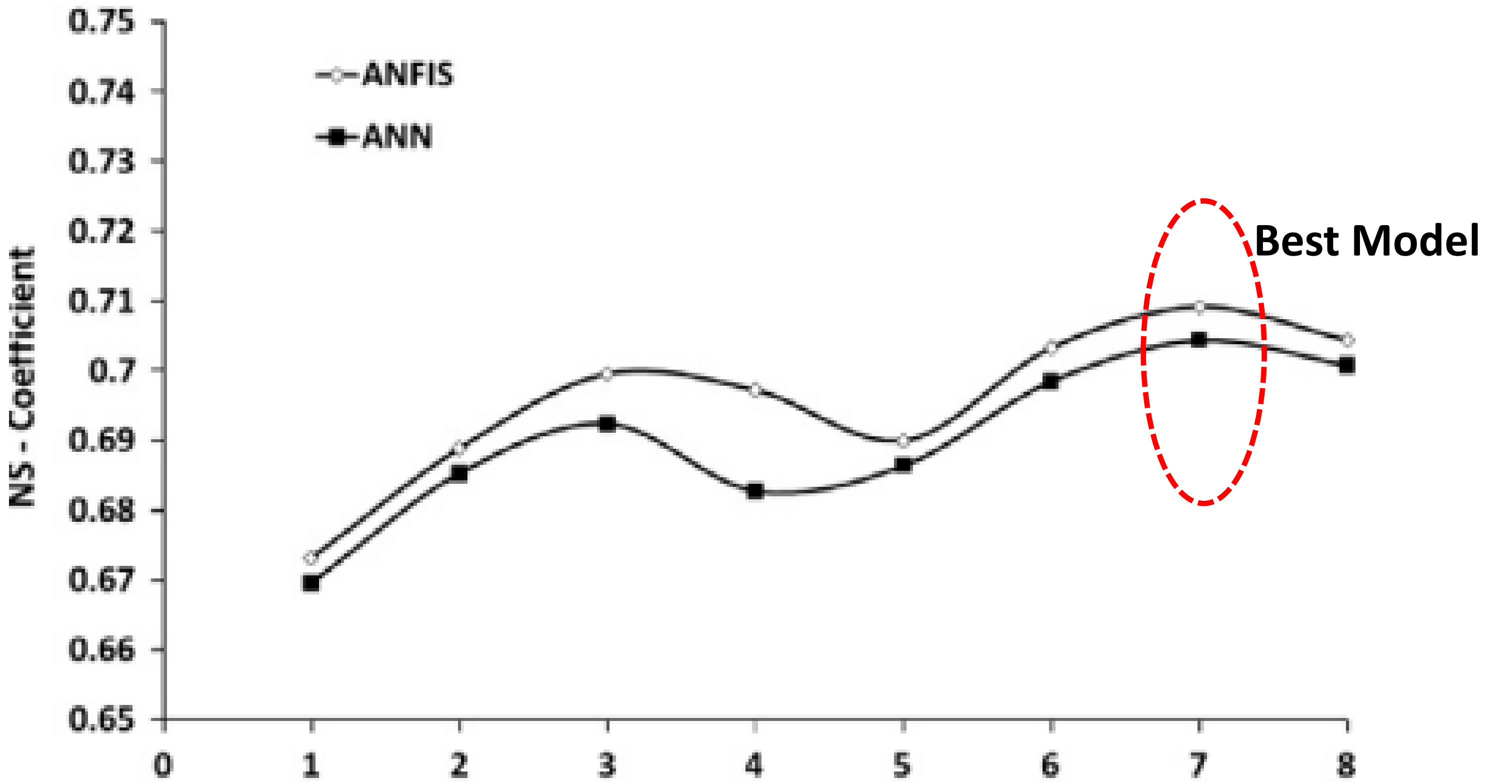
DRIP
Dam Rehabilitation & Improvement Project

Central Water Commission

## Comparison of RMSE of ANN and ANFIS models



# Comparison of NS-coefficient of ANN and ANFIS models



# CONCLUSION

- The ANFIS model outperforms both AR and ANN models to forecast inflows.
- ANFIS model also showed significantly higher accuracy in forecasting extreme inflow events compared to AR and ANN models.
- Inclusion of cyclic terms in the input data vector of ANN and ANFIS models further improves the forecasting accuracy.
- The ANFIS model can be used successfully in reservoir planning problems.